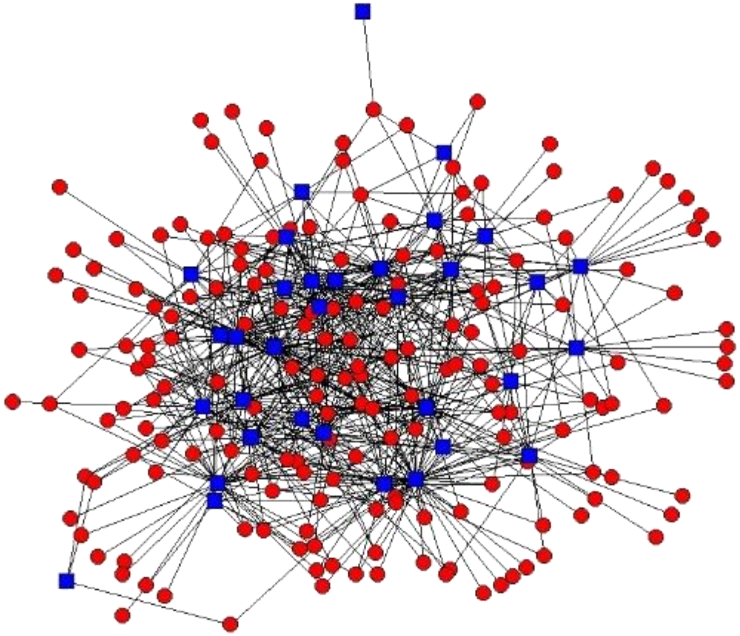
Accelerating Irregular Computations with Hardware Transactional Memory and Active Messages

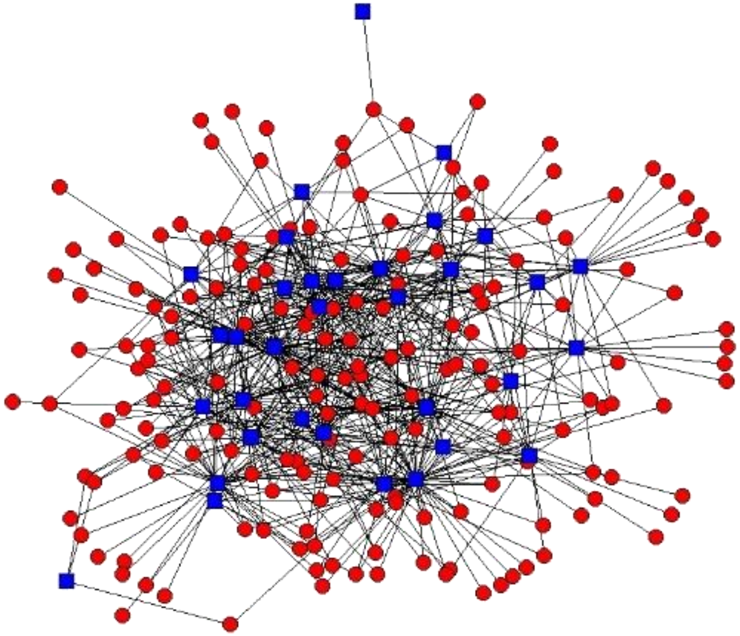
MACIEJ BESTA, TORSTEN HOEFLER

LARGE-SCALE IRREGULAR GRAPH PROCESSING



LARGE-SCALE IRREGULAR GRAPH PROCESSING

- Becoming more important [1]



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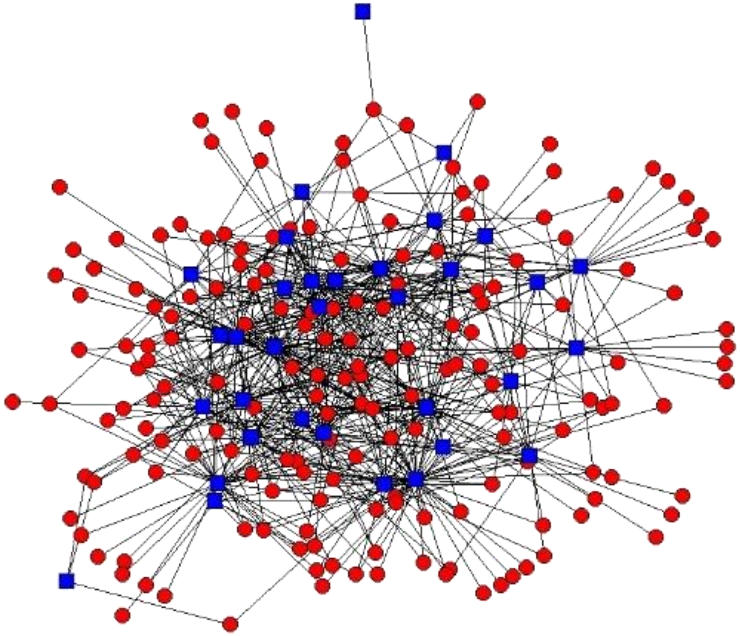
Large-Scale Irregular Graph Processing

- Becoming more important [1]
  - Machine learning



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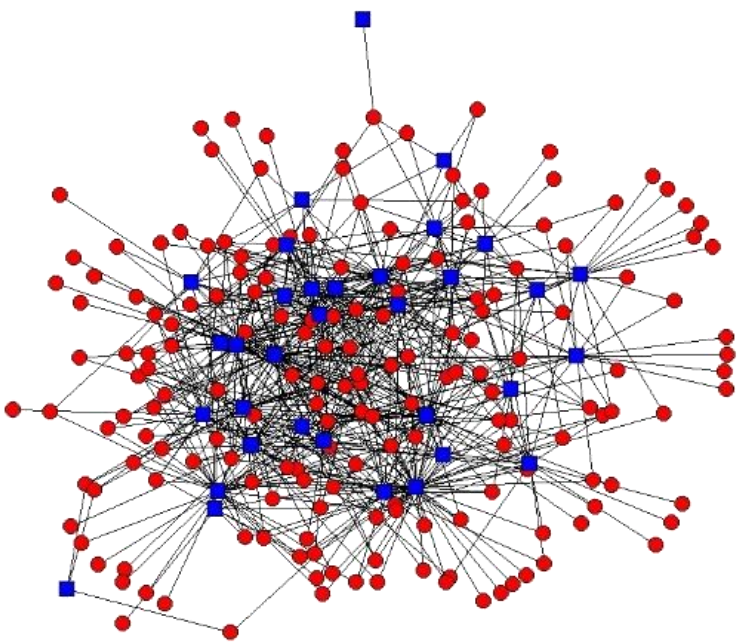
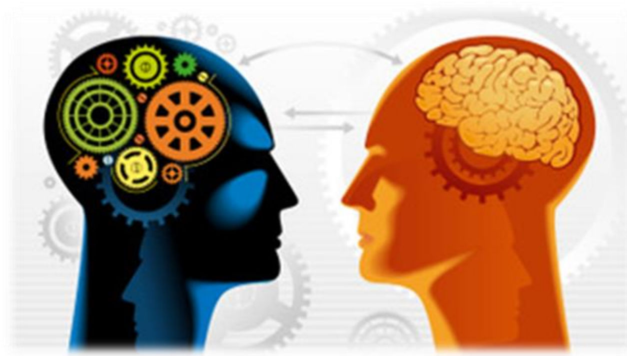
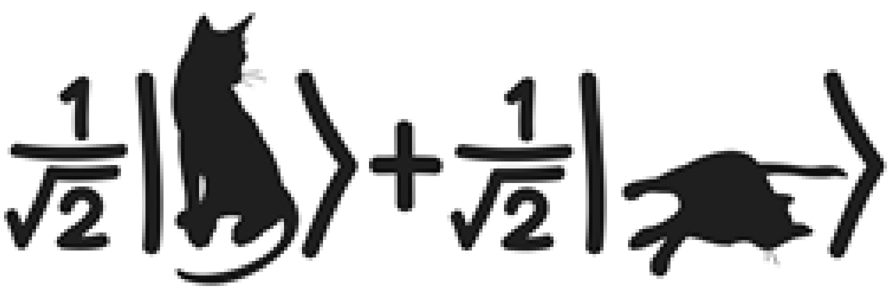
LARGE-SCALE IRREGULAR GRAPH PROCESSING

- Becoming more important [1]
  - Machine learning
  - Computational science







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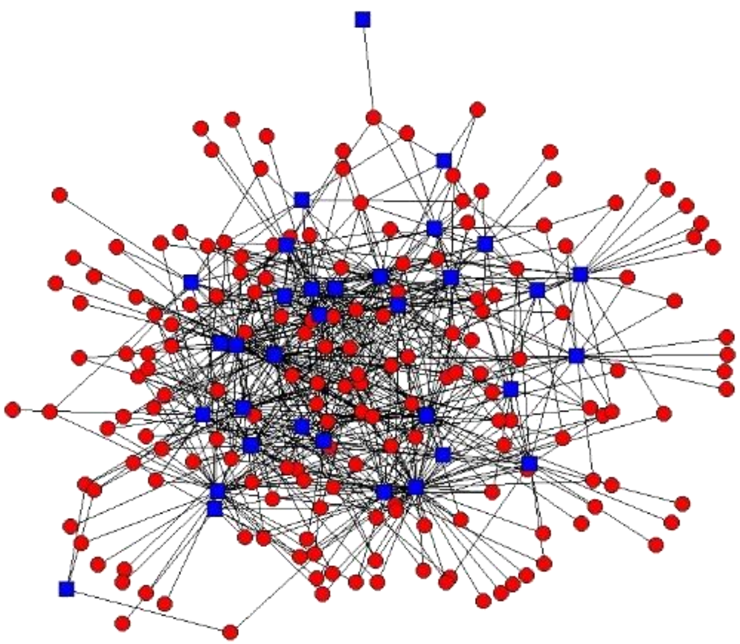
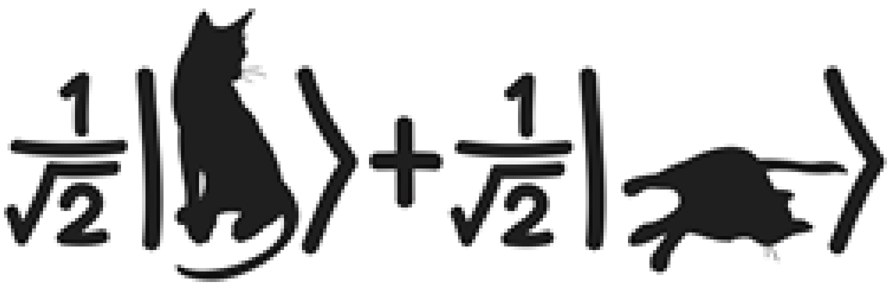
LARGE-SCALE IRREGULAR GRAPH PROCESSING

- Becoming more important [1]
  - Machine learning
  - Computational science
  - Social network analysis





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Synchronization Mechanisms

Coarse locks

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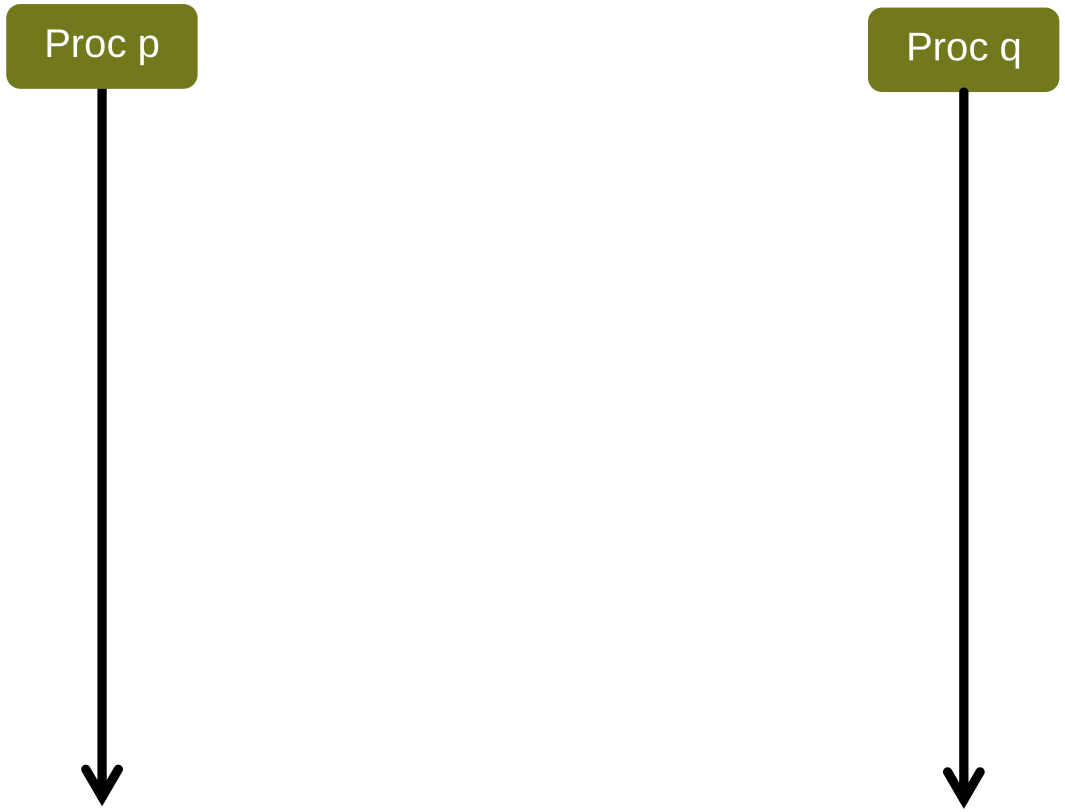

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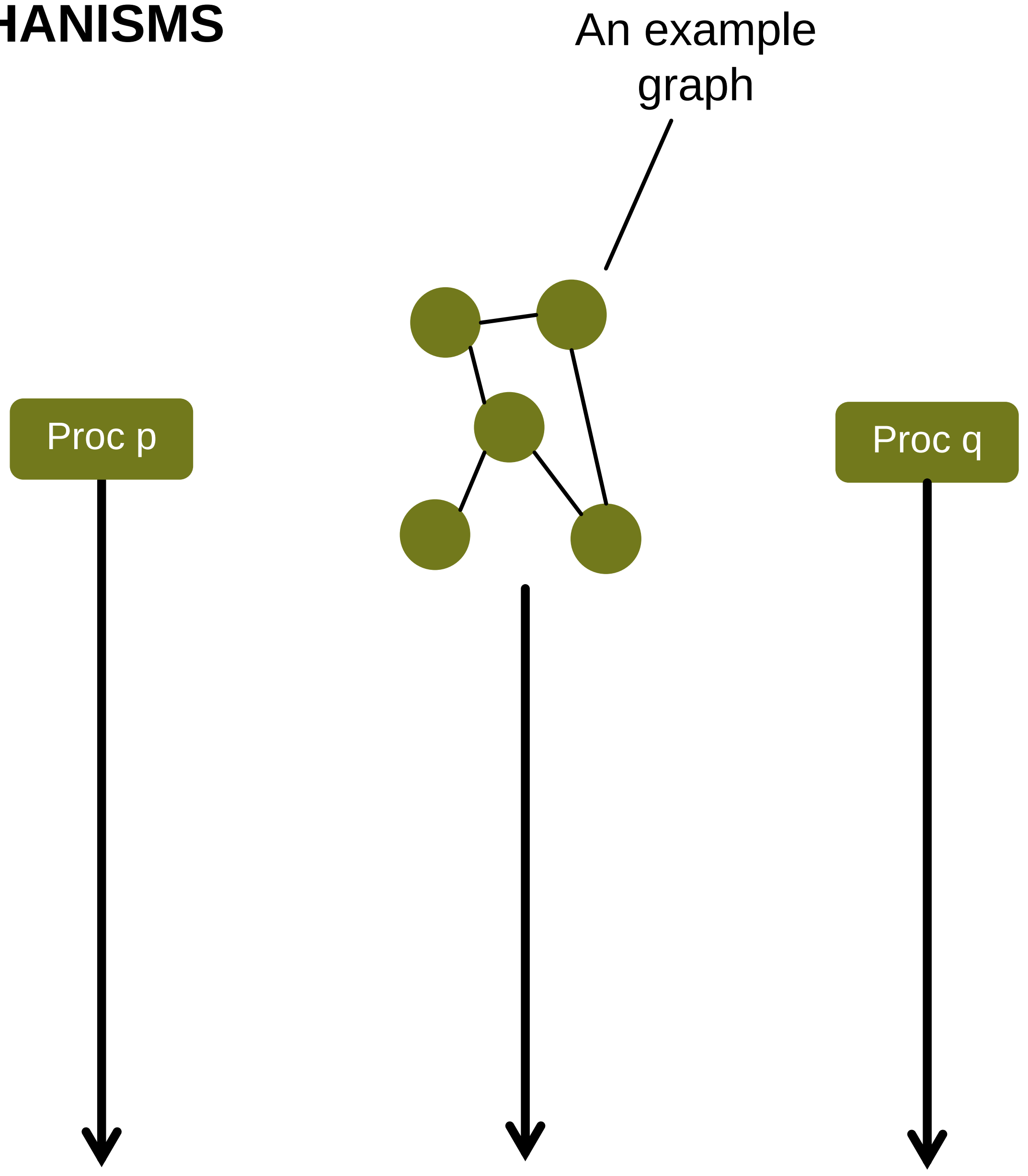

