Efficient Measurement of Data Flow Enabling Communication-Aware Parallelisation

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ABSTRACT

As multicore chips scale to higher processor counts, communication between cores becomes more and more important. Indeed, when a single application is split up among multiple cores, which are connected through a relatively slow network, the amount of communication that is required will have an essential effect on performance. Therefore, if the application can be partitioned in such a way that communication between threads is minimised, or that placement on non-uniform networks can be performed with regards to communication, a significant performance boost can be obtained. But to do this effectively, communication streams inside the application must be known. In this paper, we introduce a profiling tool for Java that can measure data flows between methods. It constructs a communication graph, which combines a traditional call graph with data flow information.

The overhead of profiling is brought down by a factor of 15 through the use of reservoir sampling. We prove that this can be done with a limited decrease in accuracy.

This way, we can quickly estimate communication flows, which forms the critical information that allows an efficient communication-aware parallelisation to be made.

Categories and Subject Descriptors

D.4.8 [**Software Engineering**]: Performance—*measurements, simulation, stochastic analysis*

General Terms

Data-flow; profiling

1. INTRODUCTION

As multicore chips scale to higher processor counts, communication between cores becomes more and more important. On a typical multicore architecture one can distinguish several levels of communication, each with different performance characteristics: threads executed on the same core communicate by means of shared memory in an on-chip cache or in in an off-chip memory only reachable through the network; threads executed on different cores can only use the relatively slow network connection. This essential difference between internal and external communication as well as the amount of inter-thread communication have a crucial impact on the final performance when a single application is split up among multiple cores. Therefore, if the application can be partitioned in such a way that communication between threads is minimised, or that placement on non-uniform networks can be performed with regards to communication, a significant performance boost can be obtained. But to do this effectively, communication streams inside the application must be known.

In this paper, we introduce a profiling tool for Java that can measure data flows between methods. It constructs a communication graph, which combines a traditional call graph with data flow information. This combined view gives the programmer the basic information needed for the parallelisation process in which several methods in the application will be combined into threads: computational requirements, dependencies and data flow measurements.

Our main contribution is the communication graph: an extension of a call graph with information on the inherent communication flow in the application, defined in Section 2. The weights of each node in our communication graph indicate the required computational power for this method; this information is used by the programmer to constrain the number of nodes put together in a single thread. The edges of the call graph represent dependencies which will determine the possible scheduling of the application on multiple cores. New in our approach is the effectively measured amount of communication between methods. This additional information enables a truly communication-aware parallelisation.

The amount of communication within a program is independent of the implementation. Indeed, parallelisation does not change the inherent communication, it only influences the ratio of internal and external communication, which in turn, influences performance. Because of this implementation independence, we can measure the inherent communication during the execution of the program on a simple, single core processor.

In this paper we do this by profiling Java programs. Java is well-suited for program analysis and for profiling. The multi-threaded nature of the language offers the opportunity to model concurrent behaviour. This gives us the opportunity to not only profile the original single-threaded application, but to also profile the application after (or even during) the parallelisation process. This way the programmer can have direct feedback on the reduction in communication cost he has realised by appropriately parallising the application. Section 3 explains how Java programs are profiled in order to build the communication graph. It should be mentioned that although the work in this paper is implemented completely in Java, the underlying principles are portable to C as well. Changing the Java profiler to a native x86 profiling framework will do.

Profiling the Java program causes a huge increase in execution time due to the extensive bookkeeping: we have to keep track of every memory read or write. To reduce this overhead we implement reservoir sampling [5]. This sampling method enables communication estimation with a pre-specified accuracy and acceptable overhead. Section 4 introduces reservoir sampling and discusses its accuracy and practical limitations.

Our approach is evaluated on the SPECjvm98 benchmark suite [4]. Section 5 shows the most important properties of the resulting communication graphs. This section also shows how reservoir sampling could reduce the profiling overhead by a factor of 15 on average and we give experimental results for the obtained accuracy.

A comparison with related work is made in Section 6 and in Section 7, concluding remarks follow.

