ETH
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Parallel Computing Patterns for Grid Workflows

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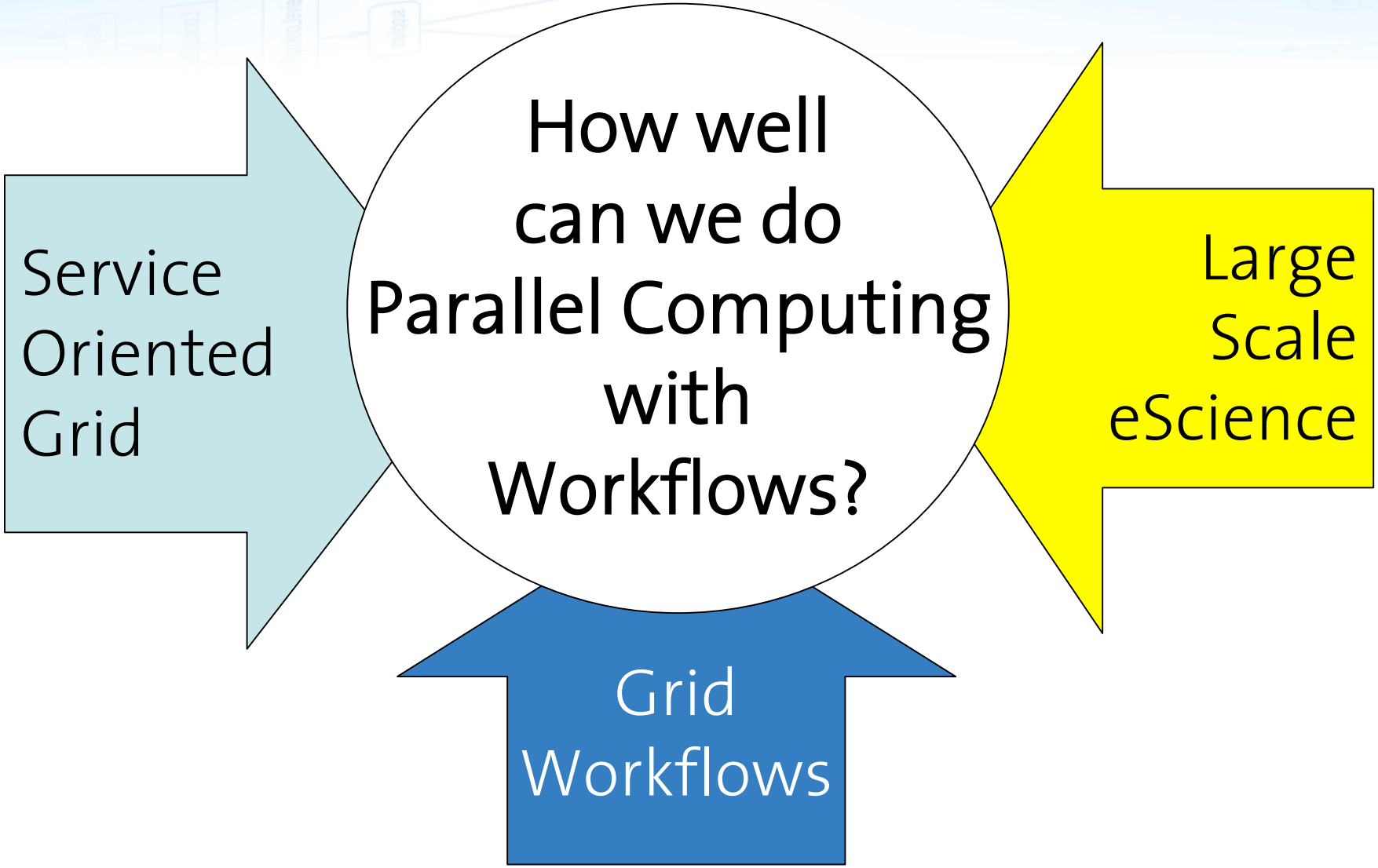
Grid Workflows for Large Scale eScience

