Optimizing Memory Management for Optimistic Simulation with Reinforcement Learning

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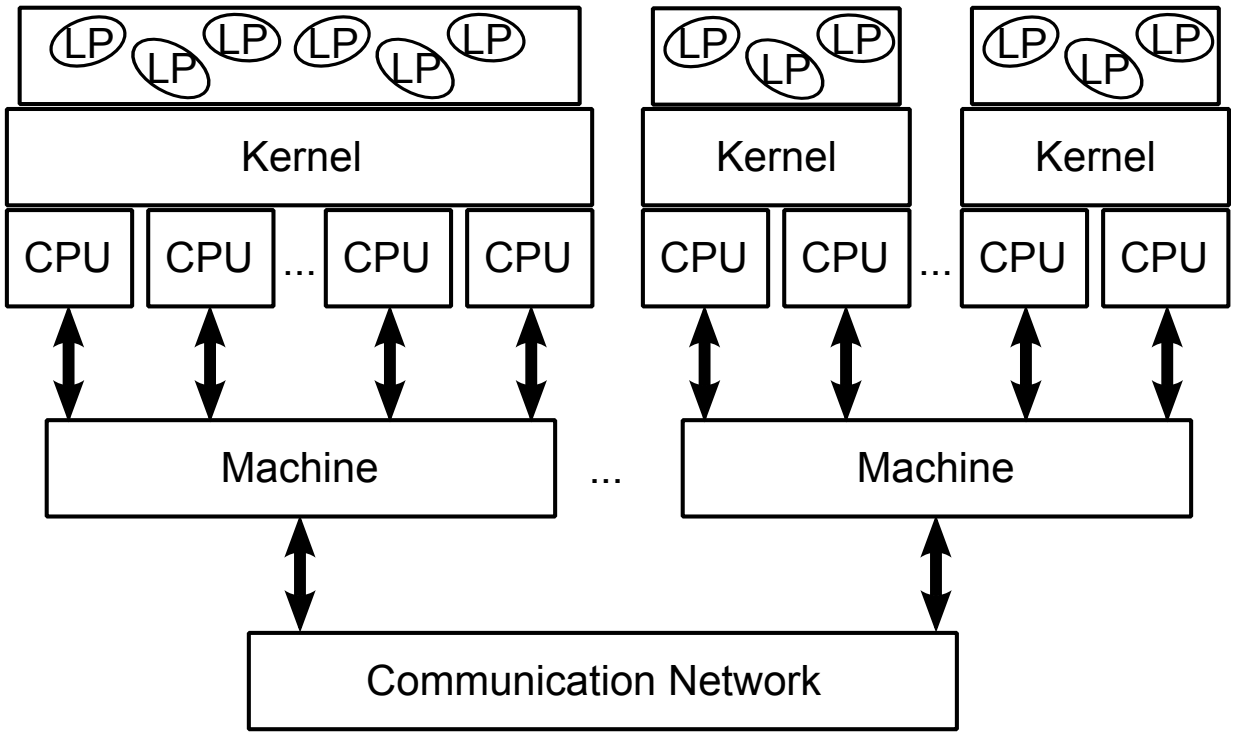
Context

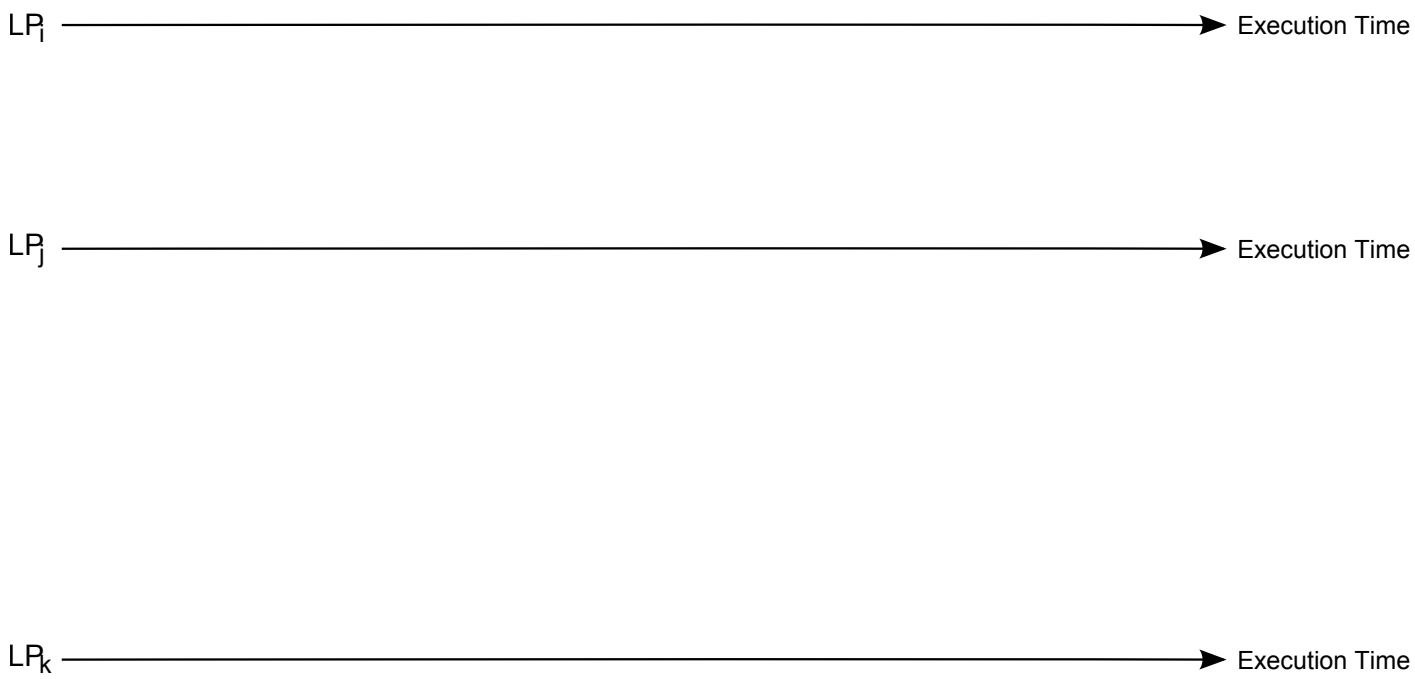
- Simulation is a powerful technique to explore complex scenarios
- Parallel Discrete Event Simulation (PDES) has been applied to a large set of research fields
- Speculative Simulation (Time Warp-based) is proven to be effective to deliver high performance simulations

- Ensuring *consistency* of speculative simulation requires effort
- Transparency towards the application-model developer is critical