2. COMMUNICATION GRAPH

Within programs, data flows from producers to consumers. That is, some methods in a program calculate values and store them in memory, i.e. these methods produce the data. Other methods need to use this data and read it from memory. These methods are consumers. Each producer-consumer pair leads to communication in the final implementation. Therefore we will call this *inherent communication.* This communication will be measured and captured in a *communication graph.*

We assume that this inherent communication, available in the original program, will remain in the final implementation after parallelisation. Methods in the executable specification will be grouped into threads and mapped onto (different) cores on the multicore architecture, but as long as the underlying algorithm remains, the communication between methods will not change. Therefore our communication graph will be completely implementation independent. When the programmer changes the program, e.g. while performing specific optimisations in order to further reduce the communication, the initial assumption does not hold anymore and the communication graph has to be rebuilt.

2.1 Example

As an introduction, a simple example of a Java program and its communication graph is given in Figure 1. A rigorous definition follows in the next subsection.

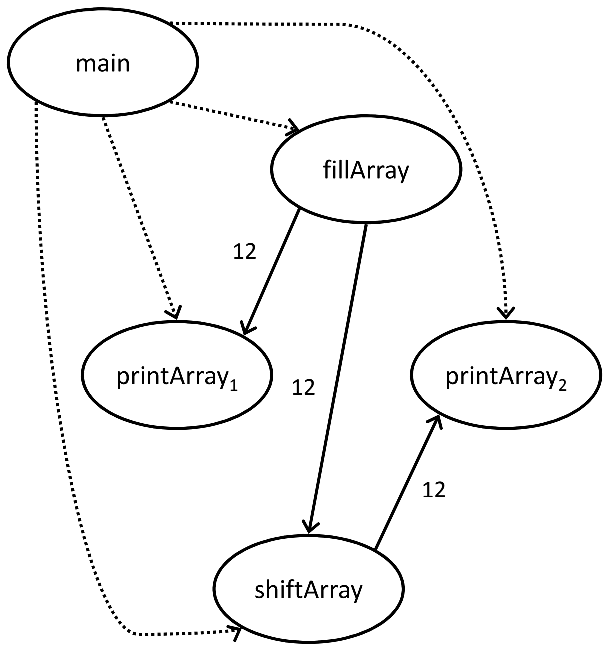
```
public class Example {
   public static void main(String[] args) {
      int array[] = new int[12];
      fillArray(array);
      printArray(array);
      shiftArray(array);
      printArray(array);
   }

   private static void fillArray(int[] array) {
      for (int i = 0; i < array.length; i++)
         array[i] = (i+1)*(i+1);
   }

   private static void printArray(int[] array) {
      System.out.print("array: ");
      for (int i = 0; i < array.length; i++)
         System.out.print(array[i] + " ");
      System.out.println();
   }

   private static void shiftArray(int[] array) {
      int temp = array[0];
      for (int i = 0; i < array.length-1; i++)
         array[i] = array[i+1];
      array[array.length-1] = temp;
   }
}
```

(a) Java code of class Example



(b) Communication graph (solid line) and the Call graph (dotted line)

```
array: 1 4 9 16 25 36 49 64 81 100 121 144
array: 4 9 16 25 36 49 64 81 100 121 144 1
```

(c) Console output

Figure 1: Java code and its communication graph.

The `main` method of the `Example` class creates an array of 12 integers, which is filled with $1, 4, 9, 16, \ldots$ by `fillArray`. When the `printArray` method is called for the first time to print these numbers to the console, method `printArray` consumes the values which were produced by method `fillArray`. This can be seen in the communication graph as a solid edge with label 12 from node *fillArray* to node $printArray_1$.

After filling and printing the array, `main` calls the `shiftArray` method to shift the values in the array. The shifted array is then printed by a second call of `printArray`. This makes method `shiftArray` a consumer of the values produced by `fillArray` and a producer for the new values used by the `printArray` method. The communication graph therefore contains two more solid edges: an edge from *fillArray* to *shiftArray* and another one from *shiftArray* to $printArray_2$.

