The Flexible Preconditions Model for Macro-Dataflow Execution

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***Abstract*—In this paper, we propose the *flexible preconditions* model for macro-dataflow execution. Our approach unifies two current approaches for managing task dependences, *eager execution* vs. *strict preconditions*. When one of the two outperforms the other, flexible preconditions can always attain, and possibly surpass, the performance of the better approach.**

This work focuses on the performance of parallel programming models based on *macro-dataflow*, in which applications are composed of tasks and inter-task dependences. Data-flow models usually make a choice between specifying the task dependences before task creation (as strict preconditions), or during task execution, when they are actually needed (eager execution). This paper shows how the choice between eager execution and strict preconditions affects the performance, memory consumption and expressiveness of macro-dataflow applications.

The flexible preconditions model is sufficiently flexible to support both eager execution and strict preconditions, as well as hybrid combinations thereof. This capability enables programmers and future auto-tuning systems to pick the precondition combination that yields the best performance for a given application. The experimental evaluation was performed on a 32-core SMP, and is based on a new macro-dataflow implementation, QtCnC, that supports eager execution, strict preconditions and flexible preconditions in a single framework. (QtCnC is an implementation of the CnC model on the QThreads library.) For applications where all dependences are known ahead of time, flexible and strict preconditions execute up to 56% faster than eager execution (for the benchmarks and platform used in our study). On the other hand, for applications where the complete set of per-task dependences is determined after the tasks are spawned, flexible preconditions and eager execution perform up to 38% better than strict preconditions.

I. Introduction

Many programming models typically limit the available parallelism to that exploitable from domain decomposition. In contrast, the dataflow model [1] is capable of exposing far greater levels of parallelism across statements, loops and procedures. Macro-dataflow models [2], [3] further extend this promise by supporting dataflow tasks expressed at granularities suitable for modern machines.

Macro-dataflow models usually consist of parallel tasks and some mechanisms for dataflow communication and synchronization among them. When implemented for multicore architectures, macro-dataflow models usually rely on a threading library (such as Pthreads, used in TFlux [4]), a task library (such as Intel Threading Building Blocks, used in Intel Concurrent Collections [5]) or a language that can express parallelism (such as Cilk, used in Nabbit [6] or Habanero Java [7], and Habanero-C [8] used in Habanero Concurrent Collections [5]).

The schedulers used in many of these models are work stealing schedulers [9] that offer good load balancing and theoretical time and space bounds for fork-join parallelism [10]. However, using these schedulers for macro-dataflow programs can be sub-optimal because unoptimized implementations of the dataflow model can easily overwhelm the resources of the machine [11].

The solution we propose consists of a new model — flexible preconditions — that generally matches the performance of the better of the two most widely used approaches for macro-dataflow execution, even though each performs better on specific types of applications. We present a performance evaluation of these approaches and flexible preconditions. We show when each of the previous models is better than the other and explain why flexible-preconditions can perform as well as the better of them in each case.

The rest of the paper is organized as follows. Section II summarizes past approaches for eager execution and strict preconditions. Section III introduces the flexible preconditions model. Sections IV and V present the design and implementation of the flexible preconditions model in the QtCnC framework. Section VI discusses experimental results for a set of dataflow benchmarks, and Section VII contains our conclusions.

II. Background

The active parallelism and resource usage in a macro-dataflow program execution is determined by the precise timing of task creation in the scheduler. Tasks that are not yet expressed to the scheduler consume no resources other than the space needed to store the task closure. The task spawning mechanisms of a given dataflow implementation determine the costs and trade-offs involved, which in turn affects the performance tuning of a dataflow program. The following subsections describe two common approaches used in today's data-flow task schedulers.

A. Eager execution

The first option is to use an eager approach, in which tasks are spawned as soon as the necessity for them is recognized, independent of whether their dataflow dependences are available.

[1]This work was done while the author was employed by Sandia National Laboratories.

The tasks optimistically start executing, but may have to wait if their dataflow dependences are unavailable when needed. For thread-pool based schedulers (which include work-sharing and work-stealing policies [9], [12]), eager implementations must provide a mechanism for worker threads to recover from missing dependences and continue executing other work. This mechanism may span the range from blocking on the missing dependence to deferring the execution of the remainder of the task via a continuation or re-execution.

The main advantage of the eager model is that it is easy to understand and offers full flexibility for describing applications. Another advantage is that, if a task starts with a computation that doesn't require dataflow dependences (or needs only some of them), that part of the task can execute without waiting for all input data to be produced. Such an example is an AND-reduction, where an eagerly spawned task may be able to finish execution using only a few of the inputs available, without the need to wait for all data to become ready.

A common problem with eager task creation approaches is that the memory and other resources needed by the tasks to execute must be allocated as soon as the task is produced, and may not be released when the task is deferred. This resource allocation puts pressure on the memory and runtime systems.

B. Strict preconditions

An alternative to eager spawning is to use the strict preconditions model in which tasks are spawned only when all their dataflow dependences are satisfied. We call this approach *strict preconditions* because the availability of inputs becomes a precondition to running tasks, while *strict* refers to the fact that *all* input data must be available before a task starts executing.