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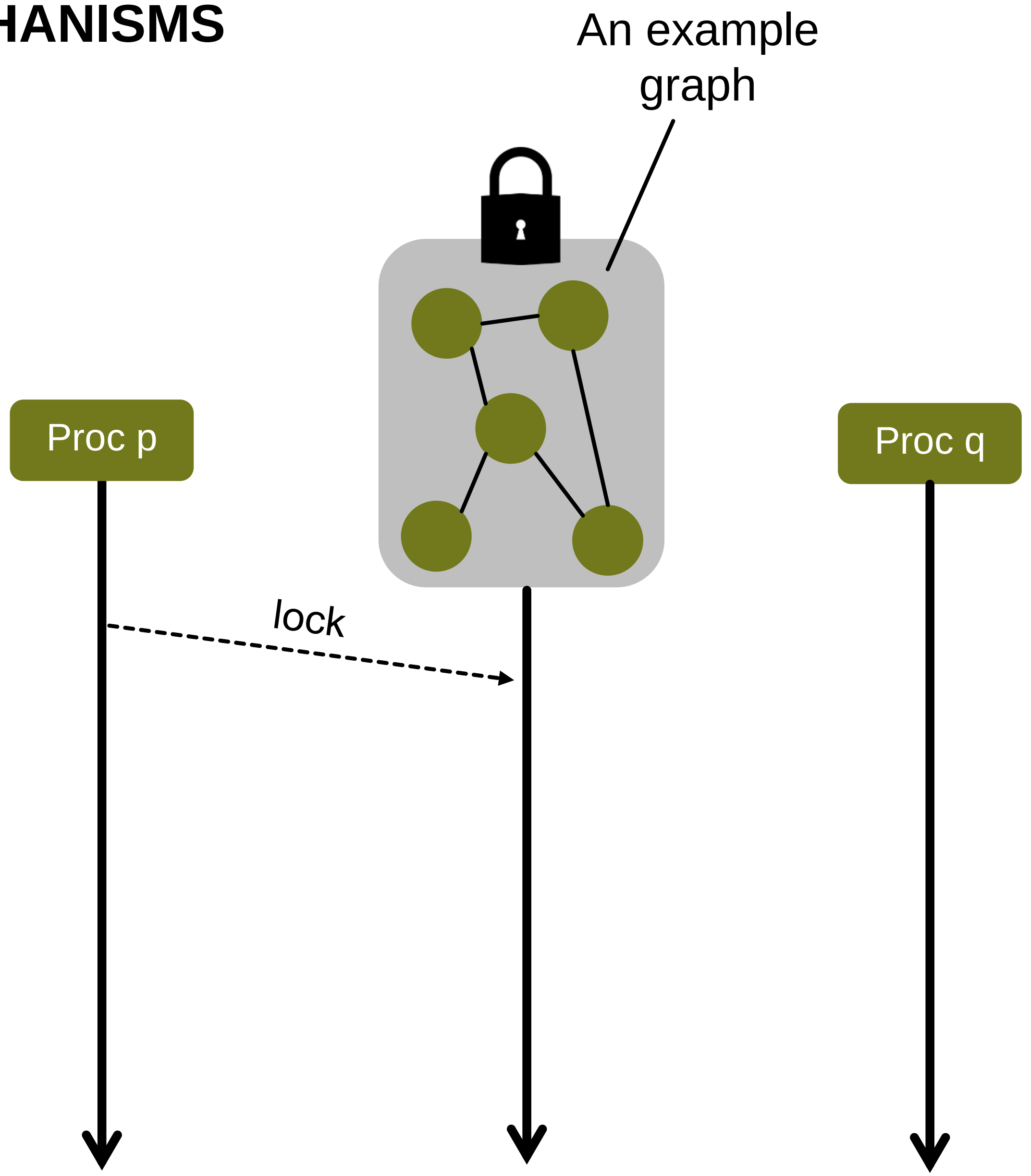

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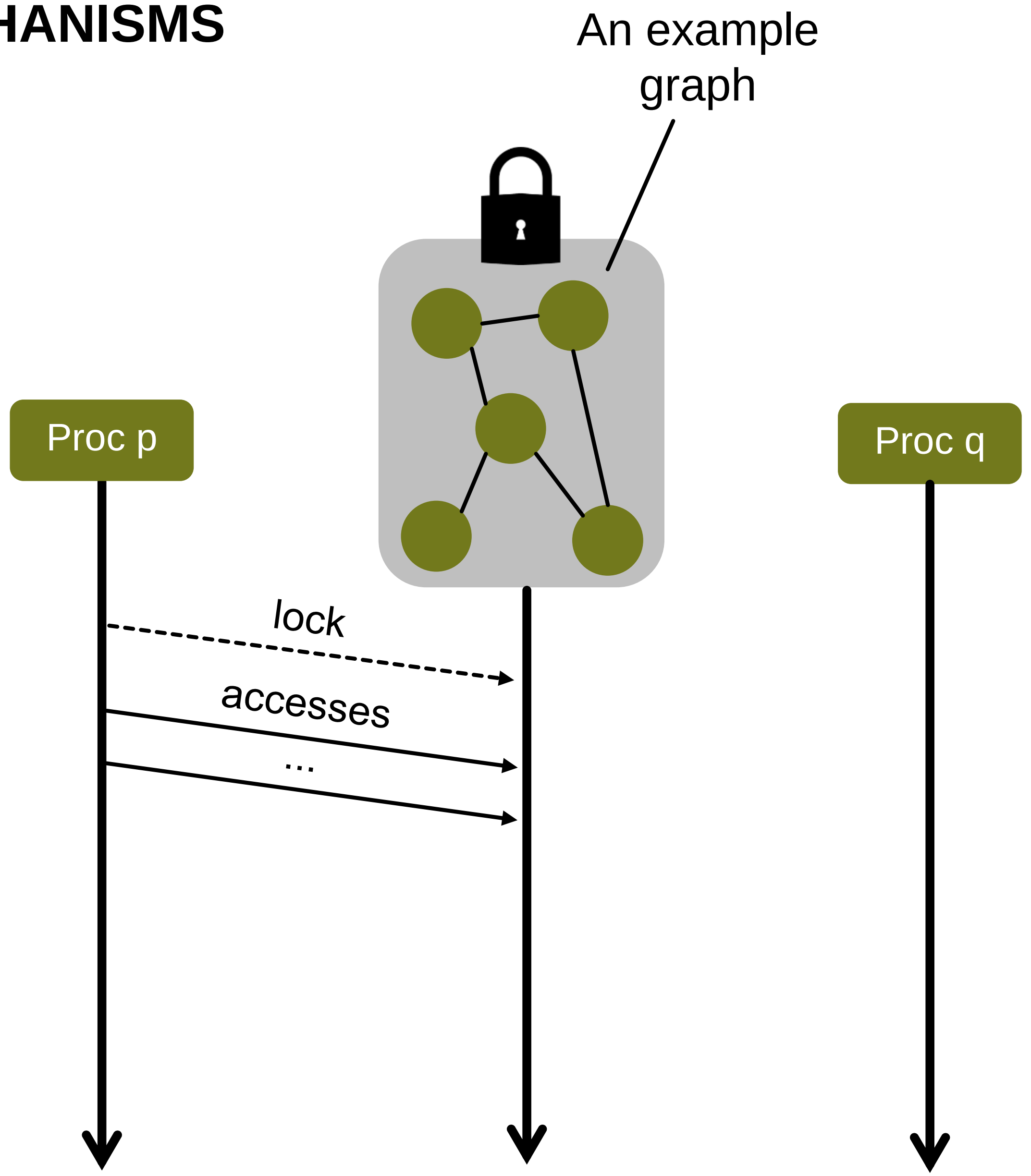

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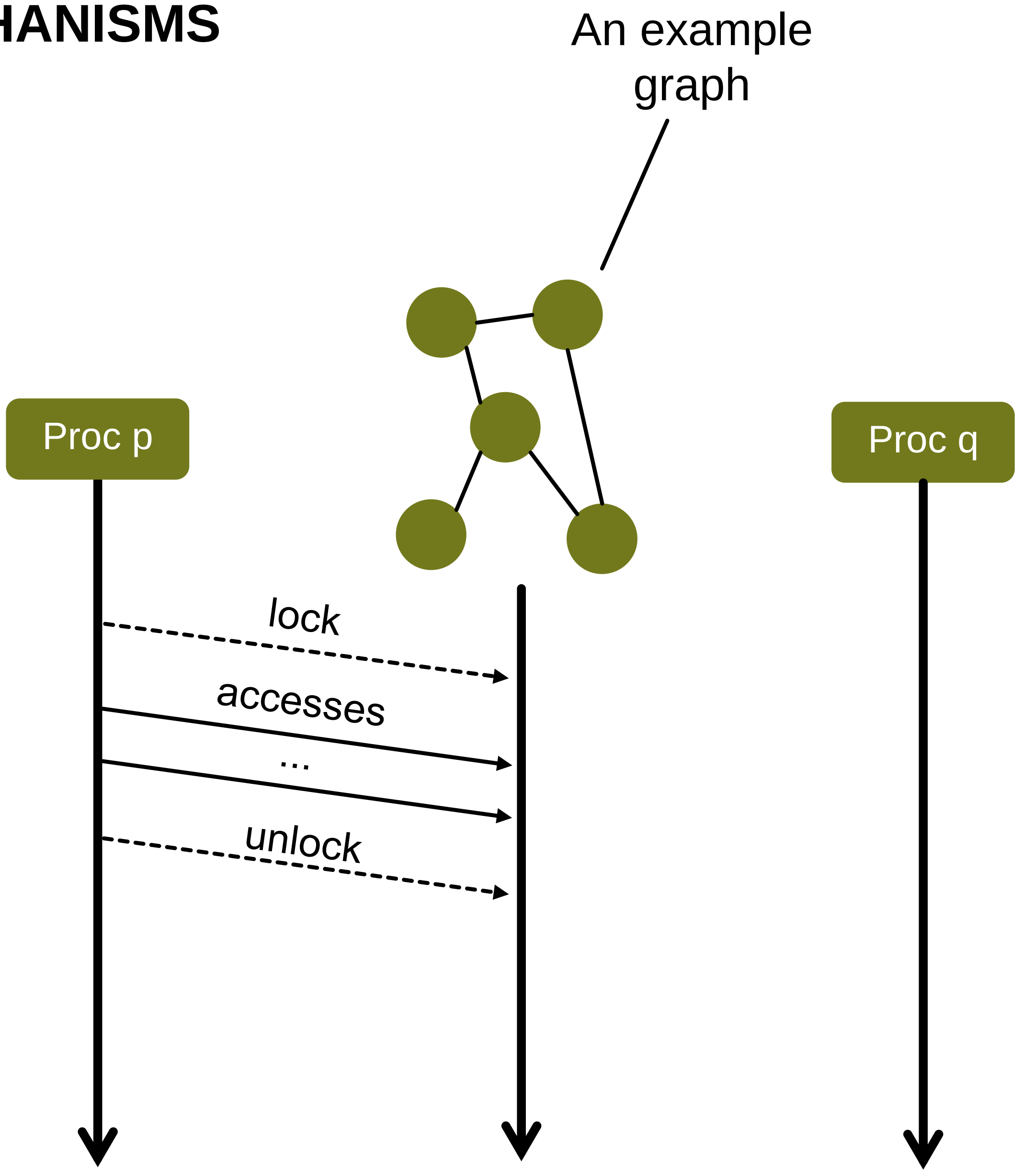

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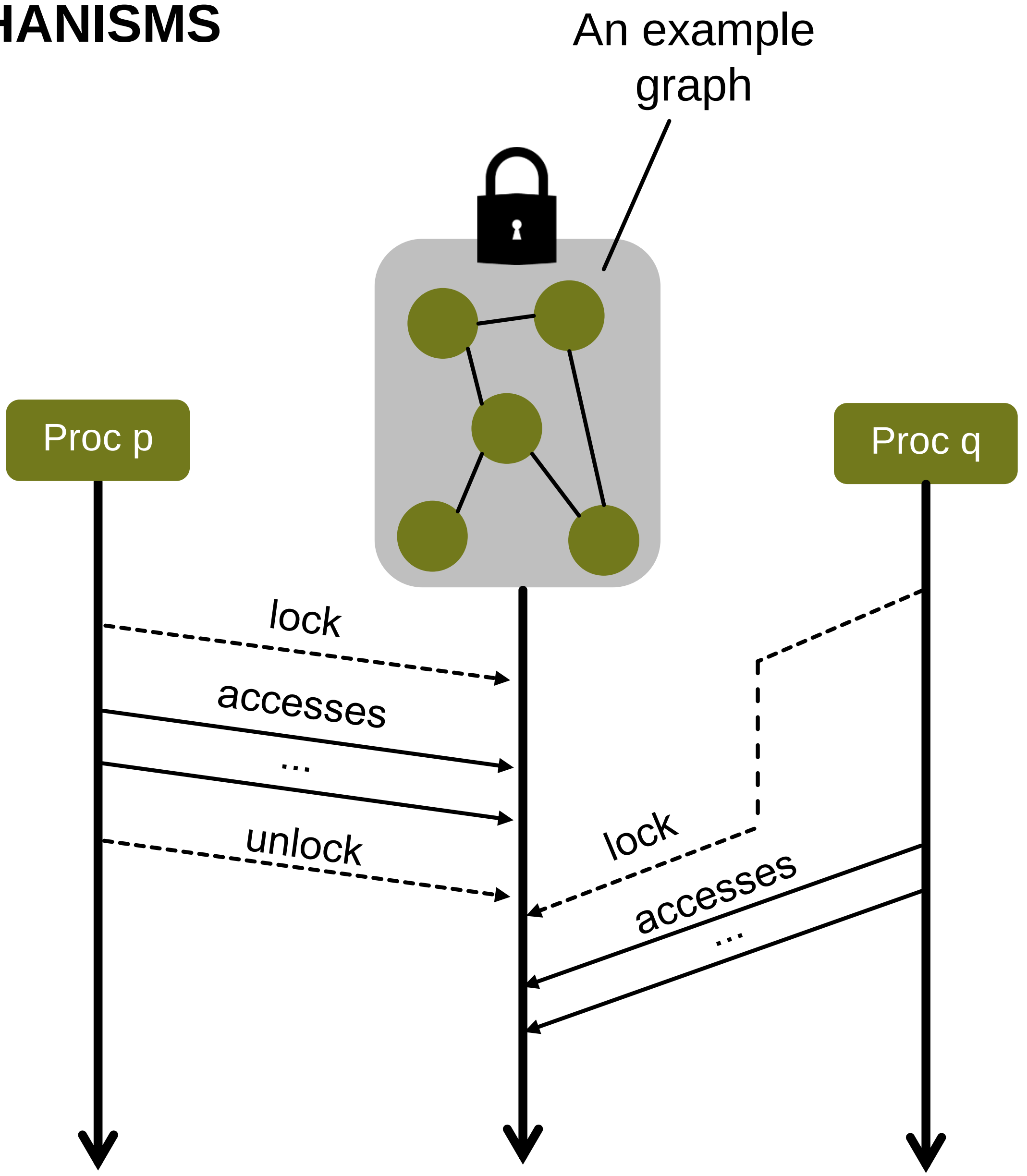

Synchronization Mechanisms
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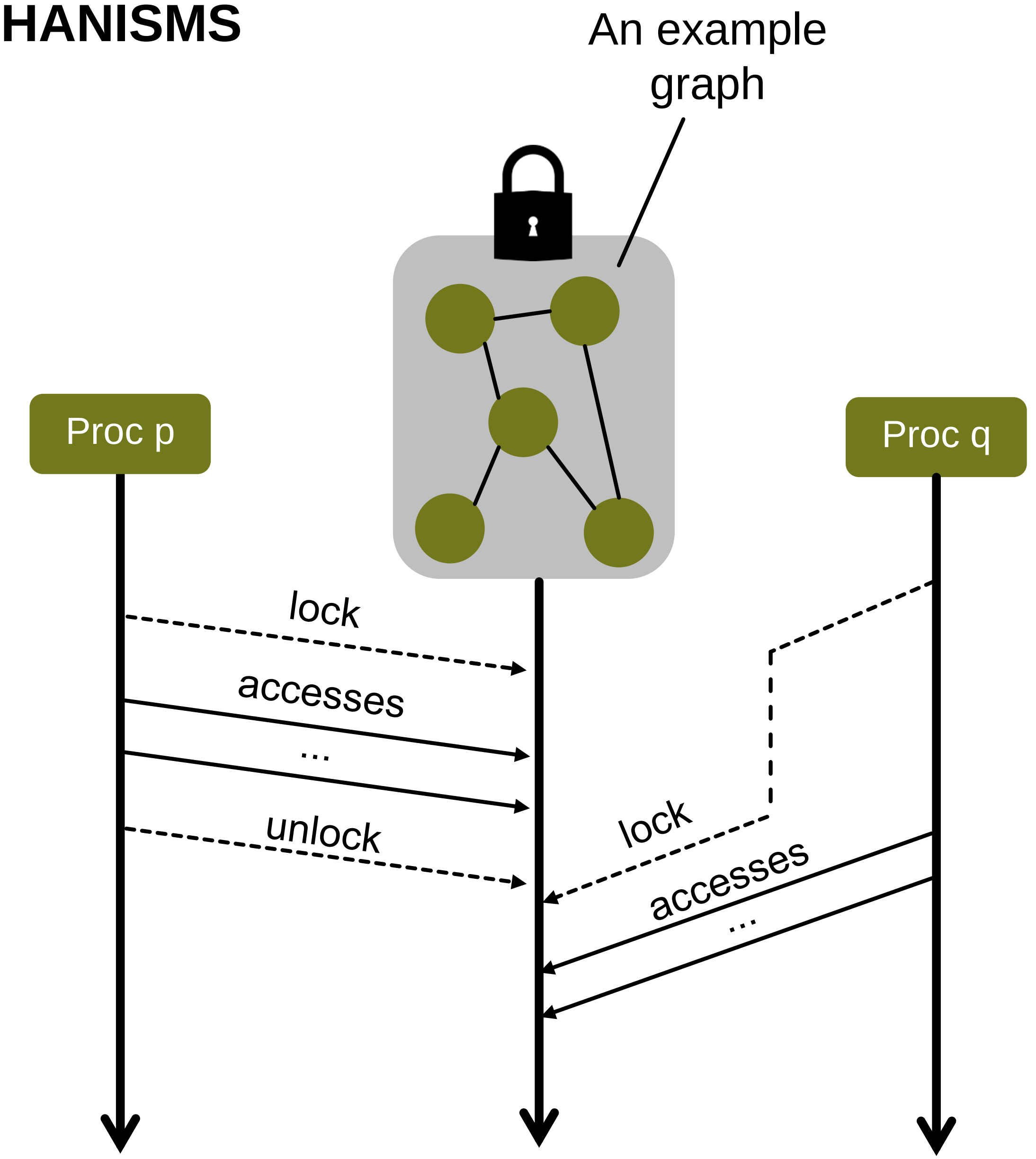
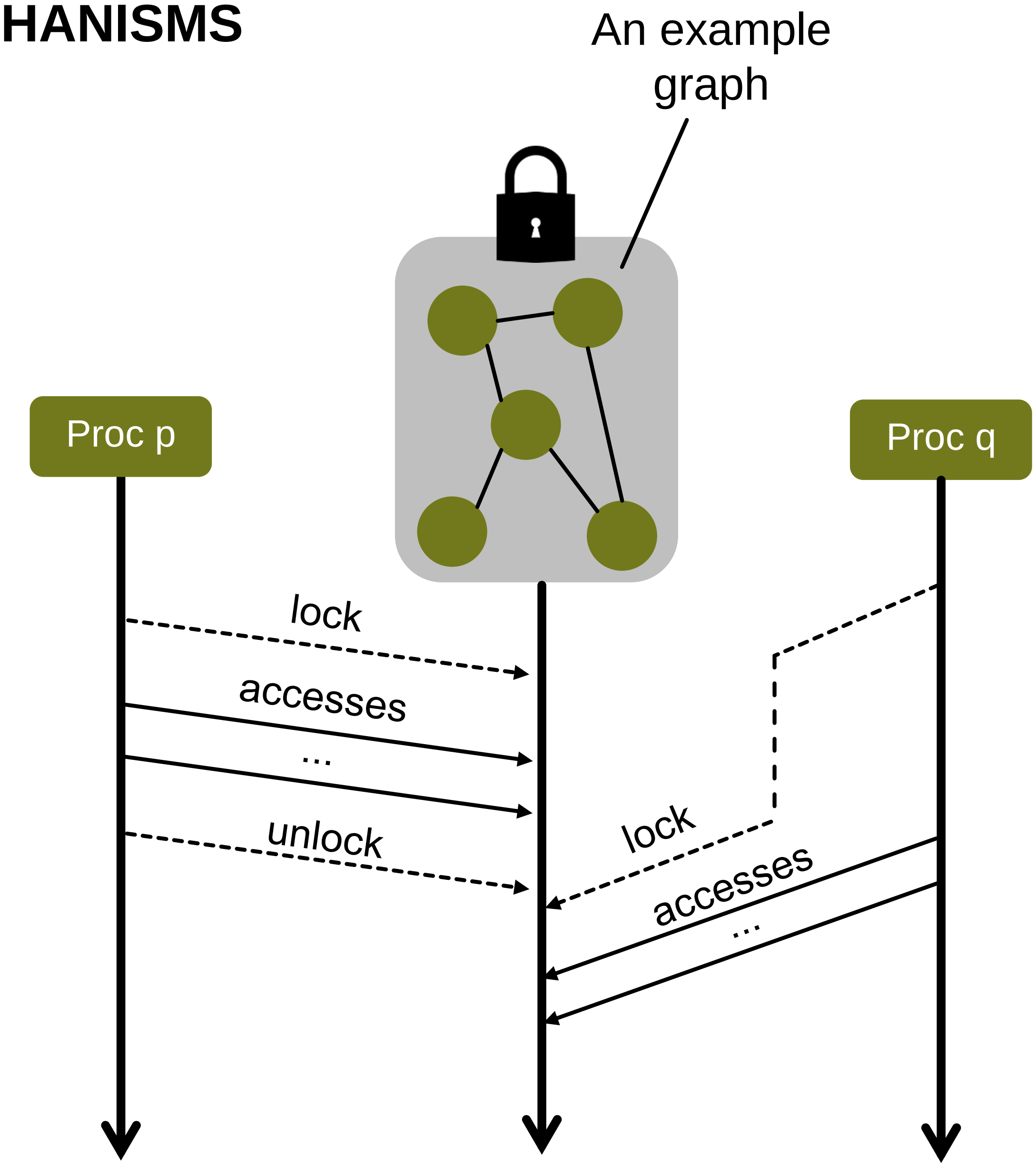
Simple protocols



