Configurable Strategies for Work-stealing*

Martin Wimmer¹, Daniel Cederman², Jesper Larsson Träff¹, and Philippas Tsigas²

¹Faculty of Informatics, Vienna University of Technology, Favoritenstrasse 16, 1040 Vienna, Austria, \{wimmer,traff\}@par.tuwien.ac.at
²Computer Science and Engineering, Chalmers University of Technology, 412 96 Göteborg, Sweden, \{cederman,tsigas\}@chalmers.se

May 29, 2013

Abstract

Work-stealing systems are typically oblivious to the nature of the tasks they are scheduling. For instance, they do not know or take into account how long a task will take to execute or how many subtasks it will spawn. Moreover, the actual task execution order is typically determined by the underlying task storage data structure, and cannot be changed. There are thus possibilities for optimizing task parallel executions by providing information on specific tasks and their preferred execution order to the scheduling system.

We introduce scheduling strategies to enable applications to dynamically provide hints to the task-scheduling system on the nature of specific tasks. Scheduling strategies can be used to independently control both local task execution order as well as steal order. In contrast to conventional scheduling policies that are normally global in scope, strategies allow the scheduler to apply optimizations on individual tasks. This flexibility greatly improves composability as it allows the scheduler to apply different, specific scheduling choices for different parts of applications simultaneously. We present a number of benchmarks that highlight diverse, beneficial effects that can be achieved with scheduling strategies. Some benchmarks (branch-and-bound, single-source shortest path) show that prioritization of tasks can reduce the total amount of work required compared to standard work-stealing execution order. For other benchmarks (triangle strip generation) qualitatively better results can be achieved in shorter time. We also demonstrate that strategies are composable. Other optimizations, such as dynamic merging of tasks or stealing of half the work, instead of half the tasks, are also shown to improve performance. Compositionality of strategies is demonstrated by examples that combine different strategies, both within the same kernel (prefix sum) as well as when scheduling multiple kernels (prefix sum and unbalanced tree search).

1 Introduction

Work-stealing is a popular way to schedule parallel work-loads of independent tasks [5] and is used by well-known frameworks such as Cilk [4], Cilk++ [17], Intel Threading Building Blocks [16] and X10 [7]. Whenever new tasks are created within an application, they are stored in a local queue owned by a specific thread. When a thread runs out of work in its own queue, it tries to steal work out of the queues of other threads.

*The research leading to these results was partially funded by the European Union Seventh Framework Programme (FP7/2007-2013) under grant agreement no. 248481 (PEPPHER Project, www.peppher.eu). A short poster summary of this paper was presented at the 18th ACM PPoPP 2013 conference [24].

arXiv:1305.6474v1 [cs.DC] 28 May 2013
Standard work-stealing schedulers are oblivious to most properties of individual tasks and treat tasks equally. The execution order of tasks owned by a thread is instead indirectly determined by the data structure used for storing the tasks. A commonly used data structure for work-stealing systems is the lock-free work-stealing deque by Arora et al. [2] that is optimized for local accesses. The owning thread accesses the queue from one end, whereas stealing threads access it from the other. The order of tasks in the queue is often a good heuristic for an efficient execution order of tasks. First, the owning thread accesses the queue like a stack, which leads to a depth-first execution of tasks and often results in good performance because of good memory use and locality [1]. Second, stealing threads access the queue from the other end, resulting in a first-in-first-out access pattern. This leads the stealer to acquire a new task near the root of the task graph, thereby generating more local work and reducing the number of further steals.

While the execution order effected by work-stealing deques is good for some applications, other execution orders are better for other applications. Search-based algorithms can profit from prioritization to explore the most promising branches early. Other algorithms, like prefix-sums (as presented in Section 4), can combine two passes on data into one if the tasks are executed in the right order. Other applications benefit from a regime which gives priority to tasks that access data already in the cache [24], and such locality-aware scheduling regimes are often used [13]. Another type of regime would prioritize a task depending on how recently it was previously scheduled [23]. Another common heuristic is to prioritize tasks on the critical path [22]. Resource obliviousness has been achieved with a special priority scheduling scheme [9]. A variety of task-parallel application kernels that profit from prioritization is presented by Lenharth et al. [18]. The authors postulate that a global priority ordering for tasks is often not beneficial for performance, and that different priority orderings within the same application/system are required.

In this paper we present scheduling strategies as a way of informing the scheduling system about properties of tasks and as a way to prioritize tasks. This makes it possible for a work-stealing scheduler to improve the execution without losing any generality of the scheduler. In contrast to scheduling policies, which are global in nature, strategies allow specification of those properties at the level of individual tasks. Strategies in our system are composable. Regardless of which strategies/types of strategies are combined the behavior of the scheduler is always well-defined. Different kernels with different strategies can therefore be combined in a single parallel execution with the same scheduler.

We define scheduling strategies in Section 2 and explain the kinds of optimizations that we can currently support. Section 3 gives glimpse of our strategy-aware work-stealing scheduler, without presenting, however, the details about the data structures required to support strategies; these will be presented separately. Example application kernels and the strategies used to improve them are discussed in Section 4. Corresponding experimental results in Section 5 show that considerable performance improvements can often be achieved.