For this approach, dependences must be known a priori; this restricts the expressiveness of the programming model and has implications on the API exposed to the user. For example, *optional* or *data-dependent inputs* are usually forbidden with strict preconditions, and have to be implemented by spawning data-dependent continuations as new tasks. Applications that rely on short-circuit reduction as a performance optimization may not be expressible in this model. Additionally, these models need a model to determine when all a task's inputs are available these models need a mechanism to determine when a task is ready to be scheduled. For example, this support can be provided [3], [6] by maintaining one task-descriptor per task, each with an *atomic counter* whose value decreases when each dependence is satisfied. When the counter reaches zero, the corresponding task can safely be spawned. These counter decrements are a source of overhead and possible contention. Strict preconditions offer better performance than eager execution if the overhead of deferring and re-executing tasks in the eager runtime is larger than that of this atomic-counter based synchronization.

A second advantage is that, since all inputs are known to be available, data can be accessed without the possibility of blocking during task execution, thus avoiding the synchronization overhead for accessing those inputs. Another argument for using strict preconditions is its lower memory consumption. With all inputs known a priori, tasks can never suspend and, as a result, there is no additional memory requirement to save their intermediate state.

C. Dependency handling in previous work

This section surveys existing projects and shows that each model chooses either eager execution or strict preconditions. Some projects make the choice depending on project specific goals (such as the need to support heterogeneous CPU+accelerator execution [8], [13]), but each model has its own advantages and disadvantages which makes them perform better on different classes of applications. One of the goals of this paper is to shine light on the performance and memory implications of the choice between the two, so that future projects can make a more informed decision.

Many models that evolved from task parallelism as opposed to dataflow tend to prefer eager semantics for task creation [10]. For example, both versions of Nabbit (for static and dynamic graphs, respectively) [6] use eager task creation. TFLux [4] also uses eager task creation. For this reason neither of these systems need to know the dependences of a task at task creation time. In contrast, the SMPSs [14] and Habanero data-driven-task [3] models both use strict preconditions resulting in a straightforward API for specifying preconditions. (One difference between the two is that SMPSs requires that a default sequential execution be provided, but the Habanero DDT model does not have that constraint.) Kaapi [15] is another model which opts for strict preconditions, proposing a model suitable for cluster execution as well; it builds upon Athapascan [16] which takes the same approach.

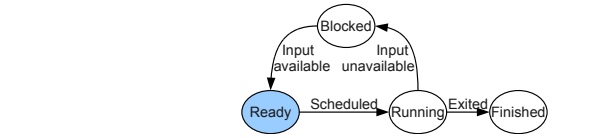
The Intel Concurrent Collections (CnC) implementation [5] offers both an eager approach and a preconditions based approach using the abort-and-restart mechanism. An alternative implementation of the CnC model, CnC-HJ [17], allows the programmer to pick between eager task creation (with different runtimes supporting continuations, blocking and abort-and-restart) and strict preconditions. CnC-HC [8] takes a similar approach by offering two alternative runtimes (strict preconditions and eager task creation), but also targets heterogeneous platforms. CnC-HC motivates the need for strict preconditions for heterogeneous computing by showing that, for GPUs, the high cost of communication can be made more efficient by grouping all dataflow dependences in a single data transfer performed before the task is started.

III. Flexible preconditions

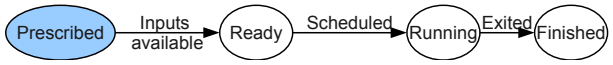
We propose the *flexible preconditions model* which is a combination of the eager task creation and the strict preconditions models: tasks do not start until the items listed as preconditions are available, but are able to wait for additional dataflow inputs that are identified during task execution. This results in behavior identical to the eager model if the preconditions list is empty and identical to the strict model when the list includes all dataflow dependences. It also opens up the possibility of supporting a wide set of intermediate behaviors not covered by either model.

In the flexible preconditions model, tasks go through the following states:

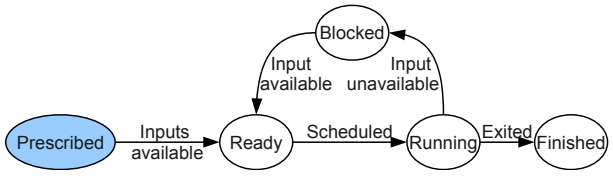
prescribed tasks are those whose creation has been requested but whose preconditions are not yet satisfied.



(a) Eager



(b) Strict Preconditions



(c) Flexible Preconditions

Fig. 1: State transition diagrams for the eager, strict and flexible preconditions models. Initial states are in bold.

ready tasks are those whose preconditions are satisfied, but have not yet been scheduled to run.

running tasks are those currently executing.

blocked tasks are those that have previously been running and have attempted to read an input that was not listed as a precondition and that input was not available.

finished tasks are those that have completed execution.

The state transition diagram in Figure 1 visually compares the flexible preconditions model (Figure 1c) with eager task creation (Figure 1a) and strict preconditions (Figure 1b). The extra state that the flexible model has compared to the eager model is the prescribed state, in which tasks are waiting for preconditions. Strict preconditions do not have a blocked state as tasks never need to wait.

