Scalable, Fast Cloud Computing with Execution Templates

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Abstract

Large scale cloud data analytics applications are often CPU bound. Most of these cycles are wasted: benchmarks written in C++ run 10-51 times faster than frameworks such as Naiad and Spark. However, calling faster implementations from those frameworks only sees moderate (3-5x) speedups because their control planes cannot schedule work fast enough.

This paper presents execution templates, a control plane abstraction for CPU-bound cloud applications, such as machine learning. Execution templates leverage highly repetitive control flow to cache scheduling decisions as *templates*. Rather than reschedule hundreds of thousands of tasks on every loop execution, nodes instantiate these templates. A controller's template specifies the execution across all worker nodes, which it partitions into per-worker templates. To ensure that templates execute correctly, controllers dynamically patch templates to match program control flow. We have implemented execution templates in Nimbus, a C++ cloud computing framework. Running in Nimbus, analytics benchmarks can run 16-43 times faster than in Naiad and Spark. Nimbus's control plane can scale out to run these faster benchmarks on up to 100 nodes (800 cores).

1 Introduction

The CPU has become the new bottleneck for analytics benchmarks and applications. One recent study found that the big data benchmark (BDBench), TCP decision support benchmark (TCP-DS), and production workloads from Databricks were all CPU-bound. Improving network I/O would reduce their median completion time by at most 2% and improving disk I/O would reduce their median completion time by at most 19% [30].

At the same time, systems such as DMLL [13] and DimmWitted [26] have shown it is possible to achieve orders-of-magnitude improvements in CPU performance over frameworks such as Spark [38]. Comparing the performance of C++ and Spark implementations of two standard machine learning benchmarks, we find that the C++ implementations run up to *51 times faster*. Modern analytics frameworks are CPU-bound, but most of these cycles are wasted.

One straw man solution to improve performance is to have a framework call into C++ implementations of computational kernels, e.g., through the Java Native Interface (JNI). In Section 2.2, we show that this only sees modest speedups (5x rather than 50x): worker nodes spend 90% of their cycles idle. The central Spark *controller*, which is responsible for telling to workers to execute tasks, cannot schedule tasks quickly enough. The framework's control plane becomes a bottleneck and workers fall idle. In Section 5 we show that Naiad [28], another framework, has similar control plane bottlenecks.

Current frameworks do not scale to run optimized tasks on many nodes. They can either run on many nodes or run optimized tasks, but not both, because the control plane cannot schedule tasks fast enough. Prior scalable scheduling systems such as Sparrow [31], Omega [33], Apollo [12], Mercury [25], Hawk [16] and Tarcil [17] all propose ways to distribute the scheduling of many jobs which together overwhelm a single controller. Scheduling a job requires centralized state, and so for all these systems, tasks from a single job still go through a single scheduler. Optimized tasks, however, mean that a *single* job can saturate a controller.

Section 3 presents *execution templates* a control plane abstraction which scales to schedule optimized tasks on many nodes. The key insight behind execution templates is that long-running CPU-bound computations are repetitive: they run the same computation (e.g., a loop body) many times. Rather than reschedule each repetition from scratch, a runtime caches scheduling decisions as an execution template of tasks. A program invokes a template, potentially creating thousands of tasks, with a single message. We call this abstraction a template because it can cache some decisions (e.g., dependencies) but fully instantiating it requires parameters (e.g., task identifiers).

Section 4 describes an implementation of execution templates in Nimbus, a C++ analytics framework that incorporates execution templates. Compared to Spark and Naiad, benchmarks in Nimbus run 16-43 times faster. Rewriting benchmarks in Spark and Naiad to use optimized tasks reduces their completion time by a factor of

3.7-5. However, Section 2.2 shows results that neither can scale out past 20 worker nodes because the control plane becomes a bottleneck: running on more than 20 nodes *increases* completion time. Using execution templates, implementations of these benchmarks in Nimbus scale out to 100 nodes (800 cores), seeing nearly linear speedups.

Execution templates allow a centralized controller to handle tasks shorter than 1ms, or 100 times shorter than what prior systems support [31]. This makes whole new applications possible. We have ported PhysBAM, a graphical simulation library [18] used in many feature films[1] to Nimbus. PhysBAM has tasks as short as 100μs, yet execution templates can execute extremely large simulations within 15% of the speed of PhysBAM's hand-tuned MPI libraries.

This paper makes five contributions:

1. A detailed analysis of how Spark spends CPU cycles, finding that C++ implementations run 51 times faster and most of Spark's cycles are wasted due to runtime and programming language overheads (Section 2.1).
2. Results showing Spark and Naiad's control planes are a bottleneck when running optimized (C++) tasks and so they can only provide modest speedups (Section 2.2).
3. Execution templates, a novel control plane abstraction that allows optimized tasks to run at scale (Section 3).
4. The design of Nimbus, an analytics framework that incorporates execution templates and a data model based on mutable data objects which permit in-place modifications (Section 4).
5. An evaluation of execution templates, finding they allow Nimbus to run optimized tasks with almost no overhead, scaling out to 100 nodes (800 cores) while running 30-43 times faster than Spark and 16-23 times faster than Naiad. Execution templates also allow Nimbus to support large, complex applications with tasks as short as 100μs (Section 5).

Section 4 provides details on the Nimbus implementation of execution templates, including the dynamic program analysis that ensures they execute properly despite variations in control and data flow. Section 6 presents related work and Section 7 concludes.

2 Motivation

A recent study found that Spark analytics applications are CPU-bound [30]. Increasing server RAM and easy parallelization means that many applications can keep their entire working set in RAM and completion time is limited by CPU performance.

[1] PhysBAM is a cornerstone of special effects at Industrial Light and Magic and is also used Pixar.

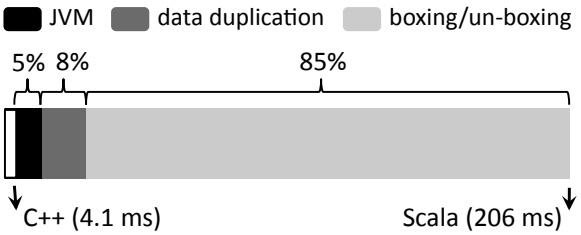


Figure 1: Logistic regression execution time implemented in Scala and C++. C++ is 51 times faster than Scala. These results are averaged over 30 iterations and discard the first iteration to allow Java Virtual Machine (JVM) to warm up and just-in-time compile.

