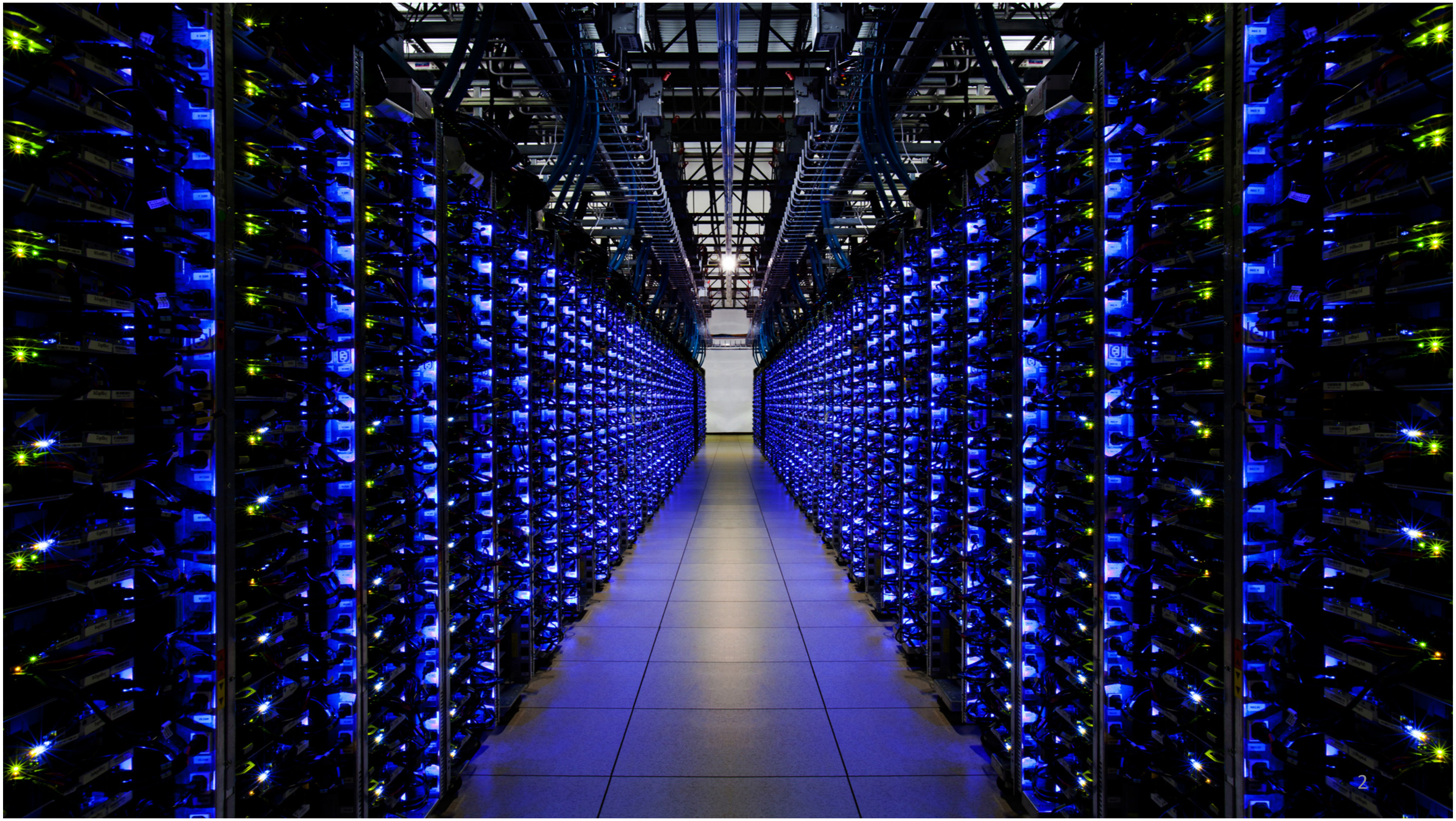
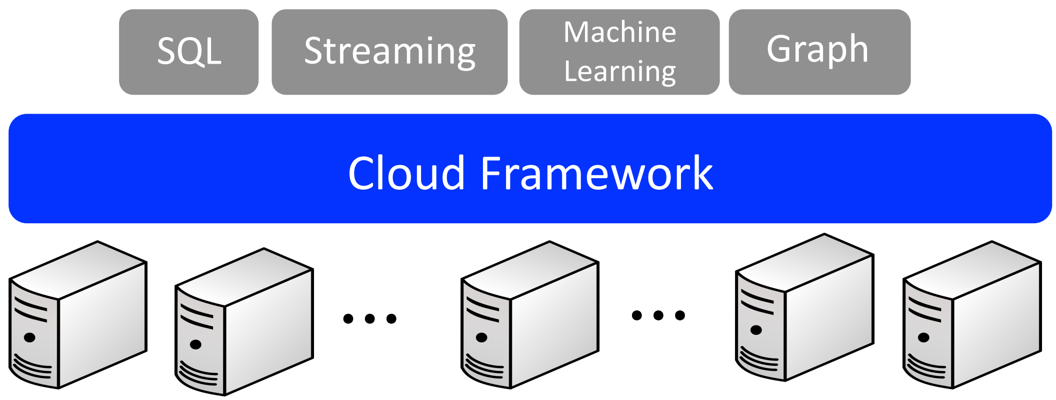
Execution Templates: Caching Control Plane Decisions for Strong Scaling of Data Analytics

Omid Mashayekhi Hang Qu Chinmayee Shah Philip Levis

July 13, 2017



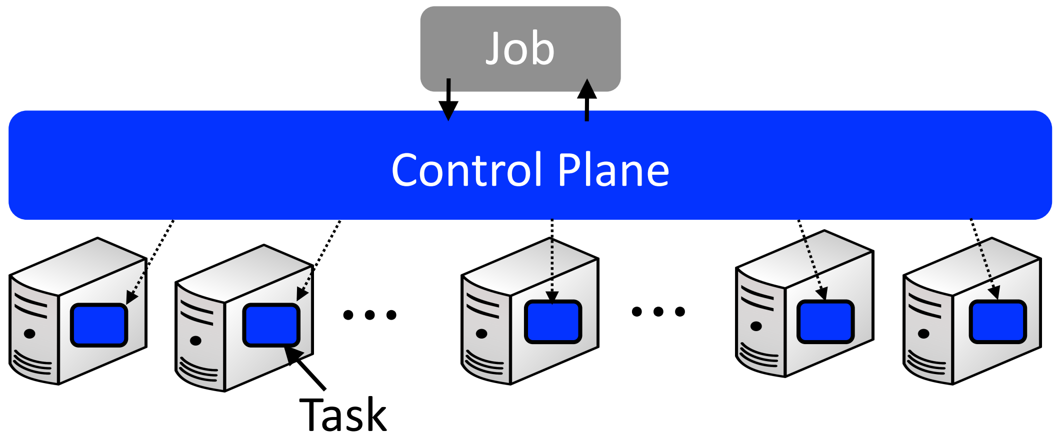
Cloud Frameworks



Cloud frameworks abstract away the complexities of the cloud infrastructure from the application developers:

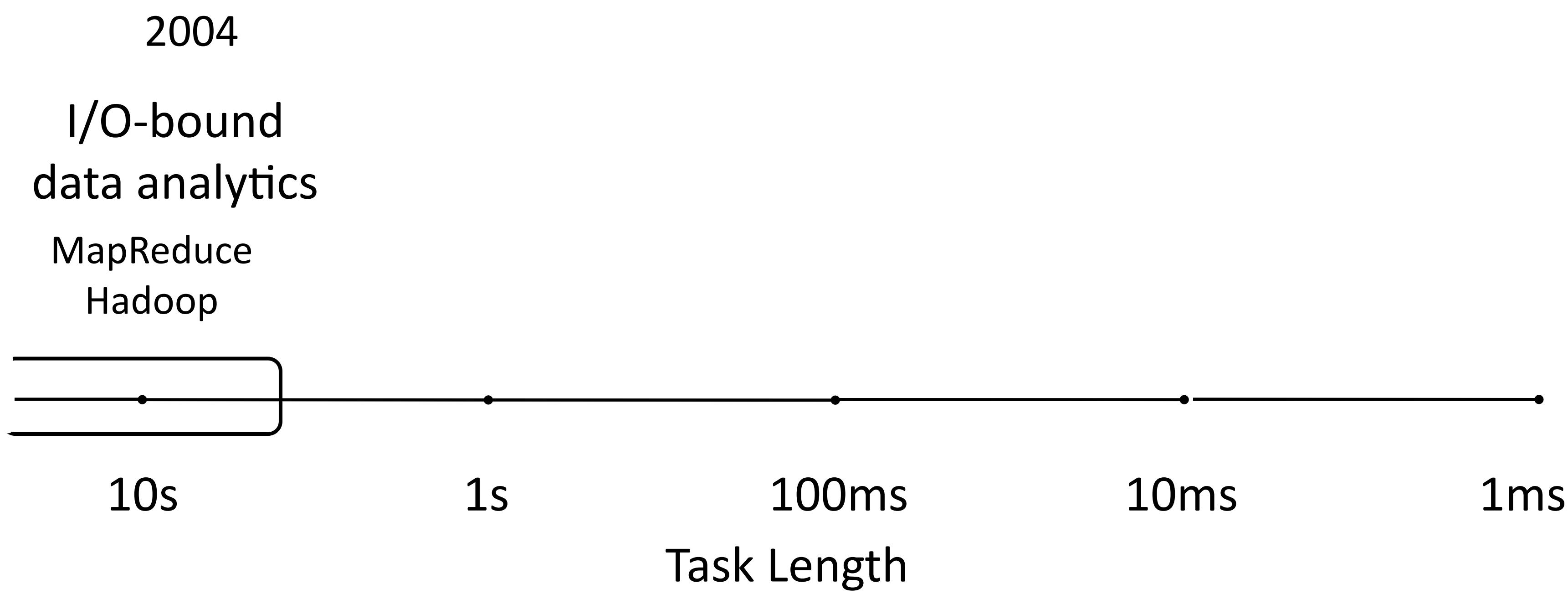
1. Automatic distribution
2. Elastic scalability
3. Multitenant applications
4. Load balancing
5. Fault tolerance

Cloud Frameworks

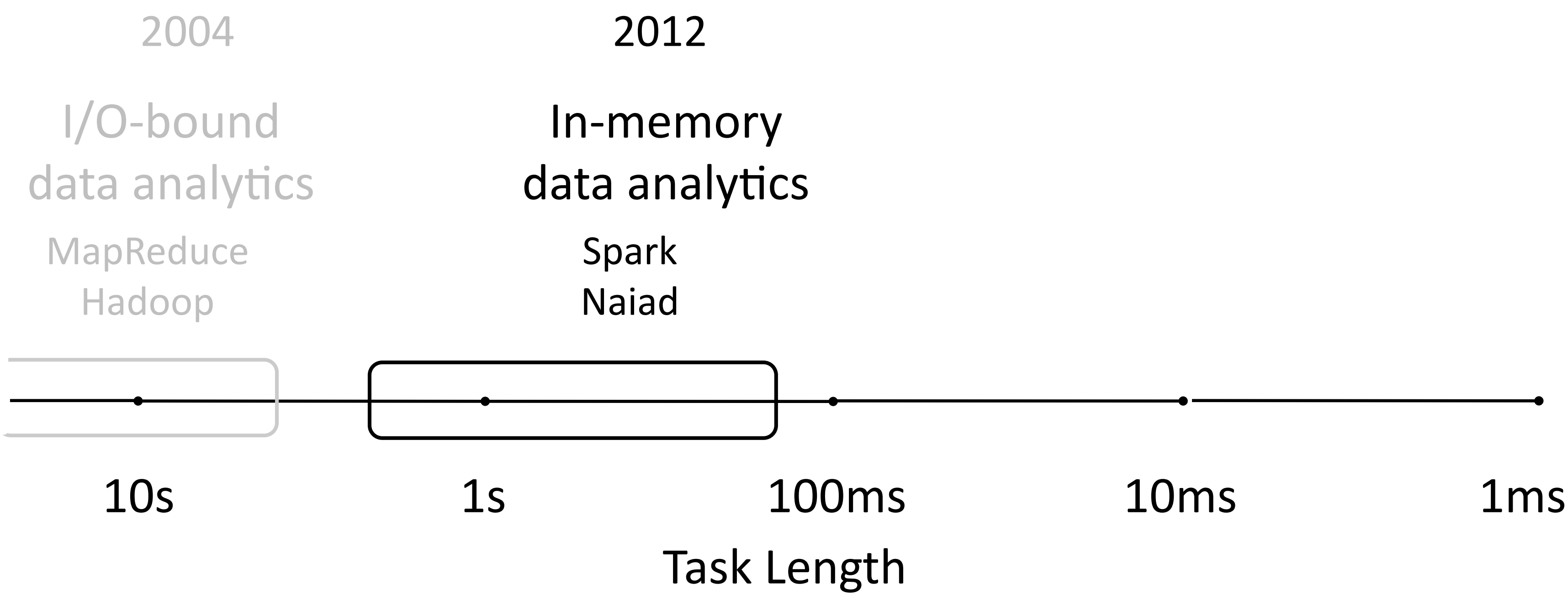


- **Job** is an instance of the application running in the framework.
- **Task** is the unit of computation for the job.
- **Control plane** partitions job in to tasks, schedules task, and recovers from faults.