2 Strategies

Scheduling strategies is a mechanism to inform a work-stealing scheduling system about properties of individual tasks in order to influence and improve the execution. A strategy can be associated with a task at spawn time. In contrast to scheduling policies that are global in nature the scope of a scheduling strategy is an individual task. This allows to influence the scheduler behavior for a single task without incurring possibly negative effects for (all) other tasks. Scheduling strategies are composable, and different strategies can be used in a single task-parallel execution because there is a well-defined way in which such strategies interact.
Spawn to call For tasks with small granularity, spawn overhead can significantly influence the total application execution time. On the other hand, too coarse grained tasks may lead to too little parallelism or less than optimal load-balancing. Spawn overhead can be reduced by converting task spawns to function calls at run-time. This should preferably be done dynamically, when the scheduler has a large number of unprocessed tasks in its queues, thereby trading excess parallelism for a lower scheduler overhead. We have noticed that this simple heuristic can lead to a significant performance improvement for applications with either small variance in task granularity (algorithms on same-sized blocks) or decreasing task granularities (divide-and-conquer algorithms). For other types of algorithms, the heuristic can be problematic since it is oblivious to task granularity. In the worst-case, high granularity tasks would be converted to function calls, and low granularity tasks put into the task queues. Strategies avoid such pathologies by allowing for specifying the task granularity within the strategy.

Strategies make it possible to control the conversion of task spawns to synchronous function calls based on properties of the task to be spawned and the state of the system. A transitive weight is associated with tasks to be used as an estimate of the work that will be generated by a task and its descendants. Below a certain threshold which can depend dynamically on, e.g., the number of tasks in the local task queue, the spawn is converted to a function call. It is also possible to disable call conversion and this is done by default in strategies, unless explicitly enabled.

Number of tasks to steal For work-stealing systems it is well known that it is usually better to steal half the work instead of only a single task [3], the advantage being that work available in one queue quickly disseminates to the whole system. In standard work-stealing systems the amount of work incurred by the tasks is not known (by the scheduler), and stealing half the work is approximated by stealing half the tasks. In many cases, this approximation is highly inaccurate. For example, in many divide-and-conquer algorithms the amount of work is halved at each spawn. To steal half the work in such algorithms it would be sufficient to steal only the task with the largest amount of work, instead of half the tasks.

The transitive weight associated with tasks can be used to estimate the work required by each new task and its descendants. This allows the stealing procedure to terminate as soon as half the work has been stolen, irrespectively of the number of tasks in the queues.

Priority An application specific execution order of tasks can lead to higher efficiency (performance, memory usage, quality of the results) than a fixed execution order like last-in-first-out. Strategies can be used to suggest an execution order to the scheduling system by giving the user a means to prioritize tasks of the same type. Prioritization is implemented by a comparison function that takes two instances of strategies of the same type and determines which should be preferred over the other. Since each instance of a strategy is associated with a single task, the prioritization of an instance leads to the prioritization of a task.

The prioritized order of tasks is used locally and when stealing tasks. Global prioritization is not enforced, since this could compromise locality and scalability of the work-stealing system; this is, however, dependent on the data structures used for storing tasks (and subject to current work not described here). Also note that conversion of spawns to function calls may violate the prioritization.

Dead tasks For certain applications, like search-based algorithms, newly calculated results can make tasks obsolete so that they do not need to be executed any more. Strategies allow the user to expose such dead tasks so that they can be removed early and will not be stolen by other threads.
Figure 1: A hierarchy of scheduling strategies with LIFO/FIFO as the base strategy.

**Locality** Together with the notion of *place*, which denotes a single execution unit in a scheduling system and its supporting data structures, the task prioritization mechanism provided with strategies can be used to implement many spatial and temporal locality optimizations. Typically the number of places equals the number of processors in a system. To facilitate locality optimizations, each place is bound to a specific processor in the system.

Standard work-stealing systems employ a simple locality optimization, which is surprisingly good for many applications. Each place has its own queue of tasks that are processed in *last-in-first-out* order. This increases temporal locality, since newly created tasks often work on the same data as their parent tasks. The queues of other places are not touched as long as the queue of the place is not empty, which reduces interference. When stealing tasks from another place, they are stolen in *first-in-first-out* order, which means that tasks with higher temporal locality are not stolen. For the remainder of this paper we will call the standard work-stealing prioritization the *LIFO/FIFO strategy*. This is the default prioritization for tasks in our system.

Some applications may profit from problem specific locality optimizations. For algorithms with little temporal locality in the default strategy a completely different execution order for tasks may be better.

All the described cases can be covered using the prioritization function, which was explained previously. Each instance of a strategy is associated with a place specified by the programmer. By default the place is set to where the associated task was spawned. The implementer of the prioritization function can query the associated places as well as the (memory) distance to the place that requests the prioritization. Thereby, the programmer can create place-specific orderings, e.g., by prioritizing tasks with a smaller memory distance. Since each place may see a different order of tasks, this must be supported by the task storage data structure.

**Composability** A major design goal of scheduling strategies is composability. It should be possible for different applications or parts of the same application that use different strategies to run concurrently within the same, single scheduler. While this is simple to achieve for properties that are specific for individual tasks, like the *transitive weight* of tasks, it is much more difficult for prioritization.