It should be noticed that the two calls to method `printArray` are represented in the communication graph by two different nodes $printArray_1$ and $printArray_2$. As can be seen from Figure 1 (b), our communication graph also contains a call graph. Edges of the call graph are represented as dotted lines.

2.2 Communication Graph

The communication graph G is a directed graph, defined by a set of nodes V and two sets of directed edges: E_1 and E_2.

The vertices in V represent *communicating partners*. These communicating partners are producers and/or consumers of data. They form the finest granularity for our profiling. In the previous example, each method invocation introduced a new communicating partner in the graph G. Sometimes a coarser view of the execution is more appropriate. Several alternatives for grouping producers and consumers into communicating partners will be discussed in the next subsection.

The edges in set E_1 are weighted edges. These edges represent the amount of data flowing between two communicating partners, measured in bytes of the complete the runtime of the application. The non-weighted edges in E_2 represent the call graph of the program. Each edge points from a caller to a callee.

In this paper we present a methodology to build the communication graph during the execution of a program. It should be mentioned that this graph is a representation of the communication during this specific execution. For non-deterministic programs the result may vary from execution to execution.

This definition of a communication graph, brings us to a definition of producer-consumer pair. A pair of communicating partners (p, c) is a producer-consumer pair when: the producer p has written some data d in memory and later on the consumer c had read this same data d without any other communicating partner has written to d in between the production and the consumption.

This definition is useful for single-threaded applications as well as for multi-threaded applications in which the producer and the consumer might be in different threads.

2.3 Practical Considerations

The communication graph is built by analysing the execution of a Java program. In Java the producers and consumers of data are individual bytecode instructions, which are interpreted by the Java Virtual Machine. This enables us to measure local data flow between these bytecodes. This local information is neglected nevertheless, because global data flow between methods is more important for parallelisation than local data flow.

In order to capture global data flow in the communication graph, we decided to consider methods as the finest granularity for the profiling. This means that one communicating partner surveys information about the data production and consumption of one invocation of a certain method. For small programs, as the above example, this may be a good choice, but for larger programs this granularity is too fine and this results in an unmanageable number of nodes. The number of method invocations in the programs of the SPECjvm98 benchmark suite can be found in Table 1.

To keep the communication graph manageable, we have to raise the abstraction level by reducing the number of nodes. This is done by grouping several nodes into bigger nodes. For this grouping we implemented various alternatives that are based on one of the following important properties of the Java language.

Hierarchy Java programs inherently have a hierarchical structure. Methods are declared within classes, which are part of packages. These abstraction levels can be used by our profiler too. As explained earlier the finest level is that where individual method invocations have their own node in the communication graph. At the method level, all invocations of the same method are grouped in one communicating partner. At class level even all methods declared in the same class are grouped. The abstraction can be raised further by grouping all methods declared in the same package. The resulting number of nodes in the entire communication graph for these three abstraction levels (method-level, class-level and package-level) is shown in Table 1.

Call Tree Apart from the statical grouping using the Java class hierarchy, our profiler can also perform a dynamic grouping of nodes based on the call graph. Instead of creating a new node in the communication graph for each invocation of every method, the call tree mode of our profiler will group all method invocation with the same call stack in a single node.

Concurrency Java can express concurrent behaviour by implementing parallel threads. Our profiler is initially meant for profiling single-threaded applications, but it can also measure communication between different threads. Each thread is then considered as a communicating partner and has thus its own node in the communication graph. This gives us the opportunity to profile the application after (or even during) the parallelisation process. This way the programmer can have direct feedback on the reduction in communication

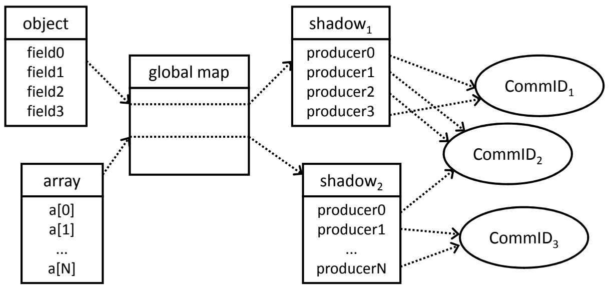


Figure 2: Objects and the corresponding shadow objects.