Organization of a Time Warp Kernel



The Synchronization Problem



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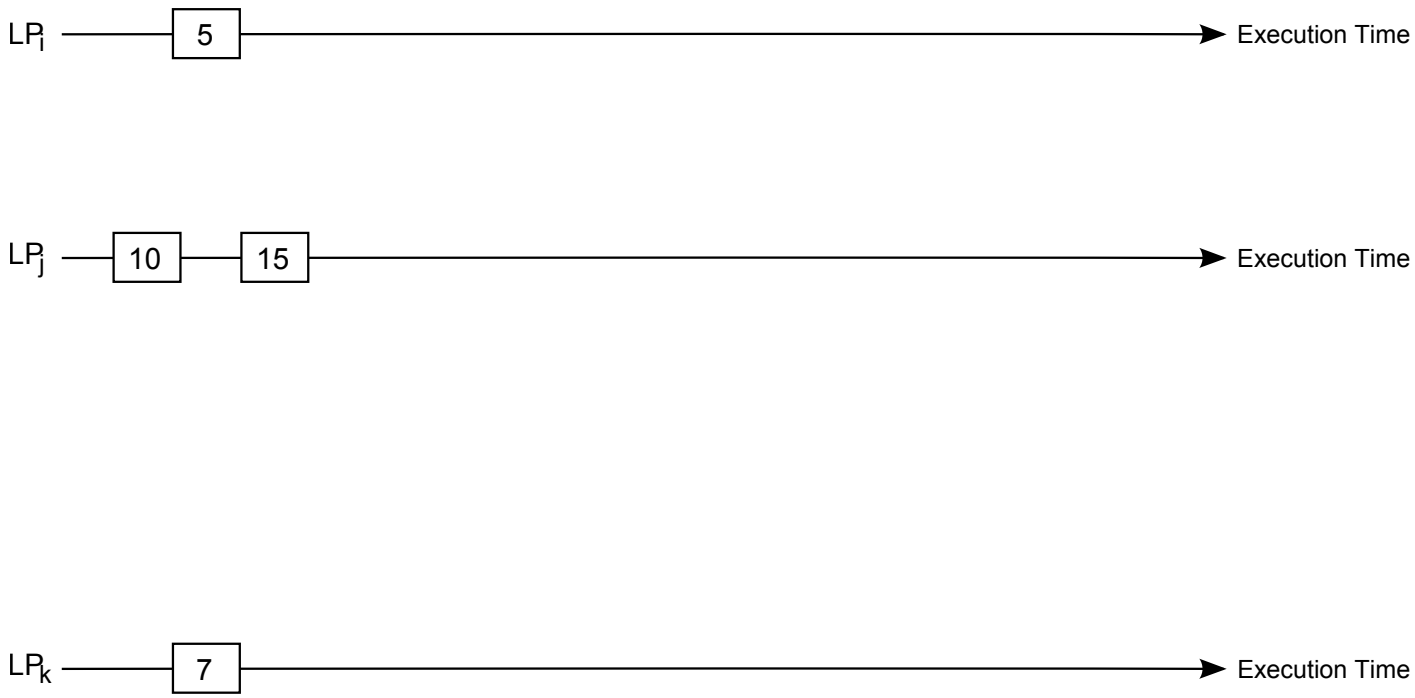

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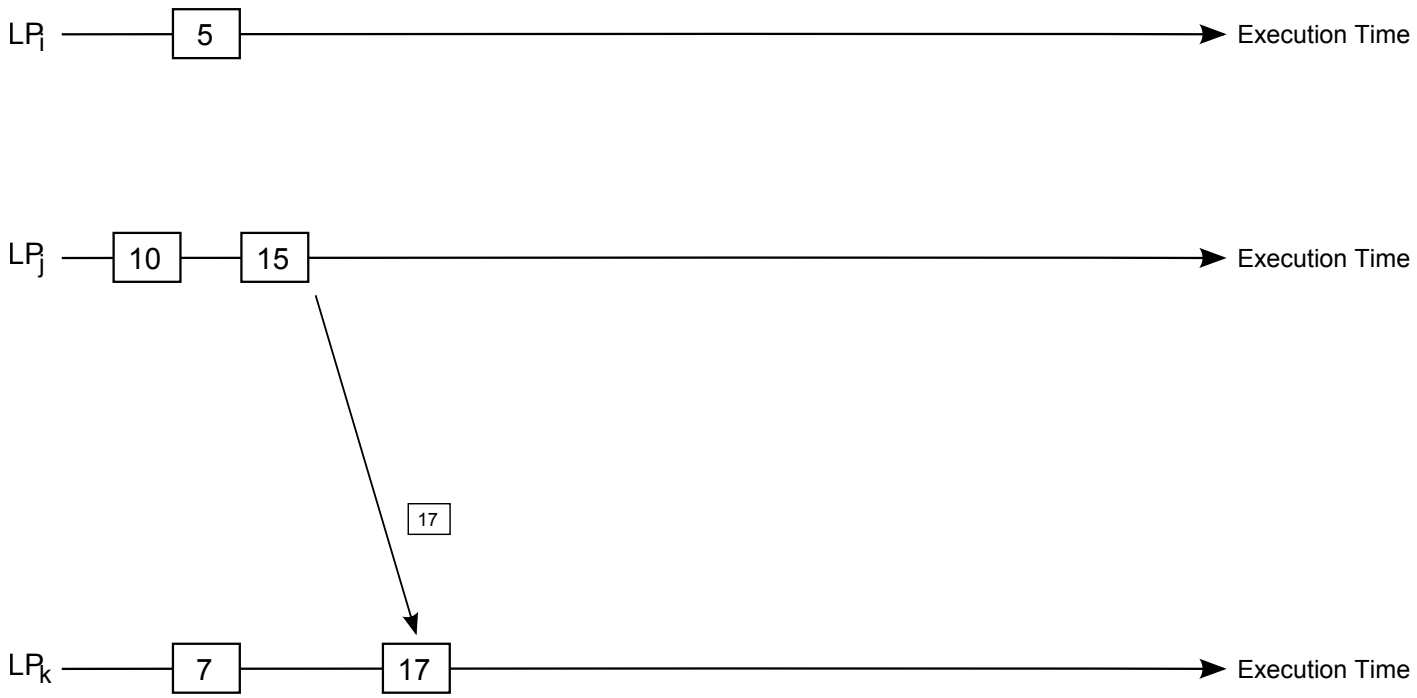