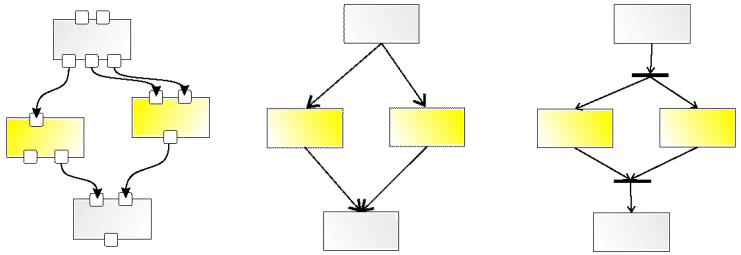


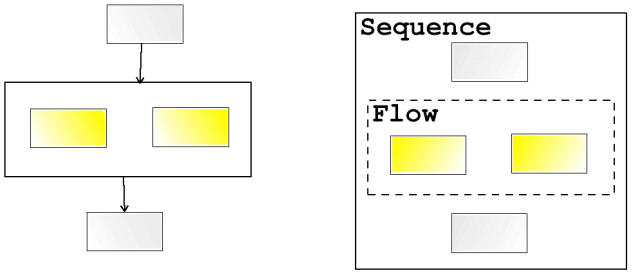
Why Parallel Computing Patterns?

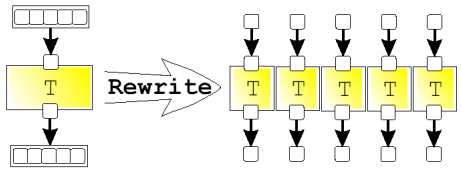
- Language primitives for modeling parallelism
  - Common classification
  - Unify different syntax/notations
  - Test of expressive power
- Efficient implementation for Grid workflows
  - Do all systems support all patterns?
  - What is the semantics of parallelism?
  - Impact on scheduling, data management, lineage tracking features

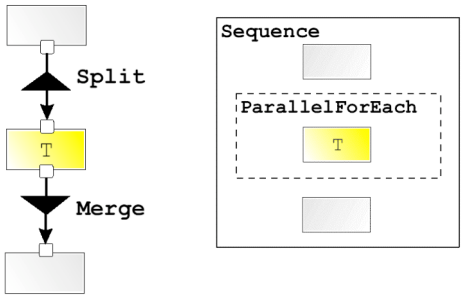
Overview

- Parallel Execution
  - Simple Parallelism
  - Data Parallelism
- Pipelined Execution
  - Best Effort
  - Blocking
  - Buffered
  - Superscalar
  - Streaming







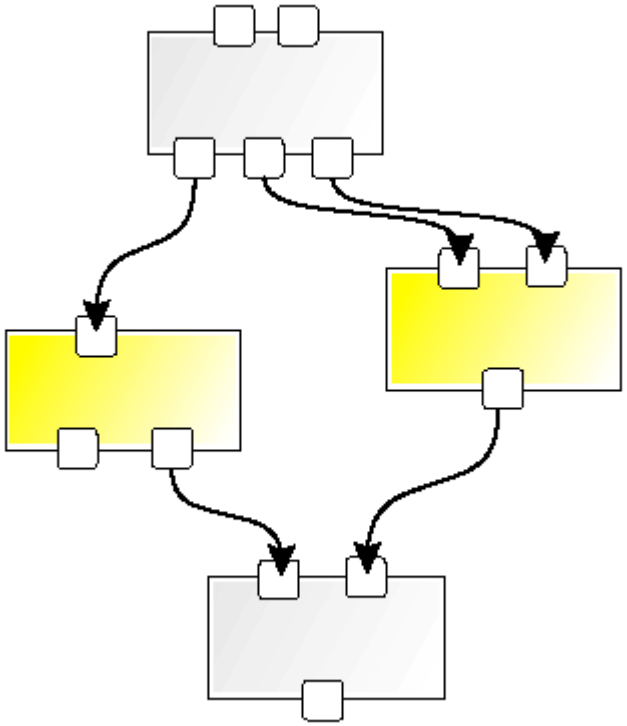


Parallel Execution: Simple Parallelism

- Parallel split (Classical Control Flow Pattern)
- Independent tasks...
  - ...run in parallel (*strong semantics*)
  - ...may run in parallel if enough resources are available (*realistic implementation*)
  - ...are serialized non deterministically (*weak semantics*)
- Modeling:
  - Explicit or Implicit
  - Control flow or Data flow
  - Graph based or Block based (or both)

Modeling Simple Parallelism

- Data Flow, Graph Based, Implicit



Examples:

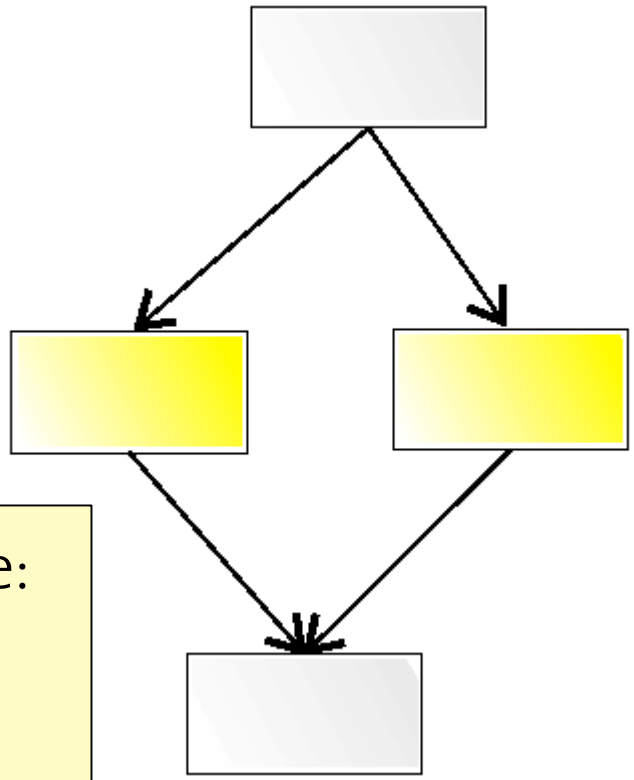
SCIRun

Kepler

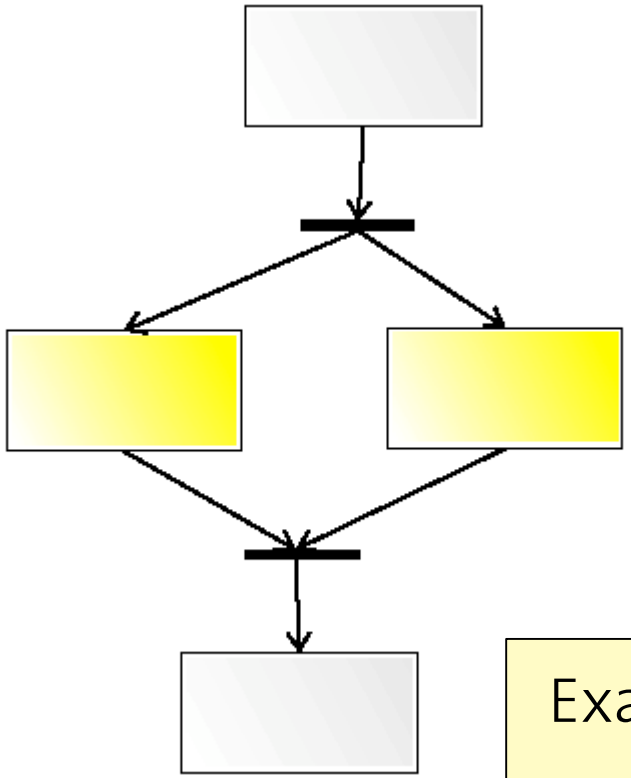
Triana

Modeling Simple Parallelism

- Control Flow, Graph Based



Example:
YAWL
JOpera
GEL