We will use an AND-reduction example to illustrate the flexible preconditions model. This example is a fragment of an image processing application, in which an input image is split into multiple tiles indexed by iteration-number and tile-id. Tiles are updated independently by different tasks which produce new tiles used in the next iteration of the algorithm. Then, a reduction task checks if all tiles pass a convergence condition. If a tile is found that does not respect the condition, a new iteration is started. When such an input tile is found, any other tiles not tested need not be read. This access pattern is typical for AND-reductions. The pseudo-code for the reduction task is shown in Listing 1. The main program (Listing 2) for the AND-reduction creates the initial set of tiles and starts the first reduction task (line 4). In the pseudo-code, calls to `get` perform reads of dataflow dependences, while `put` calls produce them. The behavior of these access functions will vary depending on the macro-dataflow execution model used.

In an eager implementation, any instance of the `get` call on line 4 of Listing 1 may block waiting for the tile parameter to be produced by `UpdateTileTask`. When the `UpdateTileTask` instance performs a `put` on that tile, the reduction task will become unblocked and continue execution until it blocks again on another unavailable tile.

Getting strict precondition behavior requires the user to write additional code, such as in the pseudocode in

```
1 function ReductionTask(iteration)
2   i = 0
3   boolVar = false
4   while( !boolVar )
5     crtTile =  get( tile [iteration, i] )
6     boolVar = ConvergenceCheck(crtTile)
7     i = i + 1
8     if(boolVar)
9       spawn new ReductionTask(iteration+1)
10      for i from 0 to N
11        spawn new UpdateTileTask([iteration,i])
```

Listing 1: Pseudocode for AND reduction for eager execution

```
1   iteration = 0;
2   for i from 0 to N
3       put ( tile [iteration, i] )
4   spawn new ReductionTask(iteration)
```

Listing 2: Pseudocode for starting the execution of an AND-Reduction

Listing 3. The function `declare-get`, once called from `ReductionTask-dependences(iteration)` registers the value of its parameter as a dataflow dependence for the `ReductionTask` with the same iteration number. Notice that all the tiles that could possibly be accessed by the `ReductionTask` are marked as dependences - this is a requirement of the strict preconditions model. Strict tasks will only be spawned when all the dependences (tiles 1 to N of each iteration) have been `put`. If a task only reads a few tiles, waiting on all of them to be produced would lead to unnecessarily delaying the start of the next iteration and performance degradation.

The flexible preconditions model enables a partial specification of preconditions, so that the choice of which tiles are required can be made by taking advantage of the programmer's knowledge about the application. Ideally we want to list as preconditions only the last items to be produced that will definitely be needed by the task. This minimizes the overhead of managing the preconditions by minimizing their number and does not introduce artificial latency by waiting for unneeded items. In general though, because of parallelism, there is no single dataflow dependence guaranteed to be the last one to be produced in any possible schedule. These problems make choosing an efficient preconditions list challenging. For our AND-reduction example, all instances of `ReductionTask` will read `tile[iteration, 0]`, so having only this tile as a precondition will not lead to any artificial delays (as opposed to the strict preconditions model) and also decreases the management overhead for the preconditions list from N to 1. Let us look now at how flexible preconditions compares to the eager approach. By specifying a subset of dataflow dependences as preconditions we decrease the maximum number of blocking operations required for task execution because the task will not need to block on the inputs listed as preconditions. From a memory consumption point of view, we are able to postpone

```
1 function  ReductionTask-dependences(iteration)
2       for i from 0 to N
3             declare-get( tile [iteration, i] )
```

Listing 3: Pseudocode for specification of preconditions for AND-reduction in the strict preconditions model

the allocation of task memory by keeping the task in the prescribed state as opposed to marking it as ready from the start. In the AND-reduction application, the eager execution will allocate memory before `tile[iteration, 0]`s is available; flexible preconditions (with the `tile[iteration, 0]` as precondition) may still need to block, but only for tiles 1 to N, so the wait for `tile[iteration, 0]` will be done without unnecessarily consuming memory.

As most data-flow models have an implementation similar to the pseudocode presented here, we note that the task code from Listing 1 remains unchanged in the flexible preconditions implementation, making it straight-forward to port eager/strict applications to the flexible preconditions model.

Flexible preconditions are useful for several types of applications. In these applications a partial specification of the dependences can be used to choose between the behavior of either eager task creation or strict preconditions, depending on which performs best for each application. In addition, the use of flexible preconditions opens up a number of intermediate behaviors to pick from; if one model is better for performance and the other is better for memory we may need a balanced choice between the two. We give examples, results, and discuss characteristics of these applications in Section VI.

IV. QtCnC Design

To compare the flexible preconditions model with the eager task creation and strict preconditions we needed a runtime framework that would subsume all three approaches. We chose to extend an existing macro-dataflow model called Concurrent Collections (CnC) [5]. The main reasons for choosing CnC is its generality (it does not specify the behavior as corresponding to either the strict or the eager models) and the ease of separating the specification of the preconditions from the task logic. Our implementation of CnC is a C++ library built on the Qthreads [18] runtime, similar in interface to the Intel CnC distribution [19]. The following two subsections give an overview of the CnC model and of the additions we propose to support the three macro-dataflow models.