> cost realised by performing communication-related optimisations. Since the SPECjvm98 benchmark is single-threaded, this way of grouping is not included in Table 1.

It is also possible to extend these possible granularity levels to loop-level profiling where individual loops can be treated as communicating partners. Although it is a logical extensions, this loop-level profiling is not yet implemented.

3. PROFILING THE JAVA PROGRAM

3.1 Basic Idea

We want to build the graph defined in the previous section while running a Java program. We do this by instrumenting the Java code in order to capture every single read or write operation and to perform special actions to build the graph.

The basic idea of our approach is that every data field for each object in the Java heap memory is annotated with a reference to the communicating partner which has written the current value of this field. Whenever a read operation occurs in the program (consumption of data) we need to add an edge in the communication graph. This edge connects the communicating partners of the producer and the consumer of the data. The consumer apparently is the method which performed the read operation; the producers can be quickly identified by means of the last-writer information which was annotated when the field was written.

Note that this approach requires us to instrument every write operation which causes a huge overhead in execution time. The annotations of the last writer to each data field in memory causes an overhead in memory consumption.

3.2 Data Structures Used for Profiling

Two important data structures are introduced to enable this profiling. First, there is `CommID` objects representing communicating partners. Secondly, for each object or array in the Java Virtual Machine (JVM), a `Shadow` object is created. These shadow objects contain information about the producers of the data in every field in the object or every index in the array.

Figure 2 shows a concrete example with an object and an array. As can be seen in this figure, the profiler maintains a global map, which maps object or array references to their corresponding shadow object. Every field in the shadow object links to a communicating partner represented by its `CommID` object.

It should be mentioned that this `CommID` objects are also used as nodes in the final communication graph.

3.3 Instrumentation

In order to perform the profiling, special instrumentation code has to be inserted in the original Java program. We are instrumenting the Java code at runtime, which enables us to instrument the Java program as well as all standard libraries used by this program. This is an important advantage because methods in the standard libraries are responsible for a significant fraction of the total communication in the system.

Moreover our instrumentation is targeted directly on the Java bytecode, the lowest abstraction level within the JVM. Therefore not a single byte of communication in the program, is hidden for our profiler. Notwithstanding the low abstraction level, the Java bytecode still contains the high level structure of the program as well as type information for the data that is used.

4. RESERVOIR SAMPLING

Every producer-consumer pair in the program has to be analysed by our profiler. Due to the large number of read and write operations this causes a huge overhead in execution time as well as in memory consumption. By reducing the amount of producer-consumer pairs to be analysed, the overhead can be reduced considerably.

A read operation in the program directly leads to a producer-consumer pair. The aim of the sampling method is thus to select a limited number of read operations to be taken into account for building the communication graph with an acceptable accuracy. In this paper we propose to apply reservoir sampling [5] to achieve this aim. Section 4.1 explains the general principle of reservoir sampling as well as some important properties of this technique.

Although sampling reduces the overhead, it results in errors in the communication graph. Through the fact that reservoir sampling selects a uniform random sample of producer-consumer pairs in the program, we can guarantee the error to be within a specified confidence interval. A statistical discussion is given in Section 4.2.

4.1 The Principle of Reservoir Sampling

The aim of reservoir sampling is to reduce the amount of measurement data by randomly selecting a limited number of samples from the original set, without the need to know the size of the data set beforehand.

Reservoir sampling works as follows: initially, the first n samples of the original set are placed in the reservoir. Starting from sample $n+1$ every sample is evaluated one at a time. A random decision is made whether or not to add this sample m to the reservoir. If so, a random sample $0 \leqslant a < n$ is chosen from the reservoir and this sample a is replaced by sample m. This algorithm leads to a set of exactly n

Table 1: Number of nodes in the communication graph, for different levels of hierarchical grouping.

benchmark	method invocations	method-level	class-level	package-level
201-compress	225,989,456	804	209	27
202-jess	134,689,951	1242	335	123
205-raytrace	307,946,068	952	226	28
209-db	75,641,171	818	202	27
213-javac	120,091,066	1591	341	27
228-jack	65,609,073	1048	247	27

samples, independent of the size of the data set. It can be proven [5] that these n samples form a uniform and random sample set.