Code	Nodes	Task Length	Completion Time
Scala	100 nodes	206ms	2.86s
C++	100 nodes	4ms	1.00s
C++	20 nodes	20ms	0.53s

Table 1: Effect of running optimized logistic regression tasks in Spark. Although C++ tasks can run 51 times faster, a job using C++ tasks on 100 nodes only runs 2.8x faster. It run 5x faster when run on 20 nodes. Both are much slower than the expected speedups and 20 nodes is faster than 100 due to the control plane being unable to schedule tasks fast enough.

This section motivates the need for a new control plane in cloud data analytics frameworks. It starts by examining where Spark's CPU cycles go: 98% of them are wasted. Re-implementations in C++ run up to 51 times faster. However, if a Spark job uses these faster re-implementations, it only sees modest (5x) speedups because the control plane (messages to schedule and dispatch tasks) become the bottleneck. The section concludes by observing an important property of CPU-bound applications, that their control flow and execution exhibits very regular patterns, which can be calculated, cached and reused.

2.1 Where the Cycles Go

Frameworks such as Spark [38] and Naiad [28] focus on applications whose data sets can fit in memory when spread across many nodes. At the same time, a push for greater programmer productivity has led them to support higher-level languages: 70% of Spark applications are written in Scala [37].

These two trends (in-memory datasets and higher-

level languages) conflict: for applications that operate on in-memory data, higher-level language overheads become significant. Figure 1 shows the execution time of logistic regression, a common analytics benchmark, implemented in Spark using Scala and implemented in C++. The C++ implementation runs *51 times faster* than the Spark one.

This poor performance has three major causes.[2] First, since Scala's generic methods cannot use primitive types (e.g., they must use the `Double` class rather than a `double`), every generic method call allocates a new object for the value, boxes the value in it, un-boxes for the operation, and deallocates the object. In addition to cost of a `malloc` and `free`, this results in millions of tiny objects for the garbage collector to process. 85% of logistic regression's CPU cycles are spent boxing/unboxing.

Second, Spark's resilient distributed datasets (RDDs) forces methods to allocate new arrays, write into them, and discard the source array. For example, a `map` method that increments a field in a dataset cannot perform the increment in-place and must instead create a whole new dataset. This data duplication adds an additional factor of $\approx$ 2x slowdown.

Third, using the Java Virtual Machine has an additional factor of $\approx$ 3x slowdown over C++. This result is in line with prior studies, which have reported 1.9x-3.7x for computationally dense codes [22, 21]. In total, this results in Spark code running 51 times slower than C++.

2.2 Implications of Optimized Tasks

To determine how much tasks running at C++ speeds could improve performance, we replaced the logistic regression benchmark's Spark Scala code with loops that take as long as the C++ implementations. This represents the best-case performance of Spark calling into a native method (there is no overhead).

Table 1 shows the results. While the computational tasks run 51 times faster, on 100 nodes the overall computation only runs 2.8 times faster. Worker nodes spend most of the time idle because the central Spark controller cannot schedule tasks fast enough. Each core can execute 250 tasks per second (each task is 4ms), and 100 nodes (800 cores) can execute 200,000 tasks per second. We measured Spark's controller to be able to issue $\approx$8,000 tasks per second.

This control plane bottleneck is not unique to Spark. Naiad [28] is the best available *distributed* cloud framework. In Naiad, worker nodes directly coordinate with one another rather than acting through a central controller. While Naiad code is in C# rather than Scala and so sees overall better performance than Spark, its all-to-all synchronization also becomes a bottleneck above 20 nodes. We defer detailed experimental results on Naiad to Section 5.1.

Scheduling techniques such as Sparrow [31], Omega [33], Apollo [12], Mercury [25], Hawk [16] and Tarcil [17], address the scheduling bottleneck that occurs when there are many concurrent jobs. In aggregate, many jobs can execute more tasks per second than a single controller can schedule. But since these jobs share underlying computing resources, they need to be scheduled cooperatively to prevent overloading workers or contention. Each of these systems propose ways for many separate, per-job controllers to coordinate their resource allocation and scheduling decisions. These systems all solve the problem of when the aggregate task rate of *many* jobs is greater than what one controller can handle. Optimized tasks, however, mean that *single* job can saturate a controller. None of these systems can distribute a single job's scheduling.

2.3 Observation: Repetition

Cloud computing applications are increasingly advanced data analytics including machine learning, graph processing, natural language processing, speech/image recognition, and deep learning. These applications are usually implemented on top of frameworks such as Spark [38] or Naiad [28], for seamless parallelization and elastic scalability. A recent survey [6] of Spark users, for example, shows 59% of them use the Spark machine learning library [5]. Efforts such as Apache Mahout [4] and Oryx [9] provide machine learning libraries on top of Spark. Cloud providers, in response to this need, now offer special services for machine learning models [8, 1].

One important property of analytics jobs is their computations have repetitive patterns: they execute a loop (or set of nested loops) until a convergence condition. The Ernest system [35], for example, leveraged this observation for predicting the performance and managing resources. Logistic regression, for example, often executes until parameters have converged and are no longer changing or a large fixed number of iterations (whichever happens first).

For example, Figure 2 shows the execution graph of the hold-out cross validation method, a common machine learning method used for training regression algo-

[2] To determine the cause of this slowdown, we configured the JVM to output the JIT assembly and inspected it. We inserted performance counters in the Scala code re-inspected the assembly to verify they captured the correct operations. To separate the cost of Scala from JVM bytecode interpretation, we decompiled the JVM bytecodes Scala generated into Java, rewrote this code to remove its overheads, recompiled it, and verified that the bytecodes for the computational operations remained unchanged.