We solve the composability problem by imposing a hierarchy of strategies as shown in Figure 1. Strategies of different types are prioritized by the strategy of their lowest common ancestor. Since the hierarchy has a single root, any two strategies have a unique common ancestor. A *LIFO/FIFO strategy*, similar to the standard work-stealing task order, is the default root strategy. The hierarchy allows for different algorithmic kernels in a single application to use different strategies as indicated in Figure 1. While some kernels might rely on the base strategy LIFO/FIFO, another kernel might exhibit better performance with a FIFO (first-in-first-out) strategy. Search algorithms, on the other hand are often faster with strategies where the most
promising path is explored first. More complex, real applications often consist of different algorithmic kernels. In Figure 1 we included an algorithm, AlgX, which calls both sorting (AlgXSort) and filtering (AlgXFilter) kernels inside. Both kernels might require specialized strategies for efficient execution. In addition, AlgX might need to reduce its critical path length by ordering different calls to sort and filter. This behavior can be achieved with a common base strategy for both the sorting and the filtering strategy for AlgX.

To impose an absolute ordering on tasks with different type of strategies, we always let child strategies overrule their ancestors. For the strategies in Figure 1 this results in the FIFO strategy overruling the LIFO/FIFO strategy. This is done by first grouping all tasks that use the FIFO strategy together and then ordering them in FIFO order. The highest priority task in the group is then compared with strategies of other types using the LIFO/FIFO strategy to determine the priority of the group as a whole.

2.1 Implementation of scheduling strategies

Our implementations are done in an object-oriented, C++ framework, called Pheet [26, 25]1. A scheduling strategy is a class derived from a base strategy class that implements base functionality required by all strategies, and a default behavior. Strategies derived from the base strategy can provide different behavior, for example a different prioritization of tasks, by overriding the default behavior. The constructor of a strategy class is allowed to take any kind of parameter the programmer desires, which allows strategies to act on problem specific information. An instance of the strategy class is created and stored for each spawned task. These objects are then used by the scheduler to make scheduling decisions for the specific task and to determine the execution order of the stored tasks.

Algorithm 1 depicts an example implementation of a strategy that provides depth-first execution for locally spawned tasks, and a breadth-first execution for tasks created at other places. It assumes a tree-like algorithm where all tasks in the subtree will be generated. The constructor of the strategy stores the height \( h \) of the given task, and sets the transitive weight of the task to \( 2^h \). We assume here that the height can never exceed the number of bits in a long integer, so that no integer overflow will occur.

To enable conversion of task spawns to function calls, which is disabled by default, the allow_call_conversion method has to be redefined to return true. More complex strategies may only allow call conversion for some tasks, by dynamically deciding on the return value.

The prioritize method determines the execution order of tasks. It takes a reference to a second strategy object of the same type as parameter and should return true if the task associated with the current instance of the strategy should be executed before the other task, and false otherwise. Algorithm 1 implements different behaviors depending on whether a task was spawned in the same place or not. Tasks spawned in the same place are prioritized for locality reasons and are executed in depth-first order. All tasks spawned in other places (e.g. stolen tasks in a work-stealing scheduler) are executed in breadth-first order to increase the amount of locally spawned work.

To facilitate locality-aware scheduling, we provide strategy objects with a way to calculate the memory distance between different places (not shown in the given example). Using this, strategies can prioritize tasks for which the data is stored in a nearby place.

1http://www.pheet.org
Algorithm 1 Example strategy for a tree-like algorithm with local depth-first execution and breadth-first stealing.

```cpp
class DepthFirstStrategy : public Environment::BaseStrategy {
public:
  DepthFirstStrategy(int depth, int max_depth)
  : depth(depth) {
    // Work is exponential in the height <= max_depth – depth
    set_transitive_weight((long)1 << (max_depth – depth));
  }

  bool allow_call_conversion() const {
    return true;
  }

  bool prioritize(DepthFirstStrategy& other) {
    if (this->place == Environment::get_place()) {
      // This task has been spawned at this place
      if (other.place == Environment::get_place()) {
        // If both tasks are spawned locally go depth-first
        return depth > other.depth;
      } else {
        // Prefer local task
        return true;
      }
    } else if (other.place == Environment::get_place()) {
      // Only other task was spawned at this place
      // Prefer other task
      return false;
    }

    // For non-local tasks go breadth-first
    return depth < other.depth;
  }
private:
  int depth;
};
```
3 Strategy scheduler

Our strategy-aware scheduler implements a typical work-stealing scheduler, but uses a priority data structure (briefly described in Section 3.1) per thread instead of a standard work-stealing deque. Each thread has affinity to a specific CPU core to allow for locality-centric optimizations, captured in the concept of place. The abstract machine/memory model used by the scheduler is a (balanced) tree, where the leaves represent processing units, and the nodes group processors that share some level in the memory hierarchy. The information needed on the concrete machine is gathered using hwloc [6]. This abstract machine model allows for another locality-specific optimization, in which tasks are stolen from neighboring processing units first. In our scheduler, newly spawned tasks are put into the priority data structure, and the continuation is executed first. This help-first scheduling policy [12] differs from the work-first scheduling policy used in work-stealing systems like Cilk [17], where the spawned task is executed immediately, and the continuation is made available to other threads to be stolen. The help-first scheduling policy is required for priority scheduling, as a decision for the execution order of spawned tasks can only be made if we first generate the tasks and then execute the task with the highest priority. The synchronization constructs used to wait for tasks are finish regions as known from X10 [7]. A finish region ensures that execution continues after the region only when all tasks spawned inside the region, including transitively spawned tasks, have completed.