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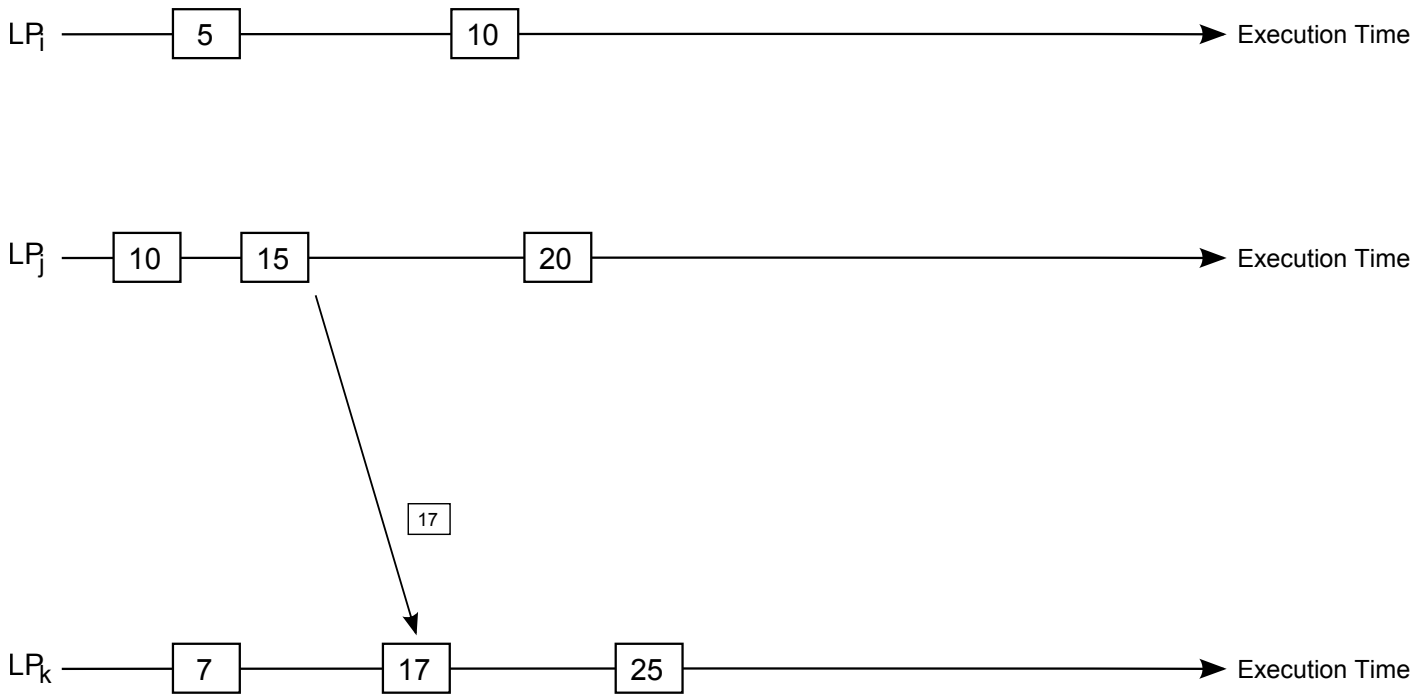

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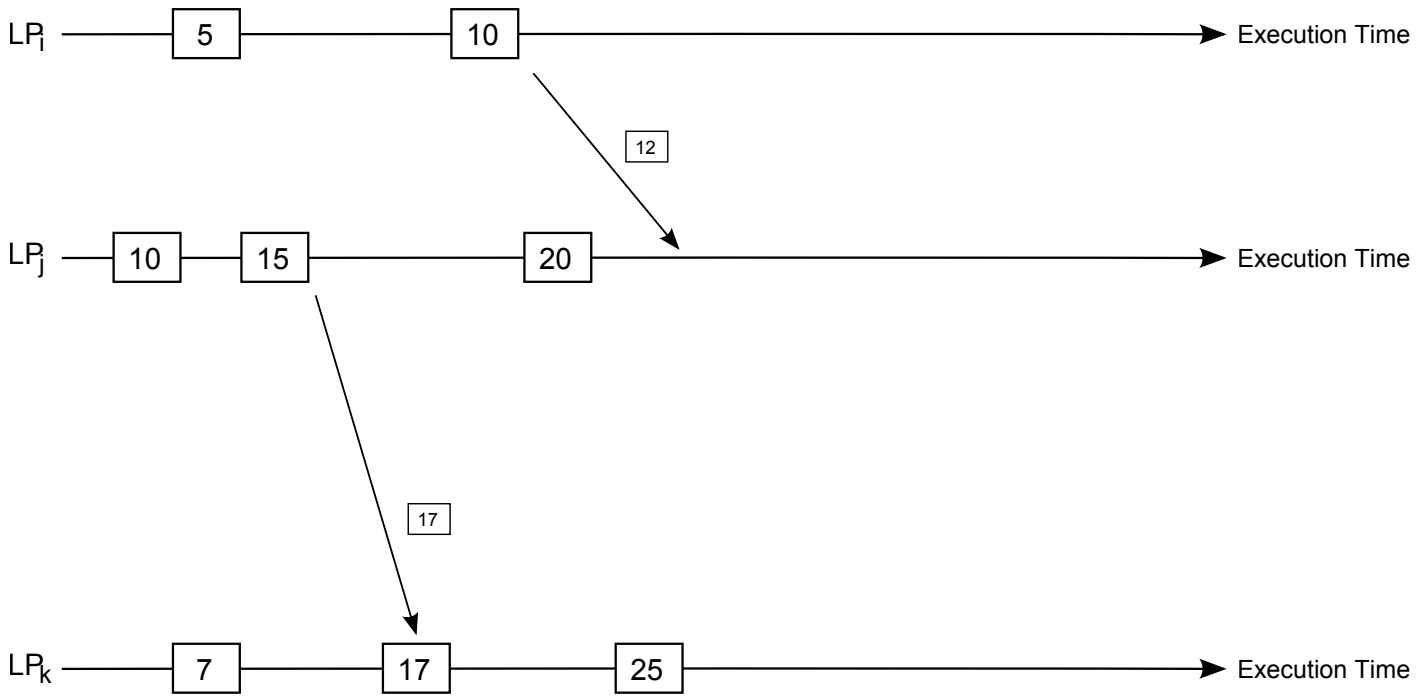