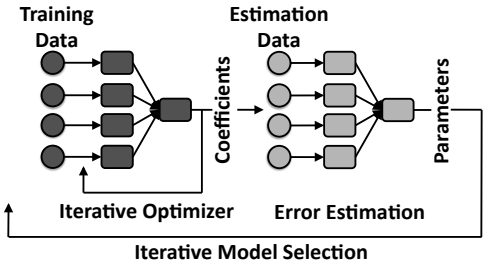


Figure 2: Execution graph of training a regression algorithm. It is iterative with an outer loop for updating model parameters based on the estimation error, and an inner loop for optimizing the feature coefficients.

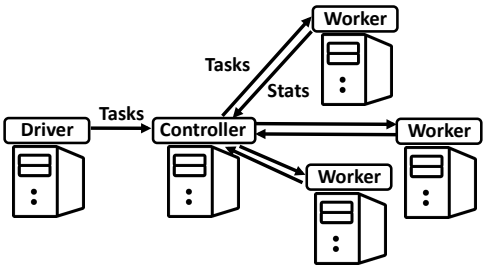


Figure 3: Architecture of a canonical cloud framework: a driver program specifies the application logic for a centralized controller, which drives the worker nodes to execute tasks.

rithms [20]. It has two stages, training and estimation, which form a nested loop. The training stage uses an iterative algorithm, such as gradient descent, to tune coefficients. The estimation stage calculates the error of the coefficients and feeds this back into the next iteration of the training phase.

Each iteration generates the same tasks and schedules them to the same nodes (those that have the data resident in memory). Re-scheduling each iteration repeats this work. This suggests that a control plane cached these decisions and reused would schedule tasks much faster and scale to support fast tasks running on more nodes. The next section describes execution templates, a control plane abstraction that achieves this goal.

3 Execution Templates

We describe execution templates, a control plane abstraction for cloud computing. Execution templates make it possible for workers to inexpensively generate and execute large batches of tasks. If a program has a loop in it, rather than resend all of the tasks for that loop to the controller on every iteration, it should instead send them once. For subsequent iterations, it can tell the controller "execute those tasks again." The same is true for the controller; rather than resend all of the tasks to the workers, it can tell each worker to "execute those tasks again."

```
while (error > threshold_e) {
  while (gradient > threshold_g) {
    // Start 1
    gradient = Gradient(tdata, coeff, param)
    coeff += gradient
    // End 1
  }
  // Start 2
  error = Estimate(edata, coeff, param)
  param = update_model(param, error)
  // End 2
}
```

Figure 4: Driver program pseudocode for the iterative application in Figure 2. There are two basic blocks. `Gradient` and `Estimate` are both parallel operations that execute many tasks on partitions of data.

Execution template	JIT compiler
Template	Function
Task (Driver→Controller)	Bytecode instruction
Task (Controller→Worker)	Native instruction
Data object	Register

Table 2: Execution templates are analogous to a just-in-time compiler for a data analytics control plane.

The execution and control structure of cloud frameworks places requirements on how templates operate. Figure 3 shows the architecture of a cloud computing framework. A *driver* program generates tasks, which it sends to a centralized *controller*. The driver and controller may or may not reside on the same node. The controller processes these tasks and dispatches them to a cluster of *workers*. The controller balances load across workers and recovers execution when one fails.

Templates optimize repeated control decisions. In this way, they are similar to a just-in-time (JIT) compiler for the control plane. A JIT compiler transforms blocks of bytecodes into native instructions; execution templates transform blocks of tasks into dependency graphs and other runtime scheduling structures. Table 2 shows the correspondences in this an analogy: an execution template is a function (the granularity JIT compilers typically operate on), a task from the driver to the controller is a bytecode instruction, and a task executing on the worker is a native instruction.

The rest of this section describes six requirements for how templates operate. While the analogy to JIT compilation fits well and many of these requirements follow from it, the driver-controller-worker execution model adds an additional requirement, the need to validate and

patch templates before executing them.

1. Templates must be dynamically generated. Controllers and workers do not have the driver program. They receive a stream of tasks, which they dynamically schedule and execute. They therefore need to generate templates in response to this dynamic stream of information. Furthermore, because a controller can dynamically shift how it schedules tasks to workers (e.g., in response to load imbalance or changing resources), it needs to be able to correspondingly dynamically create new templates. Put another way, templates cannot be statically compiled: they must instead be created just-in-time.

2. Templates must be parameterizable. Similarly to how a program must be able to pass parameters to just-in-time compiled functions, a driver must be able to pass parameters to execution templates. Analytics jobs involve many repetitions of the same loop or computation, but the repetitions are not identical. The cross-validation job in Figure 2, for example, updates `parameters`, which are then passed to the optimizer block. Each instantiation of the optimizer block must fill in `parameters` to the `find_gradient` tasks. In addition to data parameters, templates also require control parameters, such as which task identifiers to use, to ensure that two workers do not use the same globally unique identifier.

3. Workers must locally resolve dependencies. Large blocks of tasks often have data dependencies between them. For example, the line `coeff += gradient` in Figure 4 cannot run until the previous line computing `gradient` completes. For a worker to be able to execute the tasks for both lines of code locally, without coordinating with the controller, it must know this dependency and correctly determine when that line of code can run. This is similar to how a CPU uses data flow to know when it can execute an instruction that depends on the output of other instructions.

4. Workers must directly exchange data. Optimized tasks read and write in-memory data objects on workers. Often, within a single template, the output of a task on one worker is needed as the input for a task on another. As part of executing the template, the two workers need to directly exchange this data. This is similar to how two cores accessing the same memory need to be able to to update each other's caches rather than always write through to main memory.

5. Controllers must be able to quickly validate and patch templates. The driver-controller-worker execution model adds additional complexities that JIT compilers do not need to handle. Just as function calls assume that arguments are in certain registers or stack positions, when a controller generates execution templates for workers, it must assume certain preconditions on where data is located. However, a driver can insert new tasks at any time, which might violate these preconditions. For example, it might insert instructions that increment a variable and store it in a different register. When a controller instantiates a template, it must validate whether a template's preconditions hold, and if not, insert tasks to patch it. In the above example, the controller needs to detect the variable is now in a new register and issue a move instruction to put it back in the register the function call expects.

6. Templates must be fast. Finally, as the overall goal of templates is to allow the control plane to support optimized tasks at scale, the performance gains of instantiating them must be greater than their cost to generate and instantiate.