3.1 Task storage data structure

In work-stealing schedulers each place has its own task-storage data structure, where new tasks are put in and from which tasks are executed. Only when its task-storage data structure is empty does a place access the data structure of another place in an attempt to steal work. Our data structure must be able to support that each place that accesses a data structure can prioritize tasks differently. Local accesses (push and pop accesses by the owner of the data structure) are common, so the priority ordering for the owner is updated every time a new task is added using a separate local priority data structure. Since stealing accesses are rare, the priority ordering for the place that performs the steal attempt can be evaluated lazily. This lazily evaluated priority ordering is cached by the stealer and updated with newly added tasks at the next steal attempt. We have designed a lock-free implementation of this kind of data structure, the algorithmic design of which is outside the scope of this paper.

The evaluation of the priority ordering is performed using a separate heap-based data structure. This data structure is used both for the local ordering, as well as for the lazy evaluation of the steal order. To ensure composability of strategies, the priority data structure needs to be aware of the different types of strategies available in the system to first generate an ordering for each type of strategy, before creating an ordering between the highest-priority strategies of each type in their parent strategy.

4 Applications

We have selected a number of (kernel) applications that can profit from scheduling strategies in different ways to illustrate both advantages and flexibility with their use. We describe the applications and the customized strategies in this section; performance results are given in Section 5.

Graph Bipartitioning The branch-and-bound paradigm is generally well suited to parallelization [10]. Efficient parallel branch-and-bound implementations rely on a concurrent data
structure for storing unexplored subproblems \[14, 15, 21\]. Performance depends crucially on
the order in which subproblems are explored in order to quickly find new feasible solutions to
bound subproblems that do not have to be explored. We use strategies to effect the prioritized
execution order.

We focus on the well-known, NP-hard graph bipartitioning problem \[20\] where the vertices
of an undirected, weighted, \(n\)-node, \(m\)-edge graph are to be partitioned into two sets with given
sizes with minimum total cut weight. For bounding (elimination) of subproblems we use a
simple, easily computable lower bound \[8\] with an additional improvement for dense graphs.
Incrementally updating the lower bound for each new node subproblem takes \(O(n \log n + m/n)\)
(amortized) steps.

Algorithm 2 Branch-and-bound task with strategies.

```cpp
if (sub_problem->lower_bound >= *upper_bound)
    // Bound: a better solution is already known
    return;

// Branch: generate two new subproblems by assigning
// most promising vertex to either subset
SubProblem* sub_problem2 = sub_problem->split();

if (sub_problem->is_solution()) {
    // New feasible solution; update upper bound atomically
    sub_problem->update_solution(upper_bound, solution);
} else if (sub_problem->lower_bound < *upper_bound) {
    spawn_s<BBTask>(
        // strategy for scheduling */ Strategy(sub_problem, upper_bound),
        // parameters for task */ sub_problem, upper_bound, solution);
}

// same for other sub_problem
```

The C++ code fragment in Algorithm 2 shows task parallel implementation of the branch-
and-bound paradigm.

In our implementation subproblems are represented as tasks. The value of the currently
best known feasible solution is kept in a global variable that is updated atomically as tasks find
better solutions. When a task is executed it first checks whether the computed lower bound
exceeds the global best known solution (upper bound). If this is not the case, the problem
is split at a chosen branching vertex and two new subproblems are spawned. At spawn time
subproblems/tasks are assigned a scheduling strategy, which can use the information known
about the subproblems to influence subproblem exploration order. We use an estimate on the
best solution value for the subproblem which can be computed together with the lower bound
in \(O(n)\) steps. The estimated solution value for each subproblem is used to prioritize tasks. At
each place, the task with the smallest estimate is executed first. Since the estimate is mostly
decreasing, this leads to a depth-first execution, where the most promising branches are executed
first. When a place runs out of tasks, it steals tasks from another place. We prefer to steal tasks
that have a high uncertainty, by which we mean the difference between the estimated solution
value and the lower bound for the subproblem. Such tasks are likely to generate much work
and subproblems that may lead to a good solution. This reduces further interaction (stealing)
between places.

We also use strategies to convert spawns into function calls. Many tasks do not generate
much work since they lie on branches that are cut off early. Also, for many problem instances
most of the time is spent not on finding the best solution, but on verifying that no better solution
exists among the still active subproblems. The overhead for creating and scheduling those tasks can be significantly reduced by performing call conversion for tasks that are not expected to generate much work. To do this, the transitive weight of each task has to be estimated. A rough estimate on the depth that needs to be explored for a task is given by the value of the best known solution minus the current lower bound divided by the average contribution of each node to the best known solution. We assign a transitive weight of $2^d - 1$ to the task, where $d$ is the estimated depth, under the expectation that the full subtree of height $d$ has to be generated.