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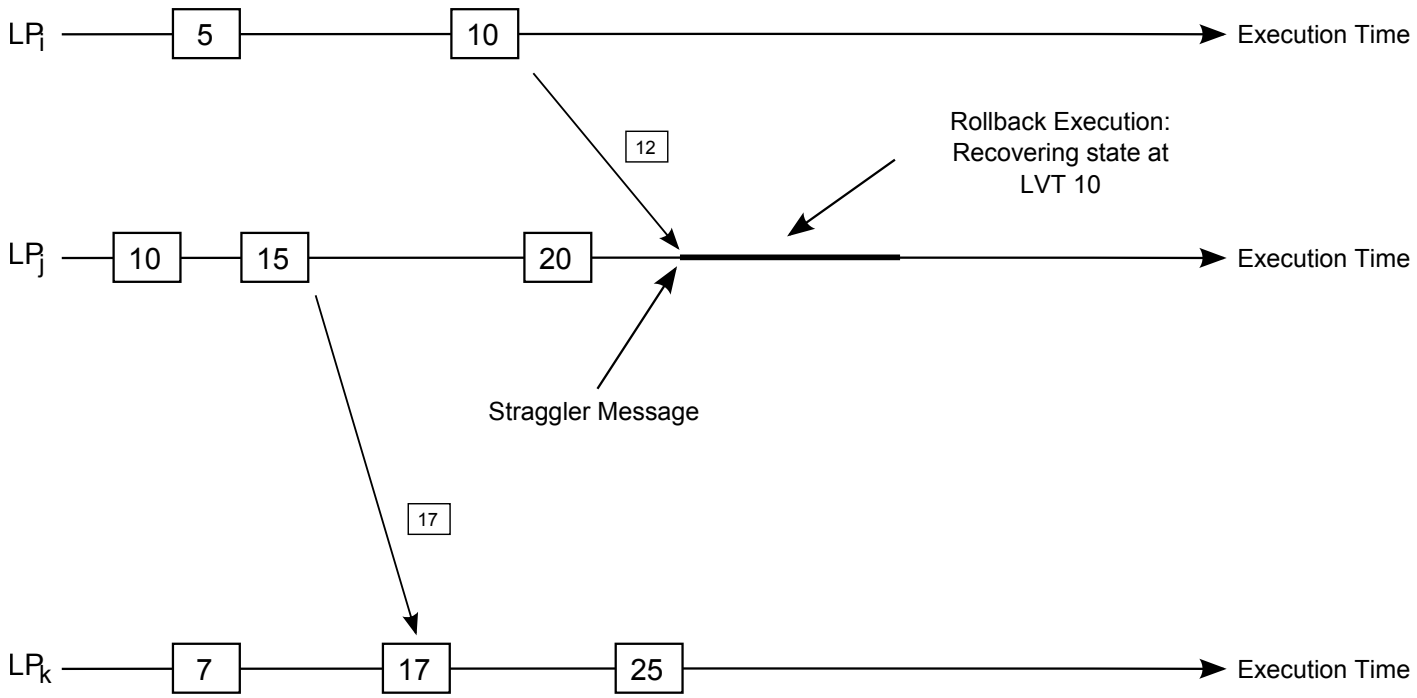

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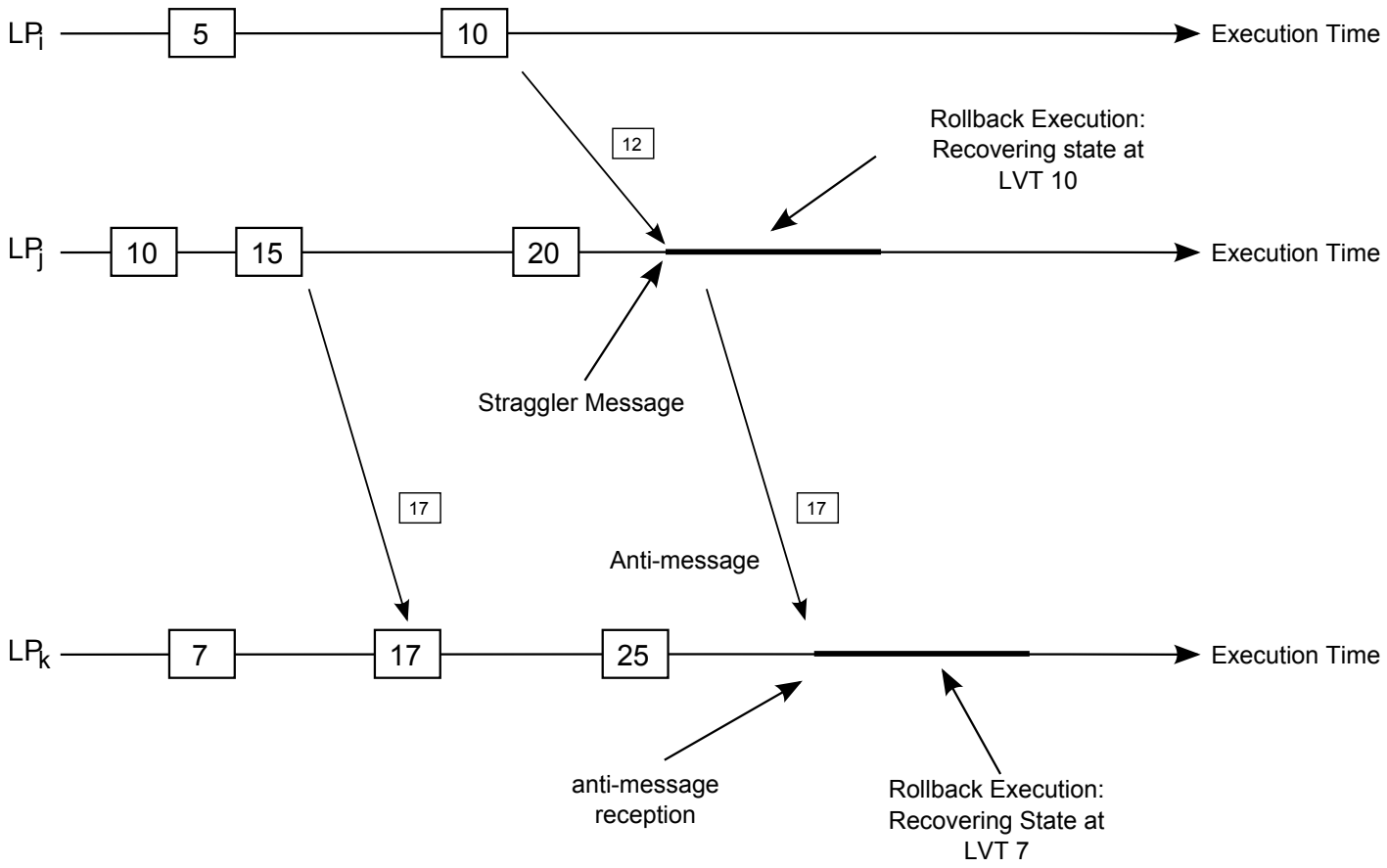