In the beginning most records are selected to be stored in the reservoir, but as the algorithm continues, more and more records are skipped, i.e. the probability of a record to be put in the reservoir decreases during the run of the algorithm. We implemented an extension to the basic principle, algorithm L described in [2]. Instead of randomly deciding, for each record individually, whether it should be added to the reservoir, algorithm L directly makes a random decision of the number of records to be skipped each time a record is selected. This enables speeding up the reservoir sampling process without sacrificing the statistical properties. Indeed, Li [2] proves that the probability distribution of algorithm L is the same as the original algorithm.

4.2 Statistical Discussion

The most important advantage of reservoir sampling over other techniques, is the fact that it provides a uniform random sample set. This allows following analysis.

The aim of our profiling is to estimate the amount of data flowing over every edge in the communication graph. In the non sampled version we can obtain absolute values, for the sampled version we want to estimate the relative importance of each edge, the fraction of the total communication which is going over this edge.

Let F_e be the fraction of communication going over edge e. This fraction can be calculated as f/N, where f is the total number of producer-consumer relations on this edge e and N is the total number of producer-consumer relations in the complete communication graph G. The estimation $\hat{F}_e$ of F_e will be calculated as c/n, where c is the number of producer-consumer pairs on edge e in the sample set with size n.

According to [6] the large sample confidence interval for $\hat{F}_e$ is given by

$$\hat{F}_e \pm z_{\alpha/2}\frac{s}{\sqrt{n}}, \tag{1}$$

where s is the sample standard deviation. The sample variance s^2 can be computed as

$$s^2 = \frac{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2}{n(n-1)}. \tag{2}$$

In our case x_i are either 1 (producer-consumer relation is on edge e) or 0 (producer-consumer relation is on another edge). Therefore our sample variance s^2 can be written as

$$s^2 = \frac{nc - c^2}{n(n-1)}, \tag{3}$$

which makes that

$$\frac{s}{\sqrt{n}} = \sqrt{\frac{(c/n)(1-c/n)}{n-1}} = \sqrt{\frac{\hat{F}_e(1-\hat{F}_e)}{n-1}}. \tag{4}$$

The expected relative error r for a given $\alpha\%$ confidence interval can be defined as

$$r = z_{\alpha/2}\sqrt{\frac{\hat{F}_e(1-\hat{F}_e)}{n-1}}/\hat{F}_e. \tag{5}$$

This expression can be rearranged in order to calculate the number of samples n necessary to obtain a given relative error r, for an expected accuracy F_e. This results in:

$$n \geqslant z_{\alpha/2}\frac{1-F_e}{r^2 F_e}. \tag{6}$$

The following particular example illustrates this approach. In order to obtain, with 95% probability ($z_{\alpha/2} = 1.96$), an estimation that is accurate to within 5%, of the bandwidth for edges, representing a fraction of at least 0.1% of the total communication graph ($F_e \geqslant 0.1\%$), we need at least 1,535,048 samples.

It should be mentioned that this statistical discussion only covers important bandwidths in the system. Communication over edges representing smaller bandwidths ($F_e < 0.1\%$) can only be estimated accurately when all producer-consumer pairs are taken into account. A sampled approach, reservoir sampling or any other sampling technique, cannot guarantee any accuracy at all for such small bandwidths. However, small bandwidths barely influence the communication cost so this approximation should have no effect on the overall system performance.

5. RESULTS

We evaluated our approach with the SPECjvm98 benchmark suite. The six programs were run on an Opteron 242 with clock frequency 1.6 GHz and 4 GiB RAM memory.

In our first experiment we measured the communication graph for the SPECjvm98 programs. We did a full profiling with the finest granularity, i.e. every method invocation was measured separately. Table 1 illustrates the extensiveness of the resulting communication graphs.