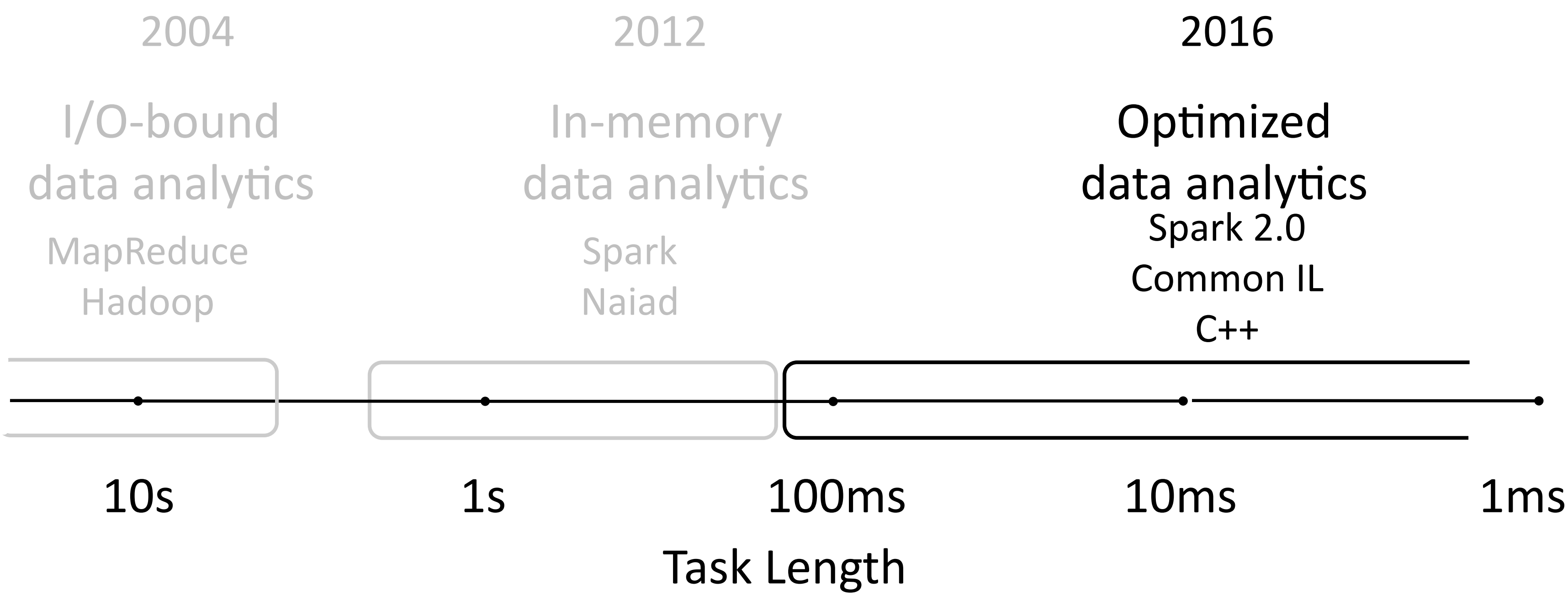
Evolution of Cloud Frameworks



Evolution of Cloud Frameworks



Evolution of Cloud Frameworks

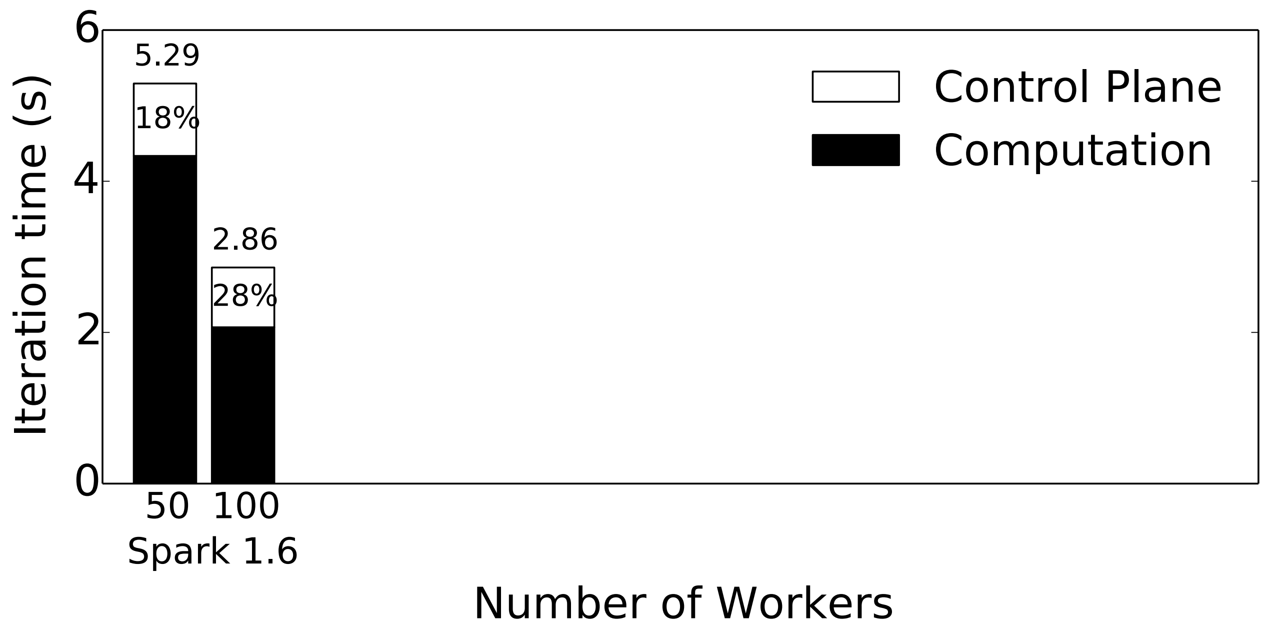


Individual tasks are getting faster.

But does it necessarily mean that
job completion time is getting shorter?

Control Plane

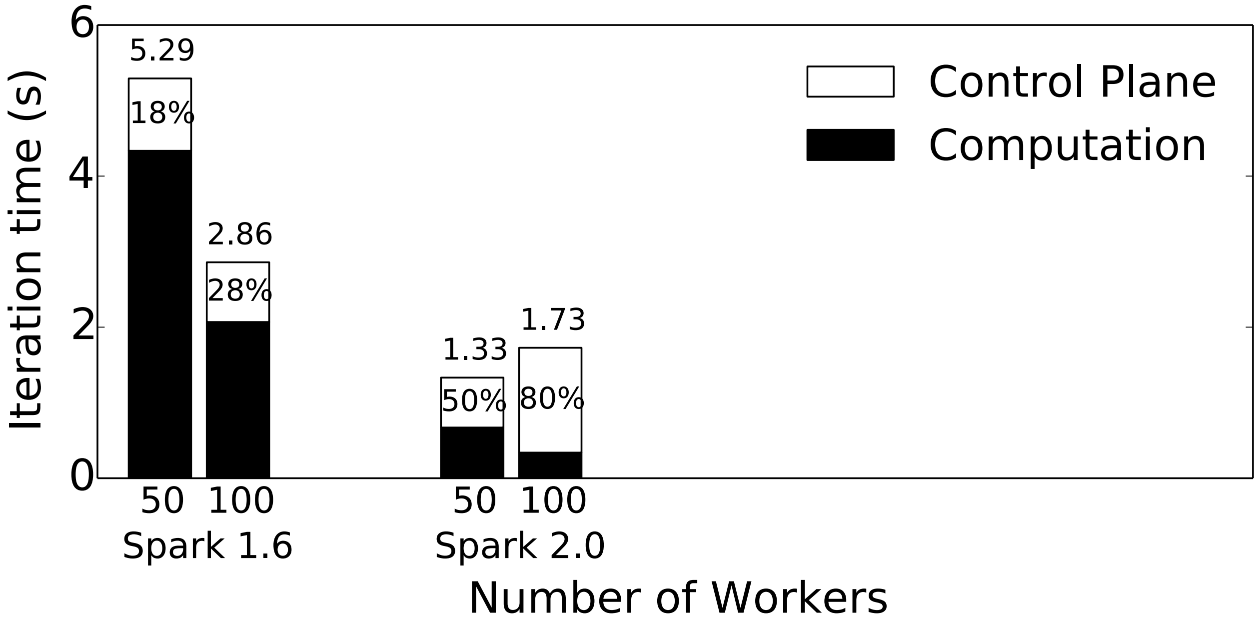
The New Bottleneck



- Logistic regression over a data set of size 100GB.
- Classic Spark used to be **CPU-bound**.

Control Plane

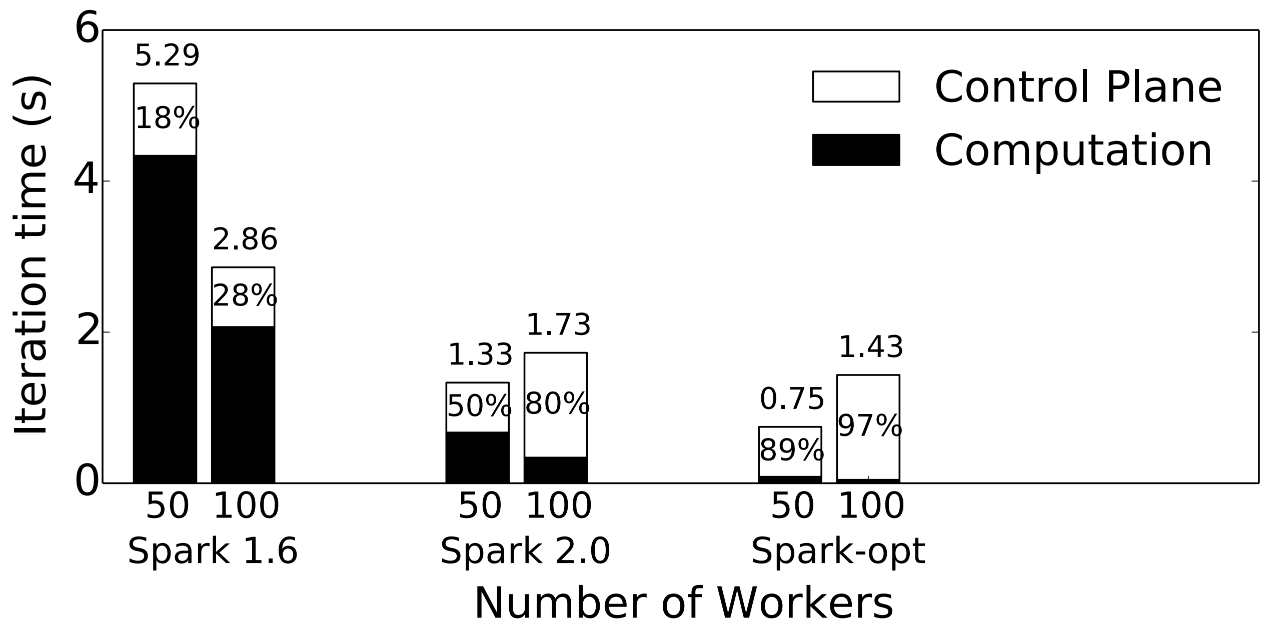
The New Bottleneck



- Logistic regression over a data set of size 100GB.
- Spark 2.0 with Scala implementation is already **control-bound**.

Control Plane

The New Bottleneck



- Logistic regression over a data set of size 100GB.
- Spark-opt: hypothetical case where Spark runs tasks as fast as C++.

Control plane is the emerging bottleneck for the cloud computing frameworks.

Control Plane Design Scope

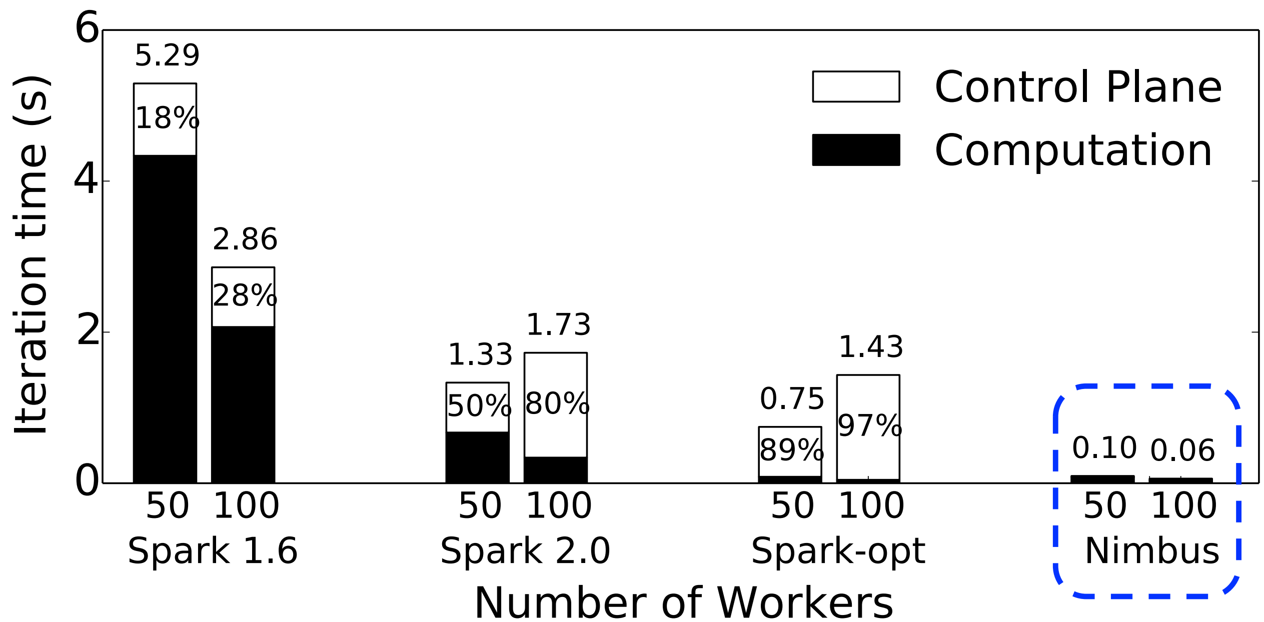
Control Plane Design	Example Framework	Task Throughput (task per sec)	Scheduling Cost (per task)
Centralized	MapReduce Hadoop Spark	$\approx 1,000$	$\approx 100\mu s$
Distributed	Naiad TensorFlow	$\approx 100,000$	$\approx 100,000\mu s$

- Centralized controller adapts to scheduling changes reactively with a low cost, but has limited task throughput and bottlenecks at scale.
- Distributed controller scales well, but any scheduling change requires stopping all nodes and installing new data flow with high latency.