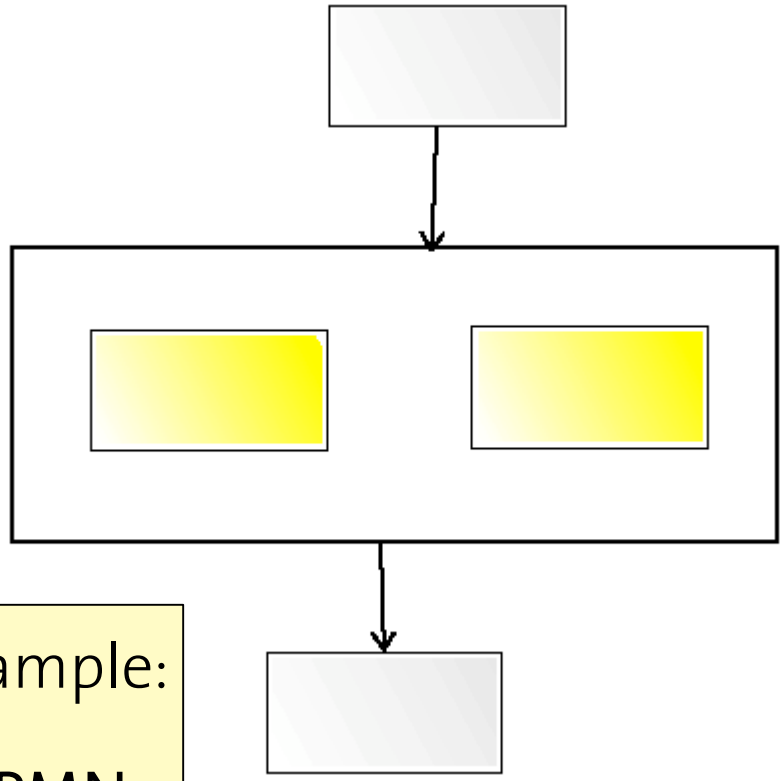
Example:
UML

Modeling Simple Parallelism

- Control Flow, Block Based, Explicit

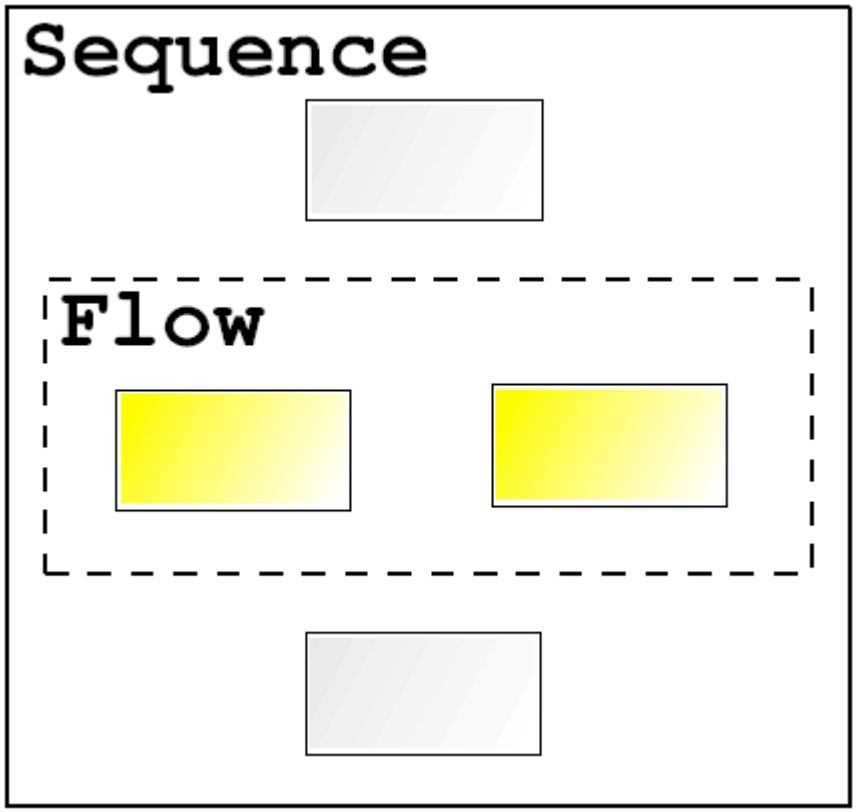
Example:

BPEL4WS



Example:

BPMN

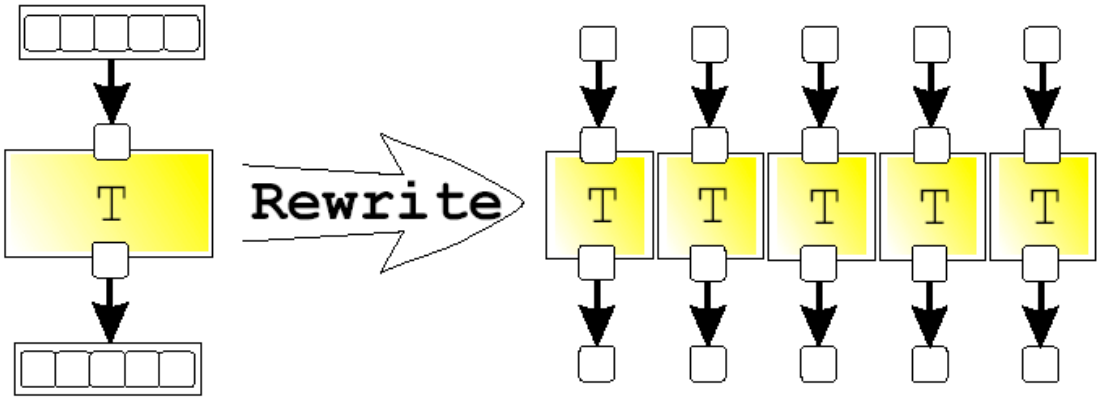


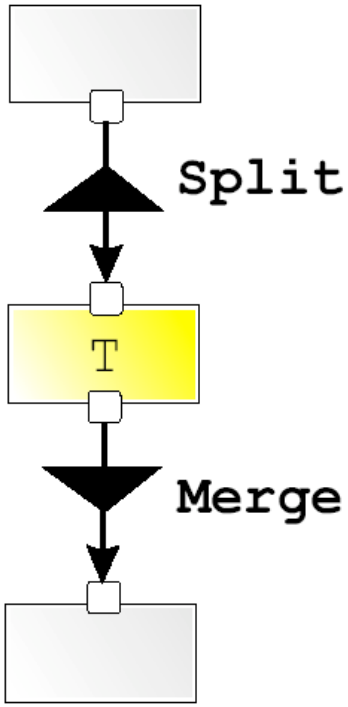
Parallel Execution: Data Parallelism

- SPMD: Run a copy of the same task over multiple data elements (in parallel)
- How to control the amount of parallelism?
  - Static (Design-time) vs. **Dynamic** (Run-time)
  - Manual vs. Adaptive
  - Homogeneous vs. Heterogeneous partitions
- Modeling
  - Data Flow or Control Flow
  - Graph Rewriting, Block based
  - First-Order Functions (Map)

Modeling Data Parallelism

- Data Flow, Graph Rewriting





- Static or Dynamic

Examples:

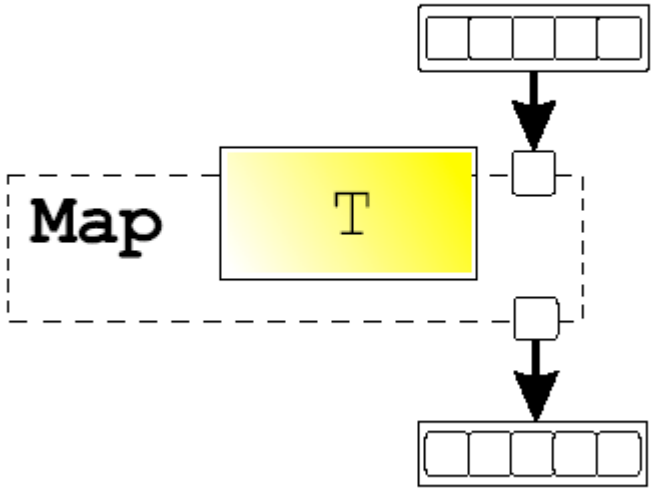
Triana

Taverna

JOpera

Modeling Data Parallelism

- Data Flow, First-Order Functions

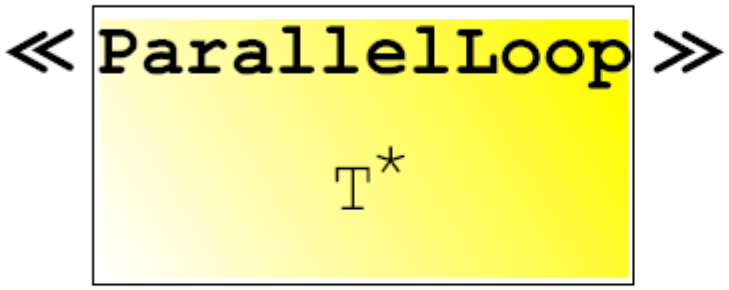


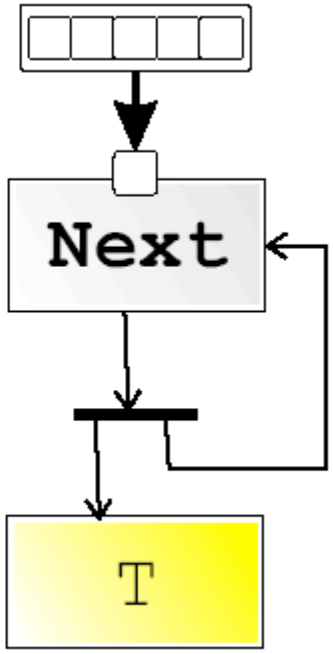
Example:

Kepler

Modeling Data Parallelism

- Control Flow, Graph Based





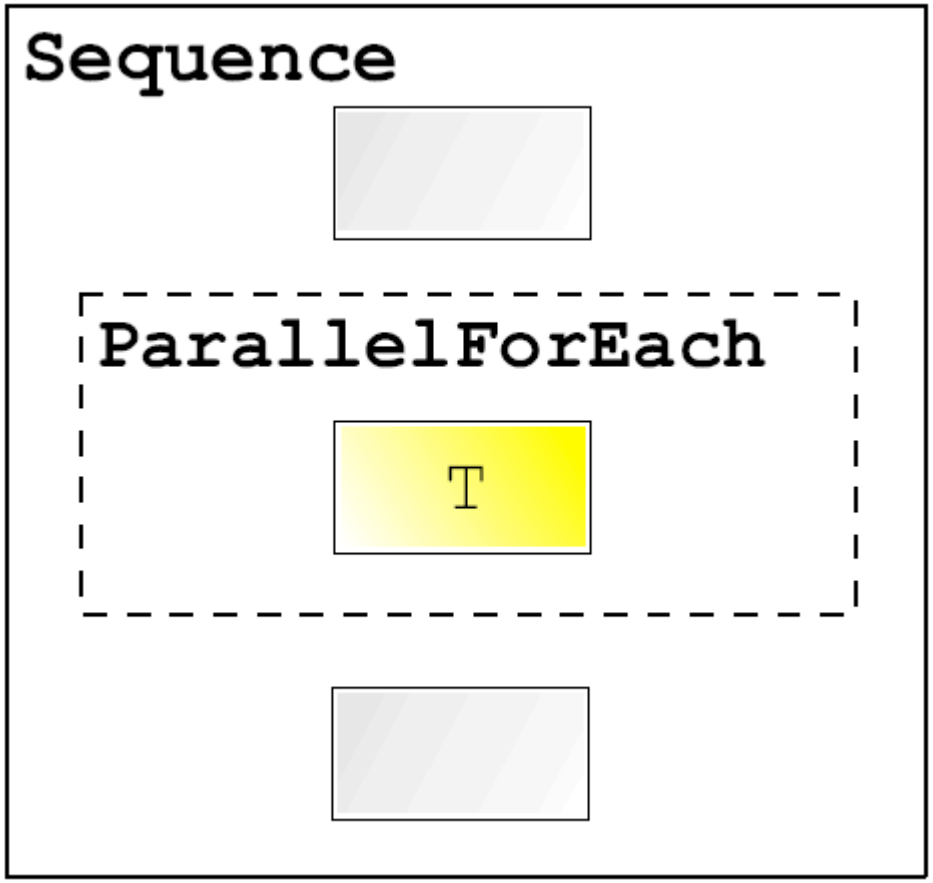
Examples:

Teuta

UML

Modeling Data Parallelism

- Control Flow, Block Based



Examples:

WS-BPEL

AGWL

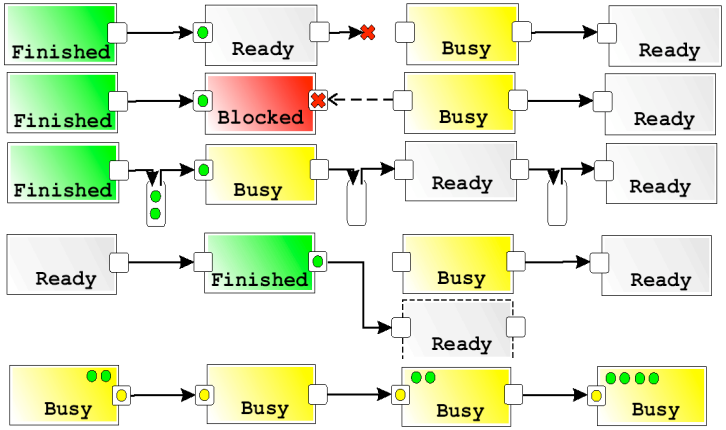
Karajan

GEL

Overview

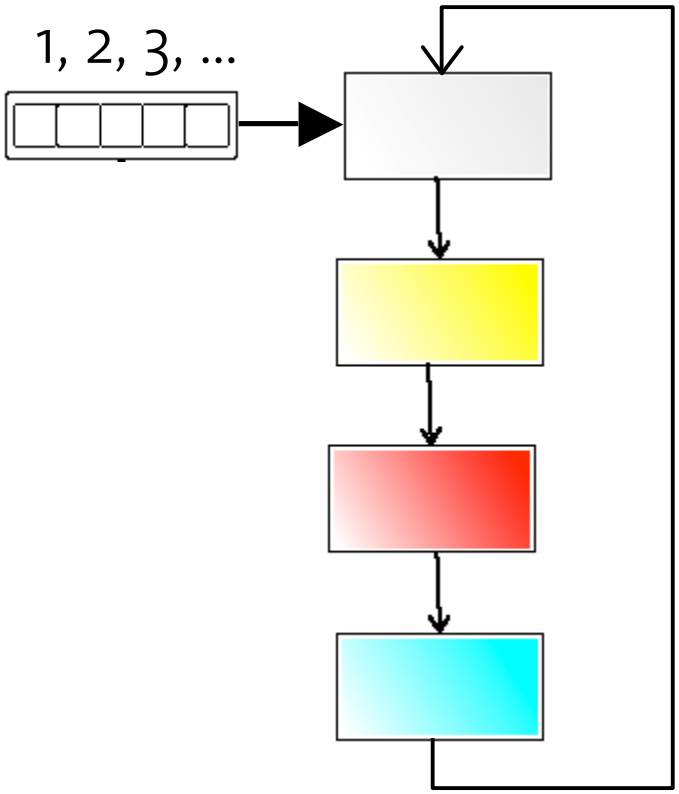
- Parallel Execution
  - Simple Parallelism
  - Data Parallelism