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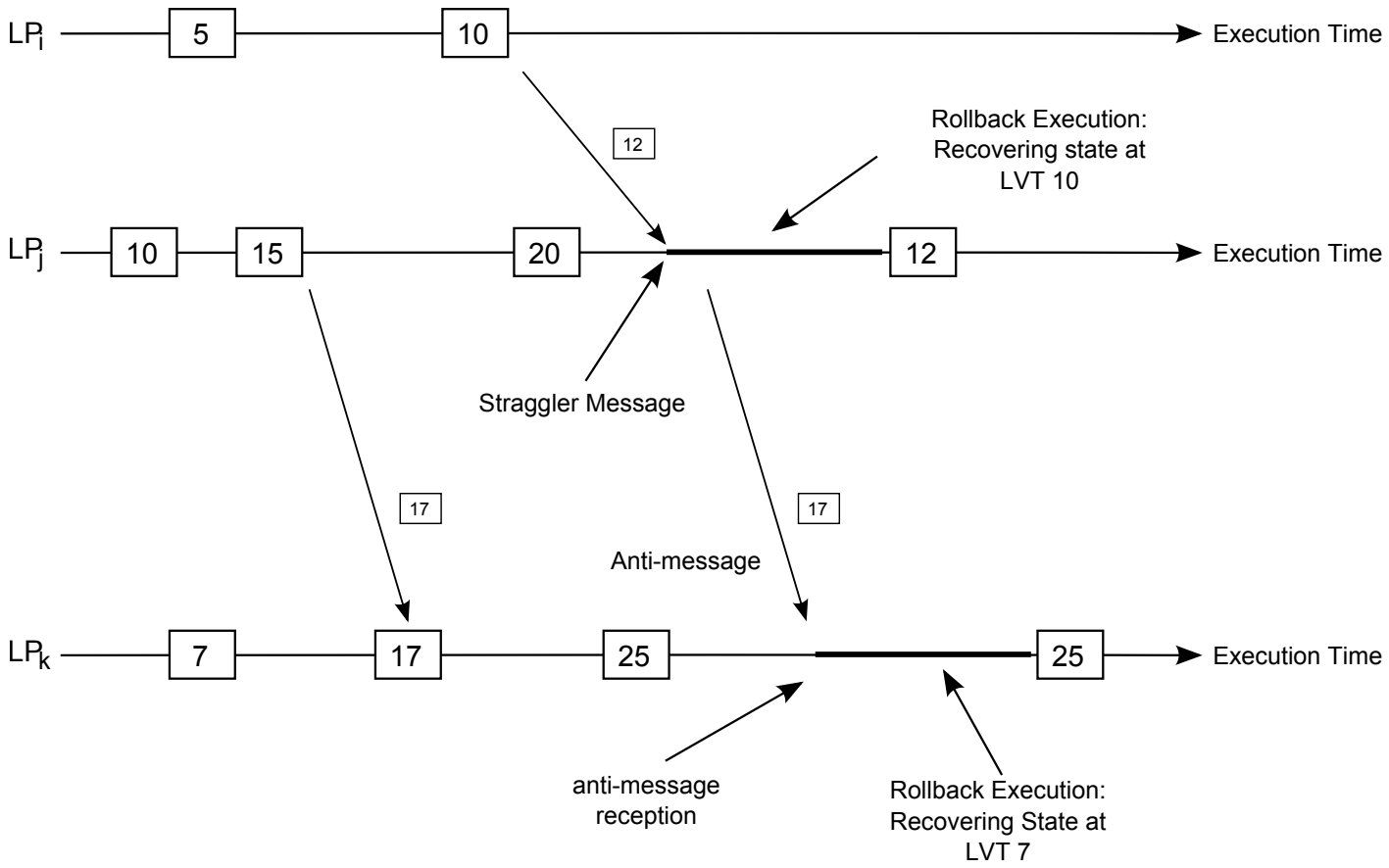

Memory Management and Rollbacks

- How can a runtime environment restore a state?

Memory Management and Rollbacks

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- It has to know the complete memory map of each LP
- It should take "sometimes" a snapshot of that map
- The snapshot could be either full or incremental

- Memory management is fundamental to Time Warp systems
  - Too many snapshots: memory/latency inefficiency
  - Too few: rollbacks are long!
  - Full vs incremental: how to decide?

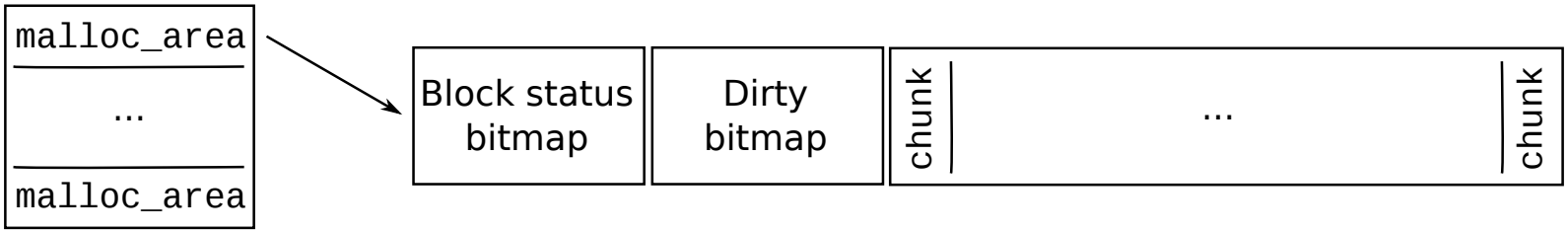
Our memory management organization

- **Transparency**
  - Interception of memory-related operations (no platform APIs)
  - No application-level procedure for (incremental) log/restore tasks
- **Optimism-Aware Runtime Supports**
  - Recoverability of generic memory operations: *allocation*, *deallocation*, and *updating*
- **Incrementality**
  - Cope with memory "abuse" of speculative rollback-based synchronization schemes
  - Enhance memory locality

Our memory management organization

- **Lightweight software instrumentation**
  - Optimized memory-write access tracing and logging
  - Arbitrary-granularity memory-write tracing
  - Concentration of most of the instrumentation tasks at a pre-running stage:
    - No costly runtime dynamic disassembling
- **Standard API wrappers**
  - Code can call standard malloc services
  - Memory map transparently managed by the simulation platform