A. The Concurrent Collections Model

CnC applications consist of collections which encapsulate tasks (step collections), control of tasks (control collections) and values (item collections) [5]. Item collections enable communication among tasks. They can be thought of as repositories for dynamic-single-assignment values that are indexed by `key`s. For example, to perform a read of a value from item collection `ic`, given its key [it, i], one would use `ic.get([it, i])`; to produce that value, another task will need to perform a `put` operation: `ic.put([it, i], new Tile(...))`.

The CnC runtime has two main responsibilities:

- enforcing the dynamic single assignment rule by throwing a runtime error if two different `put` operations are performed on the same item collection with the same `key`. This ensures datarace-freedom for CnC programs.
- implementing the dataflow dependences between items and tasks. If a task performs a `get` on an item with a particular `key`, that task will not proceed until the item with that `key` has been produced. This makes CnC programs deterministic by default.

```
1 int Reduce::execute(const int & it, ... ) {
2   for(int k = 0; k < N ; k++) {
3     Tile *crt;
4     tile_item_collection.get(pair(k, it), *crt);
5  } ...
6   reduce_control_collection.put(it+1);
7   return CnC::CNC_Success;
8 }
```

Listing 4: QtCnC code for AND-reduction.

```
1 aligned_t** Reduce::get_dependences (
2         const int & it, int & no )  {
3   aligned_t** preconds;
4   read = malloc( N*sizeof(aligned_t*) );
5   for(int k = 0; k < N; k++) {
6     tile_item_collection.wait_on(
7         pair(k, it),
8         &(preconds[k]) );
9   }
10  return read;
11 }
```

Listing 5: Specification of preconditions in QtCnC.

As an example, Listing 4 shows part of the QtCnC step collection code for the reduction tasks in AND-reduction. The `execute` method is the code that is called for each `put` on the `reduce_control_collection`. It receives as parameter the tag, in this case the iteration number for which the reduce should be performed. On line 6 the call to `get` is performed to access a tile with key [k, it]; on return, its second parameter (crt) contains a pointer to the tile. On line 11, the next reduction task is started by calling `put` on the appropriate control collection with it+1 as tag.

B. Strict, eager and flexible models in QtCnC

As described in the previous subsection, QtCnC can support the eager task creation model. To express strict and flexible preconditions we enhanced it with additional APIs.

To specify preconditions in QtCnC, one needs to implement a `get_dependences` function for each step collection. Listing 5 shows such an implementation for the strict preconditions model in AND-reduction. On line 5, an array is allocated with one entry for each precondition; then, on line 7, it is filled in by calling the runtime function `wait_on` and specifying two parameters: the key of the item that will be a precondition and the array position in which to put this precondition. The array is then returned on line 10.

To use the flexible model as opposed to the strict preconditions one, there is no additional API needed - one just needs to write a smaller list of items as preconditions and compile with a flag specifying that flexible preconditions behavior is desired.

V. QtCnC Implementation

The QtCnC runtime is an open-source runtime[1] built on top of the Qthreads tasking library [18] which we use for

[1] https://code.google.com/p/qthreads/wiki/qtCnC

task scheduling and synchronization support. The *preconditioned tasks* and the *full-empty memory* mechanisms of Qthreads are well suited for enforcing the preconditions in preconditions-based models. Preconditioned tasks have the advantage that stacks are assigned only after the task has its preconditions available and is scheduled to run. They are spawned by calling the `qthread_fork_precond` function and providing a pointer parameter to an array of memory words on which to wait. Only when these words have been marked as full will the task be spawned. The words can be marked full by using the full-empty mechanism API call `qthread_fill(aligned_t* word)`.

New APIs in the QtCnC runtime include the `get_dependences()` and `wait_on()` public functions, which are used for specifying preconditions. The following paragraphs discuss the implementation of these functions.

To track item availability, shadow state is maintained for each item, consisting of a single memory word; this state is abstracted away from the user through the item collection classes and the `ic.wait_on` API, which writes into its second parameter a pointer to this shadow state. When `ic.put(key, value)` is called, it records the availability of the item by marking the shadow word for that item as full (through a `qthread_fill` call).

The user function `get_dependences` fills the array `preconds` with pointers to shadow words and then returns it to its caller. The QtCnC runtime performs a call to this function before spawning a task, to obtain the preconditions it needs before running. It sends the array of preconditions to Qthreads when it performs the spawn through a call to `qthread_fork_precond`.

An additional optimization we performed in the strict preconditions model involved the spawning of *stackless tasks* (called "simple tasks" in Qthreads). These tasks use the stacks of the thread they are scheduled on, instead of allocating their own and are prevented from performing any blocking synchronization operations.

Shadow word management is made more complex because the words have to be created by the first of following three APIs that is called: `ic.get`, `ic.put` or `ic.wait_on`. This management is performed by the item collections. Item collections are implemented in QtCnc via a C++ template class that wraps a concurrent hashtable indexed by item keys. The concurrent hashtable ensures that concurrent calls to the previously mentioned three functions do not cause dataraces. We built the split-ordered-list concurrent hashtable described in [20] with dynamic resizing. This concurrent hash table is now included in the latest Qthreads distribution.