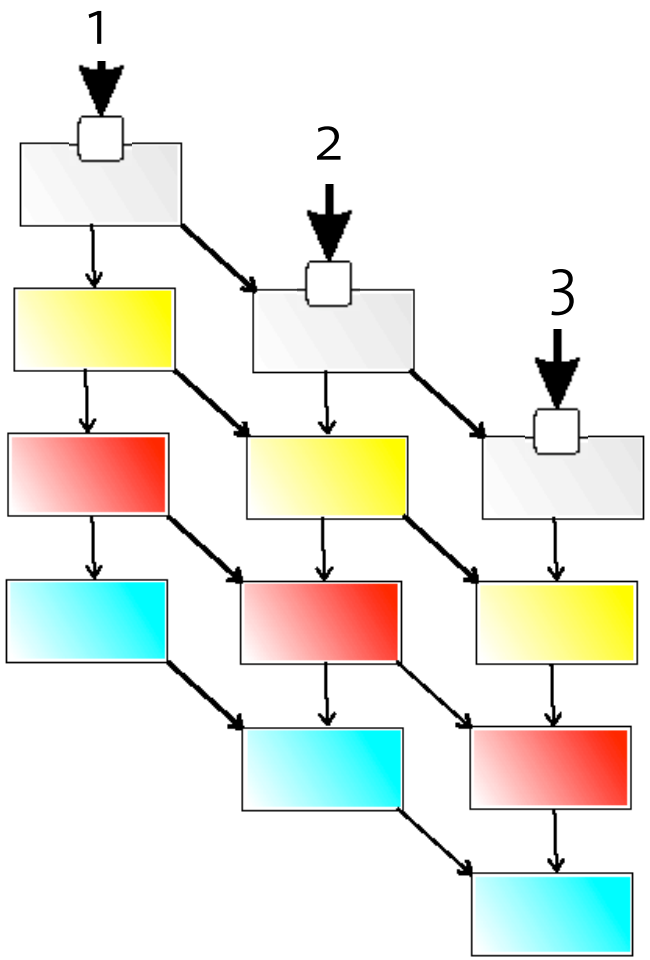
- Pipelined Execution
  - Best Effort
  - Blocking
  - Buffered
  - Superscalar
  - Streaming



Parallel Execution: Pipelined Execution

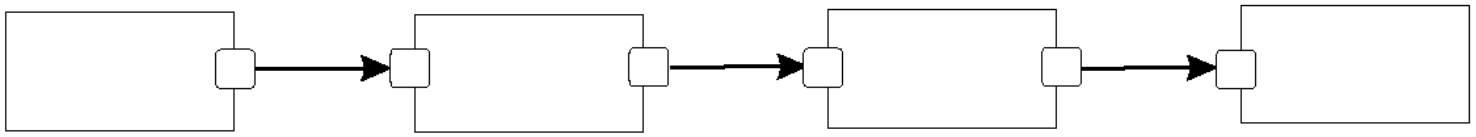
- Stream multiple data elements sequentially through a sequence of tasks





Modeling Pipelined Execution

- Syntax very similar, but semantics changes a lot!

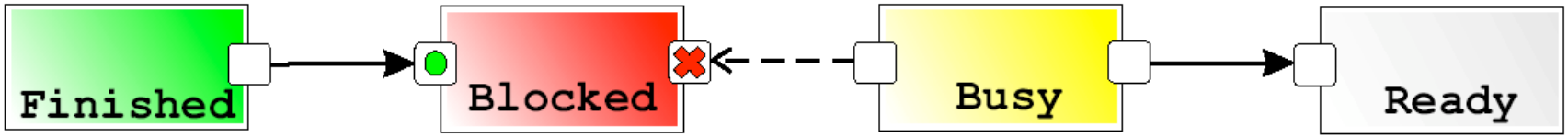


- How to deal with non uniform task duration?
  - Best Effort
  - Blocking
  - Buffering
  - Superscalar
  - Streaming