Execution templates are tightly entwined with a framework's data model and execution. The next section describes a concrete implementation of them in the context of an analytics framework designed to execute optimized tasks at scale.

4 Implementation

This section describes the design and implementation of execution templates in a C++ analytics framework we have implemented, called Nimbus. We chose to implement execution templates in a new framework in order to explore their tradeoffs when not limited by prior design decisions that might conflict with their goals. There is also discussion on how execution templates can be introduced into existing frameworks.

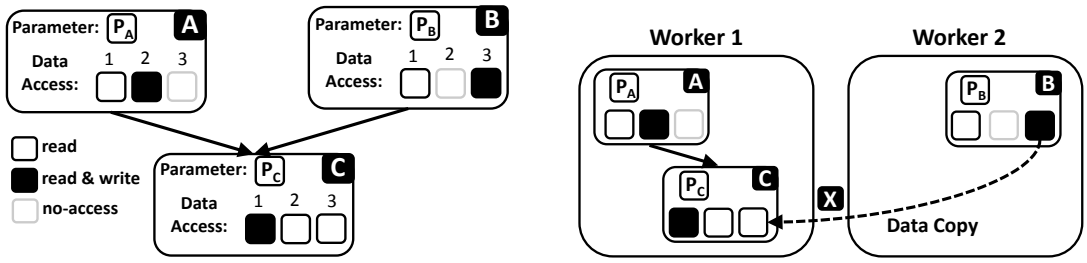
4.1 Nimbus

Because execution templates are tightly entwined with a framework's data and execution model, we first explain the relevant details of Nimbus. The core Nimbus implementation is 15,000 semicolons of C++ code.

4.1.1 Data Model

Nimbus has a data flow model similar to DryadLINQ [36], Naiad [28], and Spark [38]. A job is decomposed into *stages*. Each stage is a computation over a set of input data and produces a set of output data. Each data set is partitioned into many *data objects* so that stages can be parallelized. Each stage typically executes as many *tasks*, one per object, that operate in parallel. In addition to the identifiers specifying the data objects it accesses, each task can be passed parameters, such as a time-step value or constants.

Unlike Spark's RDDs, and to avoid the cost of data copying noted in Section 2.1, Nimbus allows tasks to mu-



(a) Simple task graph example with three tasks and three data objects. The data flow among tasks forms a DAG. For example, task C reads the updated data objects 2, and 3 after execution of task A, and B.

(b) Mapping of the task graph in Figure 5(a) over two workers. Each task graph embeds per worker task dependencies and data copy among workers. Task graph dependencies allow workers to proceed without controller's middling.

Figure 5: Simple task graph example (a) and how it maps into per worker task graph in Nimbus (b).

tate data in place. Mutable data has the additional benefit that multiple iterations of a loop can access the same objects and reuse their identifiers. This makes templates more efficient to parameterize, as the object identifiers can be cached rather than recomputed on each iteration. There can be multiple copies of a data object. However, since objects are mutable they are not always consistent. If one worker writes to its copy of an object, other workers who later read it will need to receive the latest update.

Data flow between tasks forms a directed acyclic graph (DAG), called *task graph*, whose vertices are tasks and edges are data dependencies. Figure 5(a) shows a simple task graph with three tasks that operate over three data objects. The rest of this section uses this example task graph to explain how templates are generated and instantiated.

4.1.2 Dependencies and Data Exchange

The goal of execution templates is to allow workers to generate and correctly schedule large batches of tasks. Not all of these tasks are immediately runnable. For example, when a worker instantiates the template in Figure 5(a), it cannot run task C until both A and B have completed. The ability to locally determine when it is safe to run a task is critical for reducing load on a controller; otherwise, the controller would need to publish when every task has completed. Workers need to be able to know this both when the dependent tasks are local as well as when they run on another node.

To enforce the correct execution order, each task includes a set of dependencies. These dependencies are identifiers for tasks that must complete before the worker schedules the task. As shown in Figure 5(b), these dependencies can also be across workers: task B on worker 2 must complete before task C can run on worker 1. Nimbus represents this dependency by introducing a pair of control tasks, a send task on worker 2 and a receive task on worker 1, and inserting the receive task as a dependency in C. These explicit dependencies allow workers to know when a task is ready to run without involving the controller.

4.2 Dynamic Template Generation

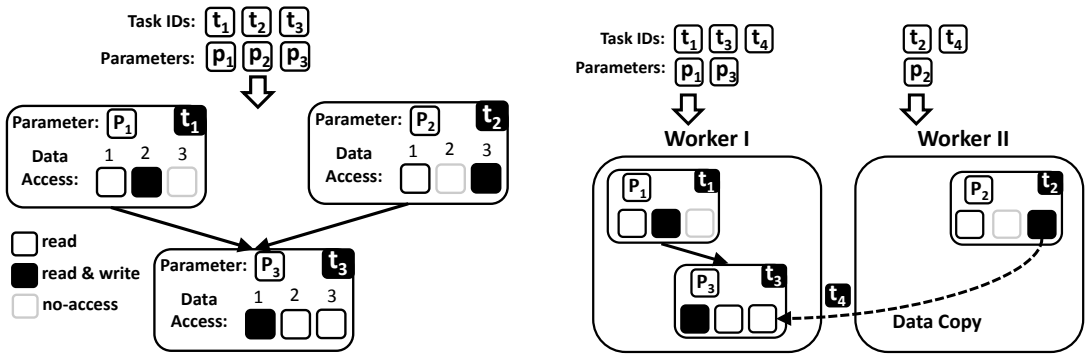
Nimbus generates execution templates on the granularity of basic blocks. A *basic block* is a code sequence in the driver program with only one entry point and no branches except at the exit. For example, in Figure 4, there are two basic blocks, the optimizer and the estimator. Each iteration of the algorithm executes the optimizer block (inner loop) multiple times and the estimator block (outer loop) once.

There are two types of execution templates. *Controller templates* are installed on a controller by the driver program; they encode the task graph of a basic block across all of the workers. Controller templates reduce the control overhead between the driver and the controller. *Worker templates* are installed on workers by the controller; they encode the task graph of a basic block for that worker. Once a template is installed, it can be invoked with a single message. When the driver program invokes a controller template, the controller typically invokes the corresponding worker template on each worker.