**Prefix sum** A typical, parallel, blocked prefix-sums algorithm computes in parallel the prefix sums for a sequence of distinct blocks, then computes (recursively) the prefix sums for the sequence block sums, and finally in parallel for each block adds the previous block prefix sum to all elements of the block. We can use strategies to reduce the extra overhead caused by the last step in cases where there is little parallelism, or where other applications are running at the same time. The observation is that if for any given block the prefix sums for the previous block have already been computed, then the previous block prefix sum can simply be added to the first element of the block before performing the prefix sums computation. This eliminates the need for the last step of the above parallel algorithm. This makes sense in cases where there is little parallelism and many blocks are processed by the same place; in such cases the performance of the parallel algorithm can be expected to be on par with a sequential prefix sums implementation, and not, as would have been the case without strategies, a factor of two slower. This example illustrates how strategies can be used to achieve algorithm adaptivity.

With strategies, tasks use a global counter to detect whether the predecessor block has already been processed: this is the case if the counter is equal to the block number. The counter is incremented whenever a block has been processed in order. The strategy ensures that some place processes blocks in order of increasing block number, and all other places in decreasing order.

**Unbalanced Tree Search** The Unbalanced Tree Search (UTS) benchmark by Olivier et al. [19] spawns a large number of small tasks, corresponding to nodes in an unbalanced search tree, according to a given distribution. The decision on how many subtasks to spawn from a given task is made with the help of a hash of the parent descriptor and the child index. This makes it possible to get the exact same tree every time, based on the parameters given to initialize the tree. This behavior makes the UTS benchmark a candidate for evaluating the spawn-to-call feature of the strategy scheduler. For our experiments we use the T5 tree from the UTS benchmark suite. This is a tree with a geometric distribution and a maximum height of twenty that generates around four million tasks. Our strategy assigns a high transitive weight to tasks close to the root and a low weight to tasks closer to the leaves. The weight increases exponentially depending on the distance from the maximum height, but is capped to not grow too large.

**Triangle strip generation** The generation of triangle strips to represent 3D models is a common optimization for improving rendering performance. Instead of passing individual triangles to the rendering hardware, adjacent triangles are combined into strips, where vertices appearing in two adjacent triangles only have to be transmitted once. This lowers the number of vertices from $3n$ to $n + 2$. In the optimal case one would need only one triangle strip to represent the entire model. The optimization problem is NP-complete and thus best solved using heuristics.

We have used a version of the so called SGI algorithm [11]: the data used is the 3D model
Lucy from the Stanford 3D Scanning Repository. The model consists of around 28 million triangles. To minimize the number of single triangle strips a node on the graph is randomly picked from the set of nodes with the lowest degree. A strip is then built by adding neighboring nodes to the strip at both ends. Priority is given to nodes with a low number of neighbors. When no more nodes can be added to the strip, a new node is randomly picked and a new strip is started. This is repeated until all nodes are part of a strip.

With this benchmark we aim to show that strategies can lead to both qualitatively better results and performance improvements. To improve the result and generate fewer and longer triangle strips, strategies prioritize picking of nodes (tasks) with a low number of neighbors.

The benchmark uses two types of tasks. The first is the StartTask, which at spawn-time is assigned a pointer to a possible node to start a triangle strip from. The strategy for this type of task stores the number of neighboring nodes that are not part of a strip, and it uses that to prioritize tasks. Generating a strip is a relatively quick operation, so it is suitable for spawn-to-call transformation and is thus given a low transitive weight. Spawning a StartTask for every node in the graph would be wasteful, as many will be part of other triangle strips and thus not eligible to start a new strip from. Instead we provide a second type of task, the SpawnTask, to gradually spawn new StartTasks when needed and only for eligible start nodes. This task spawns new StartTasks for a given interval of nodes. The strategy used has a transitive weight which is the same as the number of tasks that it will spawn. It does not allow the task to be transformed into a call. The two strategies are composed by a common parent strategy that gives priority to SpawnTasks when stealing and to StartTasks when working locally.

**Single-source shortest path**  Single-source shortest path again shows how algorithms that require prioritization of work can be parallelized in a simple way with strategies. We use an obvious parallelization of Dijkstra’s algorithm. Tasks update distance labels and the role of the priority queue is taken over by the task scheduler; this same, straightforward parallelization is also used by Lenharth et al. \[18\]. Note that although this type of parallelization may work well in average, it cannot guarantee any speed-up (some places may simply do superfluous work that a sequential execution would not), although it should never perform worse than a sequential algorithm using the same priority data structure.

The strategy for the owning thread is to explore the most promising path first. This is the task with the smallest distance value. Stealing all promising tasks might be a bad idea, since then the original owner would end up with only less promising tasks to explore. Instead, we steal random tasks. To effect this, a random number is created for each instance of the strategy, and strategies are ordered by this random number for stealing accesses.

**Quicksort**  Even simple, standard-example kernels can profit from strategies as we show with a standard, task-parallel Quicksort algorithm (with a sequential partitioning algorithm). The best cache behavior is expected if locally spawned tasks are executed depth-first, and the shorter subsequence is processed first. When stealing tasks, the largest subsequences should be stolen first to reduce interference. For the standard LIFO/FIFO strategy typically used by work-stealing schedulers, it is easy to see that most of those criteria are already fulfilled, except for choosing the smaller subsequence when going depth-first. Therefore, only small gains can be expected from choosing the smaller subsequence. More performance gains can be expected by converting task spawns to function calls, when enough tasks are present in the task queue, and by choosing a better number of tasks to steal. We achieve this by configuring a transitive weight for each Quicksort task and by enabling call conversion. The expected running time of

![http://graphics.stanford.edu/data/3Dscanrep](http://graphics.stanford.edu/data/3Dscanrep)
Quicksort for a sequence of length $n$ is $O(n \log n)$, so the transitive weight is set to $n' \log n'$, where $n' = n/b$ for some block size $b$ (a tuning parameter; as a rule of thumb $b$ is chosen such that the transitive weight for the smallest task worth parallelizing is 1).