Synchronization Mechanisms
Coarse locks

Simple protocols

Serialization

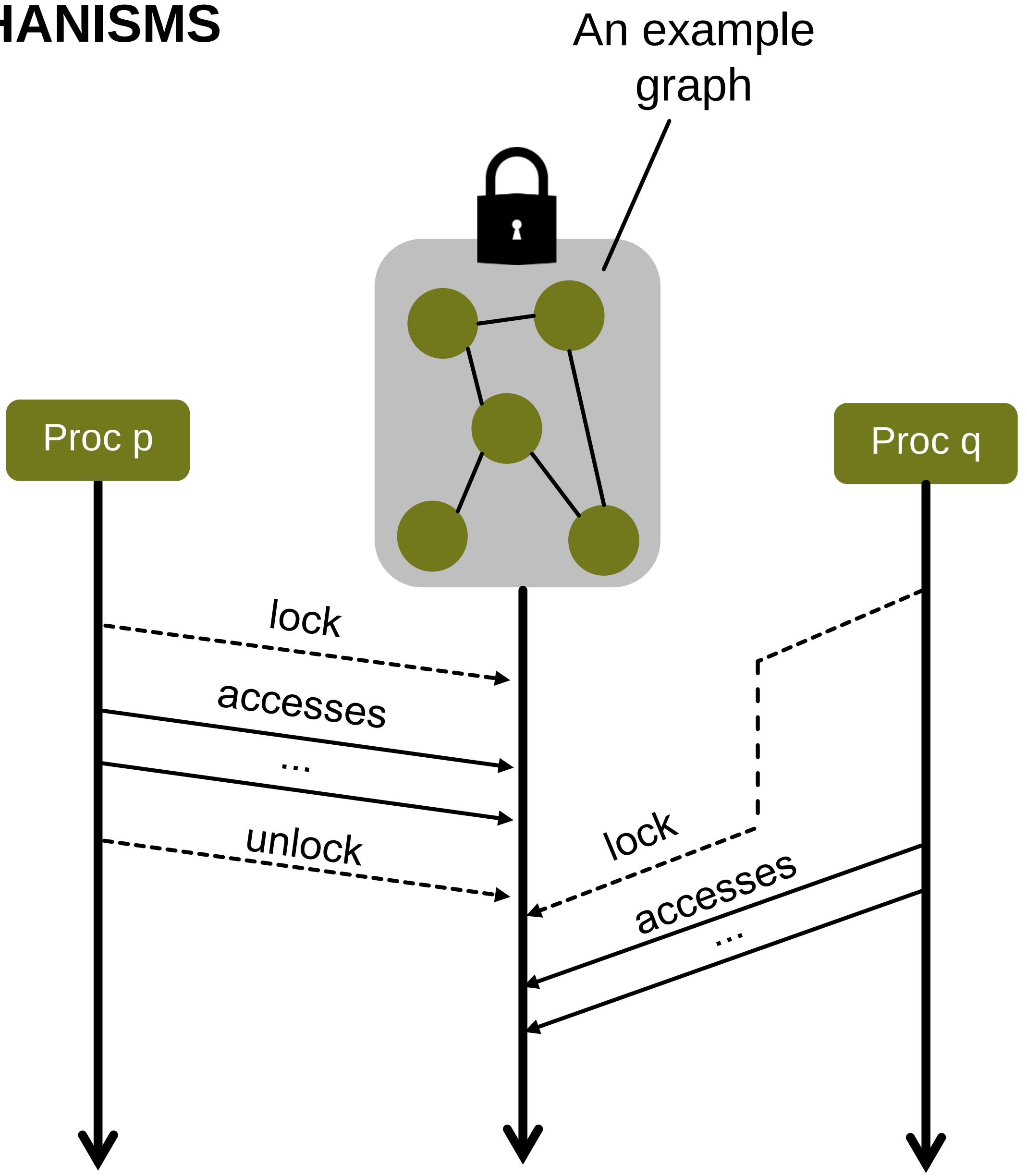


Synchronization Mechanisms
Coarse locks

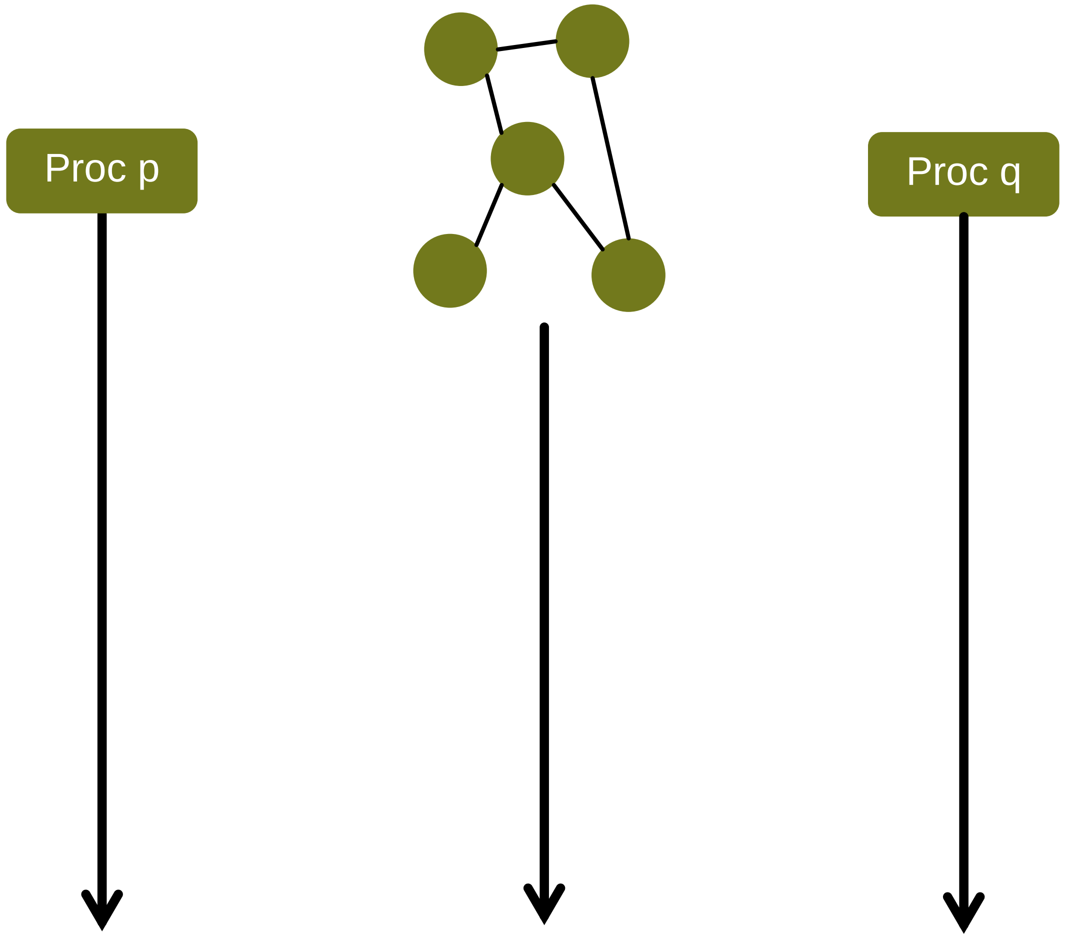
Simple protocols

Serialization

Detrimental performance



Synchronization Mechanisms
Fine locks



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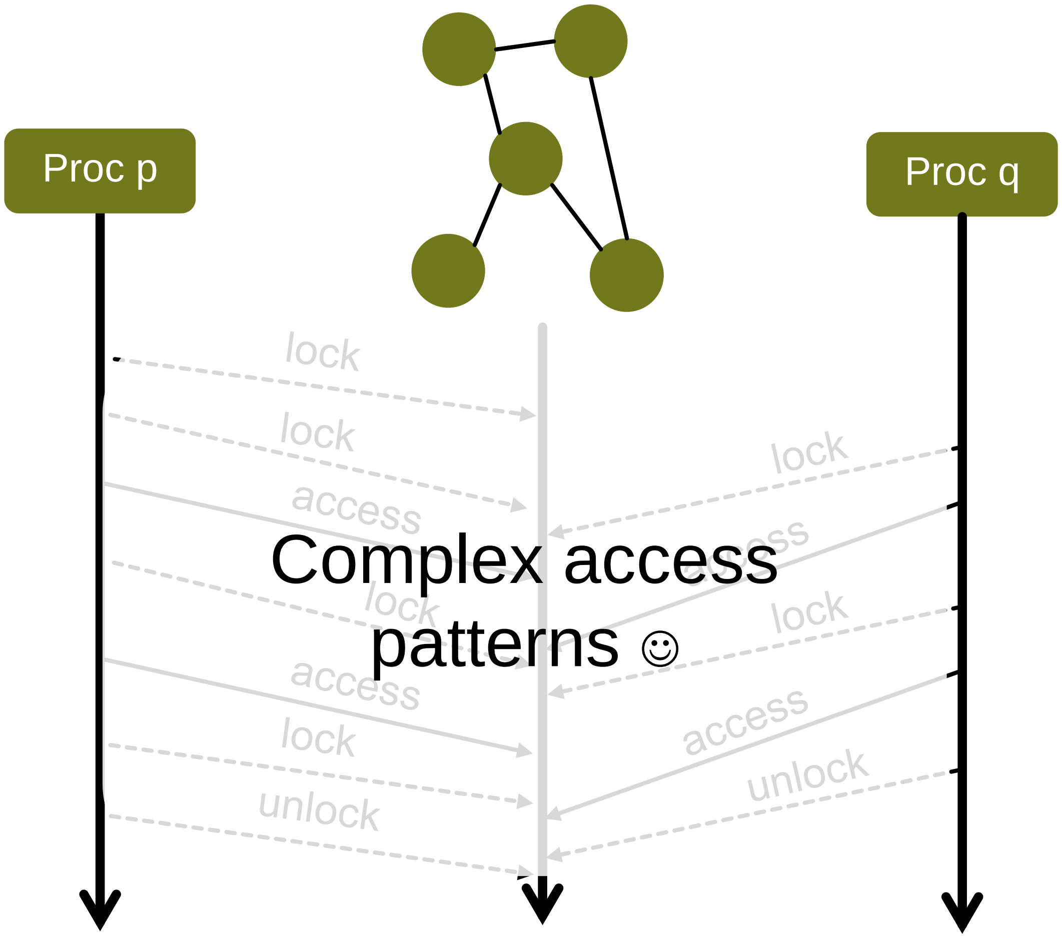

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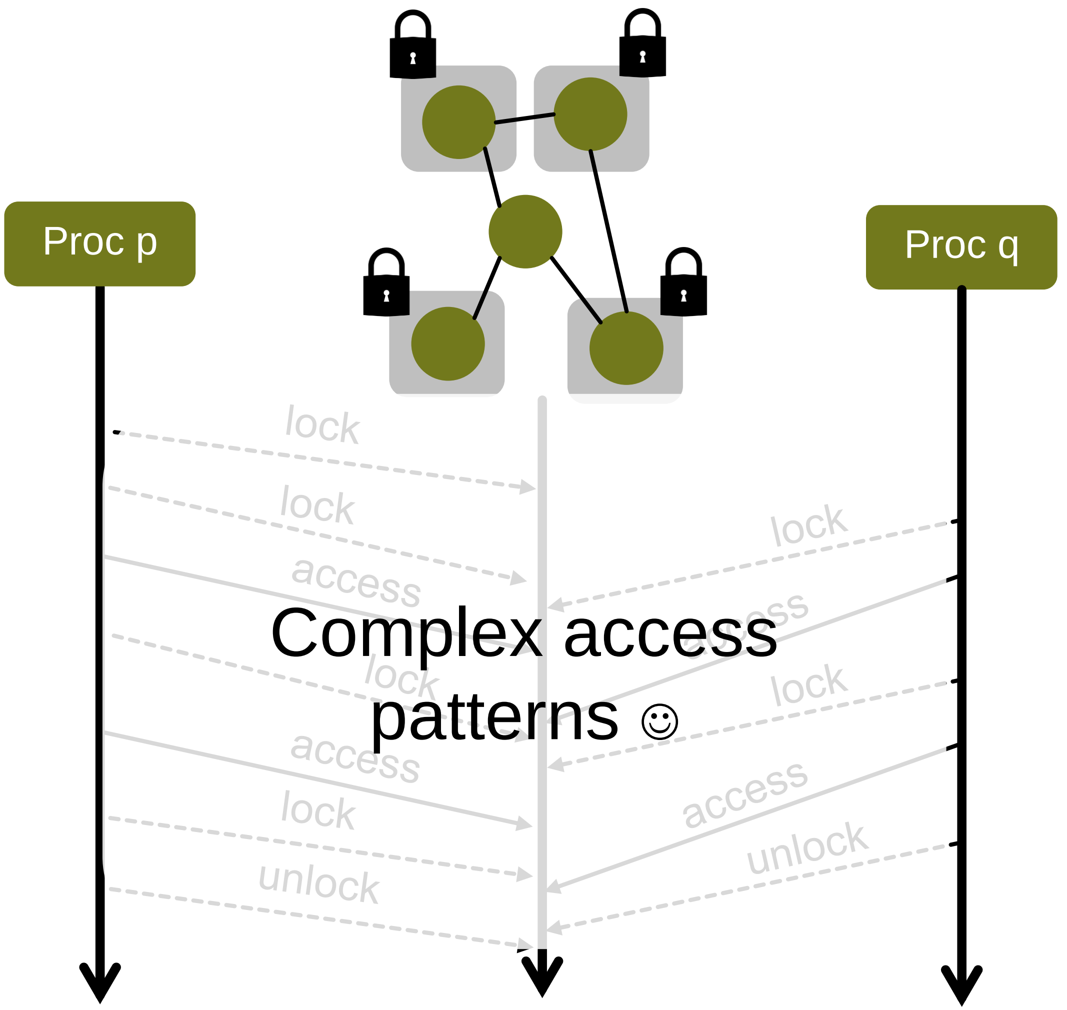
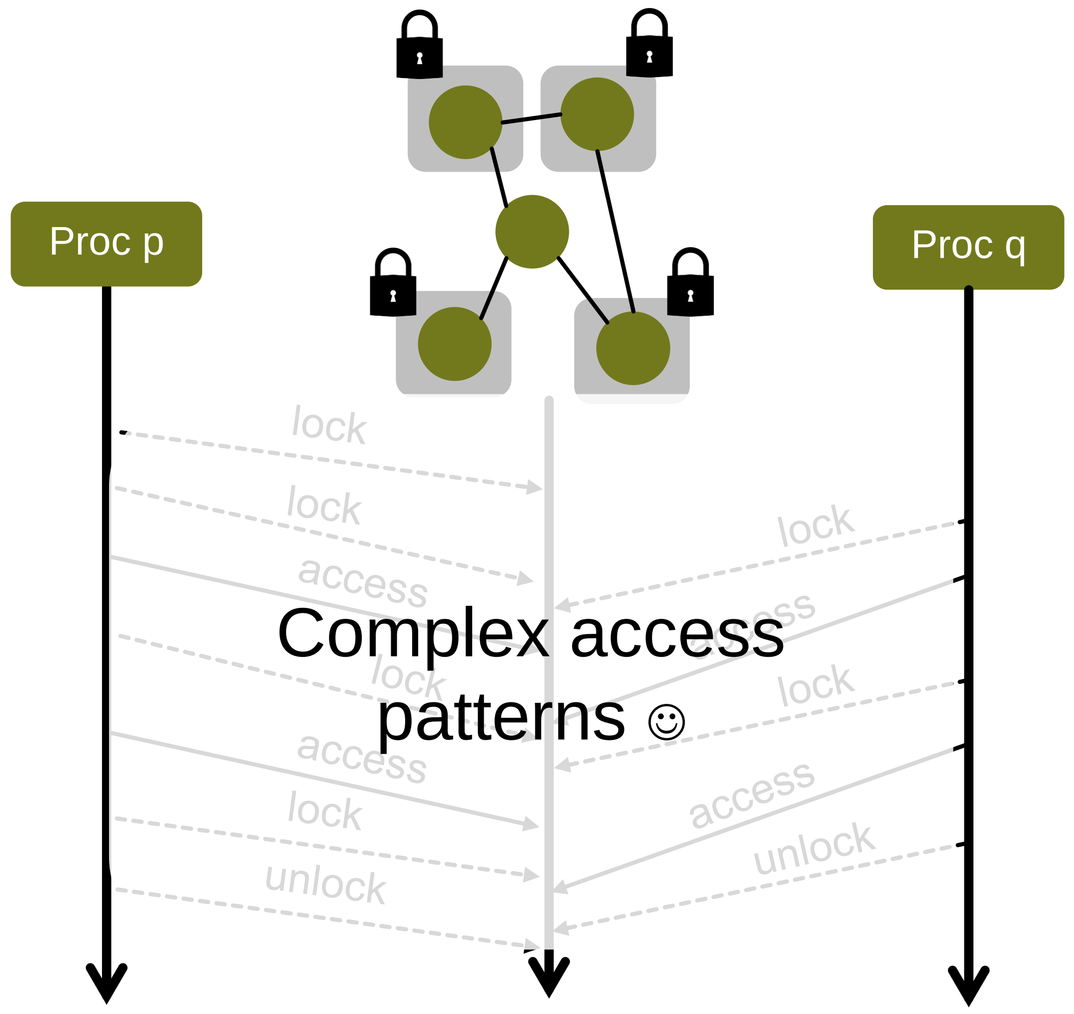