The two types of templates are decoupled to enable dynamic scheduling decisions. If a worker fails or the controller re-balances load across worker, two invocations of the same controller template can result in two different partitioning of tasks among workers. For every partitioning strategy a separate worker template is installed on the workers.

4.2.1 Controller Templates

Controller template stores control dependencies between tasks as well as which data tasks access. To create a controller template, the driver program sends a start message



(a) A controller template represents the common structure of a task graph metadata. It stores task dependencies and data access patterns. It is invoked by filling in task identifiers and parameters to each task.

(b) Each worker template stores the common structure of a task graph for execution including the data copies among workers. It is invoked by passing the task identifiers, and parameters to each task.

Figure 6: Controller template (a) and worker templates (b) for the task graph in Figure 5(a).

to the controller, which instructs to start building a template. As the controller receives each subsequent task, it both schedules it normally and adds it to the template. At the end of the basic block, the driver sends a finish message to the controller. At this point the controller processes the template it has built and generates worker templates from it. For the successive instance of the same basic block, driver only invokes the installed template by passing the task identifiers and parameters to each task. Figure 6(a) shows how the controller templates for the graph in Figure 5(a) are installed and invoked.

4.2.2 Worker Templates

A worker template has two halves. The first half exists at the controller and represents the entire computation across all of the workers. This centralized half allows the controller to cache how the template's tasks are distributed across workers and which data objects the tasks access. The second half is distributed among the workers and caches the per-worker local task graph with dependencies and data exchange directives.

As with controller templates, to generate a worker template the controller sends all tasks to workers explicitly. Workers execute these tasks and simultaneously build a template. The next time the driver program invokes the controller template, the controller invokes the templates at each worker by passing new task ids, and parameters. Figure 6(b) shows how the controller templates for the scheduling strategy in Figure 5(b) are installed and invoked.

4.3 Patching Worker Templates

Templates, when generated, assume that the latest updates to data objects are distributed in a certain way. For example, in Figure 5(b), the template on worker 2 assumes that data objects 1 and 3 contain the latest update. Since templates are installed dynamically, the runtime does not know the complete control structure of the program. It can be that there are code paths which do not leave the latest update in every object. Put in other words, the driver may have issued tasks which invalidate the template's assumptions. At the same time, the driver program does not know where data objects are placed or tasks execute, so cannot correct for these cases.

Because this problem is subtle, we provide an analogy based on JIT compilers. JIT generated blocks of native instructions assume that variables are in particular registers. If the registers do not hold the correct variables when the block of native instructions is invoked, then move, store, and load instructions must be added so the registers do hold the correct variables.[3]

Whenever a template is invoked, the controller needs to first *validate* whether the corresponding worker templates will operate on the latest updates. If validation fails, the controller patches the template by inserting control tasks that copy the latest updates to the objects. For example, if immediately after the template in Figure 6(b) the same template is invoked, then controller needs to transfer the latest update of first object (updated by task t_3) to worker 2 to satisfy the preconditions. Only after patching it is safe to invoke the template again.

Validating and patching must be fast, specially when there are many workers, data objects, and nodes. For example, the complex graphics application in Section 5.5 has almost one million data objects. Nimbus uses two optimizations to make validation and patching fast.

First, for the common case of a template executing

[3]This is one reason why JITs often operate on function boundaries, since function calling conventions specify how variables must be laid out in registers.

twice back to back, the controller ensures that the input objects to a template hold the latest updates when the template completes. This is especially important for when there are small, tight loops: the controller can bypass both validation and patching. Second, for basic blocks that can be entered from multiple places in the program (e.g., the block after an if/else clause), the controller generates a separate template for each possible control flow.

4.4 Load Balancing and Fault Tolerance

Nimbus balances load across workers by periodically collecting performance statistics at the controller. When the controller detects that certain workers are busier than others, it redistributes tasks across the workers, regenerating templates for any workers whose load has changed.

To recover from worker failures, the Nimbus controller periodically checkpoints system state. To create a checkpoint, the controller inserts tasks that commit data objects to durable storage as well as metadata on where in program execution this checkpoint is. If a worker fails and the system loses the latest update to an object, the controller halts all tasks on the workers. It restores the lost objects to their last checkpoint as well as any other objects which have been modified since that checkpoint. It then restarts execution, regenerating any worker templates as needed. If the controller fails, it can restart and restore the entire system from the checkpoint.

4.5 Templates in Other Frameworks

Templates are a general abstraction that can be applied to many frameworks. However, the requirements in Section 3 can be simpler to incorporate in some systems than others. For example, incorporating execution templates into Spark would require three significant changes to its data model and execution model, particularly its lazy evaluation and scheduling. First, it would need to support mutable data objects. When data is immutable, each execution of a template is on new data object identifiers. Second, the Spark controller needs to be able to proactively push updates to each worker's block manager. Otherwise, every access of a new data object requires a lookup at the controller. Third, in Spark the controller is completely responsible for ensuring tasks run in the correct order, and so tasks sent to workers do not contain any dependency information. Adding execution templates would require adding this metadata to tasks as well as worker control logic. While these changes are all quite tractable, together they involve a significant change to Spark's core execution model and so we are beginning to discuss this with its developers.

We are have not yet considered adding templates to Naiad since it is no longer actively supported (the last code commit was Nov 9, 2014).

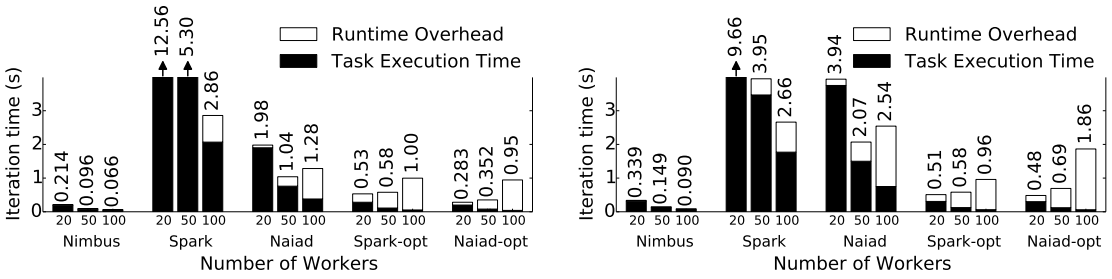
5 Evaluation

This section evaluates how execution templates can support fast, optimized data analytics jobs at scale. It compares the performance of k-means and logistic regression benchmarks implemented in Nimbus with implementations in Spark and Naiad. It measures the costs of computing and installing templates as well as the performance effect of needing to recompute worker templates due to load re-balancing. Finally, it evaluates how far execution templates can scale by measuring their effect on a distributed graphics workload whose median task length is 13ms and 10th percentile task length is 3ms.