Execution Templates is an abstraction for the control plane of cloud computing frameworks, that enables orders of magnitude higher task throughput, while keeping the fine-grained, flexible scheduling with low cost.

Control Plane

The New Bottleneck



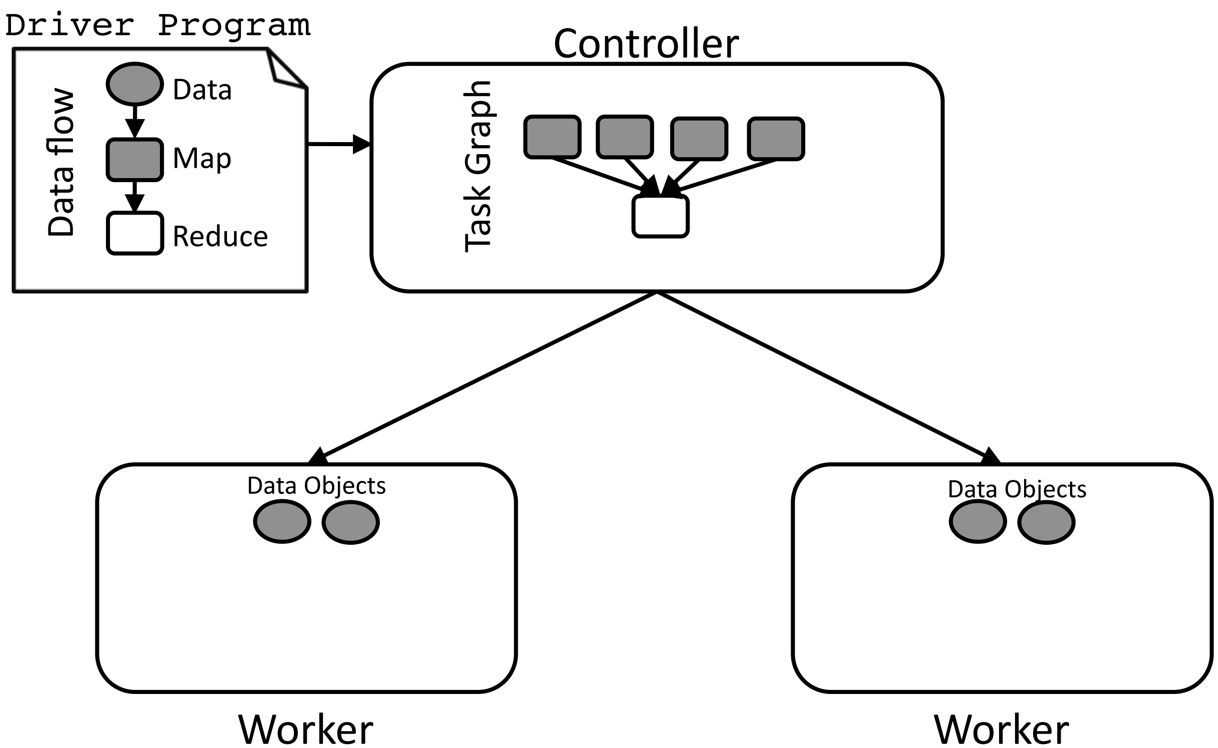
- Logistic regression over a data set of size 100GB.
- **Nimbus** with **execution templates** scales almost linearly, with low cost scheduling.

Repetitive Patterns

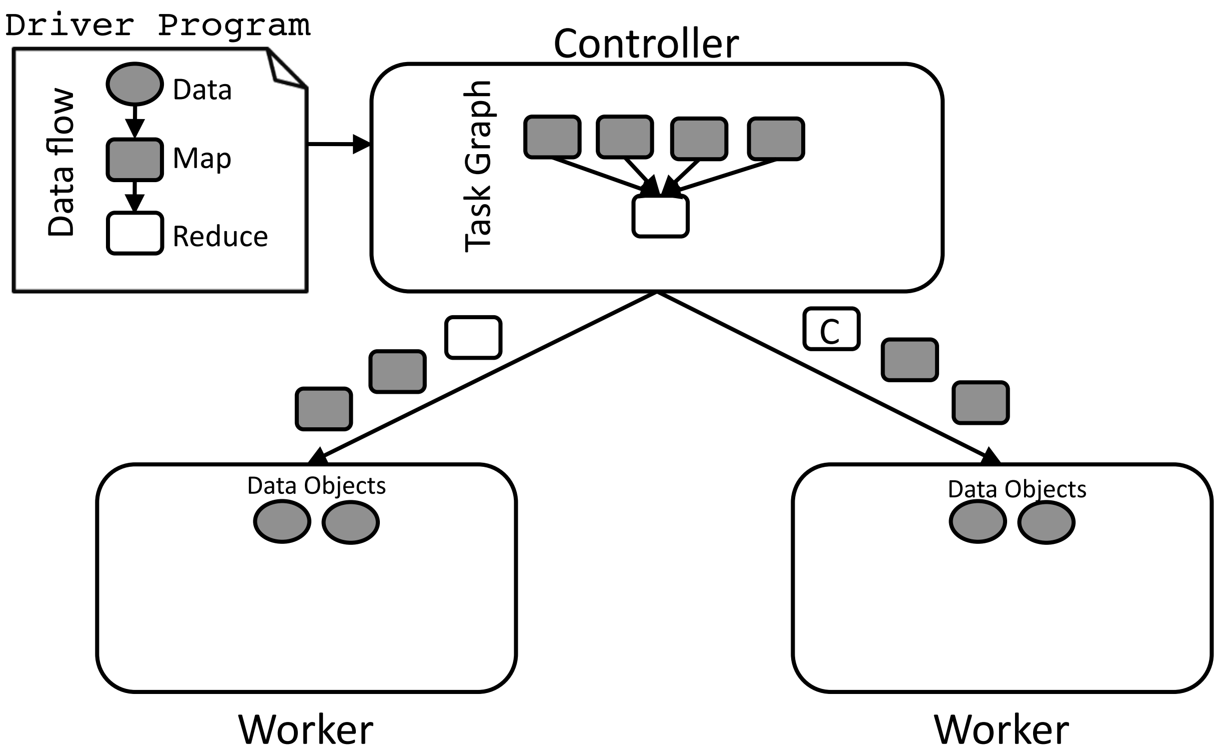
- Advanced data analytics are iterative in nature.
  - Machine learning, graph processing, image recognition, etc.

- This results in repetitive patterns in the control plane.
  - Similar tasks execute with minor differences.