Synchronization Mechanisms
Fine locks

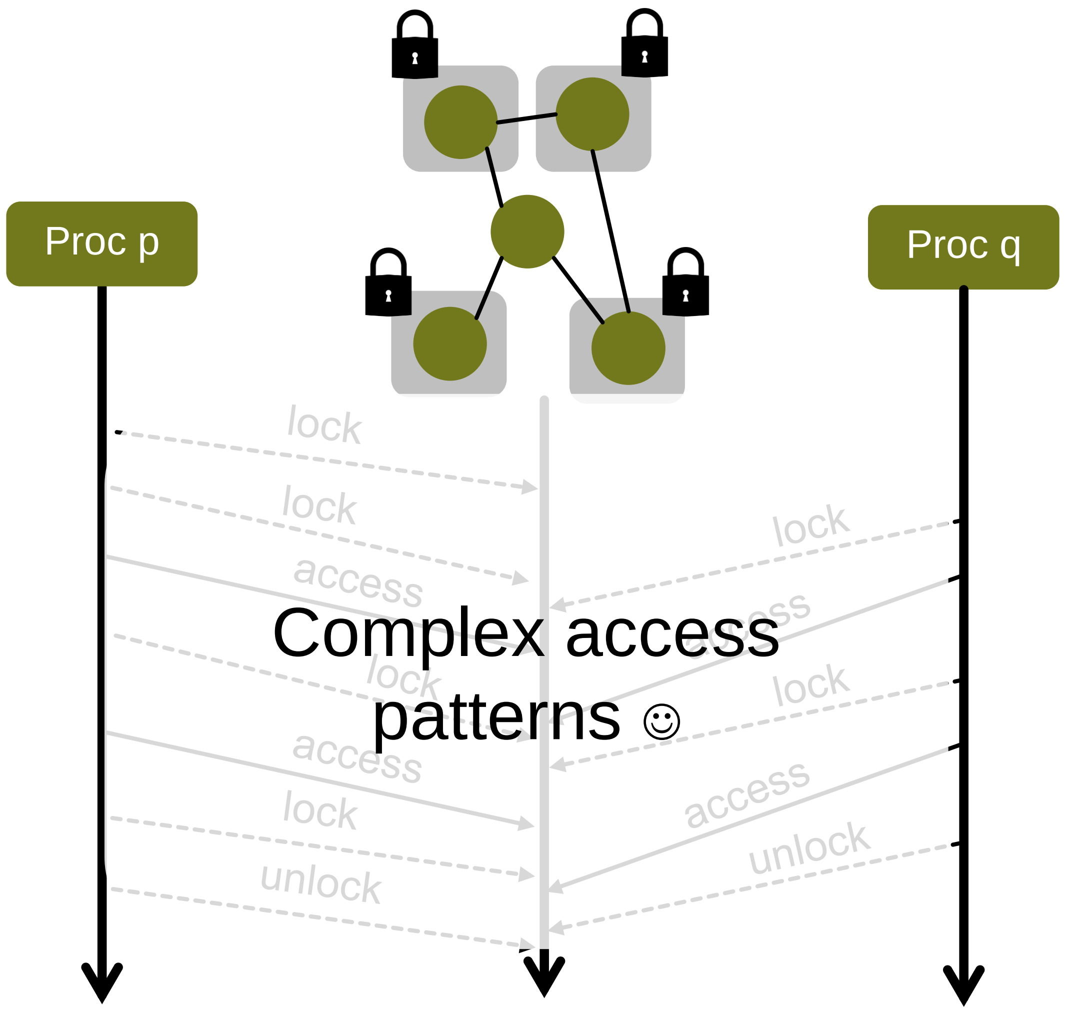
Higher performance possible



Synchronization Mechanisms
Fine locks

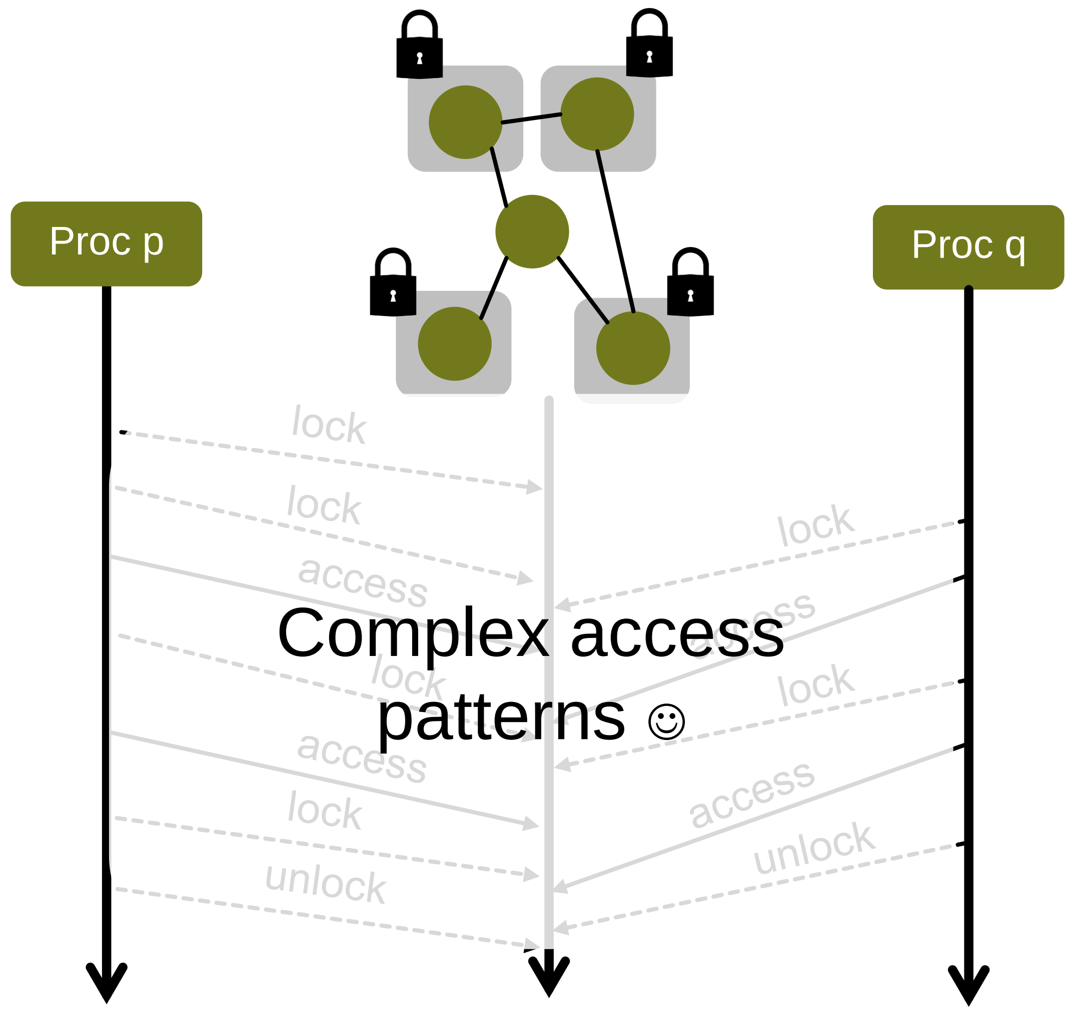
Higher performance possible

Complex protocols

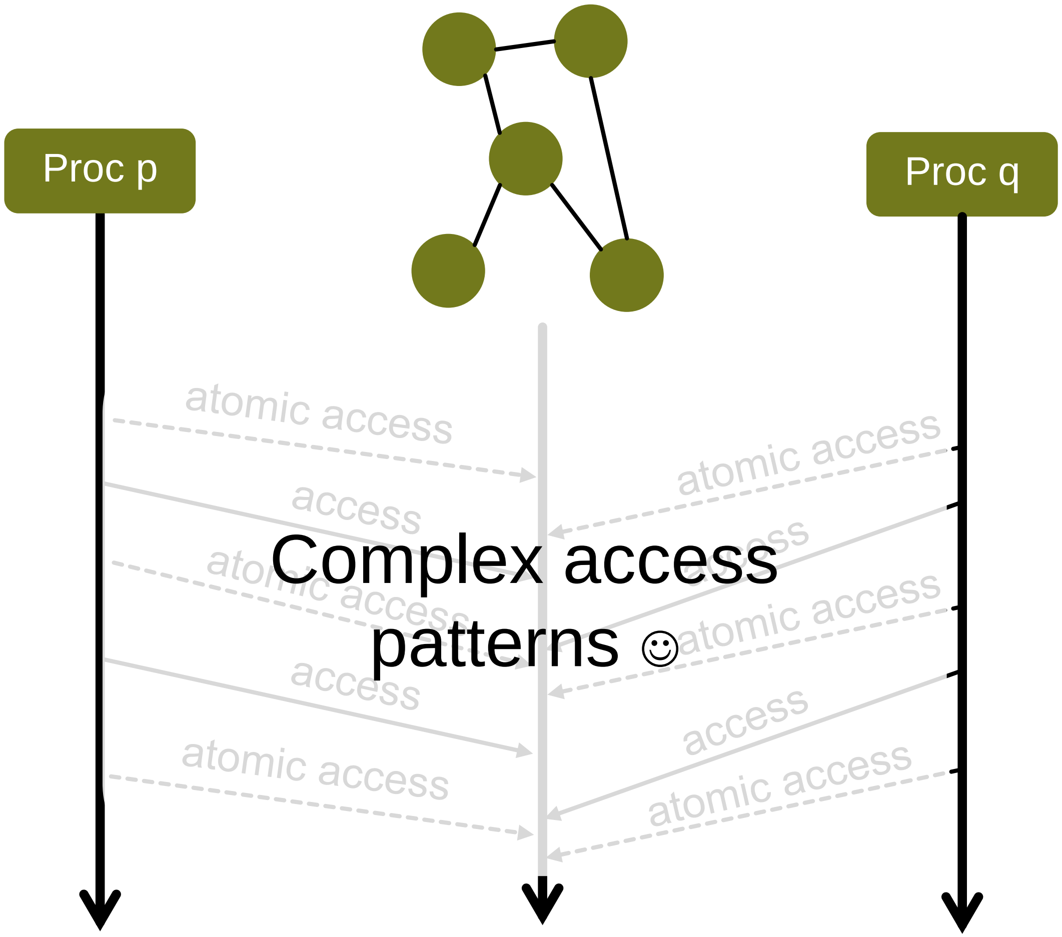


Synchronization Mechanisms
Fine Locks

- ✔ Higher performance possible
- ✘ Complex protocols
- ✘ Risk of deadlocks

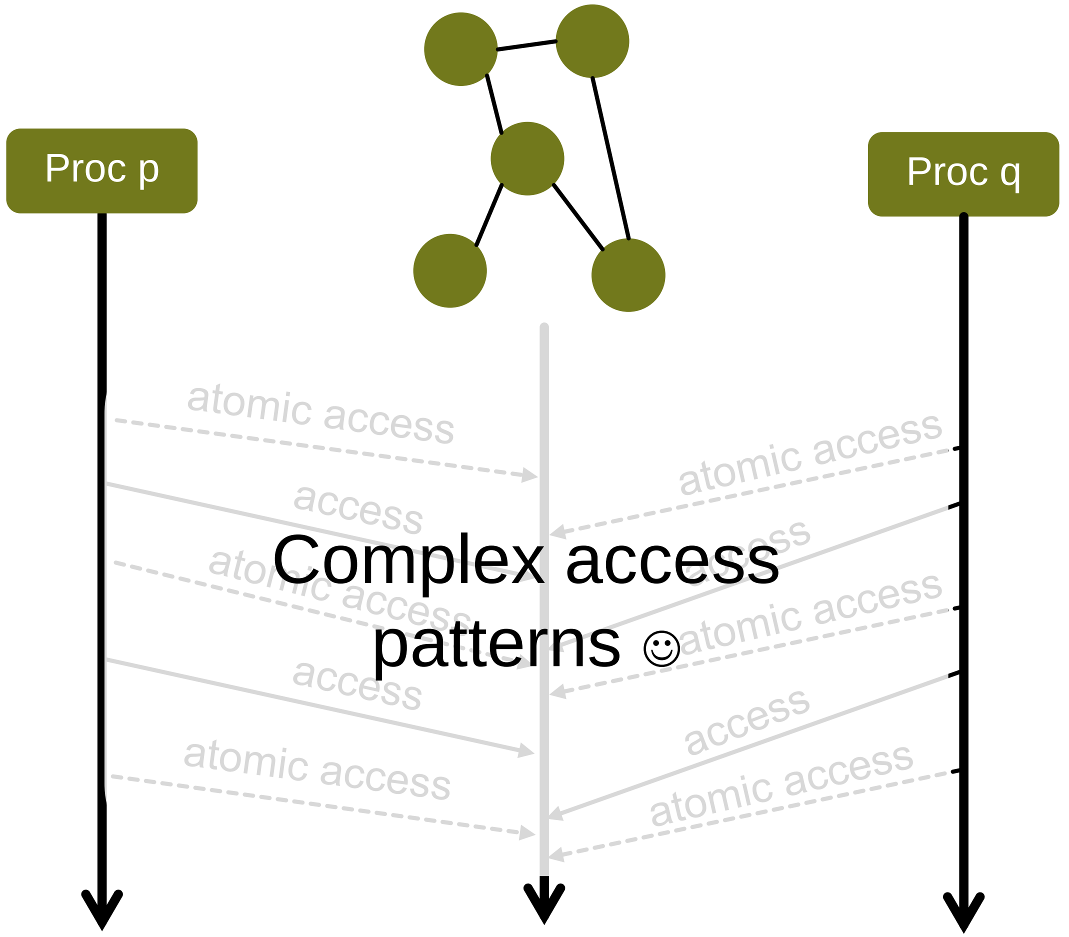


Synchronization Mechanisms
Atomic operations



Synchronization Mechanisms
Atomic operations

High performance (may be challenging to get)

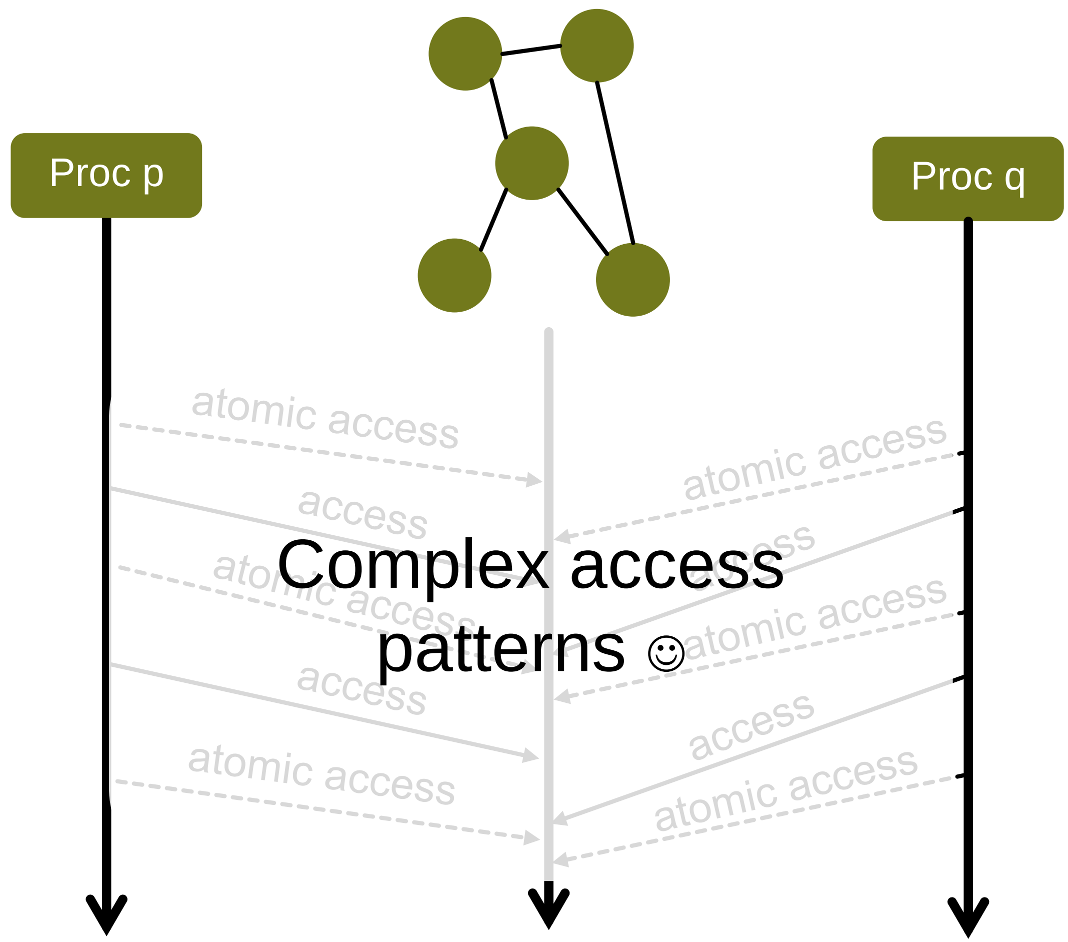


Synchronization Mechanisms

Atomic operations

High performance (may be challenging to get)