In summary, our findings show:

- Execution templates support orders of magnitude more tasks per second than existing centralized (Spark) and decentralized (Naiad) designs. Task throughput scales almost linearly with the number of workers.
- Using execution templates, Nimbus is able to run logistic regression and k-means benchmarks 16-43 times faster than Spark and Naiad implementations.
- Half of this performance benefit is from optimized tasks, the other half is from execution templates scheduling optimized tasks at scale. If Spark and Naiad use optimized tasks, they cannot scale out past 20 nodes; execution templates allow Nimbus to scale out to at least 100 nodes and cut completion times by a factor of 4-8.
- Using execution templates, Nimbus is able to run a complex graphical simulation with tasks as short as 100μs within 15% of the performance of a hand-tuned MPI implementation. Without templates, completion time increases by 520% as the controller cannot schedule tasks quickly enough.

All experiments use Amazon EC2 compute-optimized instances since they are the most cost effective for compute-bound workloads. Worker nodes are `c3.2xlarge` instances, which have 8 virtual cores and 15GB of RAM. Because we wish to evaluate how the controller can become a bottleneck, we run it on a more powerful instance than the workers, a `c3.4xlarge` instances, with 16 cores and 30GB of RAM. This shows the performance of the controller even when it has more resources than the workers. We measure completion time of different jobs on 20–100 worker nodes. Nodes are allocated within a placement group and so have full bisection bandwidth.



(a) Logistic regression (b) K-means clustering

Figure 7: Iteration time of logistic regression and k-means for a data set of size 100GB. Spark, Naiad and Nimbus, run Scala, C# and C++ respectively. Spark-opt and Naiad-opt show the performance when the computations are replaced with spin-wait as fast as tasks in C++. Execution templates helps Nimbus scale out almost linearly.

Iteration time is averaged over 30 iterations and excludes the first iteration due to its overhead of data loading and JIT compilation. We observed negligible variance in iteration times. For Nimbus, the first iteration includes the cost of template installation. We therefore quantify this cost separately from overall performance.

5.1 Data Analytics Benchmarks

Figure 7 shows the completion time for logistic regression and k-means when run in Spark, Naiad and Nimbus. In addition to a Scala implementation in Spark and a C# implementation in Naiad, we also measure performance if these frameworks could execute tasks as quickly as Nimbus. We consider the *best case* performance of no overhead for invoking native code by having them run a busy loop.

For logistic regression, Naiad's C# runs 6 times faster than Spark's Scala. The fastest Spark configuration is 100 nodes, while for Naiad it is 50 nodes. This is because Naiad's faster task execution means its control plane overhead overwhelms the benefits of running on more workers. Naiad's control overhead grows quickly because it requires O(n^2) communication among Naiad nodes, where n is the number of nodes.

C++ tasks run 51 times faster than Scala and 9 times faster than C#. When Spark and Naiad's tasks are replaced by tasks running as quickly as C++ code, neither scale out past 20 nodes. We ran them on fewer than 20 nodes: 20 is the fastest configuration. For example, running on 100 nodes, Naiad-opt runs almost 3 times slower than on 50 nodes, as its n^2 coordination overhead grows.

Nimbus runs 43 times faster than Spark and almost 16 times faster than Naiad. Its control overhead is almost negligible, even when scaled out to 100 nodes. This allows it to come very close to the expected performance benefits of C++. Even if Spark and Naiad were to run optimized tasks, execution templates lead Nimbus to run 4-8 times faster.

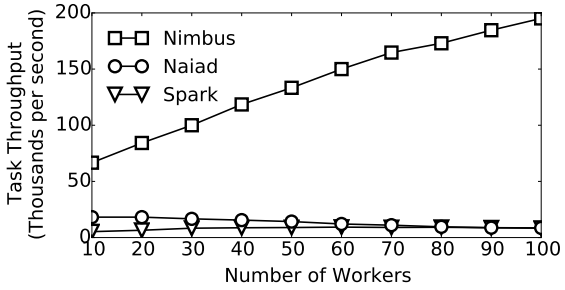


Figure 8: Task throughput of cloud frameworks as the number of workers increases. Spark and Naiad saturate at about 8,000 tasks per second, while Nimbus grows almost linearly as the number of workers increases.

K-means shows similar results to logistic regression: Nimbus runs almost 30 times faster than Spark with Scala and 23 times faster than Naiad with C#. It runs 5 times faster than Spark or Naiad even when they use optimized tasks.

5.2 Task Throughput

The results in Figure 7 show that neither Naiad nor Spark can scale out to handle optimized tasks at scale. Since progress bottlenecks at the controller, workers spend a larger fraction of time idle. Figure 8 shows the *task throughput* (the number of tasks per second that workers execute) each system sustains for logistic regression. Both Spark and Naiad saturate at about 8,000 tasks per second. Using execution templates, Nimbus is able to scale almost linearly, supporting almost 200,000 tasks/second for 100 nodes.