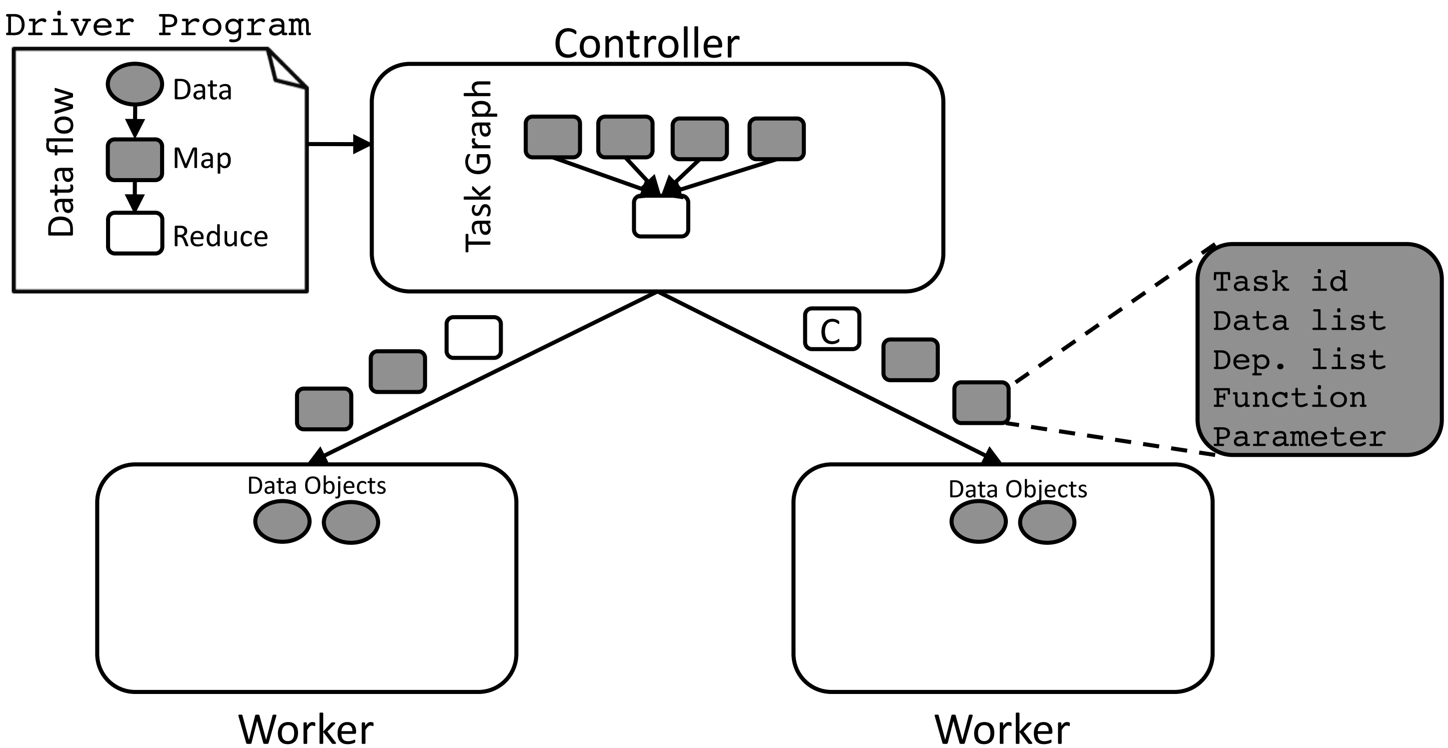
Execution Model



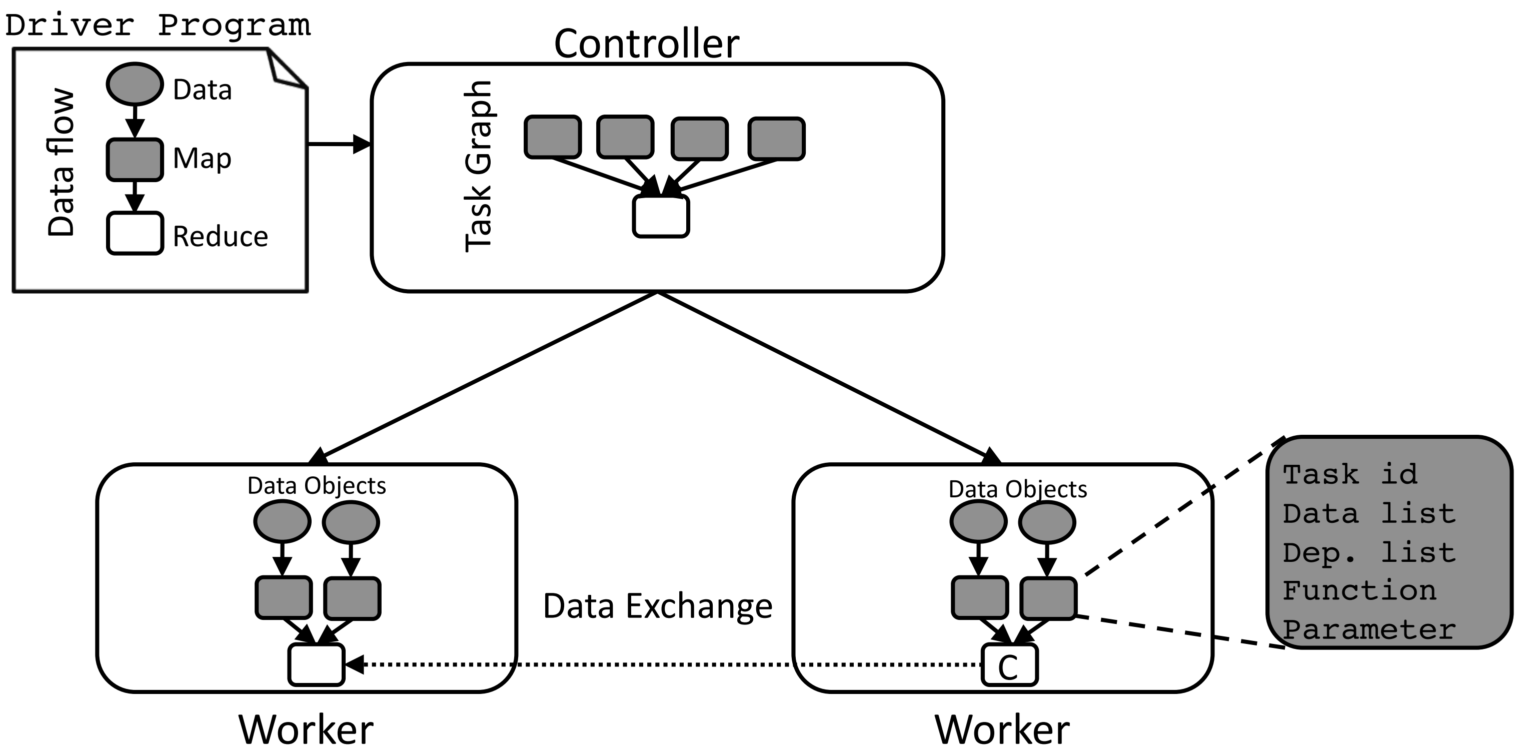
Execution Model



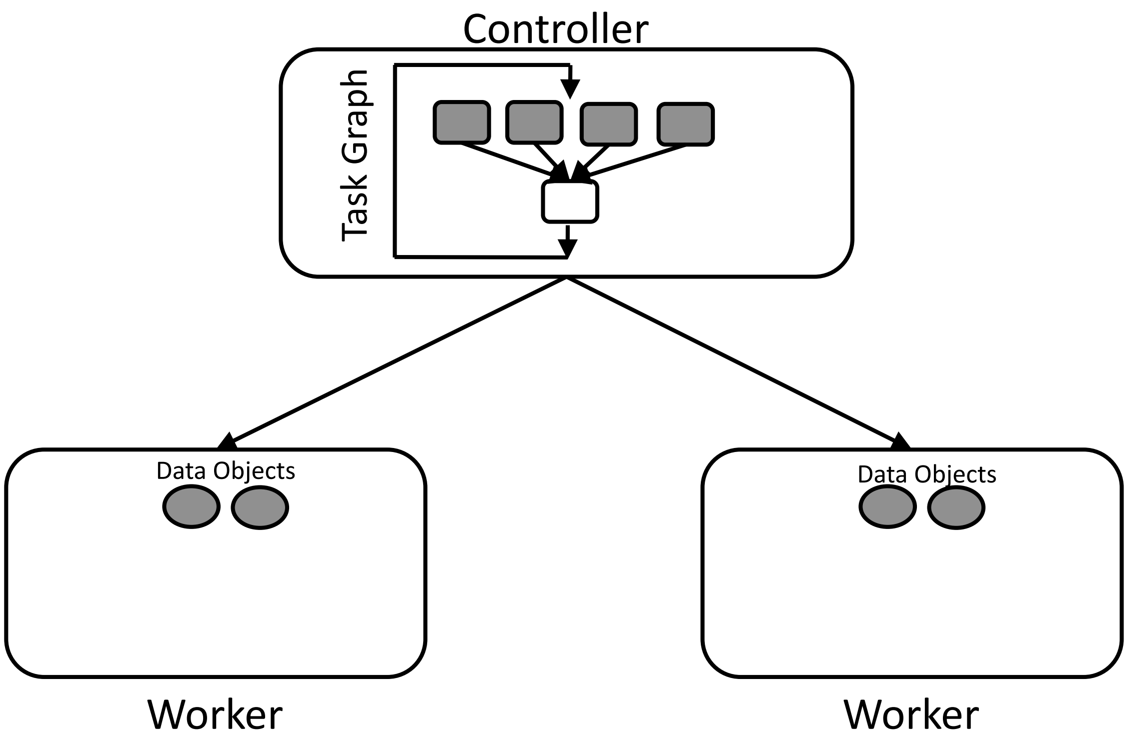
Execution Model



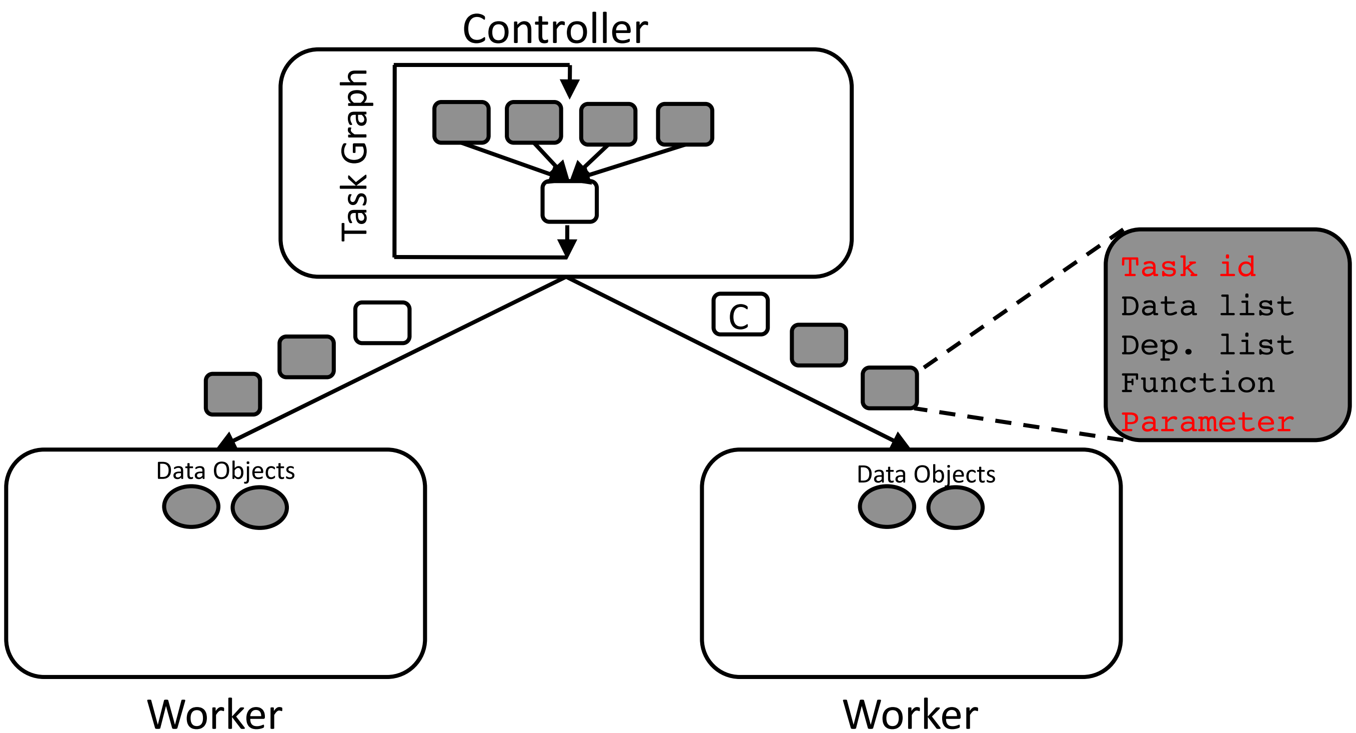
Execution Model



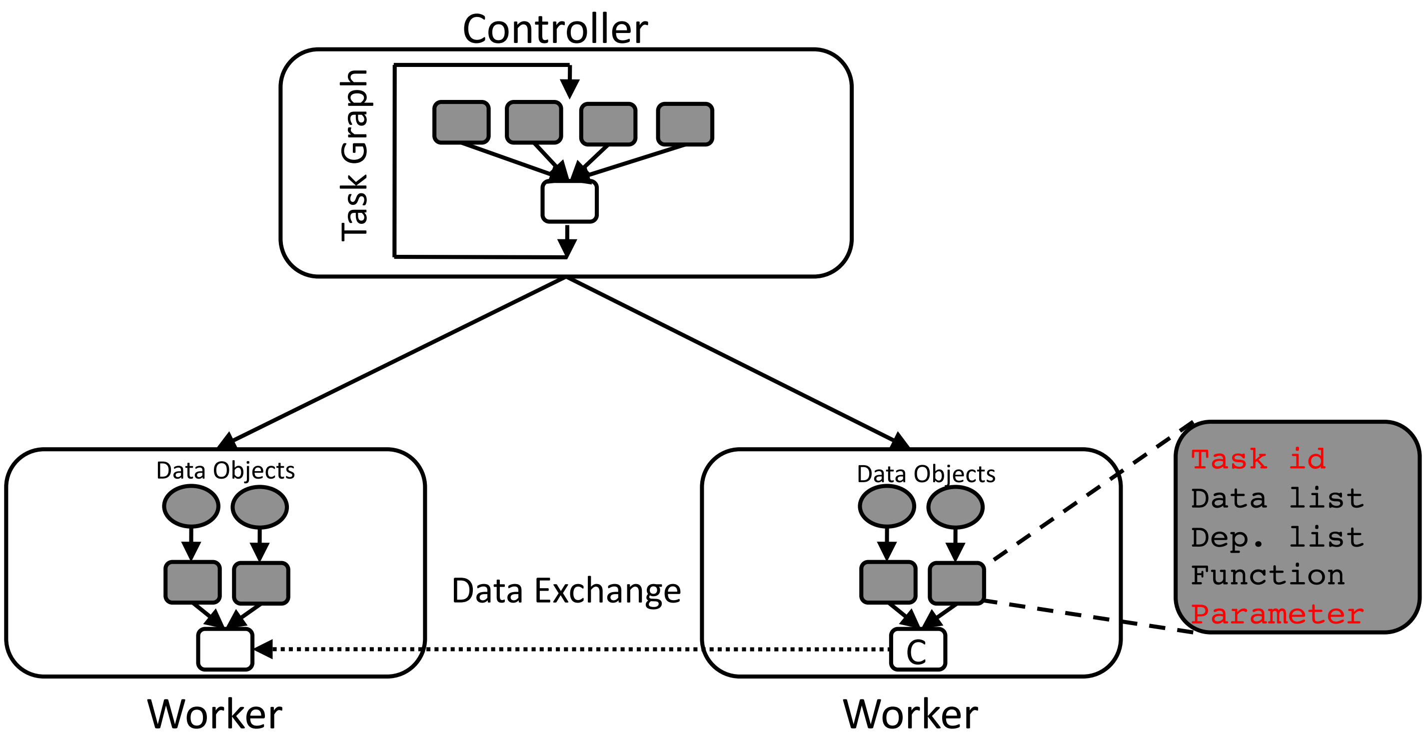
Repetitive Patterns



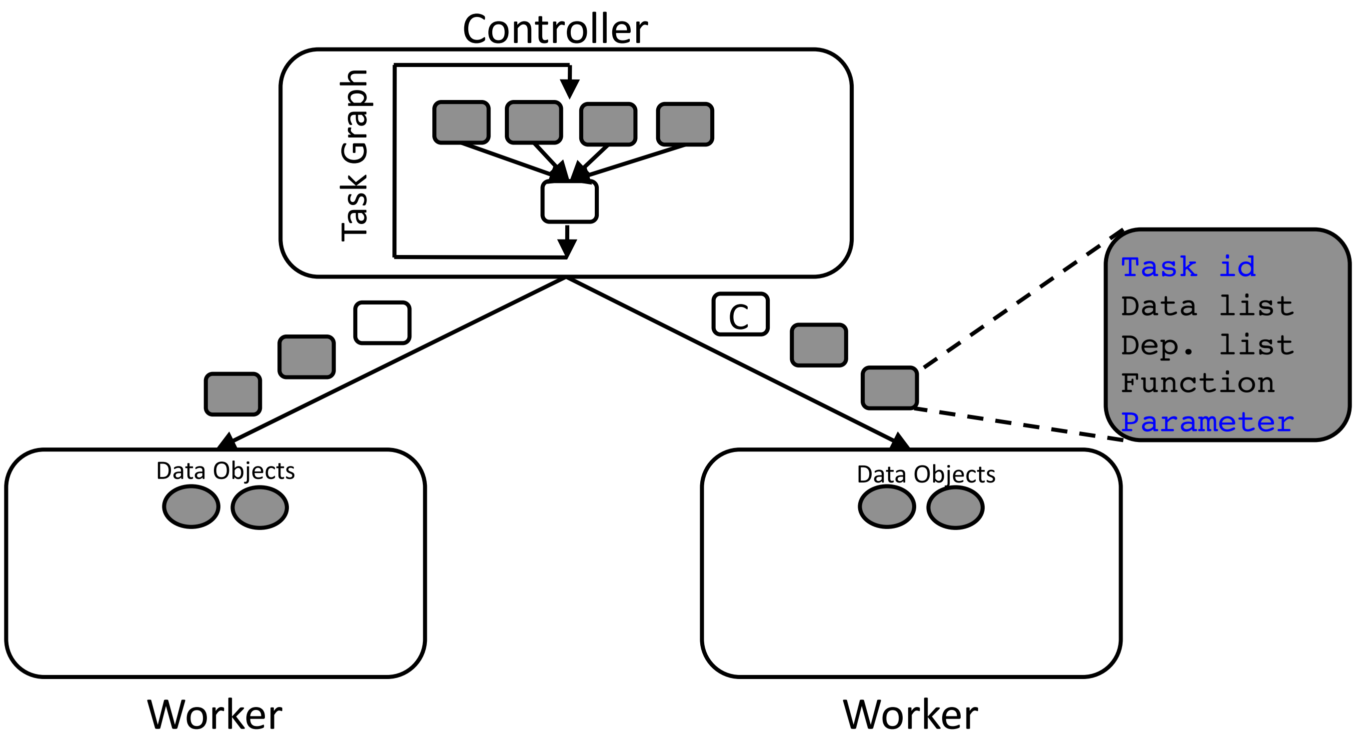
Repetitive Patterns



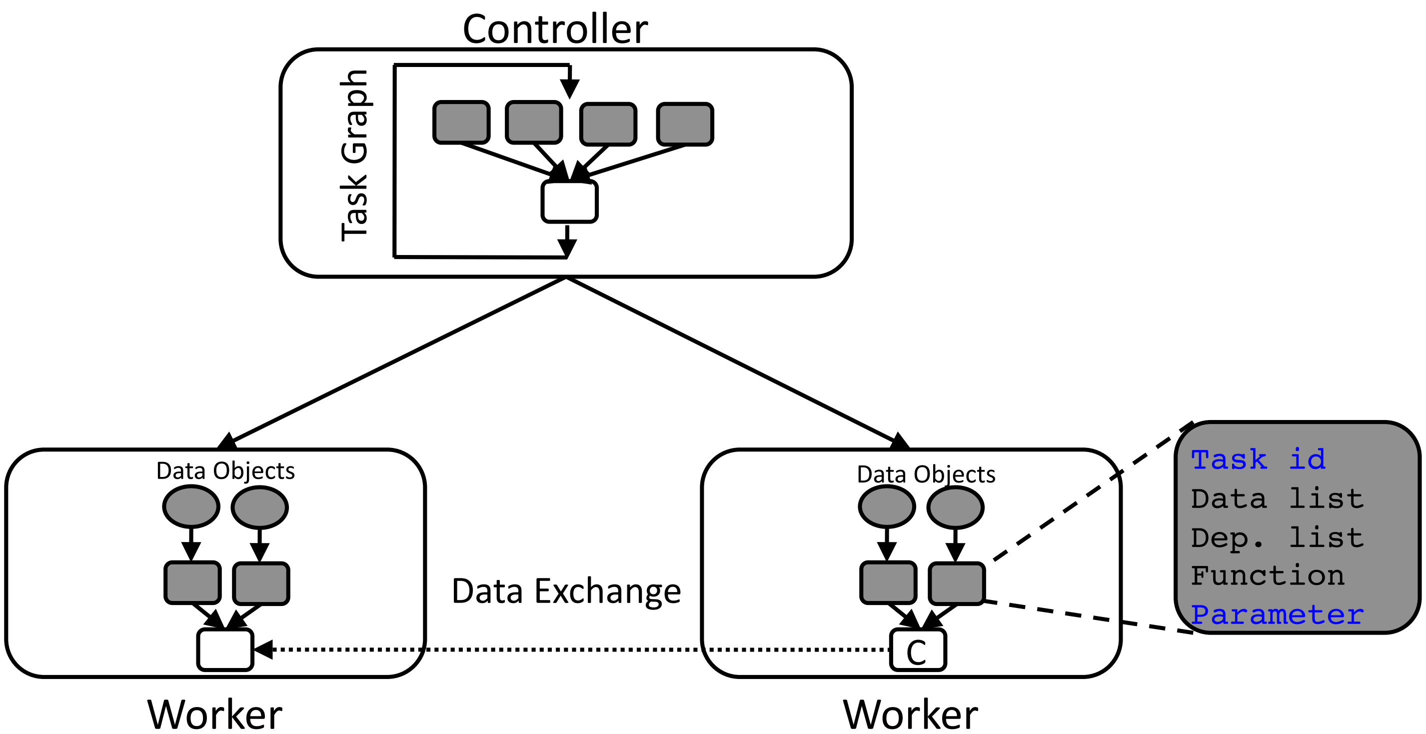
Repetitive Patterns



Repetitive Patterns

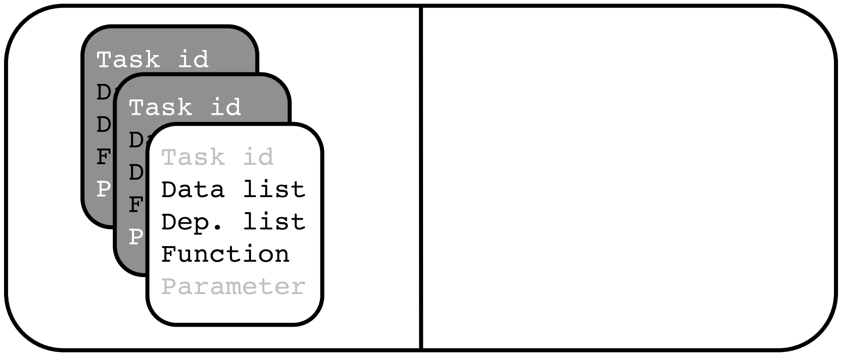


Repetitive Patterns



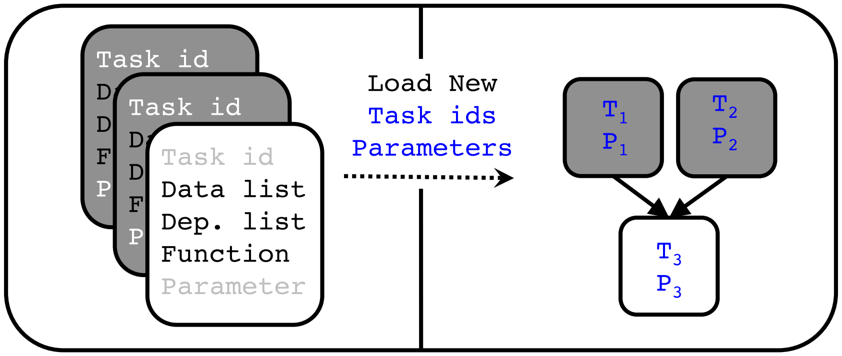
Execution Templates

- Tasks are cached as **parameterizable blocks** on nodes.
- Instead of assigning the tasks from scratch, templates are **instantiated** by filling in only changing parameters.