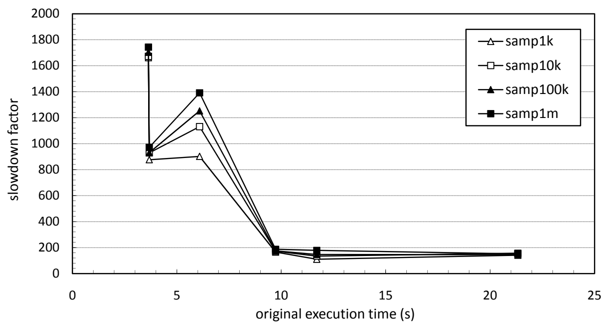


Figure 3: Relative slowdown factor in function of the original execution time

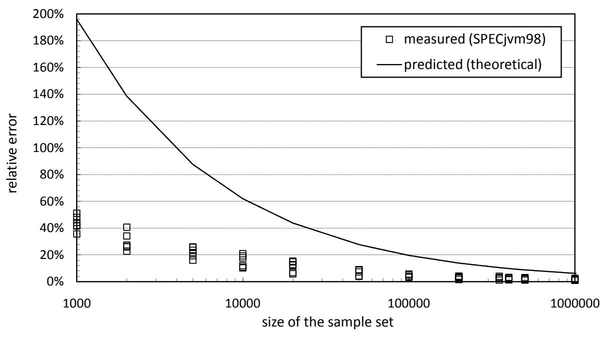


Figure 4: Relative error in function of the size of the sample set.

In a second experiment we used reservoir sampling for profiling the same communication graphs. We found that reservoir sampling can drastically reduce the overhead in execution time for the profiling: a reduction by factor of 15 on average. These results are shown in Table 2. Column *original* in this table gives the original execution time for running the benchmarks. Column *instr* shows the overhead introduced by the instrumentation framework, this is a relative factor. For these instrumentation overhead results a Java agent was written that intercepts all classes, interpretes the bytecodes with ASM, and reassembles the classes without modification. The relative overhead in execution time for a full, non-sampled profiling is presented in the fourth column *full*. The next columns show the relative overhead for the reservoir sampled approach with different reservoir sizes: from 1000 samples in column *samp1k* up to 1 million samples in column *samp1m*.

Table 3 presents absolute figures for the total average memory use of the original execution of the benchmarks. Relative figures are included for the overhead introduced by the instrumentation, for the full profiling as well as for the reservoir sampled approach.

The sampled approach reduces the overhead drastically. The sampling overhead decreases as the program runs longer. Because each of the six benchmark programs has a different execution time, we can plot the slowdown factor in function of the original execution time in Figure 3. We did this for four different sizes of the sampling reservoir. The outlier in this graph is the program 202-jess which has relatively more memory read/write operations than the other programs in the benchmark suite. Because of this, 202-jess benefits more from the ever increasing number of samples that can be skipped in the reservoir sampling algorithm.

To conclude this section, we evaluated the accuracy of this sampling method. Figure 4 compares the measured relative error (MRE) on the communication graph with the predicted relative error obtained in Section 4.2. This measured relative error is defined as

$$\mathrm{MRE} = \sqrt{\frac{1}{M}\sum_{i=1}^{M}\frac{\hat{F}_{e,i} - \hat{F}_{e,i}}{F_{e,i}}}$$

^{2}, (7)where $F_{e,i}$ is the actual relative weight of edge i in the communication graph G, $\hat{F}_{e,i}$ is the estimated relative weight of edge i in the sampled graph. Only the M most important edges where $_{e,i} > 0.1\%$ are taken into account in this equation.

This comparison proves that the predicted accuracy is also achieved in practice. The solid curve in this figure presents the predicted error for a 95% confidence interval, for bandwidths representing more than 0.1% of the total bandwidth in the full communication graph. This explains the noticeable gap between the measured errors and the predicted error. Most edges in the communication graph represent more than 0.1% of the total bandwidth and therefore they can be estimated more accurately.

6. RELATED WORK

This section presents other graphs representing data flow in a program. Some of these represent a static view of the program, others depict information on the dynamic behaviour of the program. This distinction is crucial as it determines the possible use of the graphs.