Execution templates scale slightly sub-linearly because the scheduling cost at the controller increases linearly with the number of workers. If these benchmarks were run on 800 workers with 1 core each (rather than 100 workers with 8 cores each), each worker template

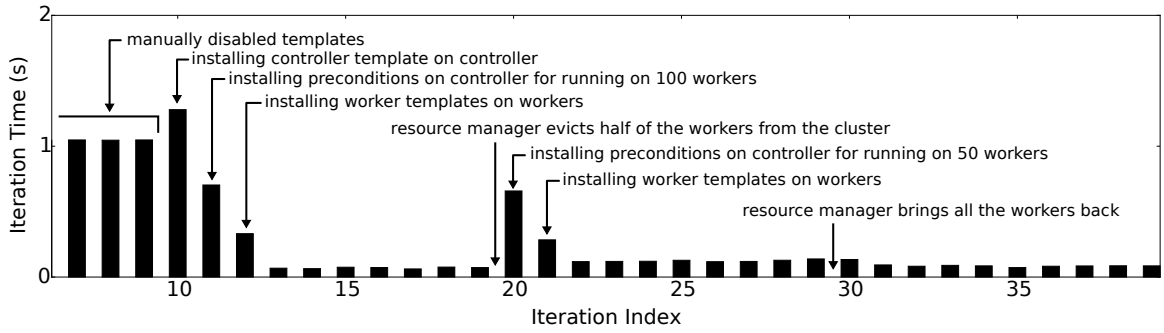


Figure 9: Adaptive behavior of execution templates as resources change. If the number of available workers changes, a controller can recompute new templates or fall back to templates it has already computed.

	Per-task cost	Iter. overhead
Controller Template	$25\mu s$	20%
Worker Template @cntrl	$15\mu s$	12%
Worker Template @work	$9\mu s$	7%

Table 3: Costs of installing templates on the first iteration of logistic regression running on 100 nodes. The cost is predominantly at the controller. Nonetheless, the one-time cost of installing templates on the first iteration causes the iteration to run 39% slower.

	Completion time
No templates	1.07s
Controller template only	0.49s
Worker & controller template	0.07s

Table 4: Execution time of logistic regression iterations (100 nodes) with and without templates.

would be 1/8th the size and the controller would have to process 8 times as many template instantiation messages. If T is the number of tasks to execute in a block and W is the number of workers, Spark's controller cost is $O(T)$, Naiad's is $O(W^2)$ and execution templates are $O(W)$.

5.3 Template Overhead and Gains

To filter out the startup cost of the JVM and CLR loading object files and just-in-time compilation, the results in Figure 7 do not include the first iteration of either computation. This also excludes out the cost of generating and installing templates. Table 3 shows the costs of installing templates in logistic regression with 100 workers.

Installing templates increases the execution time of the first iteration by 39%. This cost is predominantly at the controller, as it must generate both the controller template as well as the controller half of the worker template. Processing each task at the controller takes 40μs. A controller is therefore limited to processing at most 25,000 tasks/second on the first iteration: this is approximately 3 times what available controllers can handle.

Table 4 shows how controller and worker templates reduce control plane costs. Both controller and worker templates cut the overhead significantly as they transform thousands of tasks into a single message. Their benefits are roughly equal. A controller template transforms tens of thousands of messages from the driver to the controller to a single message. Worker templates transform tens of thousands of messages from the controller to the workers to one message per worker. Together, they reduce control plane overhead from 93% to negligible.

5.4 Template Adaptation

If a controller decides to re-balance a job across workers, remove workers, or add workers, it must recompute new worker task graphs and install the corresponding templates on workers whose responsibilities have changed. Figure 9 shows the time it takes for each iteration of logistic regression as a cluster manager adjusts the available workers. The run begins with templates disabled: iterations take 1.07s. On iteration 10, templates are turned on. This iteration takes 1.2s due to controller template installation (20% overhead). On iteration 11, the controller's half of worker templates is installed. On iteration 12, the worker's half of the worker templates is installed. We intentionally separated each phase of the template installation on progressive iterations to show the cost and gain from each. However, all phases could overlap on a single iteration (39% overhead). Once all templates are installed, the iteration time drops to 0.07s.

On the 20th iteration, the controller receives a command from a cluster manager to stop using half of its workers. This does not change the controller template, but forces the controller to recompute worker templates. It then executes at half speed (0.14s/iteration), until iter-

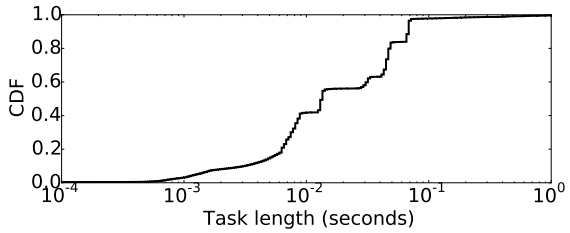


Figure 10: CDF of task durations in a PhysBAM simulation. The median task is 13ms, the 10th percentile is 3ms, and some tasks are as short as 100μs.

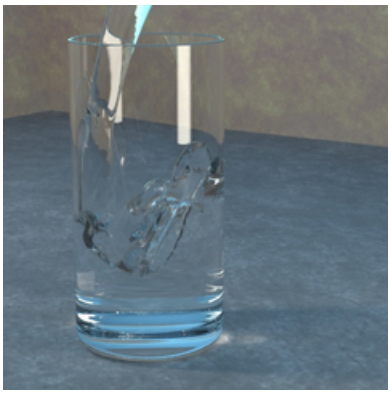


Figure 11: Still of a PhysBAM simulation of water being poured into a glass.

ation 30. At iteration 30, the 50 workers are restored to the controller. It is then able to go back to using its first set of templates, which are still cached.

5.5 Complex Applications

This final set of experiments examines how templates scale to support complex applications. PhysBAM is an open-source library for simulating many phenomena in computer graphics [18]. It is the result of over 50 developer-years of work and has won two Academy Awards. We ported PhysBAM to Nimbus, wrapping PhysBAM functions inside tasks and interfacing PhysBAM data objects into Nimbus so they can be copied and transferred.

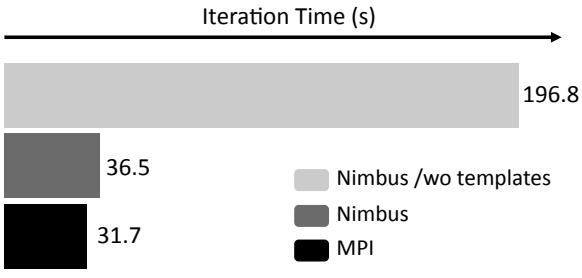


Figure 12: Iteration time of a PhysBAM water simulation in Nimbus with and without templates as well as its standard MPI implementation.