Best Effort Pipelined Execution

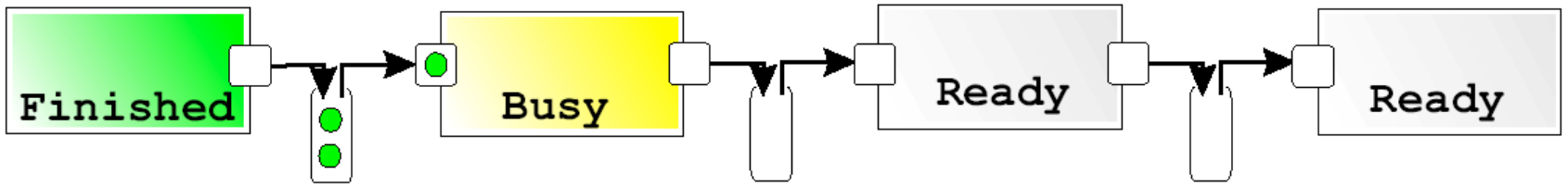
- Drop data elements on pipeline collisions
- Advantages:
  - Simplified implementation
  - Some applications may tolerate data loss
- Problem:
  - Downsampling is non deterministic

Blocking Pipelined Execution



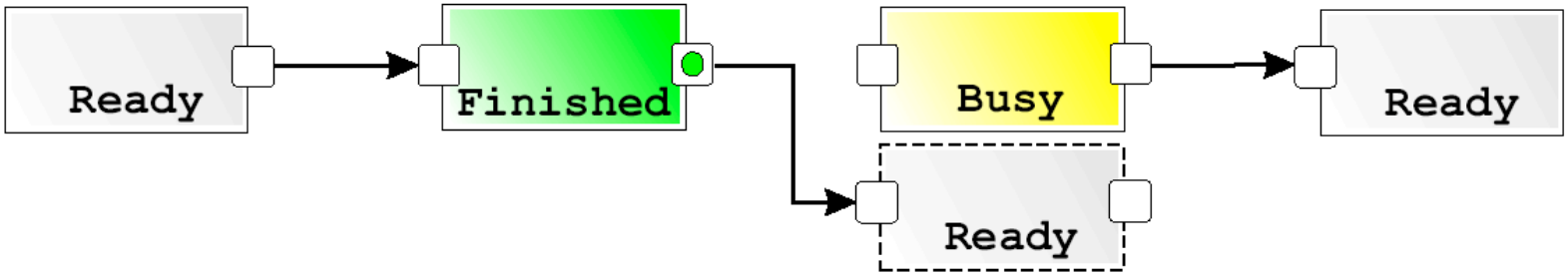
- Tasks are blocked if successors are busy
- Advantages:
  - Avoid data loss in the pipeline
- Problem:
  - Pipeline speed limited by slowest task
  - Data may be lost before it enters the pipeline

Buffered Pipelined Execution



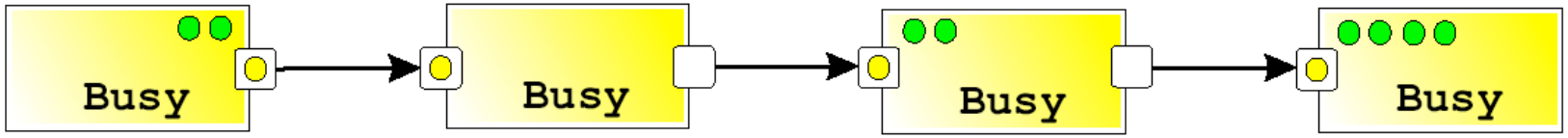
- Tasks are decoupled by buffers
- Advantages:
  - Collisions are prevented
  - Best applied to tasks having variable speed
- Problem:
  - Buffer capacity is limited (Blocking still needed)

Superscalar Pipelined Execution



- If a task is busy, create another instance
- Advantage:
  - Data loss avoided without blocking
- Problem:
  - Data elements may overtake one another
  - Where to enforce synchronization?

Streaming Pipelined Execution



- Tasks exchange data while running
- Advantages:
  - Suitable for a distributed (P2P) engine
- Problems:
  - Shifts complexity from the workflow engine to the tasks
  - Tasks exchange data while running
  - Workflow/Task interface more complex

Conclusions

- Applying parallel computing techniques to Grid workflows has become a necessity for large scale eScience applications.
- Not all Grid workflow languages/systems we surveyed support all patterns:
  - Simple Parallelism & Static Data Parallelism supported by all
  - Dynamic Data Parallelism still a challenge (for some)
  - Pipelining implemented with many different semantics
- Let us know how your Grid workflow language/tool supports these patterns!

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