Complex protocols



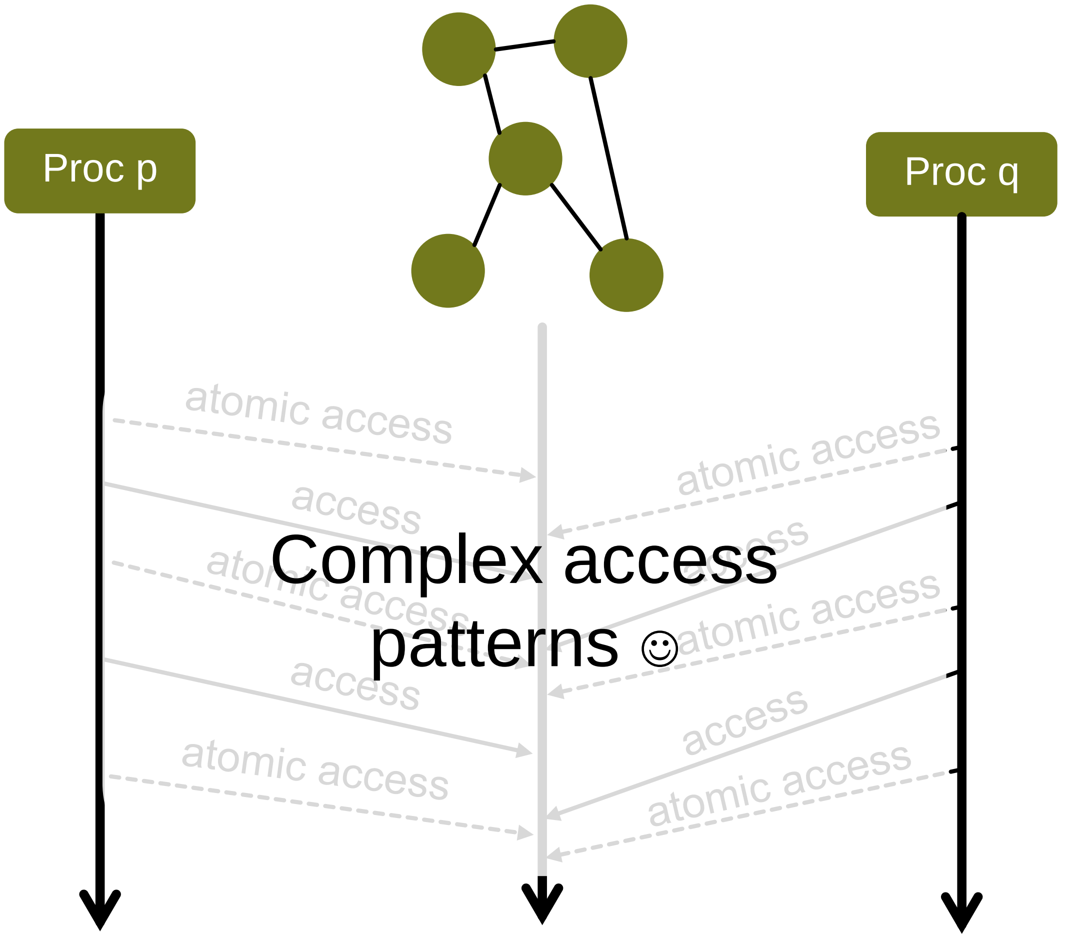
Complex access patterns ☺

Synchronization Mechanisms
Atomic operations

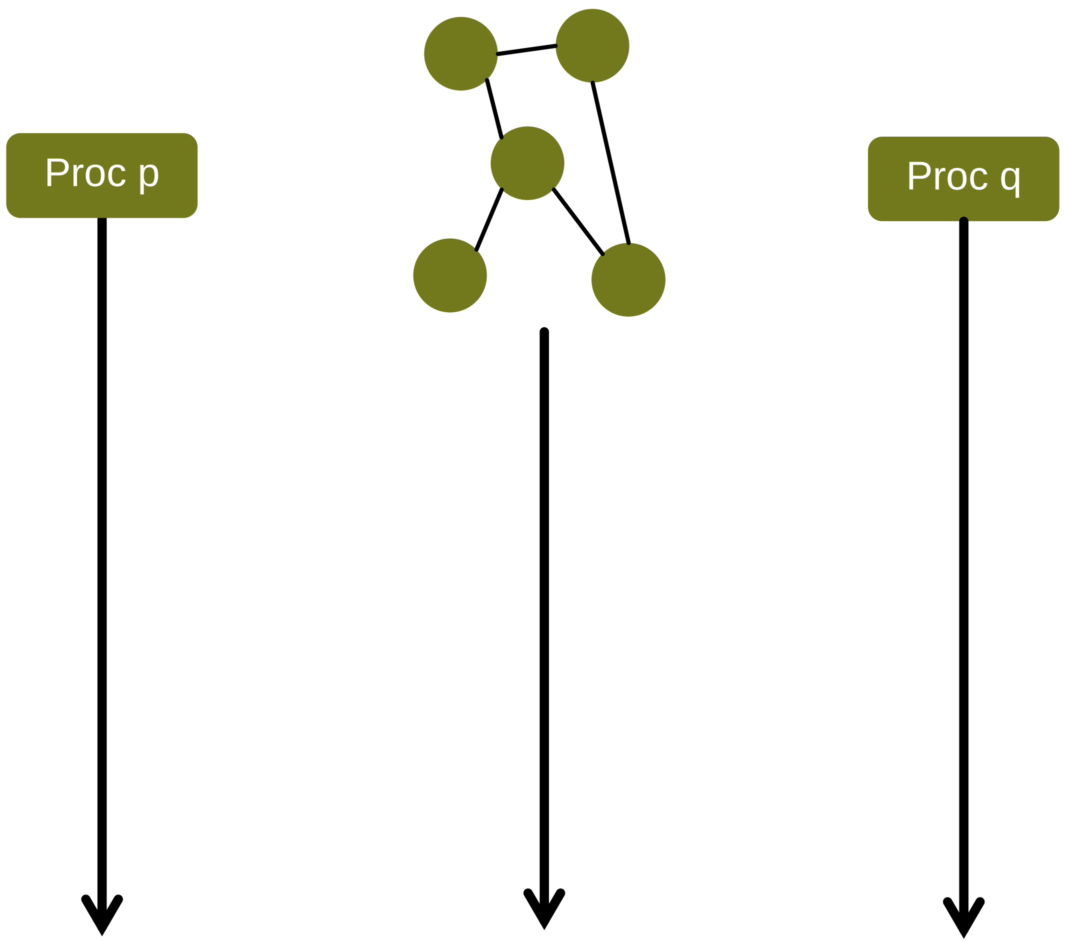
High performance (may be challenging to get)

Complex protocols

Subtle issues (ABA, …)



Synchronization Mechanisms
Software transactional memory (STM) [1]



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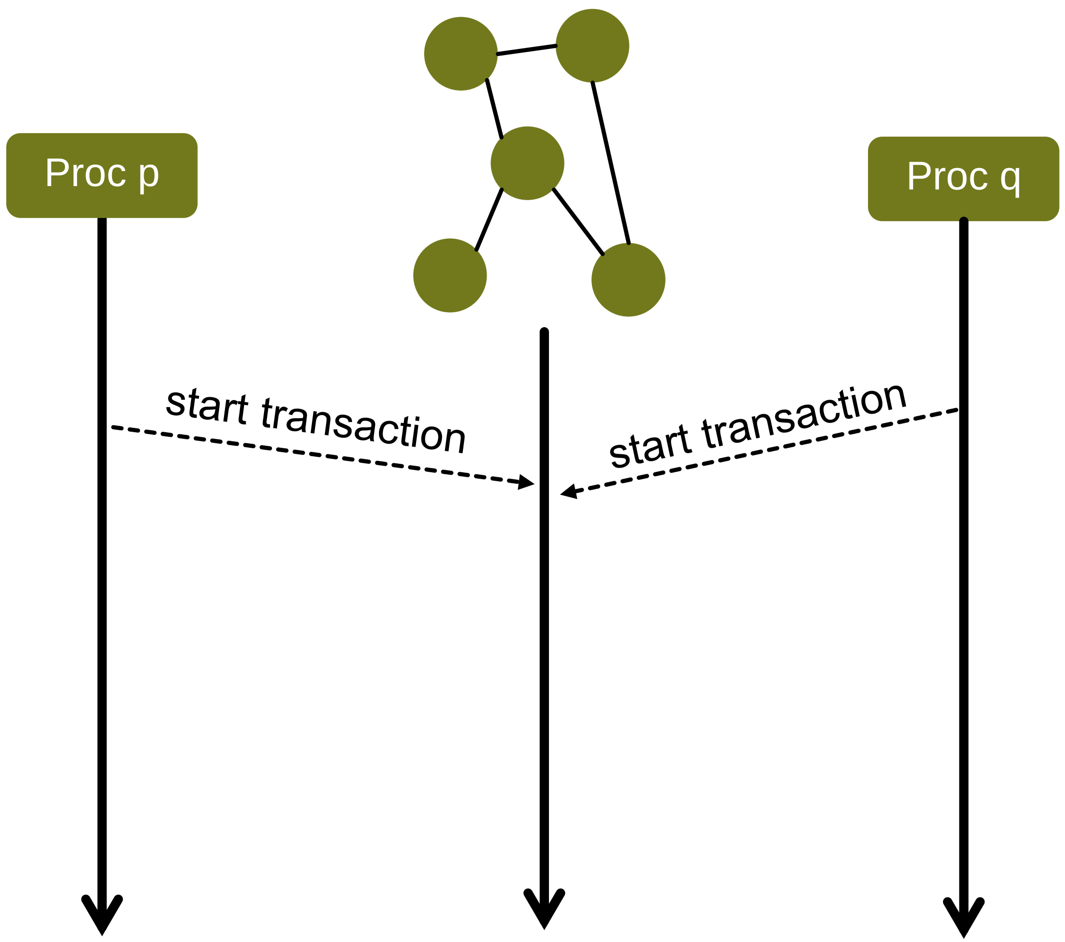

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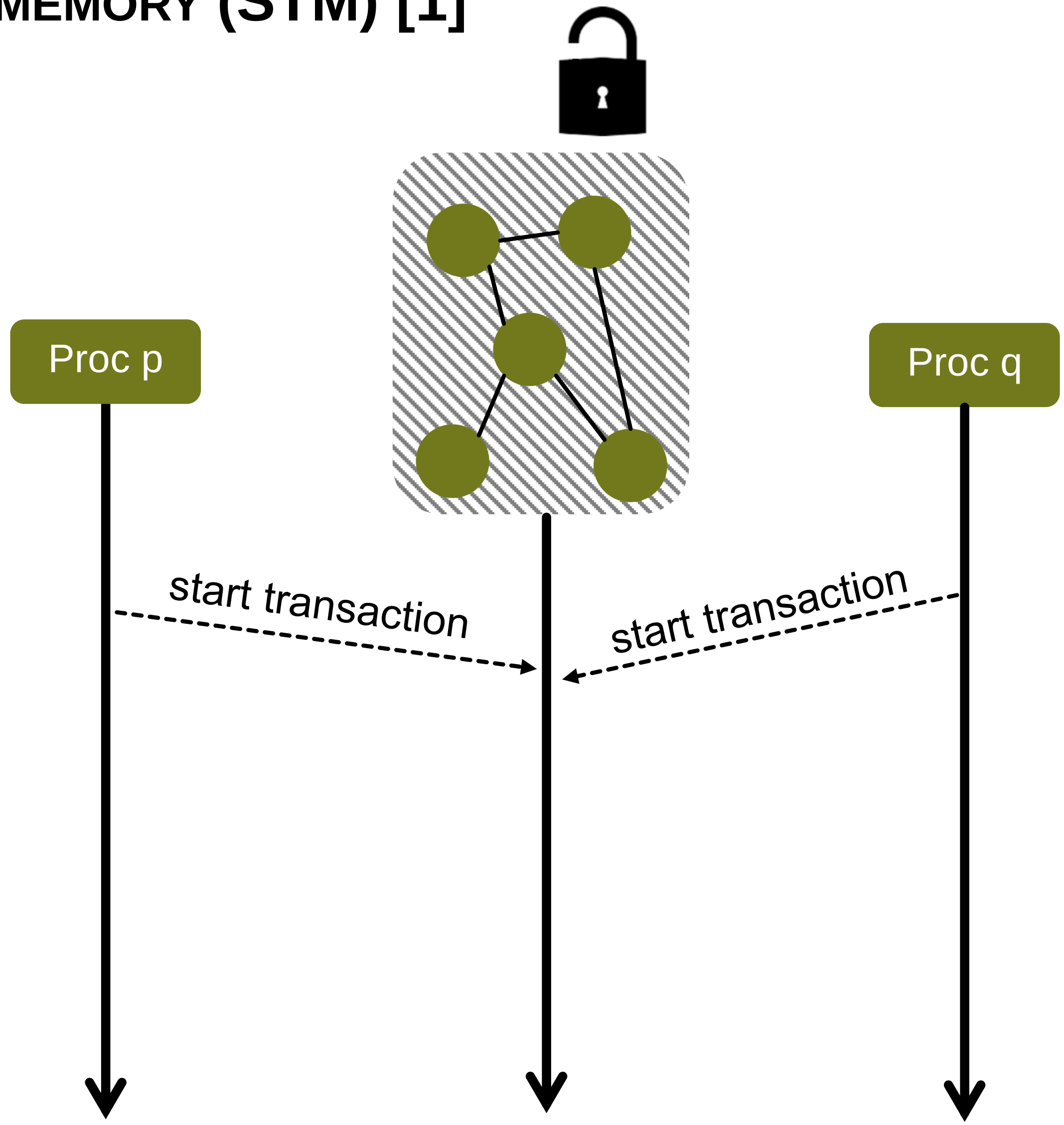

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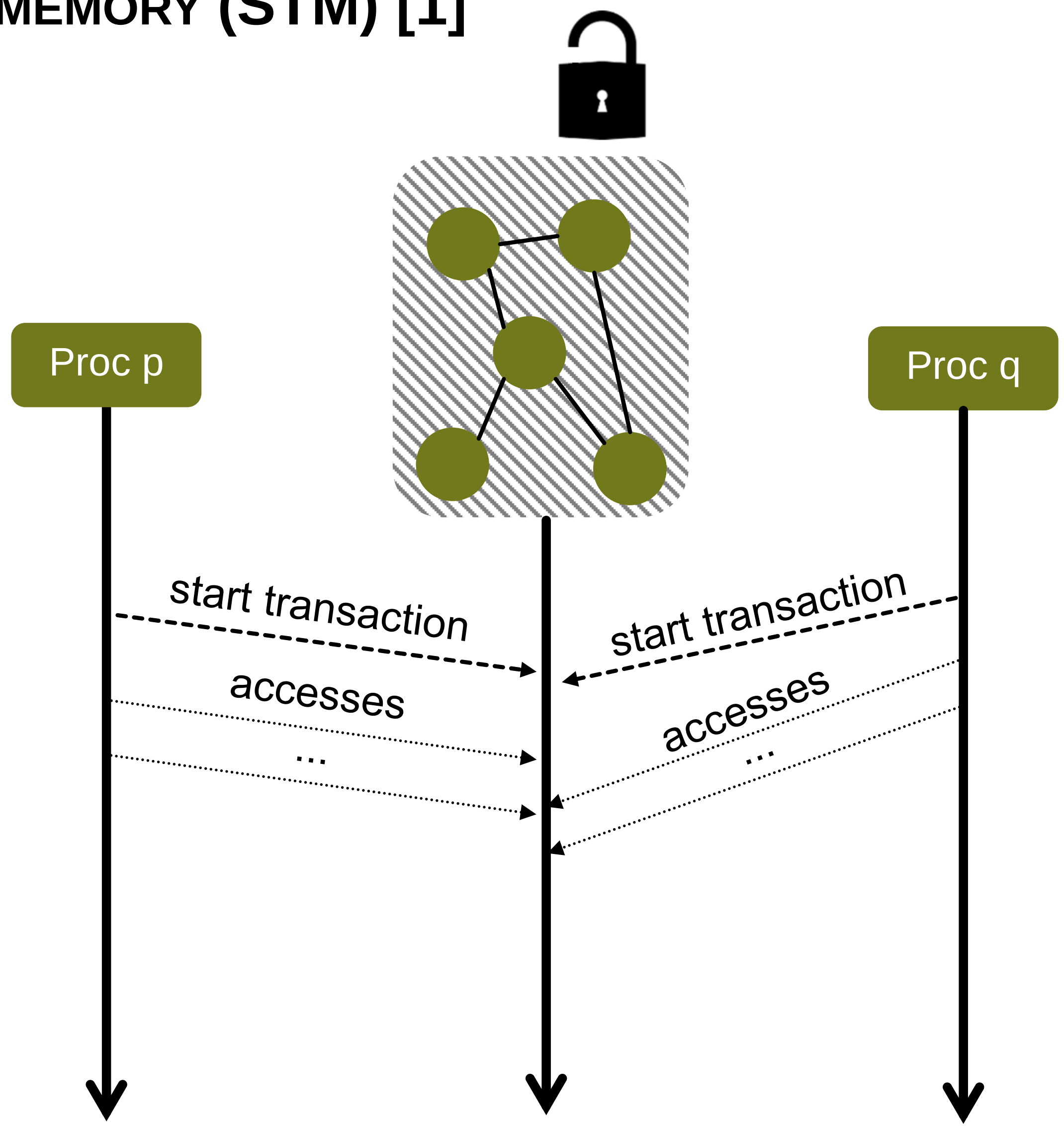