Execution Templates

- Tasks are cached as **parameterizable blocks** on nodes.
- Instead of assigning the tasks from scratch, templates are **instantiated** by filling in only changing parameters.

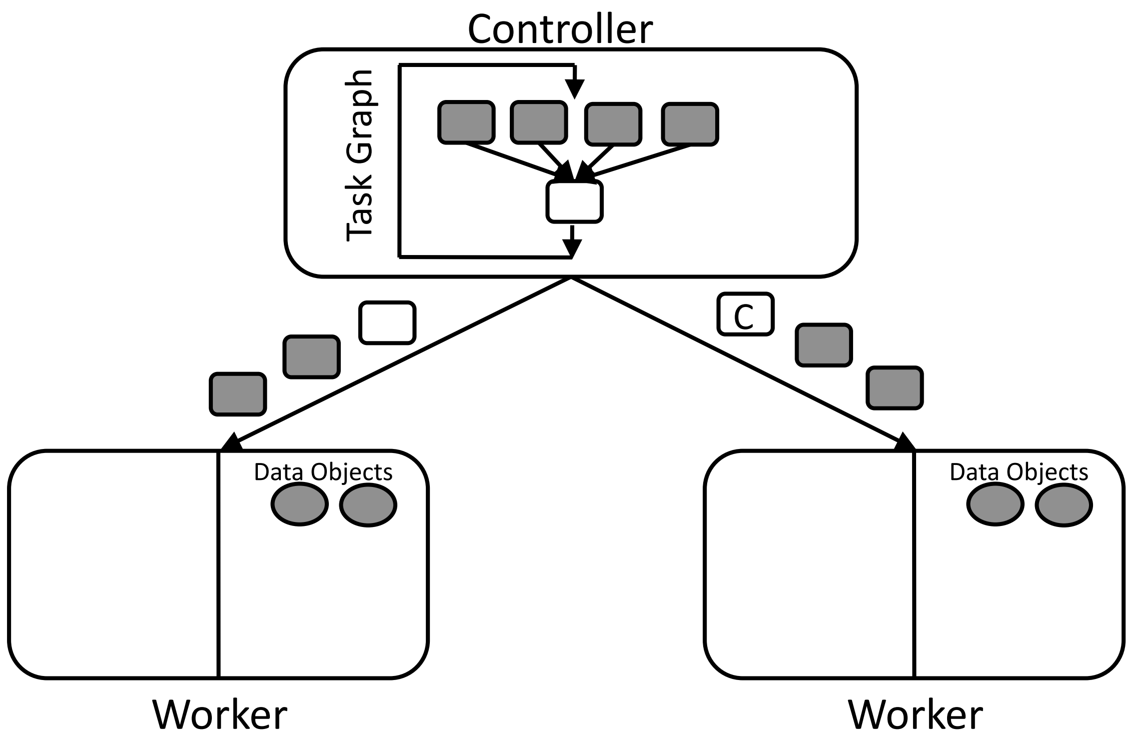


Execution Templates
Mechanisms Summary

- **Instantiation**: spawn a block of tasks without processing each task individually from scratch. It helps increase the **task throughput**.
- **Edits**: modifies the content of each template at the granularity of tasks. It enables fine-grained, **dynamic scheduling**.
- **Patches**: In case the state of the worker does not match the preconditions of the template. It enables **dynamic control flow**.