VI. Evaluation

A. Experimental Setup

Our results were obtained on a 4 socket 32 core Intel Nehalem X7550 system with 512GB memory. All tests have been performed using the default Qthreads scheduler, with `-O3` optimization and a stack size of 2MB. The stack size was chosen in accordance with the stack size used by default by Pthreads (2MB), with the reasoning that it is suitable for most applications, and is considered in previous literature to be a value that is easy to exceed [21]. The results listed are averages of 10 runs; where appropriate, we include error bars on graphs that correspond to the largest and smallest values obtained during the runs.

To measure the actual memory footprint of the programs we used the `/usr/bin/time` tool, for which the `-v` parameter outputs the maximum resident set size of the program. The memory and performance numbers were collected as averages of the same 10 runs.

B. Benchmarks

To test the performance of the precondition-based models, we use the following benchmarks. Unless specified otherwise, these benchmarks have been implemented in all three models. A summary of the results is in Table I and the results are discussed in detail in the next subsections.

Blackscholes is a financial application that computes stock values. We use the implementation from Intel CnC [19] to analyze the overhead of the three models. The input size is 1,500,000 and granularity 100.

Cholesky Factorization is the non-MKL version of the linear algebra benchmark from the Intel CnC distribution [19]. It decomposes a matrix into a lower triangular matrix and its transpose. The input matrix size used is 4000 $\times$ 4000 and tiles are 125$\times$125.

Matrix Inverse is a benchmark from the Intel CnC distribution [19]. The input matrix size is 2048 $\times$ 2048 and the tile size is 64 $\times$ 64.

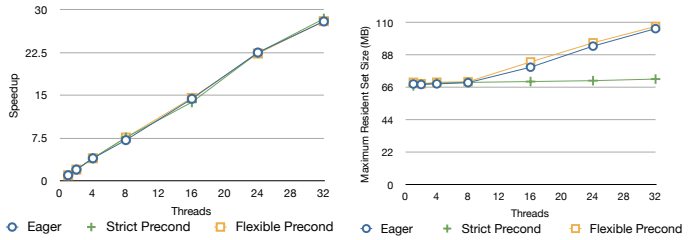
File Concatenation is a benchmark that concatenates a set of files by performing the least number of concatenations. It builds a balanced binary tree in which the inputs are leaves and each node represents a concatenation operation. This application illustrates a situation when strict preconditions cannot be directly applied, so only the flexible preconditions and eager versions are used. The number of input files is 32768.

Reduction is the kernel of the Rician Denoising [22] application that we use to assess the performance of the runtimes for cases where some gets are optional, such as in short-circuit reductions. The input size consists of 16 tiles of 10$\times$10 size and the algorithm performs 16 iterations.

C. Blackscholes

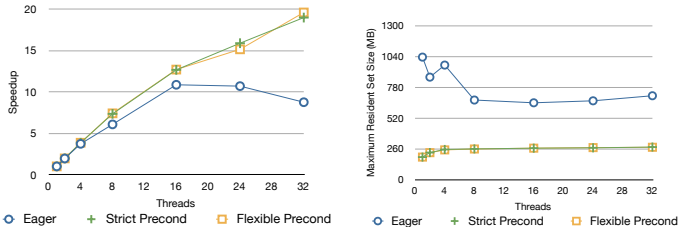
In Blackscholes, tasks perform a single `get` of inputs produced by the environment, so tasks never block. Because of this, there is no memory footprint difference between flexible preconditions and eager, as seen in Figure 2b. As expected, the strict preconditions memory footprint is almost constant because strict preconditions tasks are stackless. For flexible preconditions and eager execution, tasks may still block on inputs that are not listed as preconditions, which means tasks need to be paused and their state (such as their stack or a closure) must be saved. Because the ability of tasks to block is not used in this benchmark (all inputs are available from the start), the footprint difference is equal to the size of the task stack multiplied by the number of tasks running concurrently, which is equal to the number of worker threads.

If we look at the performance comparisons from Figure 2a, we see that the three runtimes have similar scalability. This is



(a) Speedup (b) Memory consumption

Fig. 2: Blackscholes results (a single precondition was used for both strict and flexible).



(a) Speedup (b) Memory consumption

Fig. 3: Cholesky results (1-3 preconditions used for both strict and flexible).

to be expected, as all items are available from the start (so no task ever blocks).

D. Cholesky Factorization

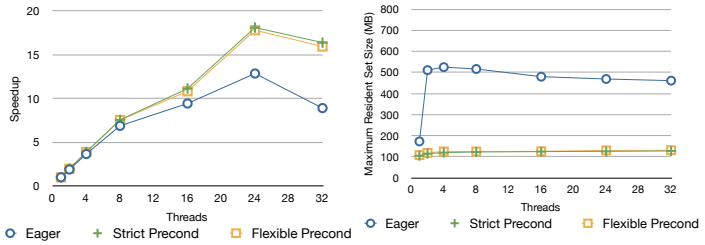
The performance results for Cholesky, Figure 3a, show a performance difference of up to 56% between the eager approach and strict and flexible preconditions. For the eager runtime, the speedup reaches a maximum at around 16 threads versus more than 32 in the other models. The reason for this is visible in Figure 3b. In the eager runtime, because the application spawns all tasks in the beginning and many of them block, their allocated stacks must be stored; the maximum memory pressure is a lot worse than for preconditions based models, where the use of preconditions lowers the memory requirements by 62% because tasks never block.