We wrote a driver program for a canonical fluid simulation benchmark, water being poured into a vessel (e.g., Figure 11). This simulation uses the particle-levelset method [19], maintaining the simulation as a volume of fixed grid cells but using particles along the surface of the water to simulate it in much higher detail. The simulation is the same core simulation used in films such as The Perfect Storm and Brave and has a triply-nested loop with 26 different computational stages that access over 40 different variables.

We ran a 1024^3 cell simulation (512GB-1TB of RAM) on 64 workers, comparing the performance of Nimbus with PhysBAM's hand-tuned MPI implementation. The MPI implementation cannot re-balance load, and in practice developers rarely use it due to its brittle behavior and lack of fault tolerance.

Figure 10 shows the CDF of task duration in PhysBAM. While the main computational tasks are 60-70ms some tasks run for only 100μs. These tasks computing minimum and maximum values over small sets. Figure 12 shows PhysBAM's performance using Nimbus and MPI. Without templates, the simulation generates tasks 8 times faster than a controller can handle: Nimbus takes 520% longer than MPI, because controller becomes a bottleneck. With templates, it runs within 15% of the MPI implementation.

6 Related Work

This paper builds on a long history of related work from several disparate fields: cloud computing, high performance computing, and programming languages.

Fast data analytics: Within the database and parallel computing communities, prior work has explored the computational inefficiency of Spark code, proposing new programming models and frameworks to replace it [26, 13]. Facebook's AI research group has open-sourced GPU modules for the Torch machine learning framework. [7]. There is also ongoing research on a common intermediate language for Spark that provides a glossary of data-parallel optimizations (including vectorization, branch flattening and, prediction), suggesting performance in some cases even faster than, hand-written C [32, 37]. The trend shows that the next generation of cloud computing frameworks will execute tasks which run orders of magnitude faster than today.

Cloud programming frameworks: MapReduce [15] is a widely used programming model for processing large

data sets. Open source MapReduce frameworks such as Hadoop and Hive [2, 3] are I/O bound: they fetch stable input data from disks, and save intermediate and final results to disks. Spark [38] uses resilient distributed datasets (RDDs) to perform computations on in-memory data, while providing the reliability that data on disk provides. For optimized data analytics with short task, however, Spark's centralized runtime system becomes a bottleneck. While Nimbus also uses a centralized controller, execution templates enable Nimbus to handle orders of magnitude higher task rate.

Naiad [28] is another framework for in-memory computations. While the distributed event-based runtime helps scalability without creating a centralized bottleneck, the cost of synchronization dominates as the number of workers grows. Logical to physical graph translation on Naiad nodes resembles the worker templates on Nimbus, however the lack of centralized controller to resolves the inter-worker dependencies leaves the burden of synchronization on the runtime system.

Dataflow frameworks such as Dryad [23], DryadLINQ [36], CIEL [29] and FlumeJava [14] focus on abstractions for parallel computations that enable optimizations and high performance. This paper examines a different but complementary question: how the runtime scales out to support very fast computations. In fact, our framework implementation that incorporates execution templates, Nimbus, resembles the data flow model in DryadLINQ [36].

Distributed scheduling systems: There is a huge body of work on distributed scheduling. They deploy various mechanisms to provide efficient scheduling decisions with high throughput. For example, Sparrow [31] uses a stateless scheduling model based on batch sampling and late binding. Omega [33], on the other hand, leverages a shared global state through atomic transactions to improve the allocation decisions. Apollo [12] benefits from a similar model, and adds task completion time estimations to optimize the scheduling decisions. Tarcil [17] is a hybrid model based on both sampling and performance estimation. Hawk [16], and Mercury [25] suggest a hybrid distribute/centralized solution to realize better efficiency in the cluster.

At a very high level, all these systems solve the same problem as execution templates do: providing higher task throughput at the runtime system. However there is a very important and subtle difference: these systems distribute the scheduling across the job boundaries. For a single job with high task rate the scheduling still goes through a single node. The distributed solution only solves the problem of multiple jobs producing high aggregate task rate in the cluster by directing the scheduling of each job to a different node. In a way, execution templates are orthogonal to theses systems. Every node in the distributed implementation could benefit from execution templates to support jobs with orders of magnitude higher task rate.

High performance computing (HPC): MPI [34] provides an interface to exchange messages between parallel computations, and is the most commonly used framework to write distributed computations in the HPC domain. MPI does not include any support for load-balancing or fault recovery. Frameworks such as Charm++ [24] and Legion [11] provide abstractions to decouple control flow, computation and communication, similar to cloud data flow frameworks. Their fundamental difference, however, is that they provide mechanisms and very little policy; applications are expected to decide on how their data is placed as well as were tasks run. The scale and cost of the machines they are designed for (supercomputers) is such that they demand more programmer effort in order to achieve more fine-tuned and optimized use of hardware resources.

Just-in-time (JIT) compilation: Finally, the idea of memoizing control flow and dynamic decisions in an execution path closely resembles the approach taken in just-in-time (JIT) compilers [10] as well as the Synthesis kernel [27]. Both of these approaches note that particular decisions, while dynamic in the general case, might lead to deterministic results in any particular case. Therefore, optimizing that deterministic result can remove all of the surrounding overhead. While a JIT compiler and the Synthesis kernel generate optimized native code for particular functions, execution templates generate optimized structures for scheduling distributed computations.

7 Conclusion And Future Work

This paper presents execution templates, a novel abstraction for cloud computing runtime systems that allows them to support extremely high task rates. The need for high task rates is driven by the observation that many modern workloads are CPU-bound, and rewriting them in high performance code can easily lead to task rates that overwhelm modern schedulers. Long-running applications with high task rates, however, usually consist of many executions of a loop. Rather than reschedule each iteration of the loop from scratch, execution templates allow a controller to cache its scheduling decisions and invoke large, complex sets of tasks on worker nodes with a single message. Using execution templates, the paper shows that some benchmark applications reimplemented in C++ can run up to 40 times faster; without templates, their speedup is limited only a factor of 5. Finally, execution templates enable whole new classes of applications to run in the cloud, such as high performance simulations used in computer graphics.

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