5 Experimental results

We have implemented and benchmarked the applications presented in Section 4 with strategies as discussed. An implementation that uses a LIFO/FIFO strategy (last-in-first-out order for local tasks, first-in-first-out order for tasks being stolen with behavior similar to the Arora et al. work-stealing deques [2]) is used as a baseline for comparison. To evaluate the overhead of the strategy enhanced scheduling framework we also compared the results to implementations executed with a standard work-stealing scheduler. To ensure a fair comparison, this work-stealing scheduler is implemented with the same techniques and optimizations as the strategy scheduler, but without support for strategies, and with a wait-free implementation of the Arora et al. deque [2]. We benchmarked this scheduler against Cilk++ [17] and Intel Threading Building Blocks [16] to validate that performance is comparable to other work-stealing systems, which it is (not shown in this paper).

System and Settings  All applications have been executed on a system with four 12-core AMD Opteron 6168 processors, for a total of 48 cores. It has 128 GB of memory, which is sufficient for all benchmarks to be processed in memory. The operating system is Linux (Debian 6.0), and the schedulers use pthreads as the threading layer. All applications have been compiled using g++ 4.7. The system is a NUMA system, and often the limited total memory bandwidth makes it hard to achieve speed-up beyond 12 cores, as experience with other memory bound (OpenMP) applications has shown.

Experiments were repeated 10 times and the average execution time is presented. For randomly generated problem instances, 10 different random seeds were used, but each test used the same 10 seeds and therefore the exact same problem instances to make scalability results comparable.

Graph Bipartitioning  The graph bipartitioning application described in Section 4 has been run with weighted and unweighted random graphs ($G_{n,p}$) with different sizes and densities. We present results for weighted graphs with 35 nodes, average density of 90% and randomly chosen integer weights in the range [1,1000], and unweighted graphs with 39 nodes and 50% density. Other inputs showed similar behavior.
The results for the unweighted graphs are shown in Figure 2(a). Independently of the number of threads in the system, strategies improve the execution time by nearly a factor of two. Without a specialized strategy, the strategy scheduler is, as expected, slightly slower than standard work-stealing. The overhead for the strategy scheduler becomes less prominent with increasing number of threads.

The performance advantages from strategies come from two factors. First, a good strategy leads to an optimal solution being found sooner, which reduces the total amount of work necessary. Second, converting task spawns to function calls reduces overhead, and stealing half the (estimated) work instead of half the tasks leads to better load balance and less steal attempts. To illustrate the influence of both factors, we also recorded when the optimal solution value was found, which corresponds to the last time the currently best solution was updated.

The results of this measurement are shown in Figure 2(b). This metric is less robust, but it gives insight into how the prioritization of tasks influences the search for the optimal value. As can be seen, the difference between the specialized strategy and standard work-stealing becomes significant, and in some cases reaches a factor of three. After the optimal solution is found, all implementation variants generate the same amount of work for a specific branch, since the same algorithm for pruning branches is used. Nonetheless, there is still a significant difference between execution times in Figure 2(a) when we subtract the time the optimal value was found. This performance difference is due to the other optimizations accomplished with strategies, namely call conversion and stealing half of the work.

Figure 5 gives the corresponding measurements for the weighted graph instances. Since our simple estimates for best cut value and amount of work generated by a subproblem become less precise for weighted graphs, we expect smaller gains by using strategies than in the unweighted case. Nonetheless, graph partitioning with strategies still outperforms the standard work-stealing scheduler. The optimal solution is again found faster with the strategy than without it, as is shown in Figure 3. However, the difference is smaller, and in some cases the work-stealing scheduler was more lucky in finding an optimum fast.

Prefix sum The prefix sum benchmark has been run on an array of $2 \times 10^8$ integers with a block size of 4096 elements for the parallel algorithm. The execution times are shown in Figure 4(a). In this example strategies are used to inflict the parallel algorithmic overhead only when enough threads are available. Since the specialized strategy implementation matches the performance of the sequential prefix sum algorithm when run on a single thread, this is obviously the case. For larger numbers of threads the advantages of the strategy are diminishing, and for 12 threads there is already no noticeable difference between a standard work-stealing implementation and the specialized strategy. Thus, we see that strategies achieve the effect
of making the algorithm adapt to the number of available threads at any given time of its execution.

To highlight the adaptive behavior, we measured the performance of 12 concurrent runs of the prefix sum computation within the same single scheduler (this could be part of an application that is heavy on prefix sums computations). The results are shown Figure 4(b). When using only one thread, the results are similar, but for larger numbers of threads the implementation with strategies yields better performance than running the 12 simultaneous prefix-sums computations with standard work-stealing.