We theorized that the lack of performance of the eager runtime is caused by additional time spent during concurrent allocations and we built a Pthreads-based micro-benchmark to verify our assumptions. The microbenchmark performs similar allocations from parallel threads and suffered from the same lack of scalability. The Cholesky application was the original motivating application for our work, as the high memory usage prevented us from running the application on larger inputs using a machine with only 2GB of memory; this happens because in the eager model, task memory is much larger than the application data.

For Cholesky, all dataflow item accesses are known in advance, so the preconditions list was complete even for flexible preconditions and the runtimes show the same performance.

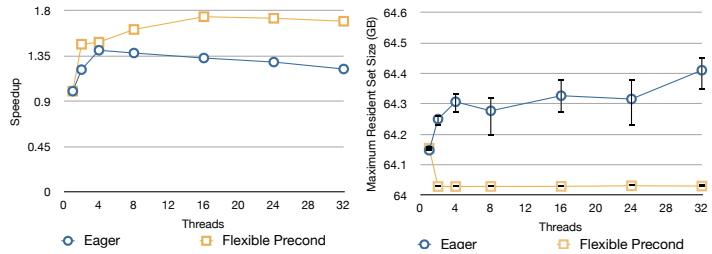
E. Matrix Inverse

For MatrixInverse, (Figures 4a and 4b) the eager approach is consistently worse (up to 44%) than both flexible and strict preconditions, while the difference between the precondition based approaches is small. The precondition-based approaches



(a) Speedup (b) Memory consumption

Fig. 4: Matrix Inverse results(1-3 preconditions used for both strict and flexible).



(a) Speedup (b) Memory consumption

Fig. 5: File Concatenation results (flexible used 1 precondition).

are so similar because all dataflow task preconditions for the application are known in advance; the difference is the overhead of the `get` calls, just as in Cholesky, and remains under 2% even at 32 threads. The memory consumption shows the footprint of the eager approach is 3.6 × larger than that of strict preconditions.

F. File Concatenation Benchmark

The File Concatenation benchmark cannot be run on the strict preconditions model, because the preconditions of each task depend on one another's value (data-dependent gets). Note that this is not a characteristic of the runtime or model, but of the way the application is written: some applications written for the eager model cannot be converted to run in a strict preconditions model without a considerable increase in the number of tasks.

In this benchmark, tasks perform `get` operations to obtain the two operating system inode structures representing the input files. These structures contain the tags of the blocks that need to be concatenated. Because this information is not known until the inodes are read, it cannot be added to the list of preconditions.

As we see in Figure 5b, even though the memory consumption difference between flexible and eager is small (less than 0.6%), in absolute value it reaches 383MB. Compared to eager execution, flexible preconditions are up to 28% faster and allow scaling up to 16 cores instead of only just 4 in the case of eager execution (see Figure 5a).

Using the file concatenation benchmark we analyzed the performance difference between an eager implementation and a flexible preconditions one, but the performance of the strict runtime was not included because porting the file concatenation tasks to a strict model is very time-consuming. The Porting

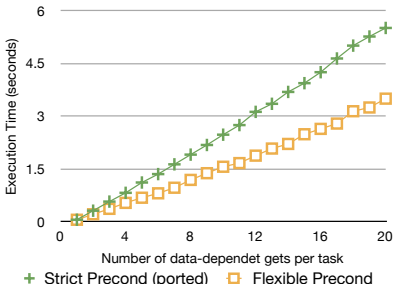


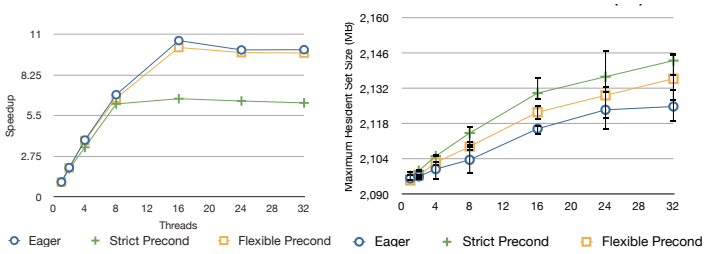
Fig. 6: Porting microbenchmark performance

benchmark takes a systematic look at the performance implications of porting applications from the eager/flexible runtimes to strict preconditions, which would enable applications with data-dependent gets to run on the strict runtime. In this microbenchmark, tasks perform data-dependent gets — gets whose keys are values of previous gets. This is not allowed in strict preconditions models because item values are not known at the time the preconditions are specified; for a strict implementation to be used, such tasks need to be split into sub-tasks, one for each of such data-dependent gets. Figure 6 shows the performance of the two runtimes in such a case. On the X axis, we have the number of data dependent gets per task, which is also the number of subtasks in which tasks are split. Flexible preconditions have better performance when such gets are few and the difference increases when there are more. This happens because with more subtasks, their spawning overhead dwarfs the useful work they perform. In fact, even for a single data-dependent get, flexible preconditions offer better performance for this microbenchmark. Of course, in a real application the difference between the performance of the two runtimes will depend on the granularity of the work performed in each task, relative to the overhead of task creation.