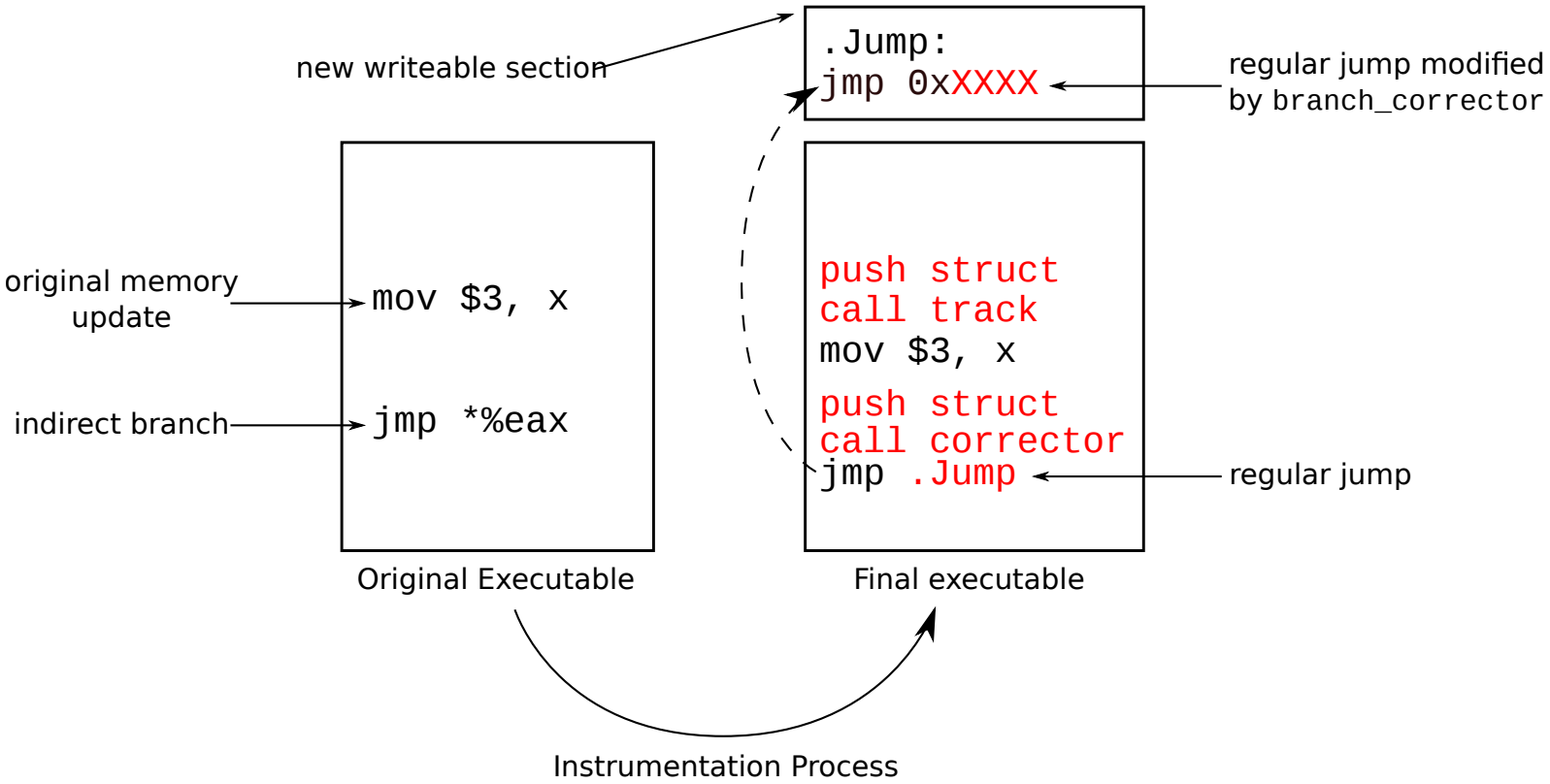
Our memory management organization



- Memory (for each LP) is pre-allocated
- Requests are served on a chunk basis
- Explicit avoidance of per-chunk metadata
  - *Block status bitmap*: tracks used chunks
  - *Dirty bitmap*: tracks updated chunks since last log

Our memory management organization

- We use Hijacker to track memory-update instructions



- Multi-code packs two different version of the program

Memory management self-optimization

- To optimize the memory manager we have to determine:
  - When to take a snapshot
  - Its mode (incremental vs incremental)
- But to take an incremental log, tracing must be active

- Traditional approaches are based on analytic models
  - Periodic recomputation (e.g., checkpoint interval)
  - Non-responsive if dynamics change fast
  - Might not capture secondary effects

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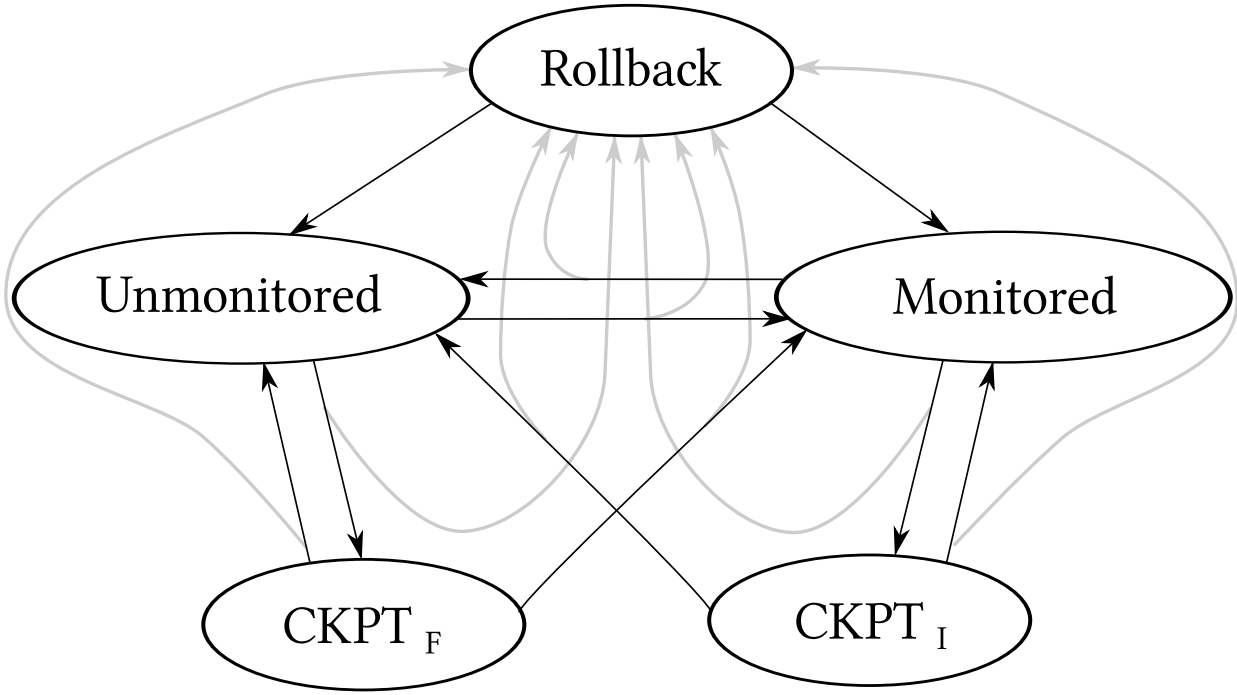
- We use *reinforcement learning*