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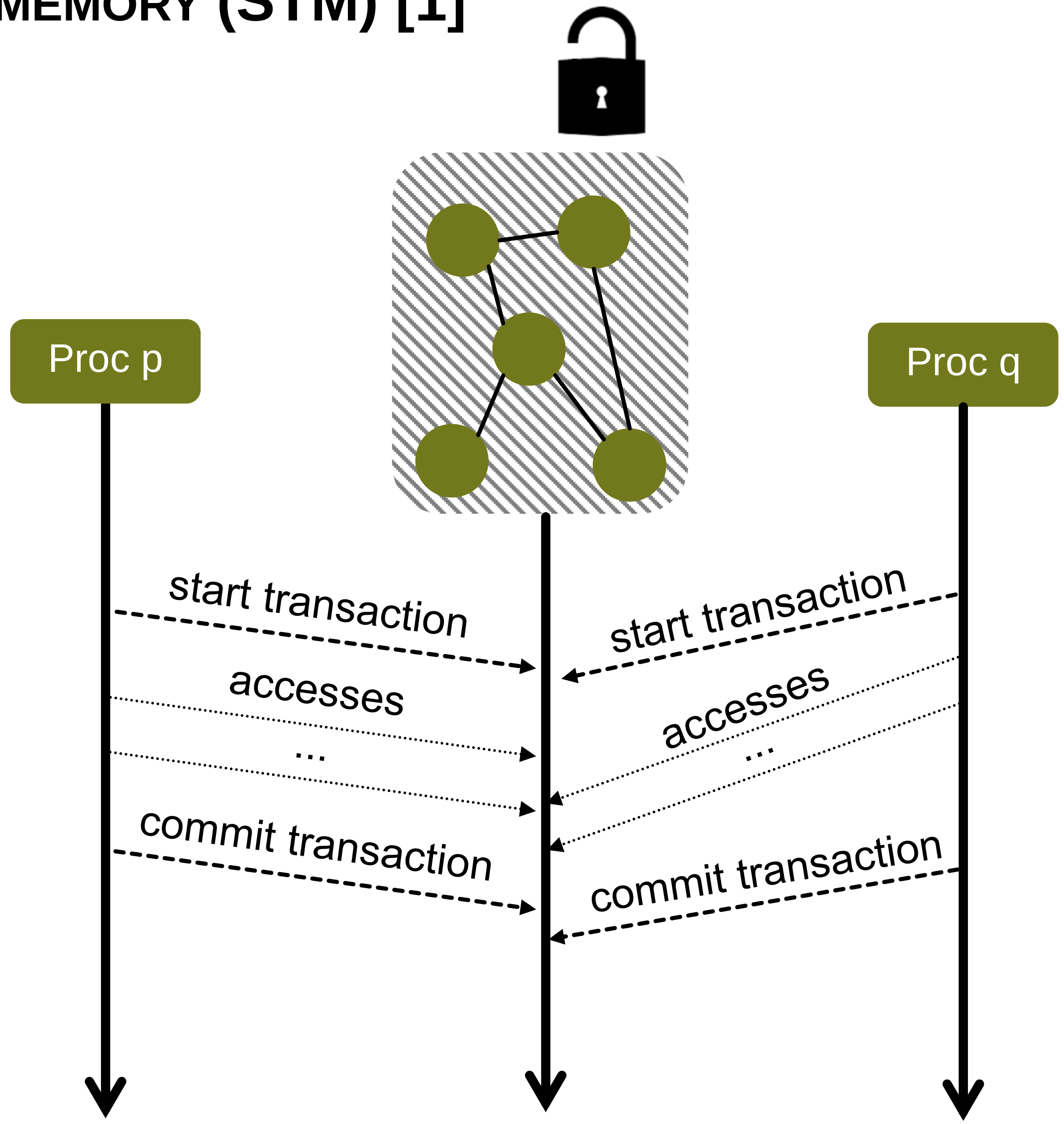

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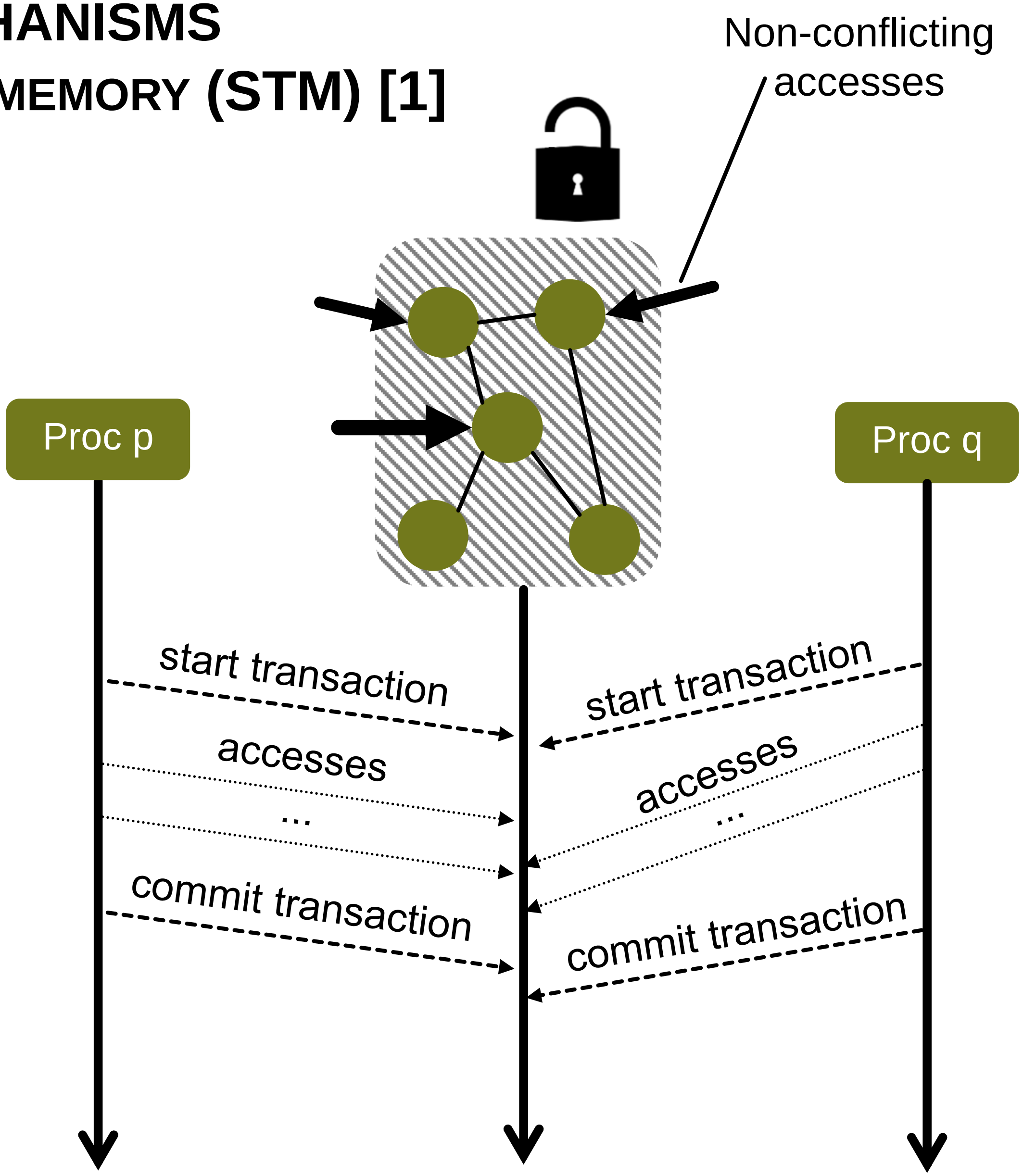

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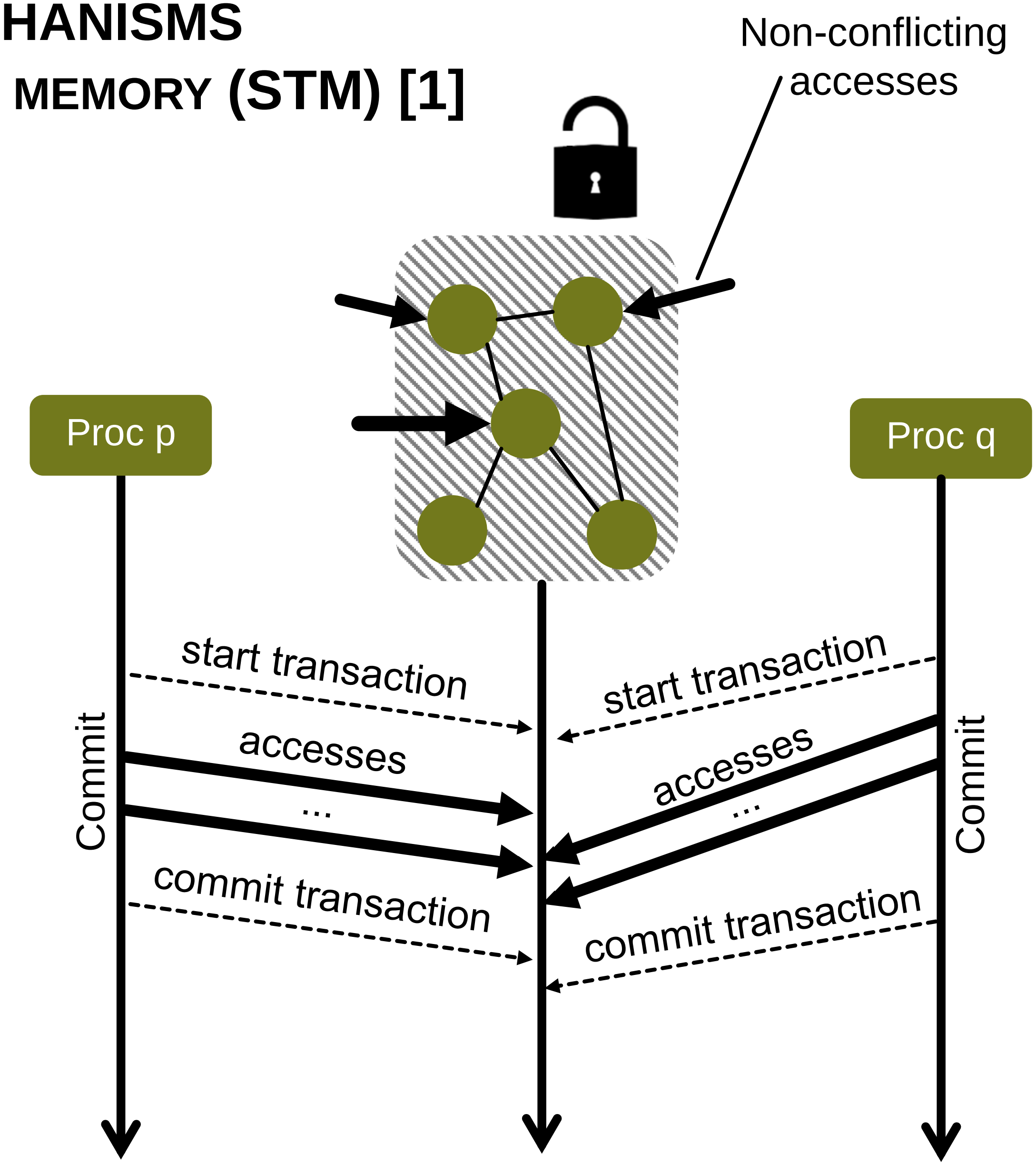

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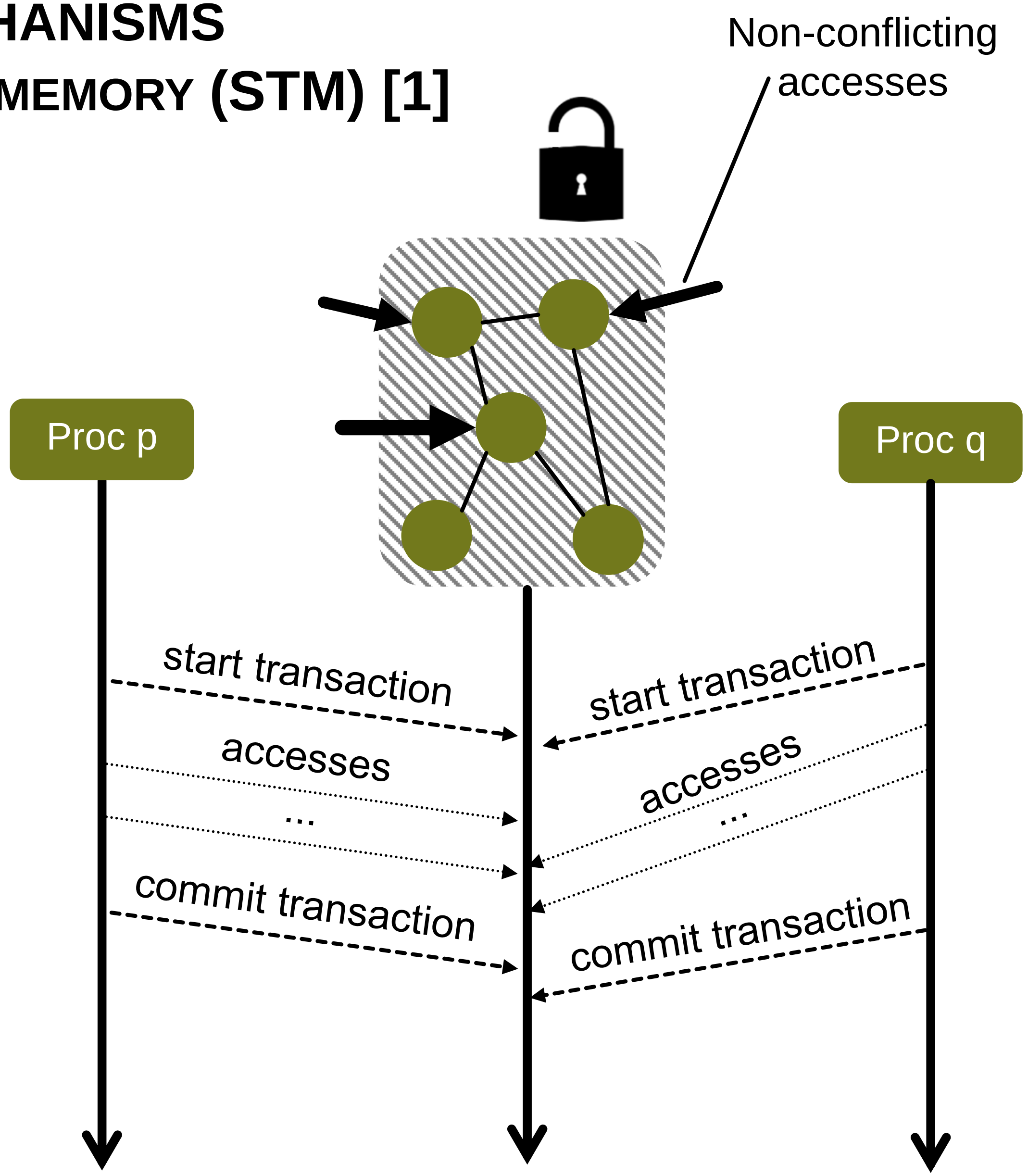

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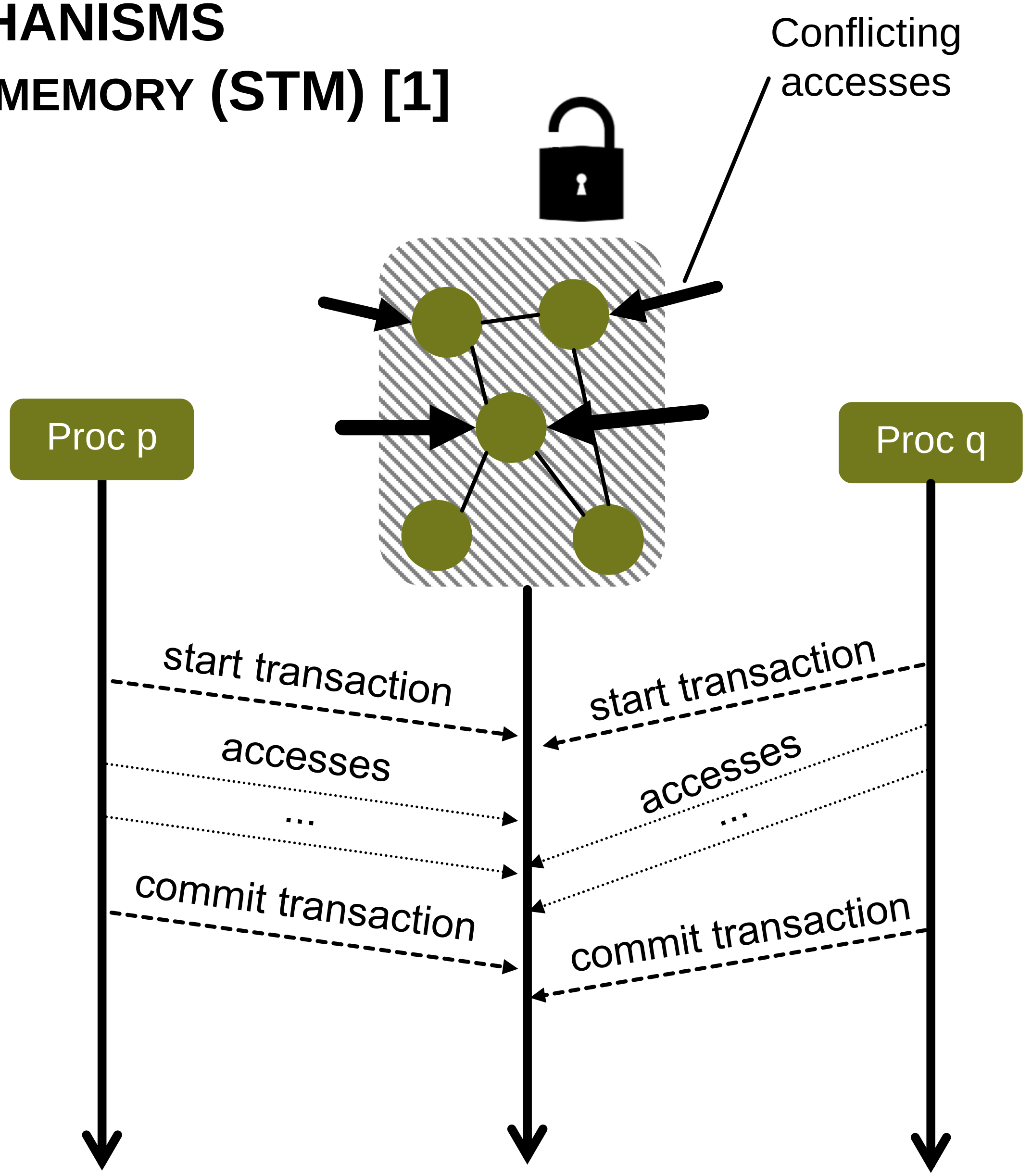