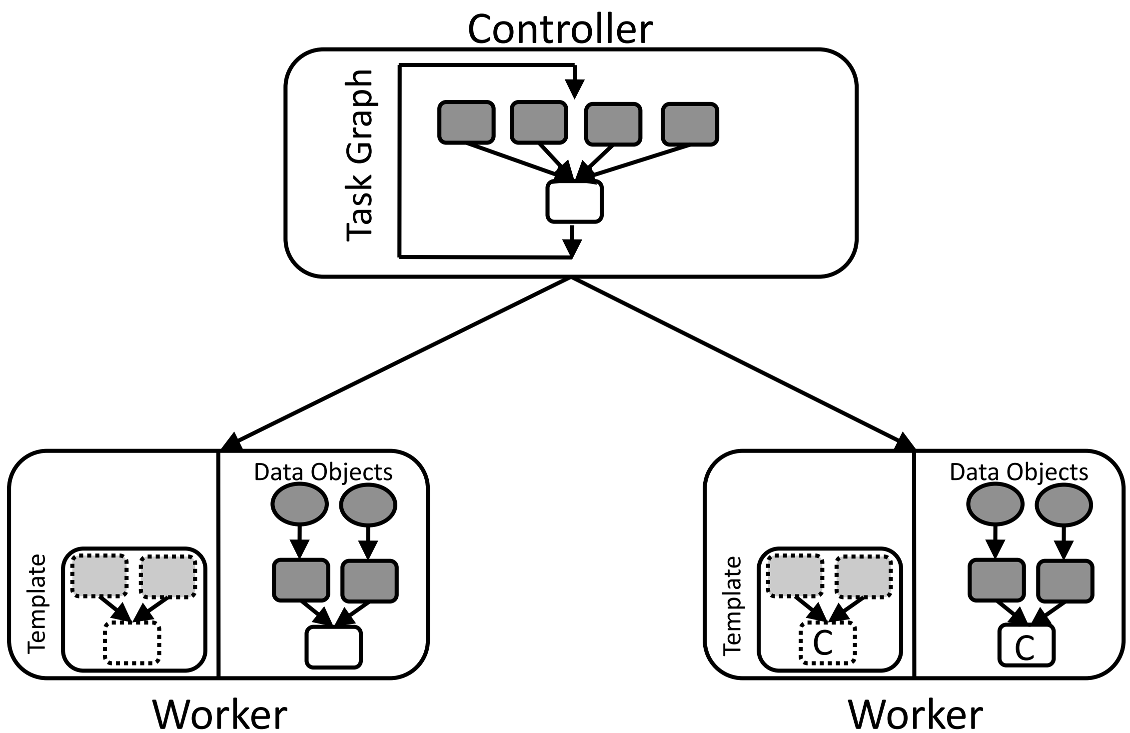
Execution Templates

Instantiation



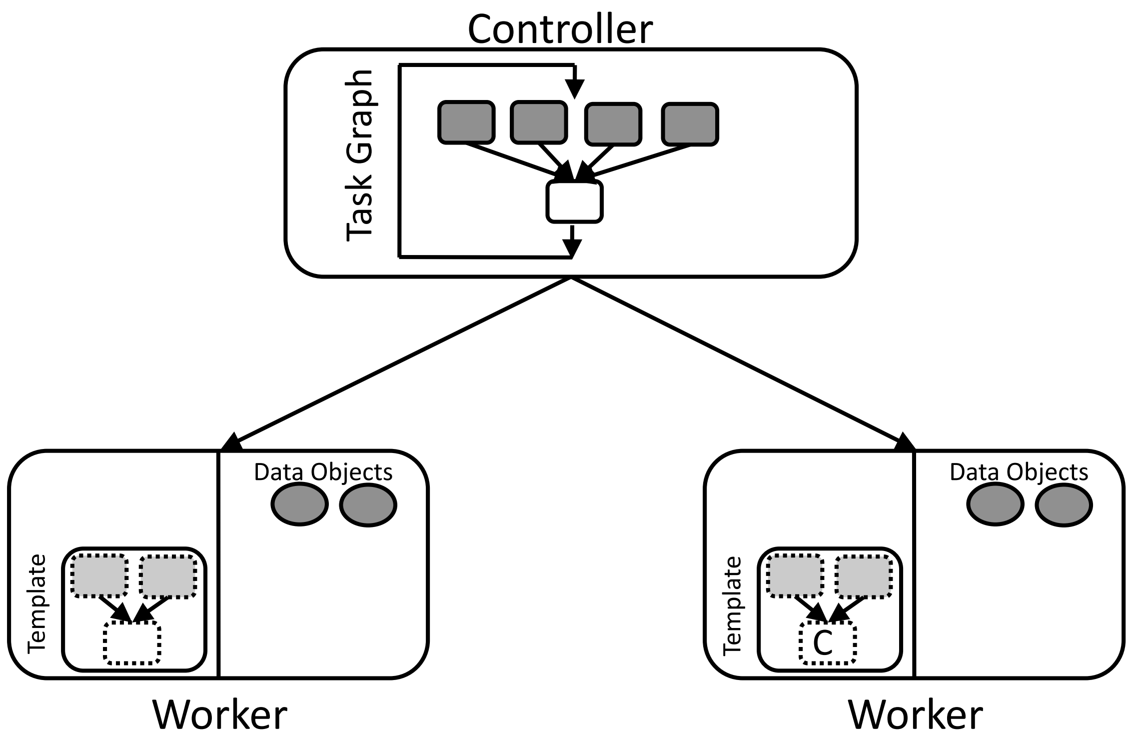
Execution Templates

Instantiation



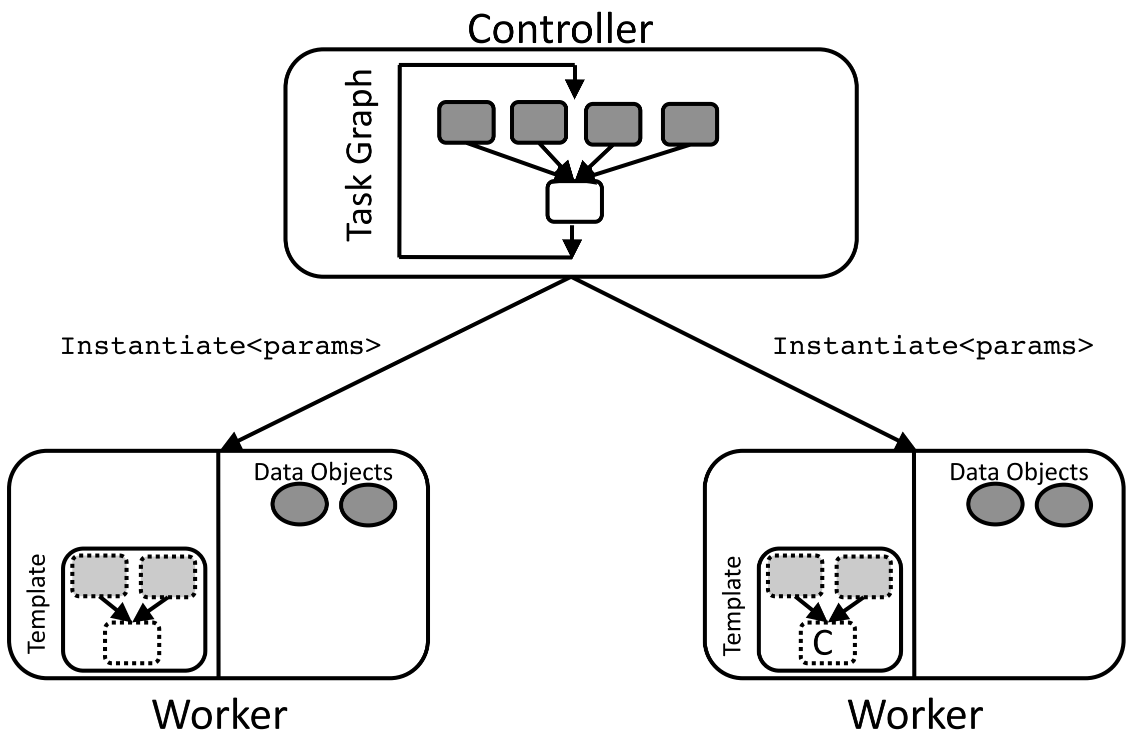
Execution Templates

Instantiation



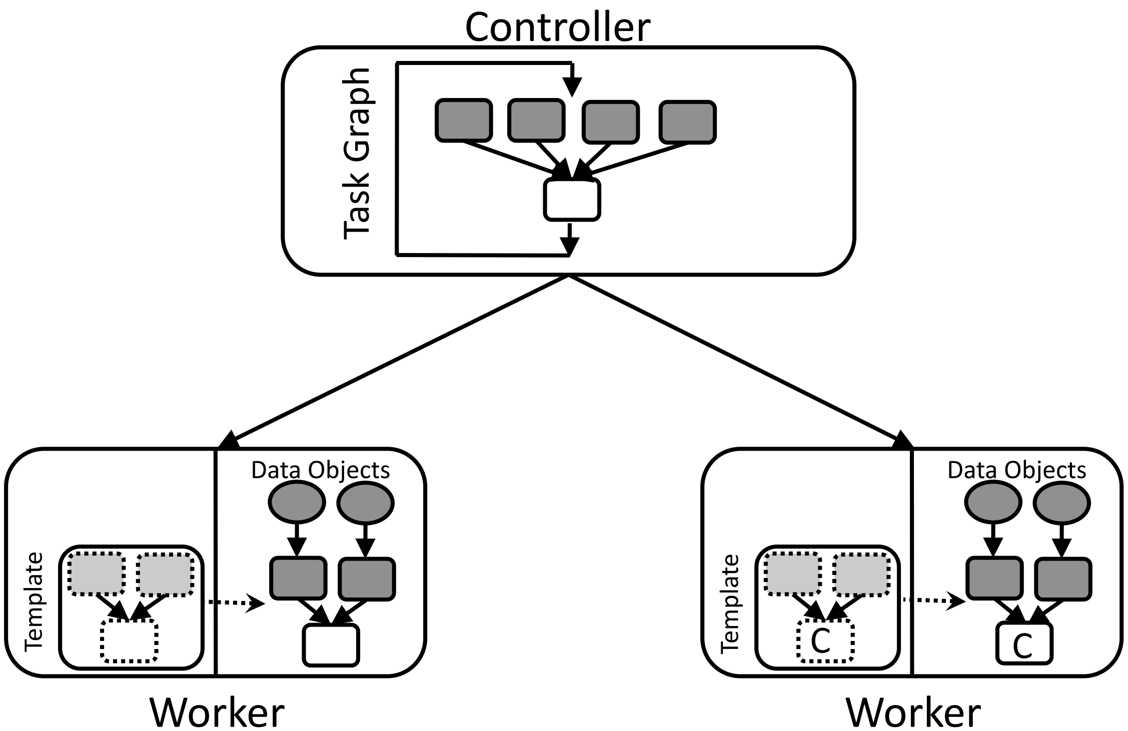
Execution Templates

Instantiation



Execution Templates

Instantiation



Execution Templates

Caching tasks implies static behavior; how could templates allow **dynamic scheduling**?

- Reactive scheduling changes for load balancing.
- Scheduling changes at the task granularity.

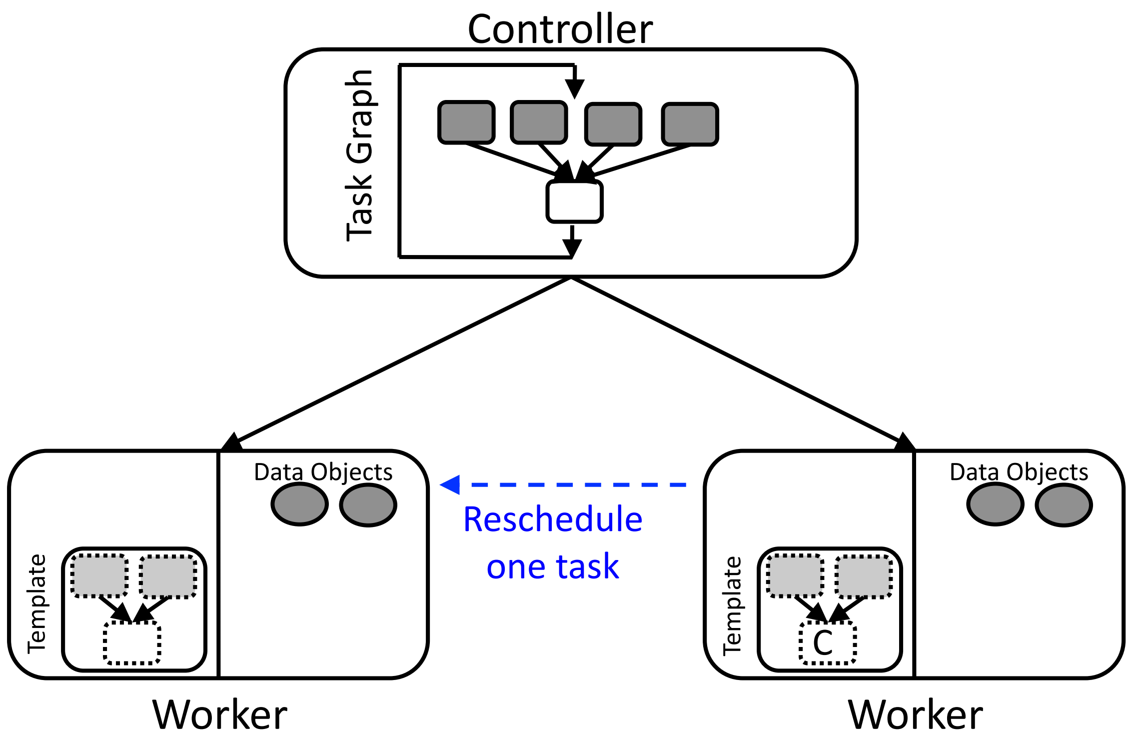
Execution Templates

Edits

- If scheduling changes, even slightly, the templates are obsolete.
  - For example rescheduling a task from one worker to another.
- Instead of paying the substantial cost of installing templates for every changes, templates allow **edit**, to change their structure.
- **Edits** enable adding or removing tasks from the template and modifying the template content, in-place.
- Controller has the general view of the task graph so it can update the dependencies properly, needed by the edits.