Reinforcement Leraning-based self-optimization

- An *agent* takes an *action* in the environment depending on the current state
- An a-posteriori reward tells whether the choice was good
- Previous decisions affect future ones (we learn from history!)
- With some random probability, we ignore history and explore

- We take an action after the execution of each event
- After some knowledge has been acquired, the system can become very responsive

States and actions



Actions: Monitored, Unmonitored, Checkpoint

The reward

- We want to reduce the time spent in non-necessary tasks
- We define the *expected computation loss*:

$$\Gamma = \mathbb{E}\left[\int_0^T X(t)dt\right]$$

- where:

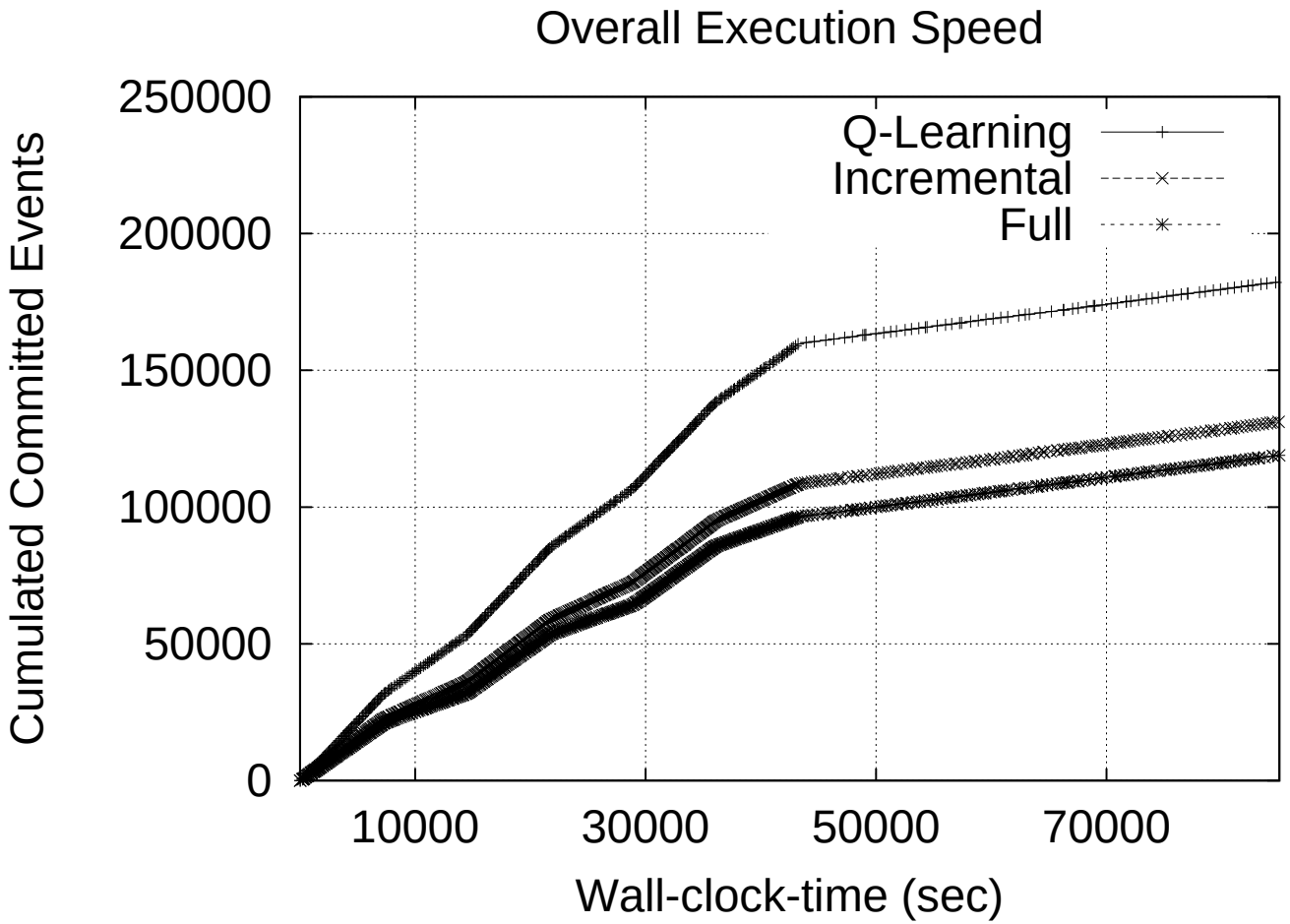
$$X(t) = \begin{cases} 0 & \text{if } x = \text{Non-Incremental} \\ \frac{\delta_M}{(\delta_e+\delta_M)} & \text{if } x = \text{Incremental} \\ 1-\gamma & \text{if } x = \text{CKPT}_I \\ 1 & \text{if } x = \text{CKPT}_F \\ 1 & \text{if } x = \text{Rollback} \end{cases}$$

Experimental Setup

- 64-bit NUMA machine, 24 cores, 32GB of RAM
- SuSe Enterprise 11, Linux 2.6.32.13

- GSM coverage simulation model
- High fidelity model (fading, power regulation, meteorological conditions)
- Ring highway coverage
- 1000 channels per cell
- Variable call interarrival (simulation of one week of traffic)