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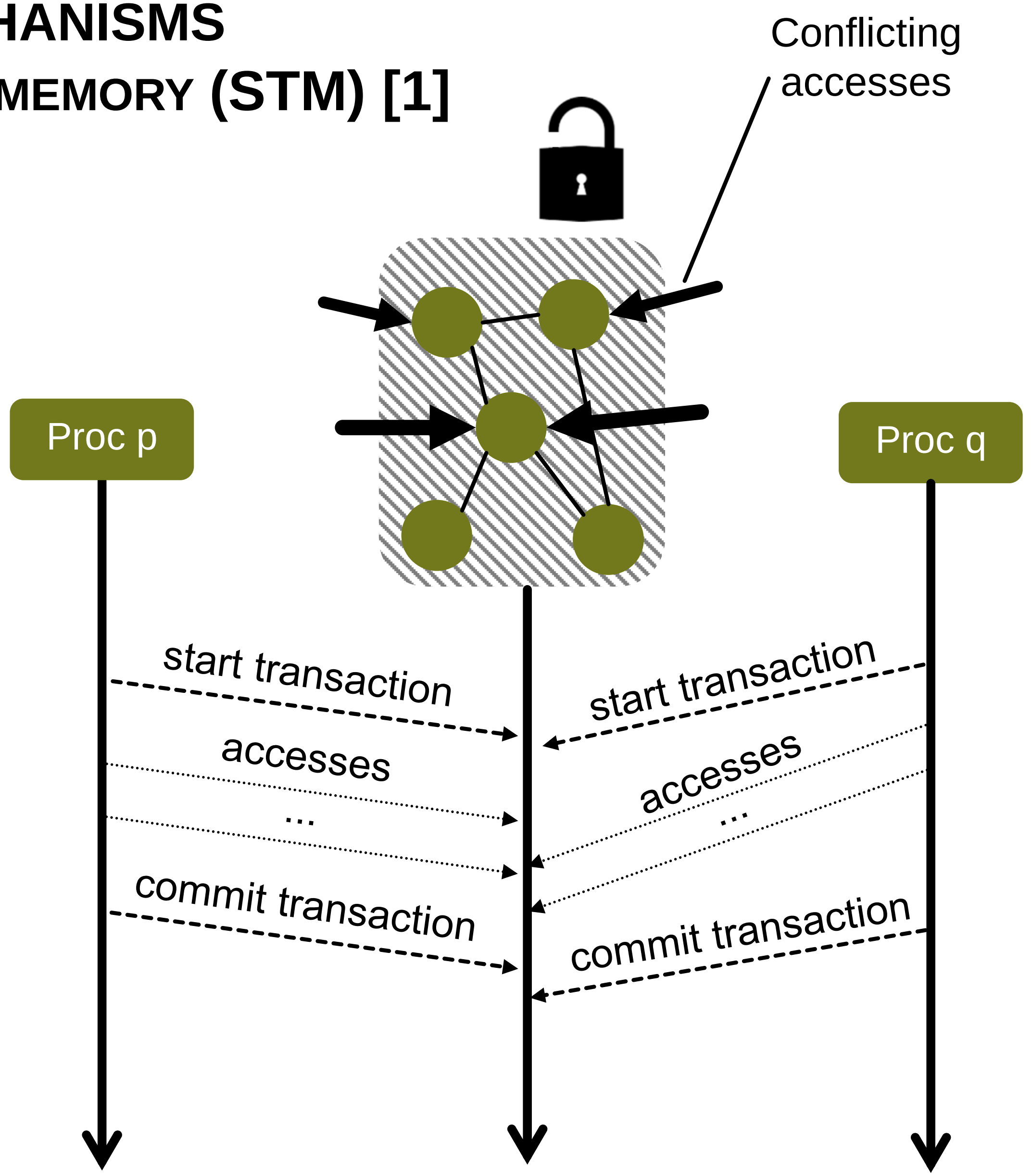

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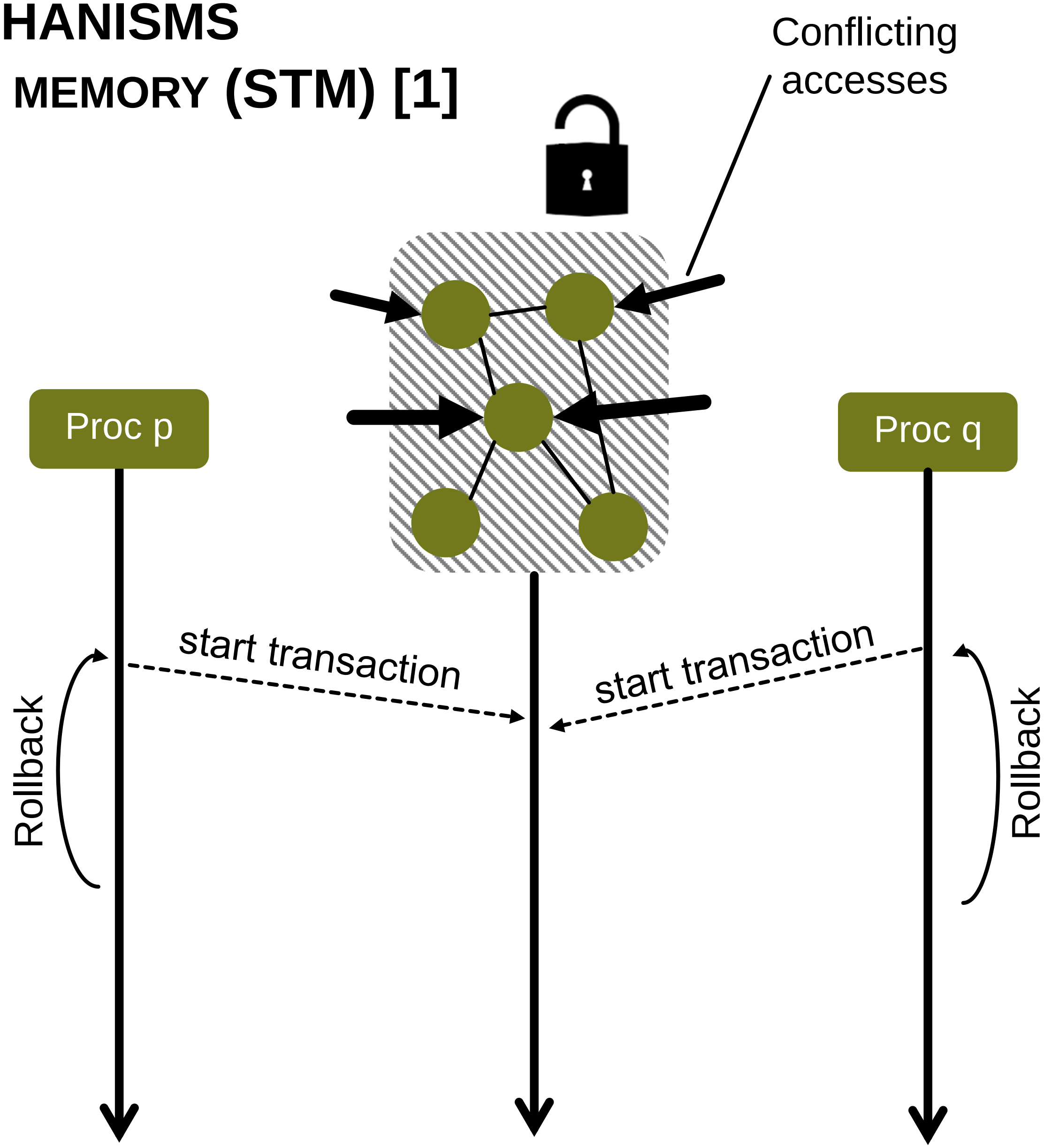

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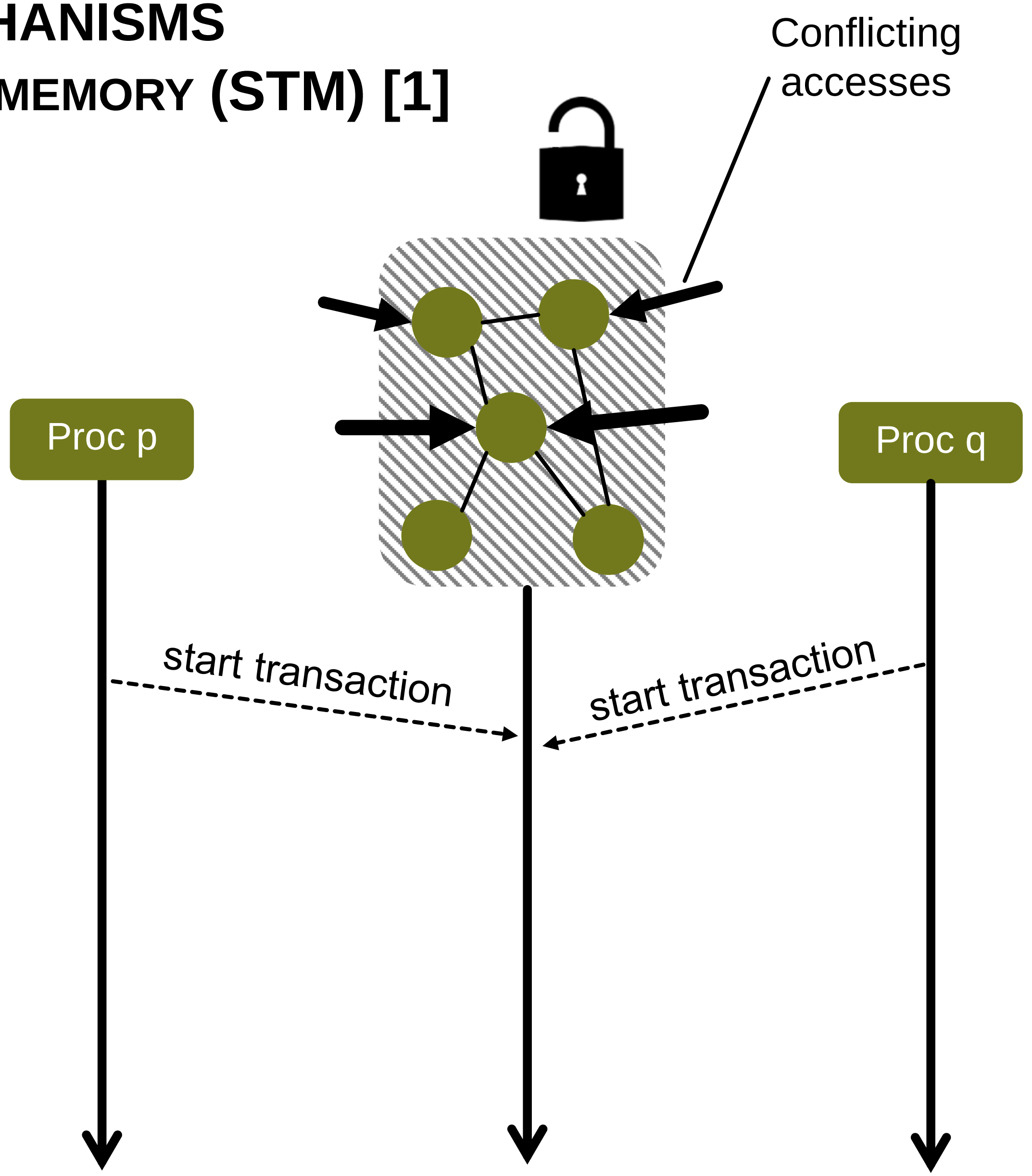

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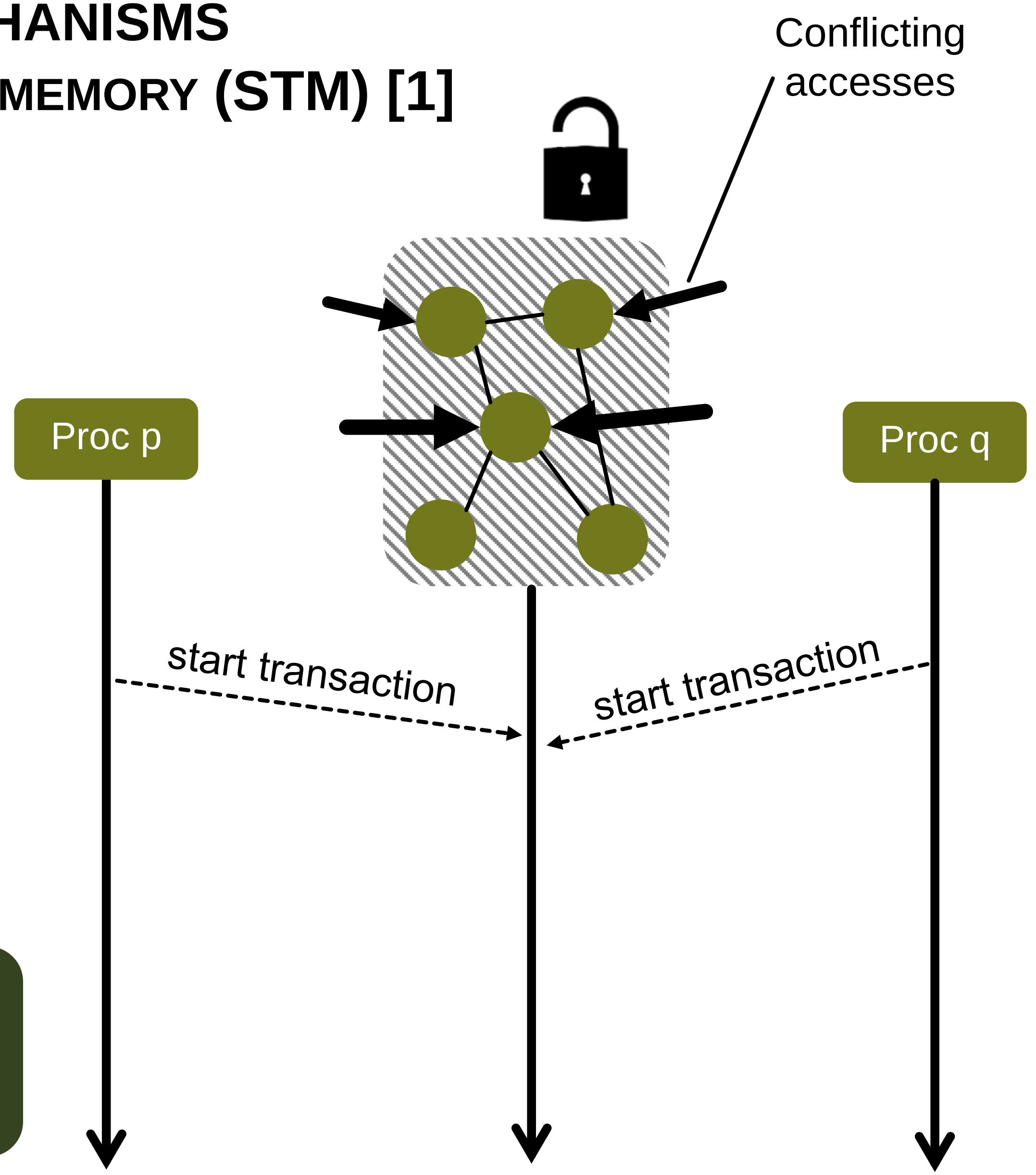

Simple protocols

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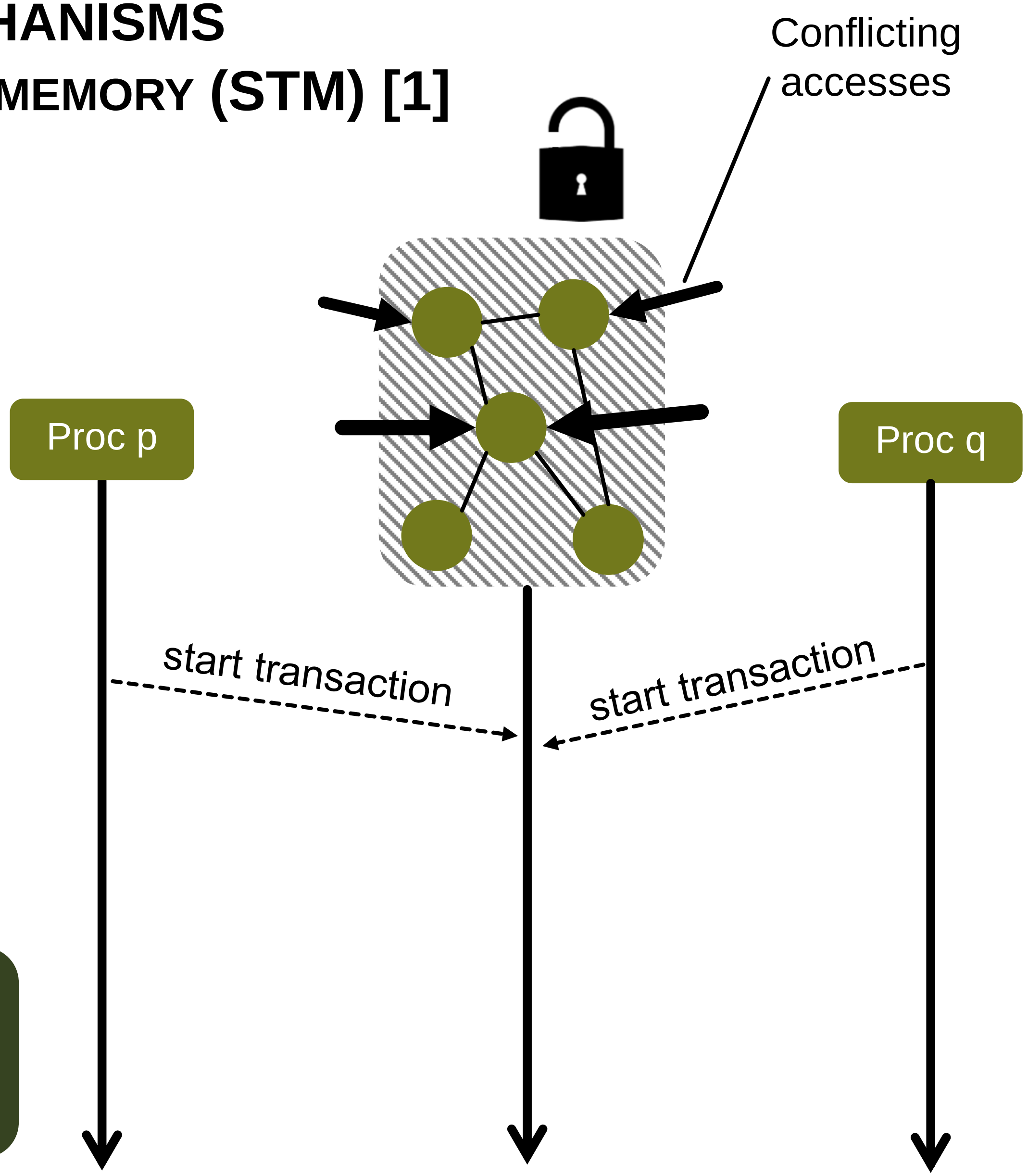