**Unbalanced Tree Search** The UTS benchmark creates a large number of small tasks in a short time-frame. This adds an unnecessary overhead to the task storage data structure, as can be seen for the LIFO/FIFO-strategy in Figure 5. By allowing smaller tasks, far down in the tree, to be executed immediately, we lower the churn on the task storage, which greatly improves the performance. The scheduler decides on when to convert a spawn to a call by using its knowledge of the number of tasks currently in the task-storage and the transitive weight of the task given by its associated strategy. The spawn-to-call optimization causes our scheduler to outperform the standard work-stealing scheduler for this benchmark.

**Triangle Strip Generation** The strategy used for triangle strip generation is mainly meant to improve the qualitative result of the algorithm. However, as the benchmark is generating a large number of relatively small tasks, we also get a performance improvement from spawn-to-
call conversion. Figure 7(a) shows that strategies perform better than the work-stealing with a fixed order.

Figure 7(b) shows the number of triangle strips generated (lower is better). The heuristics used are not guaranteed to give a better result, and there is a great deal of randomness involved in the algorithm. Despite this we obtain a better result in a shorter amount of time than compared to the other schedulers.

**Single-source shortest path** For the single-source shortest path benchmark running the algorithm with standard work-stealing makes no sense, since it could well take exponential time when distance updates are performed in some fixed LIFO order. We therefore compare to a sequential implementation of Dijkstra’s algorithm with a worst-case efficient priority queue data structure. The results for weighted graphs with 15000 nodes can be seen in Figure 6. Dijkstra’s algorithm slightly outperforms the strategy scheduler in the sequential setting. The parallel algorithm achieves some scalability, with a speedup of 3.3 over the sequential algorithm on 12 threads.

**Quicksort** For Quicksort, which fits with the standard work-stealing execution order, we do not expect much from an execution with a specialized strategy. We chose Quicksort as a benchmark to see whether some performance advantage can still be achieved with strategies, and how high the overhead of the strategy scheduler is. The implementation uses a cut-off for subsequences shorter than 256 elements, which are quicksorted sequentially. Figure 8 shows the results of those measurements. For the 1-thread run performance with strategies is similar to standard work-stealing, since the overhead for the strategy scheduler is roughly the same as the gains due to the optimizations with strategies. With more threads the overhead diminishes, and a slightly better performance is observed.

The specialized strategy is able to match the performance of the basic scheduler for low numbers of threads and can slightly outperform it for higher numbers. Given that Quicksort is a well-behaving algorithm for work-stealing this shows that even in such applications a potential for strategies exists.

**Composition of Prefix Sum and UTS** To finally demonstrate the performance composability of strategies, we combined the prefix sum and the UTS benchmark into a single application. The UTS part uses the same tree as when executed by itself, whereas the prefix sum was given a slightly longer sequence to work on, to balance the total amount of work of the two kernels. The results for the composite benchmark are compared to the running times of each of the
Figure 8: Quicksort on a sequence of 10 million elements.

Figure 9: Prefix sum for a list with $5 \times 10^8$ elements together with the UTS benchmark for the T5 tree. All measurements were done using specialized strategies.

benchmarks on their own using their specialized strategies. The results in Figure 9 show that the performance of the composed benchmark is better than the sum of its parts for two or more threads. For a single thread, similar performance is achieved.

6 Conclusion

We introduced dynamic scheduling strategies for work-stealing schedulers to enable application dependent, per-task scheduling decisions, like changing the execution and stealing order of tasks, as well as merging tasks at run-time. These decisions can be used to reduce scheduling overhead, as well as make the execution more efficient and adaptive. In contrast to global scheduling policies, our strategies can be selected on the level of individual tasks. This poses the unique challenge of making strategies composable, which is especially difficult for the prioritization of tasks, without increasing the scheduler overhead too much. However, the focus of this paper was solely on presenting the idea of scheduling strategies and giving a glimpse of what can be achieved using this mechanism.

We discussed a variety of applications that profit from such strategies and presented experimental results to show the expected gains. The paper gave but a brief, high-level overview of the scheduling system and the corresponding data structure; details will be exposed in an accompanying publication.

In future work we plan to explore additional aspects of strategies that can be used for additional optimization, but also to support more general models of parallelism like mixed-mode parallelism, where tasks in themselves can be parallel. We will also explore further applications, with the focus on applications that can profit from different types of strategies in a single execution to investigate the composability aspect further. Also, there is still room for decreasing the scheduler overhead by additional optimizations to the data structure. Finally, we plan to extend our work to heterogeneous systems, since we believe that strategies can be highly profitable to aid scheduling decisions in this context.

References

[1] U. A. Acar, G. E. Blelloch, and R. D. Blumofe. The data locality of work stealing. Theory of Computing Systems, 35(3):321–347, 2002.
[2] N. S. Arora, R. D. Blumofe, and C. G. Plaxton. Thread scheduling for multiprogrammed multiprocessors. *Theory of Computing Systems*, 34(2):115–144, 2001.

[3] P. Berenbrink, T. Friedetzky, and L. A. Goldberg. The natural work-stealing algorithm is stable. In *42nd IEEE Symposium on Foundations of Computer Science (FOCS)*, pages 178–187, 2001.