Experimental Results



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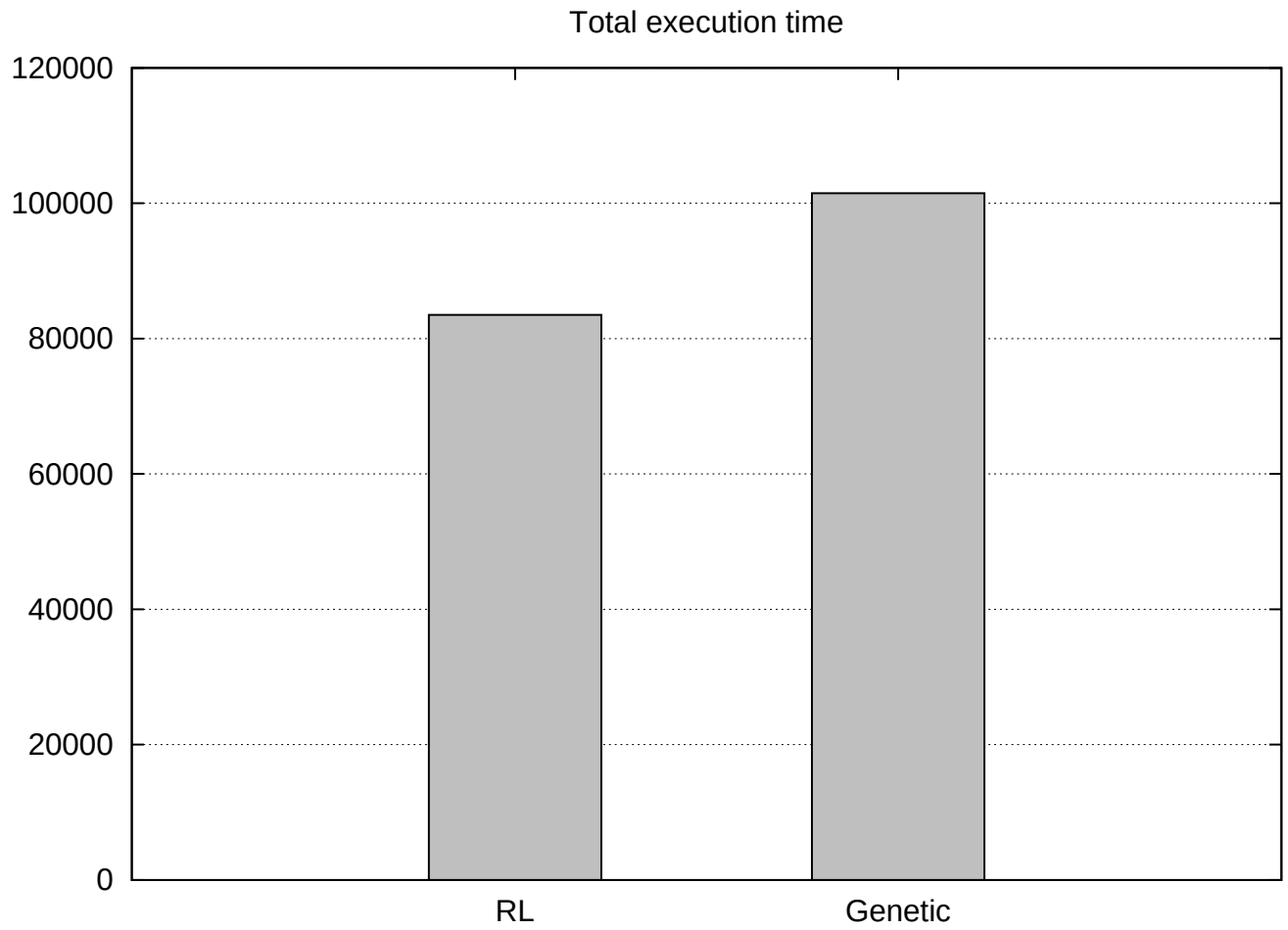

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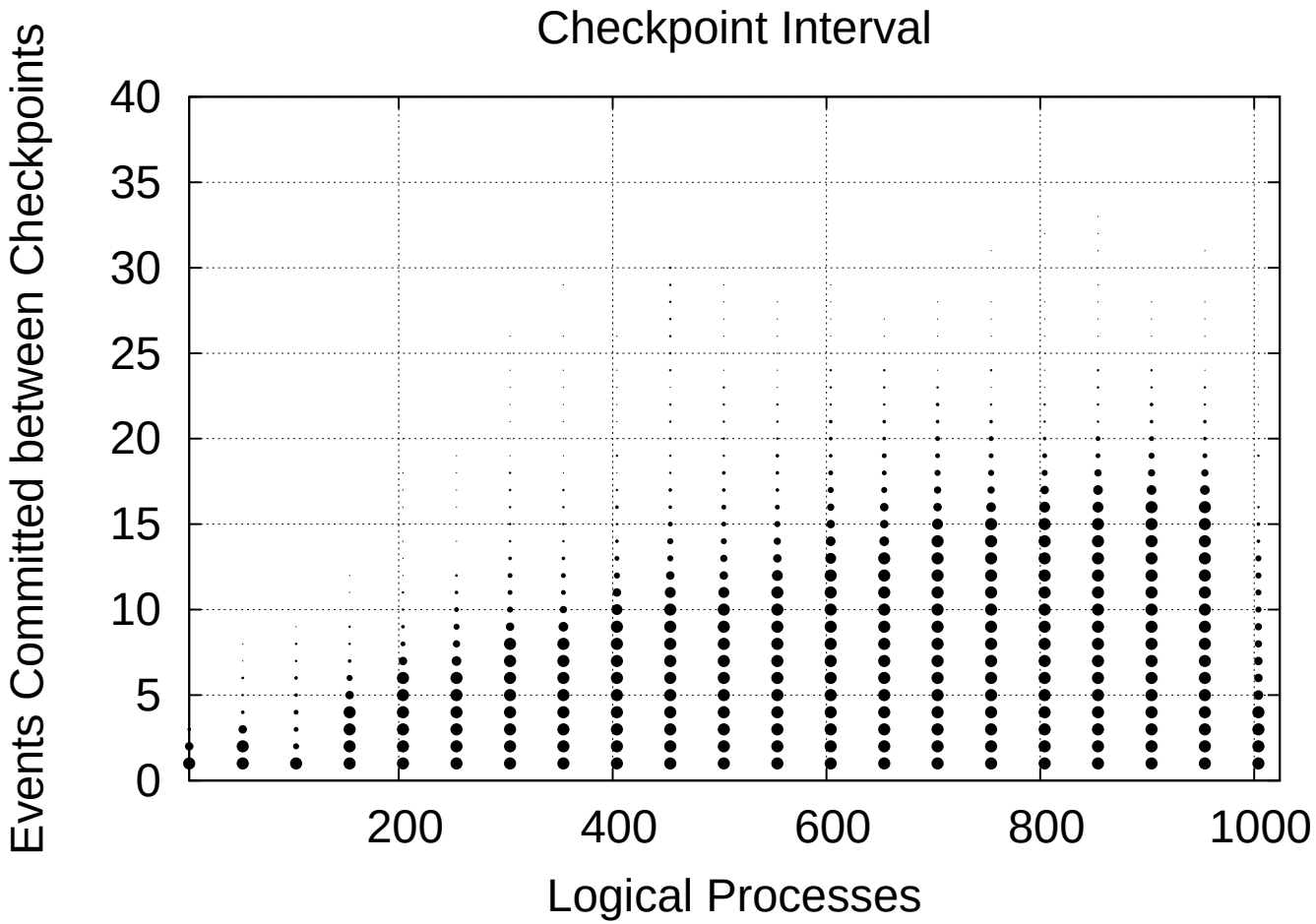

Thanks for your attention

Questions?

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http://www.dis.uniroma1.it/∼pellegrini
https://github.com/HPDCS/ROOT-Sim