Static Data Flow Graphs (SDFG), for instance, allow compilers to statically analyse data dependencies between statements in a code fragment. This static analysis enables the compiler to make sound decisions on, among other, the register allocation and optimisation. For concurrent Java code the Multithreaded Dependence Graph (MDG), an extension of the SDFG, is introduced by Zhao who used the MDG for program slicing [7]. Although SDFGs could possibly be used for parallelisation, they lack dynamic information on communication streams in the application, in contrast to our communication graph which truly facilitates communication-aware parallelisation.

Nethercote and Mycroft presented Redux [3], a profiling tool that builds a dynamic data flow graph while running a program. This is similar to our communication graph, but it differs in the abstraction level: Redux measures data flow on a low abstraction level, namely between individual x86 assembly instructions. For communication estimation in the context of parallelisation, our intention, measuring at a higher abstraction level is more useful: the use of Java enables us to capture high level type information for the edges in the communication graph. This is impossible for Redux as this

Table 2: Overhead in execution time for SPECjvm98 benchmark programs

benchmark	original	instr	full	samp1k	samp10k	samp100k	samp1m
201-compress	7.22 s	3.20x	24,692x	902x	1131x	1252x	1391x
202-jess	3.79 s	12.14x	6,432x	876x	929x	930x	971x
205-raytrace	3.62 s	4.48x	8,691x	1,662x	1,672x	1,703x	1,743x
209-db	13.51 s	2.12x	2,204x	165x	173x	174x	187x
213-javac	22.94 s	1.69x	919x	141x	156x	145x	150x
228-jack	14.15 s	2.59x	857x	110x	134x	146x	178x

Table 3: Overhead in memory use for SPECjvm98 benchmark programs

benchmark	original	instr	full	samp1k	samp10k	samp100k	samp1m
201-compress	8,8 MiB	0.85x	8.16x	11.55x	10.51x	15.91x	21.42x
202-jess	10.1 MiB	0.89x	5.33x	33.72x	35.24x	35.83x	35.28x
205-raytrace	6.7 MiB	1.31x	13.77x	79.29x	75.08x	63.78x	69.63x
209-db	8.4 MiB	0.95x	14.68x	19.09x	12.31x	18.16x	25.51x
213-javac	8.1 MiB	1.10x	13.79x	50.72x	46.78x	50.14x	45.41x
228-jack	4.7 MiB	1.68x	10.59x	27.78x	29.37x	29.51x	36.93x

information is lost after compilation to x86 assembly. Another difference between Redux and our profiler, is the fact that we are able to handle library functions as well.

The ATOMIUM profiling tool described in [1], is used to measure bandwidths to arrays. This information is used to explore a custom memory hierarchy for the system. ATOMIUM works on x86 Linux programs; the target implementation is an embedded system. Although this is similar to our profiler, there is a fundamental difference: the ATOMIUM tools measure communication to memories but loose all information about the concrete relation between producing and consuming methods which are communication through these memories. This makes our communication graph more general: from our graph we can deduct all information contained in the ATOMIUM data flow graphs…

7. CONCLUSIONS

On current multicore and future manycore platforms, the amount of inter-core communication that is required by an application will have an essential impact on the overall performance of the system. Communication-aware parallelisation is necessary in order to minimise the communication overhead.

In this paper we have proposed the communication graph as a valuable instrument which can help the programmer to perform such a communication-aware parallelisation. We have introduced a profiling tool for Java that can measure communication streams between methods. Our profiler constructs the proposed communication graph, which combines a traditional call graph with data flow information. Experimental results show that such a communication graph is huge for real-world applications. We proposed several techniques for grouping nodes in this graph to make it smaller and therefore more comprehensible.

Profiling Java programs in order to construct the communication graph incurs an overhead in execution time. We successfully brought down this overhead by a factor of 15 through the use of reservoir sampling. Moreover we could statistically prove that this can be done with a limited decrease in accuracy.

This way, we can quickly estimate communication flows, which forms the critical information that allows an efficient communication-aware parallelisation to be made.

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