G. AND-Reduction Benchmark

Reductions are a common pattern in many applications. An interesting variation is short-circuit reductions, in which not all inputs may be read. This is the case in image processing applications such as the Rician Denoising application on which this benchmark is based. Here, the reduction is a convergence criteria tested before starting the next denoising iteration: if a tile is found not to respect the convergence criteria, the following tiles need not be read. Eager execution will wait for each tile as and when it is needed and flexible preconditions allow the programmer the freedom to choose which tiles should be waited on before spawning the reduction task (in our implementation, we list only the first tile as a precondition). Strict preconditions need to declare all input tiles as preconditions and wait for the availability of them all; this behavior is a problem because, even if it does not compromise correctness, it may compromise performance, by waiting for a larger set of preconditions than are actually needed.

Figure 7a shows that the eager model and flexible preconditions offer significantly better performance. As far as memory consumption is concerned, as shown in Figure 7b, all runtimes have almost the same footprint for this application, with flexible preconditions being in the middle.



(a) Speedup (b) Memory consumption

Fig. 7: Reduction benchmark results (strict execution used N preconditions, flexible used 1).

Benchmark	Runtime	Time (s)	Δ Time (%)	Memory (MB)	Δ Memory (%)
Blackscholes	strict	1.384	-1.7	71.78	-49.7
	eager	1.408	0.1	105.96	-1.4
	flexible	1.407	0.0	107.46	0.0
Cholesky	strict	0.810	3.0	274.78	0.7
	eager	1.814	56.7	717.84	62.0
	flexible	0.786	0.0	272.89	0.0
Matrix Invert	strict	0.880	-3.4	127.63	-3.0
	eager	1.648	44.8	461.39	71.5
	flexible	0.910	0.0	131.44	0.0
File Concatenation	strict	N/A	N/A	N/A	N/A
	eager	37.786	28.5	64.41	0.6
	flexible	27.030	0.0	64.03	0.0
Reduction	strict	2.193	38.0	2143.12	0.3
	eager	1.329	-2.4	2124.89	-0.5
	flexible	1.361	0.0	2135.92	0.0

TABLE I: Summary of results for execution on 32 threads. Δ values show the relative improvement of flexible preconditions over the other two runtimes.

H. Discussion of the findings

The cause for the poor performance shown by eager task spawning may be contention in the memory allocator [23], but the problem is worse in our case, due to the quantity of memory allocated. Allocating many tasks with 2MB stacks quickly exhausts all allocation arenas and allocations are forced to call into the kernel (via `sbrk()` or similar) to enlarge the process's available memory. These kernel calls are likely serialized, given that they're all modifying the single kernel-level memory map for the process.

In light of these results, we believe that a good solution is instead to opt for models based on preconditions. For applications whose performance is extremely critical and whose design allows all dependences to be known at task creation time, strict preconditions may be suitable.

A disadvantage of the strict preconditions model is that it has performance issues when some of the items that are read in some corner case are often not read, such as in the AND-reduction example. Using strict preconditions for such applications leads to considerable performance loss compared to flexible preconditions.

A second problem with the strict preconditions model is that for some applications it is a programmability impediment. One characteristic of applications not easily expressible in the strict model is the existence of *data-dependent gets*, which are `get` operations whose keys are derived from the value of an item obtained through a previous `get`. Such accesses are used mostly for convenience in applications built for the eager model, in cases where tasks follow the natural structure of the program data (for example, in File Concatenation, reading a

file's inode is followed by reading the blocks listed in the inode structure to access the file data). Similarly, in another application, Routing simulation [22], tasks that represent routers in a network with link failures need to read the network topology to find their neighbors and then they read the routing tables of those neighbors. The network topology and routing tables of the neighbors should be preconditions, but the neighbor routing tables cannot be strict preconditions because we do not know which will be read until the topology is obtained. One solution is to add the tables of all nodes as preconditions, but that slows down the computation just as in the AND-reduction case.

Another characteristic of applications that are not easily expressed in a strict preconditions model is that these applications often perform a *variable number of gets*, depending on conditions identified in the task computation. The best example is the AND-reduction discussed in Section III and File Concatenation, where the inode of a long file contains the id of an extra block that must be read.

Our experimental results showed that the proposed flexible preconditions model performs on par with the best of the strict preconditions or eager models, while maintaining the expressiveness of the eager model making it a good alternative to both models.