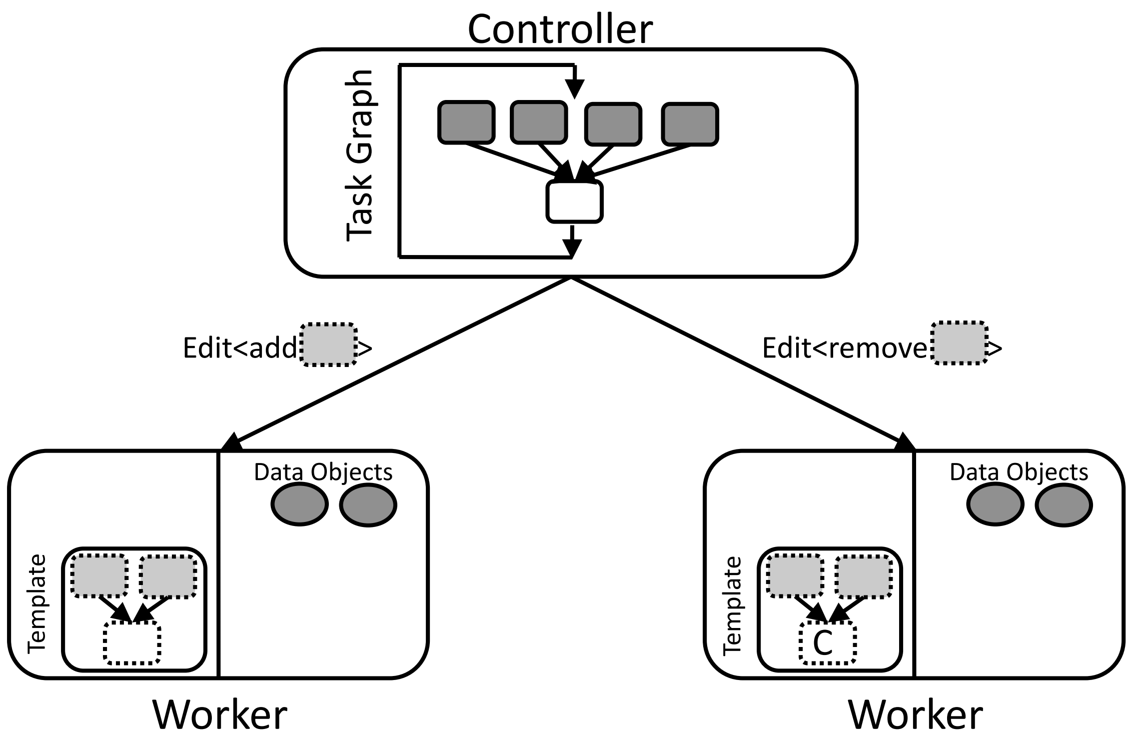
Execution Templates

Edits



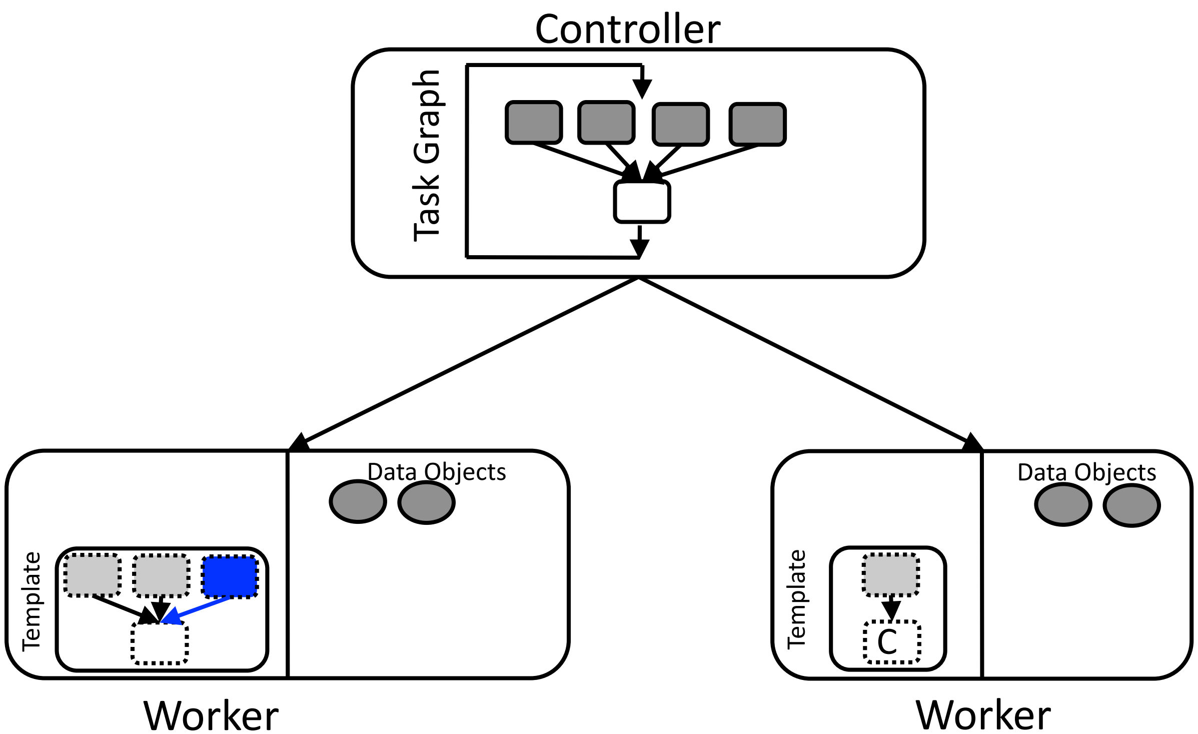
Execution Templates

Edits



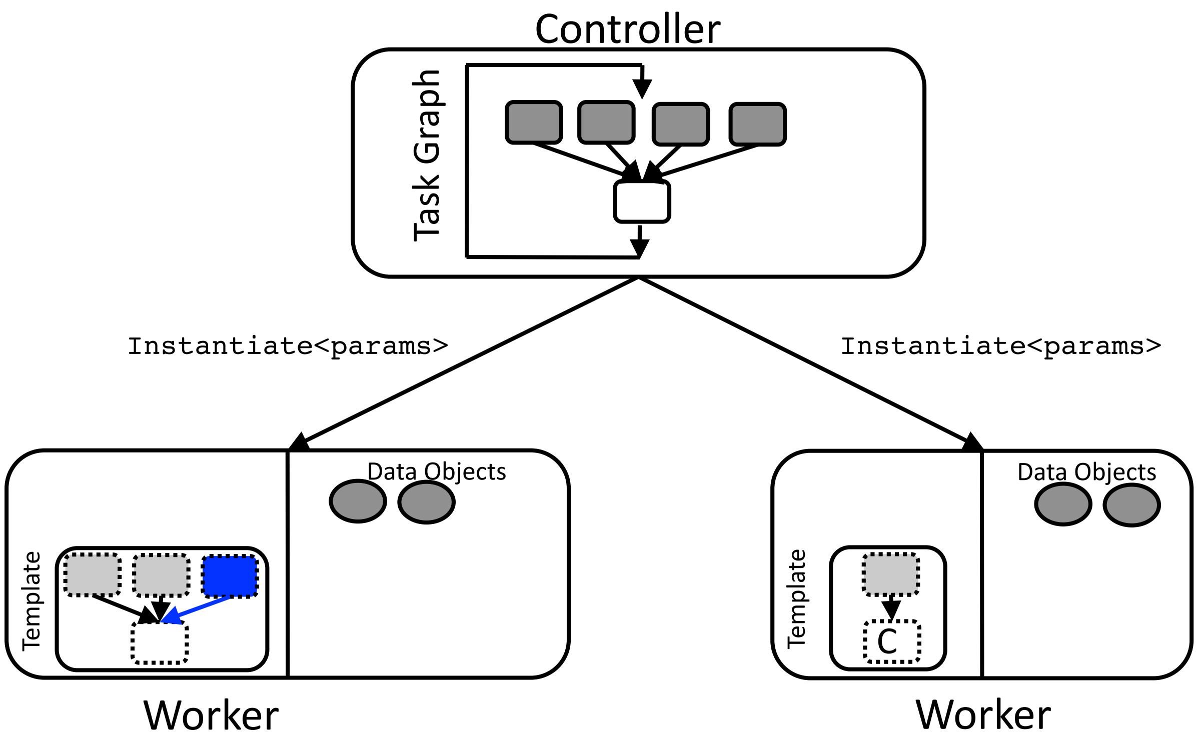
Execution Templates

Edits



Execution Templates

Edits



Execution Templates

Caching tasks implies static behavior; how could templates allow **dynamic control flow**?

- Need to support nested loops.
- Need to support data dependent branches.

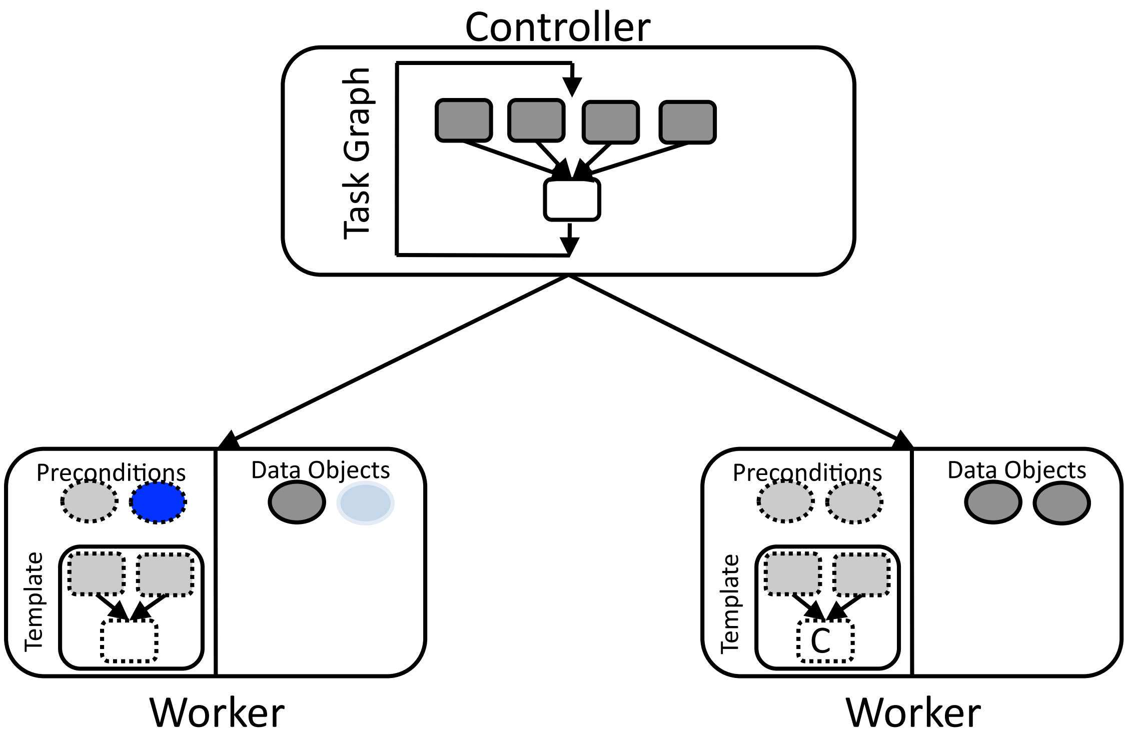
Execution Templates

Patching

- Execution templates operates at the granularity of **basic blocks**:
  - A code block with single entry and no branches except at the end.
- Each template has a set of **preconditions** that need to be satisfied.
  - For example the set of data objects in memory, accessed by the tasks.
- Worker state might not match the preconditions of the template in all circumstances.
- Controller **patches** the worker state before template instantiation, to satisfy the preconditions.