[4] R. D. Blumofe, C. F. Joerg, B. C. Kuszmaul, C. E. Leiserson, K. H. Randall, and Y. Zhou. Cilk: An efficient multithreaded runtime system. *Journal of Parallel and Distributed Computing*, 37(1):55–69, 1996.

[5] R. D. Blumofe and C. E. Leiserson. Scheduling multithreaded computations by work stealing. *Journal of the ACM*, 46(5):720–748, 1999.

[6] F. Broquedis, J. Clet-Ortega, S. Moreaud, N. Furmento, B. Goglin, G. Mercier, S. Thibault, and R. Namyst. hwloc: A generic framework for managing hardware affinities in HPC applications. In *18th Euromicro Conference on Parallel, Distributed and Network-based Processing (PDP)*, pages 180–186, 2010.

[7] P. Charles, C. Grothoff, V. Saraswat, C. Donawa, A. Kielstra, K. Ebcioğlu, C. von Praun, and V. Sarkar. X10: An object-oriented approach to non-uniform cluster computing. In *20th ACM SIGPLAN Conference on Object-Oriented Programming, Systems, Languages, and Applications (OOPSLA)*, pages 519–538, 2005.

[8] J. Clausen and J. L. Träff. Implementation of parallel branch-and-bound algorithms – experiences with the graph partitioning problem. *Annals of Operations Research*, 33:331–349, 1991.

[9] R. Cole and V. Ramachandran. Resource oblivious sorting on multicores. In *Automata, Languages and Programming, 37th International Colloquium (ICALP) Proceedings, Part I*, volume 6198 of *Lecture Notes in Computer Science*, pages 226–237, 2010.

[10] T. G. Crainic, B. L. Cun, and C. Roucairol. Parallel branch-and-bound algorithms. In E.-G. Talbi, editor, *Parallel Combinatorial Optimization*, pages 1–28. Wiley, 2006.

[11] F. Evans, S. Skiena, and A. Varshney. Optimizing triangle strips for fast rendering. In *7th IEEE Conference on Visualization*, pages 319–326, 1996.

[12] Y. Guo, R. Barik, R. Raman, and V. Sarkar. Work-first and help-first scheduling policies for async-finish task parallelism. In *23rd IEEE International Parallel and Distributed Processing Symposium (IPDPS)*, pages 1–12, 2009.

[13] Y. Guo, J. Zhao, V. Cavé, and V. Sarkar. SLAW: A scalable locality-aware adaptive work-stealing scheduler. In *24th IEEE International Parallel and Distributed Processing Symposium (IPDPS)*, pages 1–12, 2010.

[14] K. T. Herley, A. Pietracaprina, and G. Pucci. Fast deterministic parallel branch-and-bound. *Parallel Processing Letters*, 9(3):325–333, 1999.

[15] R. M. Karp and Y. Zhang. Randomized parallel algorithms for backtrack search and branch-and-bound computation. *Journal of the ACM*, 40(3):765–789, 1993.

[16] A. Kukanov and M. J. Voss. The foundations for scalable multi-core software in Intel Threading Building Blocks. *Intel Technology Journal*, 11(4), 2007.
[17] C. E. Leiserson. The Cilk++ concurrency platform. *The Journal of Supercomputing*, 51(3):244–257, 2010.

[18] A. Lenharth, D. Nguyen, and K. Pingali. Priority queues are not good concurrent priority schedulers. Technical Report TR-11-39, Department of Computer Science, The University of Texas at Austin, 2011.

[19] S. Olivier, J. Huan, J. Liu, J. Prins, J. Dinan, P. Sadayappan, and C. Tseng. UTS: An unbalanced tree search benchmark. *Languages and Compilers for Parallel Computing*, pages 235–250, 2007.

[20] C. H. Papadimitriou and K. Steiglitz. *Combinatorial Optimization: Algorithms and Complexity*. Prentice-Hall, 1982.

[21] P. Sanders. Fast priority queues for parallel branch-and-bound. In *Parallel Algorithms for Irregularly Structured Problems (IRREGULAR)*, volume 980 of *Lecture Notes in Computer Science*, pages 379–393, 1995.

[22] F. Song, A. YarKhan, and J. Dongarra. Dynamic task scheduling for linear algebra algorithms on distributed-memory multicore systems. In *High Performance Computing Networking, Storage and Analysis (SC)*, pages 1–11, 2009.

[23] M. Squillante and E. Lazowska. Using processor-cache affinity information in shared-memory multiprocessor scheduling. *IEEE Transactions on Parallel and Distributed Systems*, 4(2):131–143, 1993.

[24] B. Weissman. Performance counters and state sharing annotations: a unified approach to thread locality. In *8th International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS)*, pages 127–138, 1998.

[25] M. Wimmer, D. Cederman, J. L. Träff, and P. Tsigas. Work-stealing with configurable scheduling strategies. In *18th ACM Symposium on Principles & Practice of Parallel Programming (PPoPP)*, pages 315–316, 2013.

[26] M. Wimmer, M. Pöter, and J. L. Träff. The Pheet task-scheduling framework on the Intel® Xeon Phi™ coprocessor and other multicore architectures. In *Workshop on Multithreaded Architectures and Applications (MTAAP) at the 26th International Parallel and Distributed Processing Symposium (IPDPS)*, 2013.