VII. Conclusions

In this paper, we analyzed the performance of two widely used models for macro-dataflow execution (eager tasks and strict preconditions) and found that their performance and scalability are highly sensitive to application behavior and algorithm design. We proposed a new model — flexible preconditions — that can always match the performance of the better of the two models. On applications where all dependences are known ahead of time, strict preconditions are 38% faster than eager execution and flexible preconditions match the strict model. On the other hand, for applications where the complete set of per-task dependences is determined after the tasks are spawned, eager execution performs 57% better than strict preconditions and flexible preconditions match this model. This improvement is achieved by enabling programmers to to pick the preconditions combination that yields the best performance for each application. As future work, we plan to build an auto-tuning system that can automatically pick the best preconditions by analyzing task behavior at runtime, and also extend the scope of our work to encompass task cancellation and demand-driven evaluation as additional scheduling options.

Acknowledgment

Sandia National Laboratories is a multiprogram laboratory operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Company, for the U.S. Department of Energy's National Nuclear Security Administration under Contract DE-AC04-94AL85000.

References

[1] J. B. Dennis, "First version of a data flow procedure language," in *Programming Symposium, Proceedings Colloque sur la Programmation*. London, UK, UK: Springer-Verlag, 1974, pp. 362–376.

[2] V. Sarkar and J. Hennessy, "Partitioning parallel programs for macro-dataflow," in *Proceedings of the 1986 ACM conference on LISP and functional programming*, 1986, pp. 202–211.

[3] S. Tasirlar and V. Sarkar, "Data-driven tasks and their implementation," *41st International Conference on Parallel Processing (ICPP)*, 2011.

[4] K. Stavrou, M. Nikolaides, D. Pavlou, S. Arandi, P. Evripidou, and P. Trancoso, "TFlux: A portable platform for data-driven multithreading on commodity multicore systems," ser. ICPP '08, 2008.

[5] Z. Budimlić, M. Burke, V. Cavé, K. Knobe, G. Lowney, R. Newton, J. Palsberg, D. Peixotto, V. Sarkar, F. Schlimbach, and S. Taşirlar, "Concurrent Collections," *Sci. Program.*, vol. 18, Aug. 2010.

[6] K. Agrawal, C. Leiserson, and J. Sukha, "Executing task graphs using work-stealing," in *IPDPS'10*.

[7] V. Cavé, J. Zhao, J. Shirako, and V. Sarkar, "Habanero-Java: the new adventures of old X10," ser. PPPJ '11.

[8] A. Sbîrlea, Y. Zou, Z. Budimlíc, J. Cong, and V. Sarkar, "Mapping a data-flow programming model onto heterogeneous platforms," ser. LCTES '12. New York, NY, USA: ACM, 2012, pp. 61–70.

[9] R. D. Blumofe and C. E. Leiserson, "Scheduling multithreaded computations by work stealing," *J. ACM*, vol. 46, no. 5, pp. 720–748, 1999.

[10] G. E. Blelloch, P. B. Gibbons, G. J. Narlikar, and Y. Matias, "Space-efficient scheduling of parallelism with synchronization variables," ser. SPAA '97. New York, NY, USA: ACM, 1997, pp. 12–23.

[11] D. E. Culler and Arvind, "Resource requirements of dataflow programs," *SIGARCH Comput. Archit. News*, vol. 16, no. 2, May 1988.

[12] Y. Guo, J. Zhao, V. Cave, and V. Sarkar, "SLAW: A scalable locality-aware adaptive work-stealing scheduler," ser. IPDPS, 2010, pp. 1 –12.

[13] P. Bellens, J. M. Perez, R. M. Badia, and J. Labarta, "CellSs: a programming model for the cell BE architecture," ser. SC '06. ACM.

[14] J. M. Pérez, R. M. Badia, and J. Labarta, "A dependency-aware task-based programming environment for multi-core architectures," in *CLUSTER'08*.

[15] T. Gautier, X. Besseron, and L. Pigeon, "KAAPI: A thread scheduling runtime system for data flow computations on cluster of multiprocessors," ser. PASCO '07, New York, NY, USA, 2007.

[16] F. Galilée, J.-L. Roch, G. G. H. Cavalheiro, and M. Doreille, "Athapascan-1: On-line building data flow graph in a parallel language," ser. PACT, 1998.

[17] S. Tasirlar, "Scheduling macro-dataflow programs on task-parallel runtime systems," Master's thesis, Rice University, 2011.

[18] K. Wheeler, R. Murphy, and D. Thain, "Qthreads: an API for programming with millions of lightweight threads," in *MTAAP Workshop*, 2008.

[19] Intel, "CnC distribution 0.5 release notes," http://software.intel.com/en-us/articles/intel-concurrent-collections-for-c-050-release-notes/, accessed: 25/07/2012.

[20] O. Shalev and N. Shavit, "Split-ordered lists: Lock-free extensible hash tables," *J. ACM*, vol. 53, no. 3, pp. 379–405, May 2006.

[21] LLNL, "Pthreads documentation," https://computing.llnl.gov/tutorials/pthreads/#Stack, accessed: 25/07/2012.

[22] D. Sbîrlea, K. Knobe, and V. Sarkar, "Folding of tagged single assignment values for memory-efficient parallelism," ser. Euro-Par '12, 2012.

[23] T. B. Ferreira, R. Matias, A. Macedo, and L. B. Araujo, "An experimental study on memory allocators in multicore and multithreaded applications," ser. PDCAT '11, 2011.