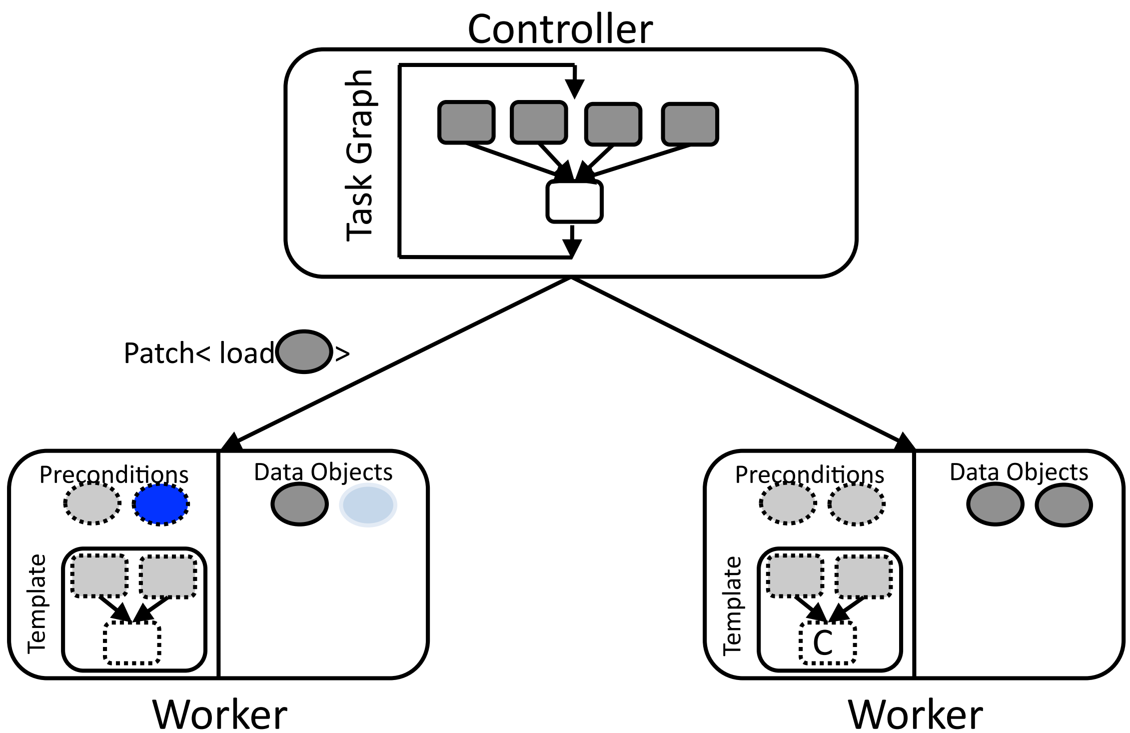
Execution Templates

Patching



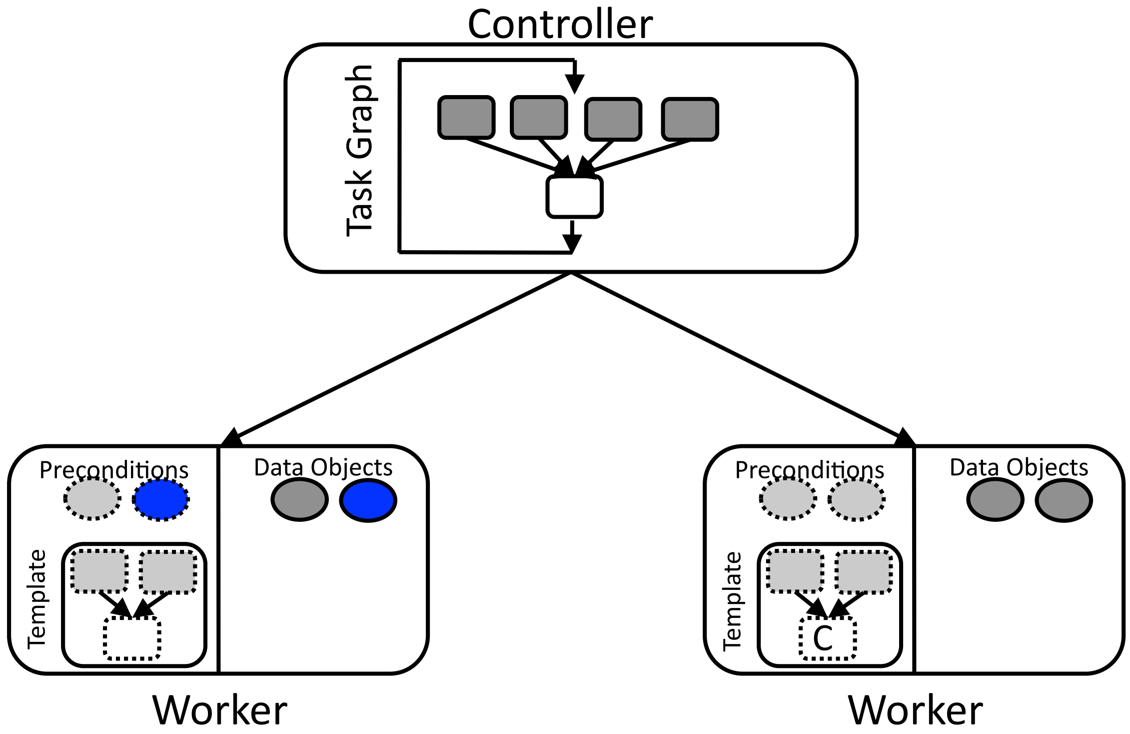
Execution Templates

Patching



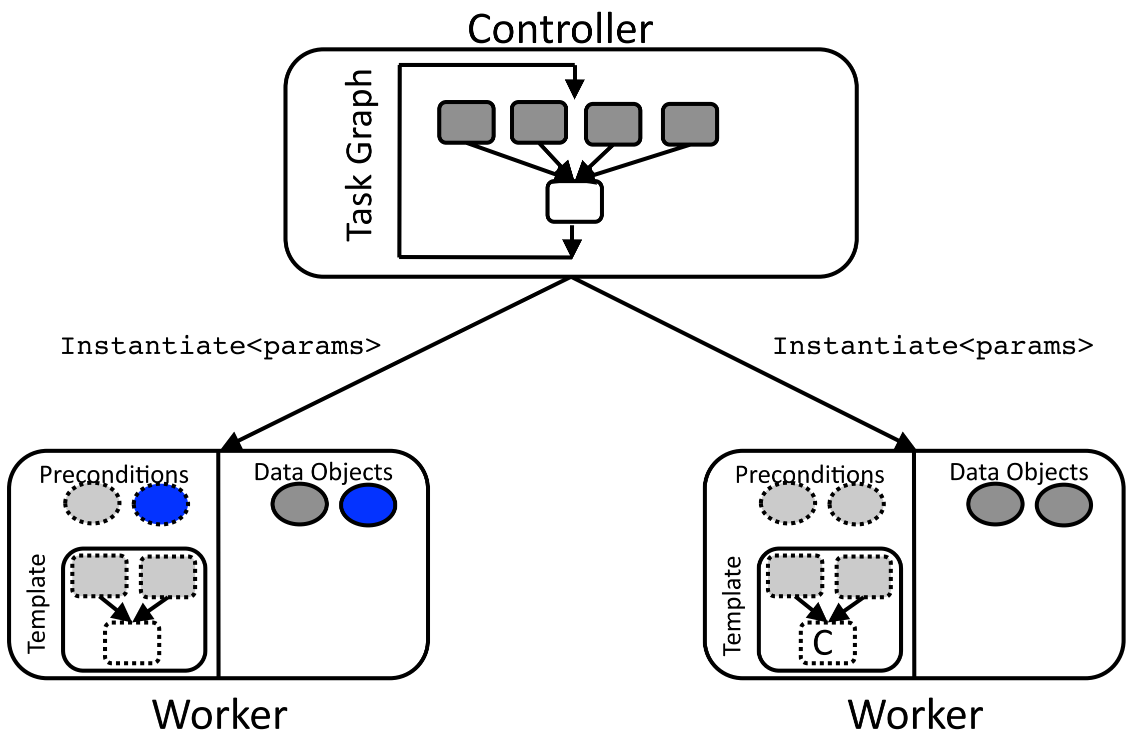
Execution Templates

Patching



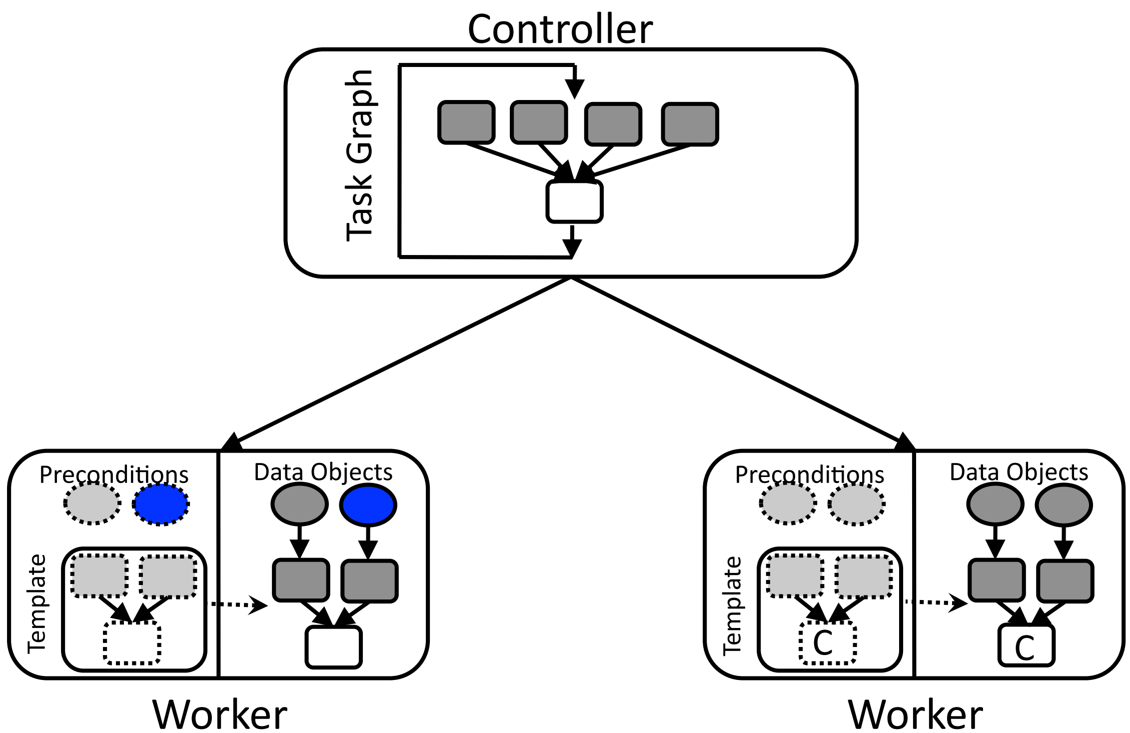
Execution Templates

Patching



Execution Templates

Patching



Execution Templates

Mechanisms Summary

- **Instantiation**: spawn a block of tasks without processing each task individually from scratch. It helps increase the **task throughput**.
- **Edits**: modifies the content of each template at the granularity of tasks. It enables fine-grained, **dynamic scheduling**.
- **Patches**: In case the state of the worker does not match the preconditions of the template. It enables **dynamic control flow**.

Nimbus

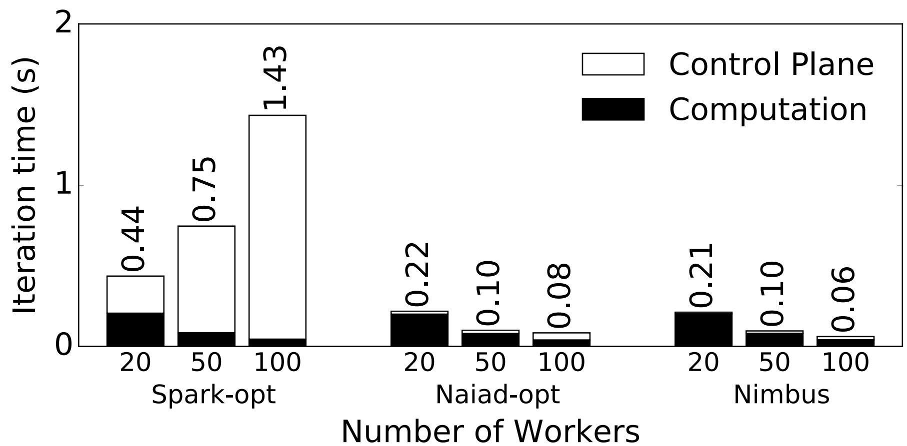
- Nimbus is designed for low latency, fast computations in the cloud.
- Nimbus embeds execution templates for its control plane.
- Nimbus supports traditional data analytics as well as Eulerian and hybrid graphical simulations; for the first time in a cloud framework.
  - Supervised/unsupervised learning algorithms.
  - Graph processing.
  - Physical simulation: water, smoke, etc. (PhysBAM library)

nimbus.stanford.edu

https://github.com/omidm/nimbus

Evaluation

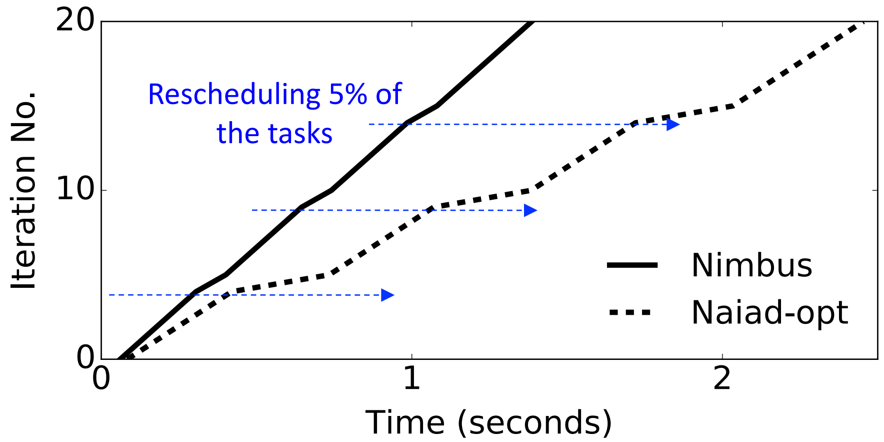
Strong Scalability with Templates



- Logistic regression over data set of size 100GB.
- Spark-opt and Naiad-opt, runs tasks as fast as C++ implementation.
- Nimbus centralized controller with execution templates matches the performance of Naiad with a distributed control plane.

Evaluation

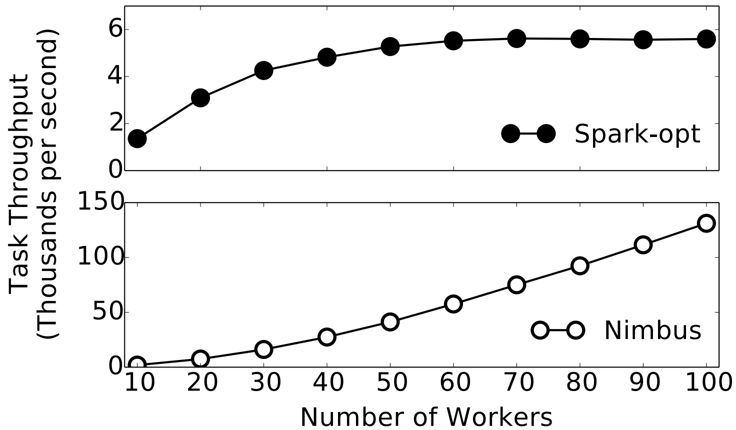
Reactive, Fine-Grained Scheduling with Templates



- Logistic regression over data set of size 100GB, on 100 workers.
- Naiad-opt curve is simulated (migrations every 5 iterations).
- Execution templates allow low cost, reactive scheduling changes.
    - Single edit overhead is only 41μs (in average).

Evaluation

High Task Throughput with Templates



- Spark and Nimbus both have centralized controller.
- Nimbus task throughput scales super linearly with more workers.
    - $O(N^2)$: more tasks and shorter tasks, simultaneously.
- For a task graphs with single stage:
    - Instantiation cost is <2μs per task (500,000 tasks per second).

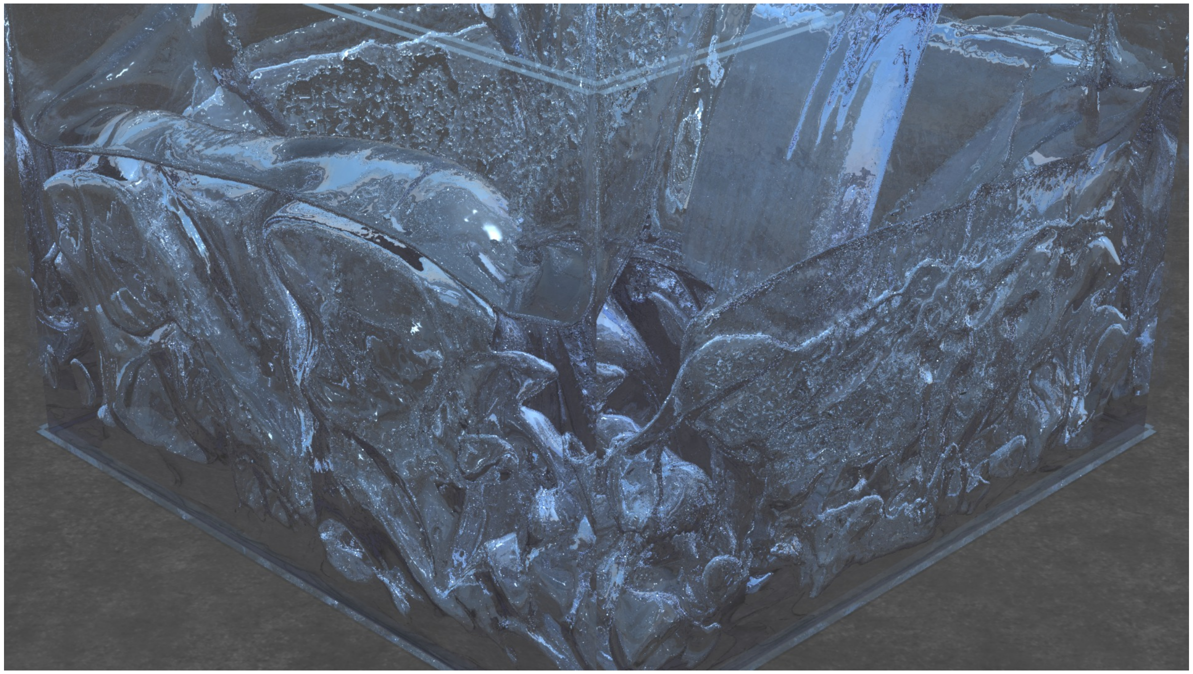
Evaluation

Graphical Simulations Distributed in Nimbus

- To show the generality of execution templates, we considered graphical simulations in Nimbus:
  - Complex, and memory intensive from PhysBAM library.
  - High tasks throughput requirements (400,000 tasks per second).
  - Nested loops and data dependent branches.
  - Require patching in very subtle cases.
  - Traditionally in the HPC domain.

Evaluation

Graphical Simulations Distributed in Nimbus



Conclusion

Control Plane Design	**Example Framework**	**Task Throughput (task per sec)**	**Scheduling Cost (per task)**
Centralized	MapReduce Hadoop Spark	$\approx 1,000$	$\approx 100\mu s$
Distributed	Naiad TensorFlow	$\approx 100,000$	$\approx 100,000\mu s$
Centralized w/ Execution Templates	Nimbus	$\approx 100,000$	$\approx 100\mu s$

Thank you!

nimbus.stanford.edu

https://github.com/omidm/nimbus