Software overheads

Simple protocols

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Synchronization Mechanisms
Hardware transactional memory (HTM)

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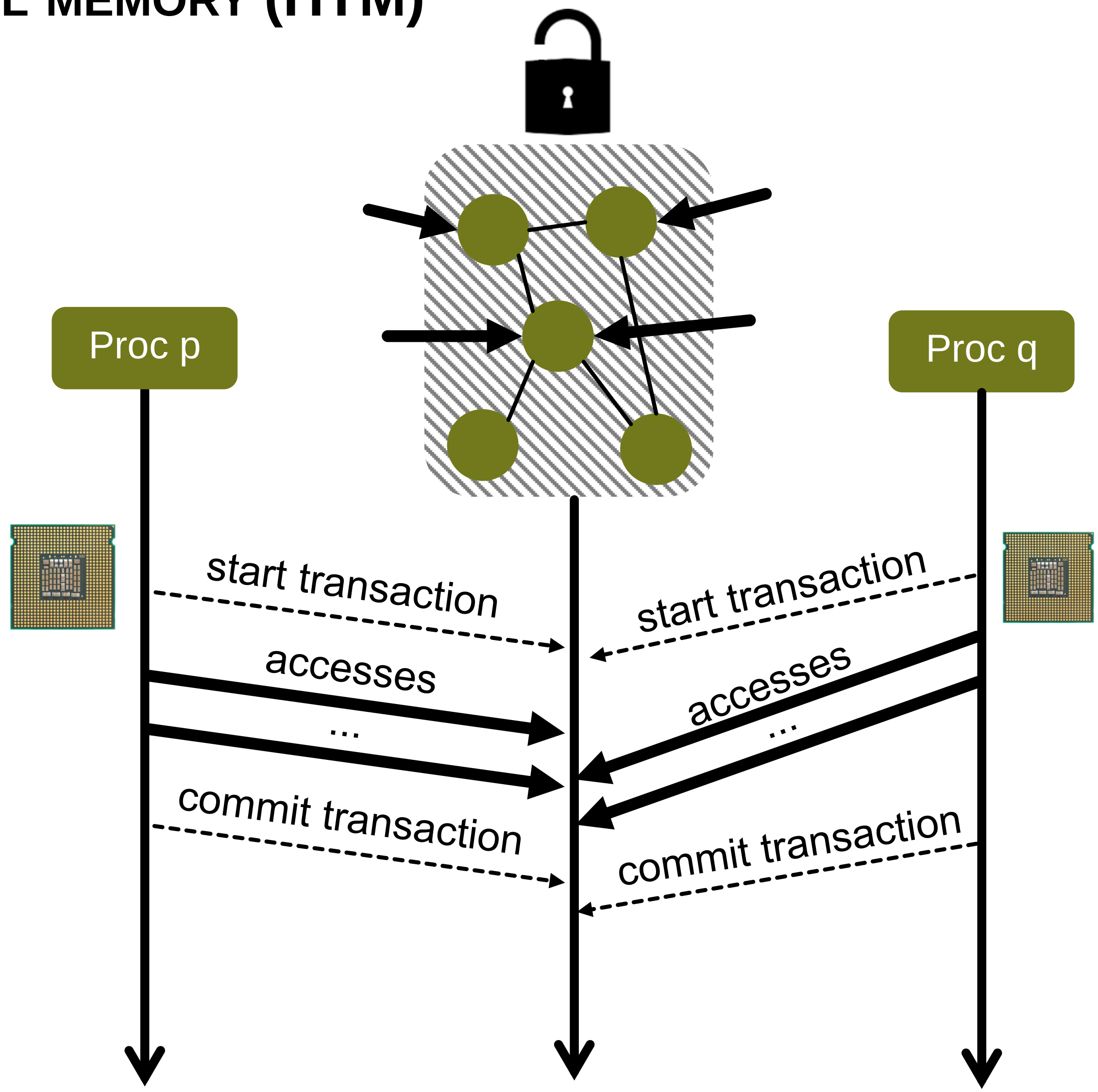

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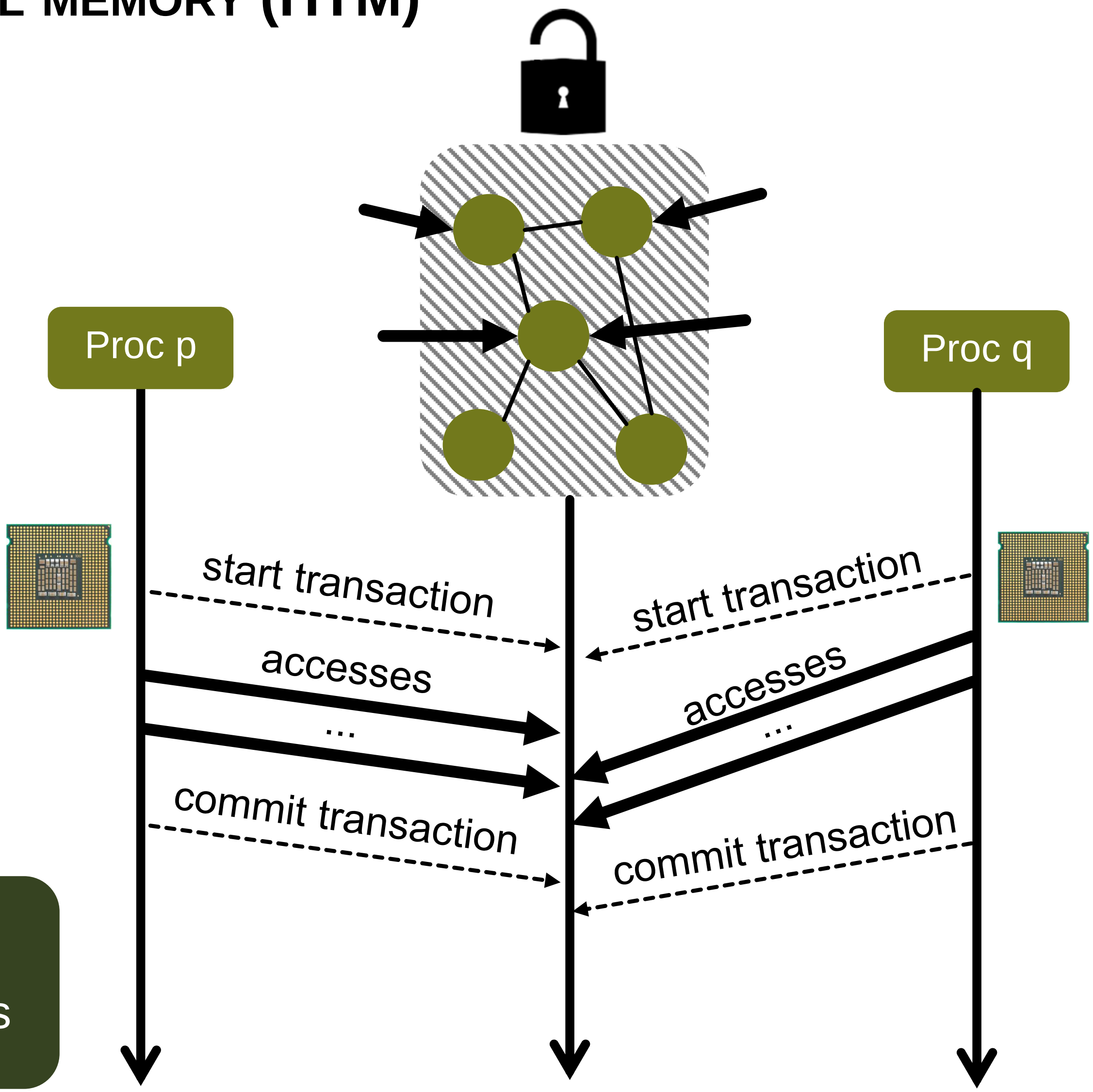

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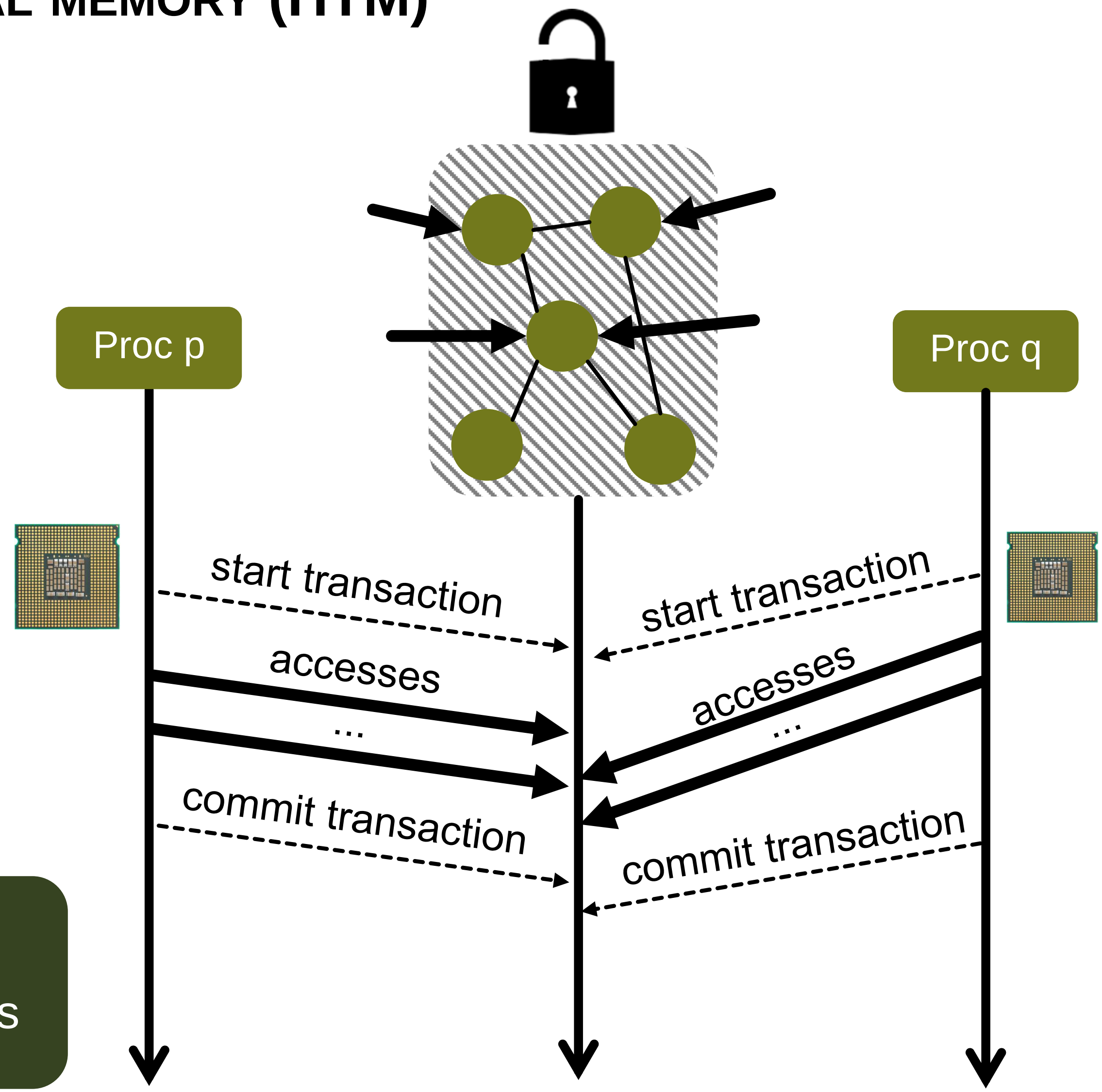
High performance? For graphs?

Simple protocols



Hardware Transactional Memory

HARDWARE TRANSACTIONAL MEMORY

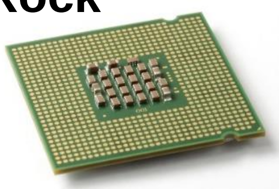
AZUL SYSTEMS®

Vega

HARDWARE TRANSACTIONAL MEMORY

Sun microsystems

Rock



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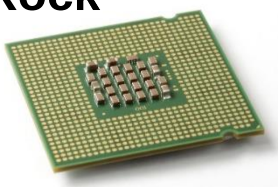

POWER8

Hardware Transactional Memory

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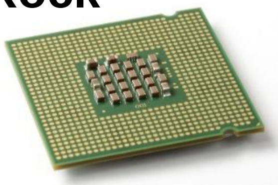

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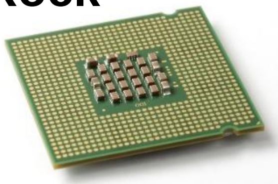

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HARDWARE TRANSACTIONAL MEMORY

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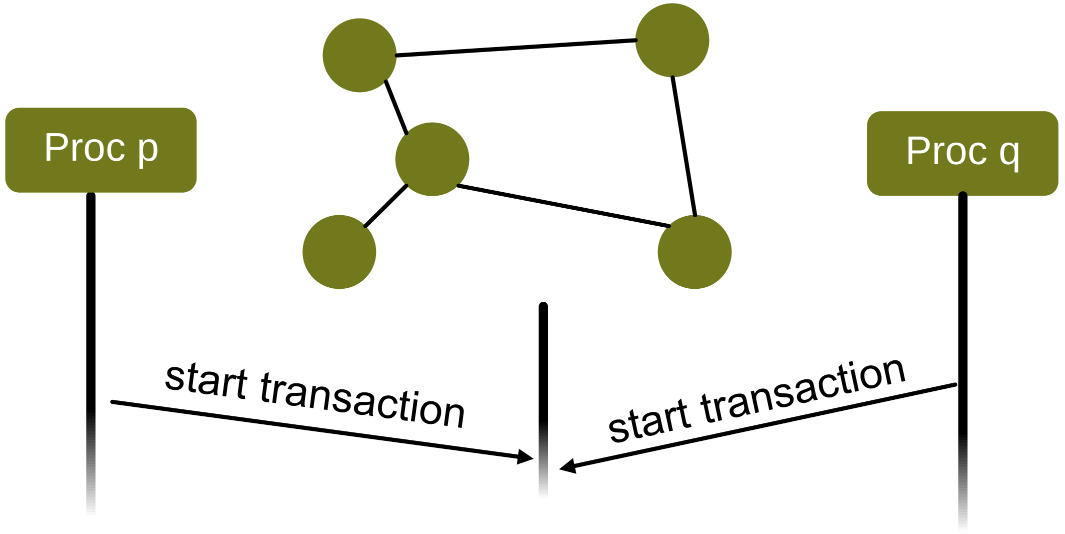
They offer programmability, how about performance?

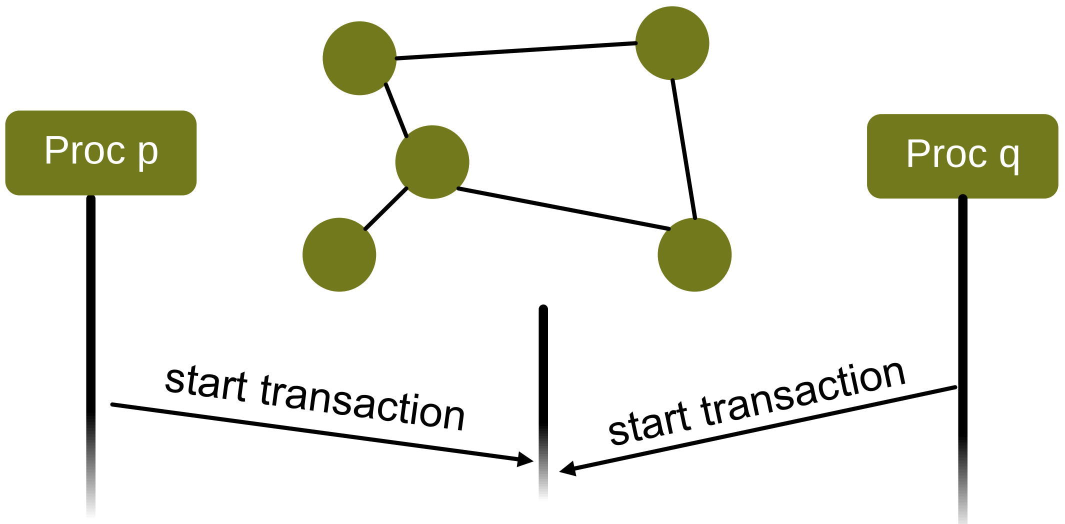
Haswell

Shared- & Distributed-memory Machines



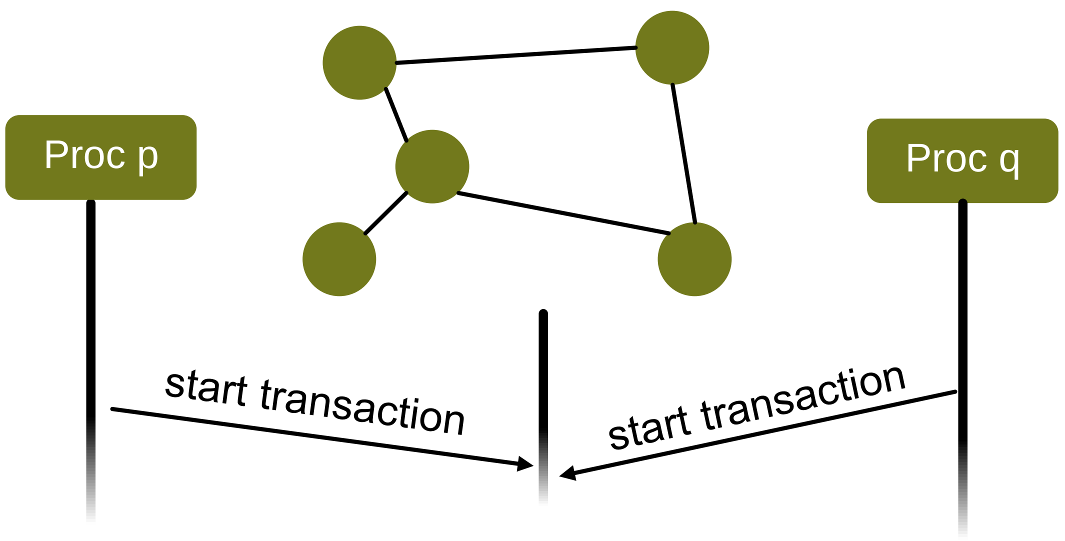
SHARED- & DISTRIBUTED-MEMORY MACHINES

- HTM works fine for single shared-memory domains



Shared- & Distributed-memory Machines

- HTM works fine for single shared-memory domains
  - Most graphs fit in such machines [1]



[1] Y. Perez et al. Ringo: Interactive Graph Analytics on Big-Memory Machines. SIGCOMM'14.

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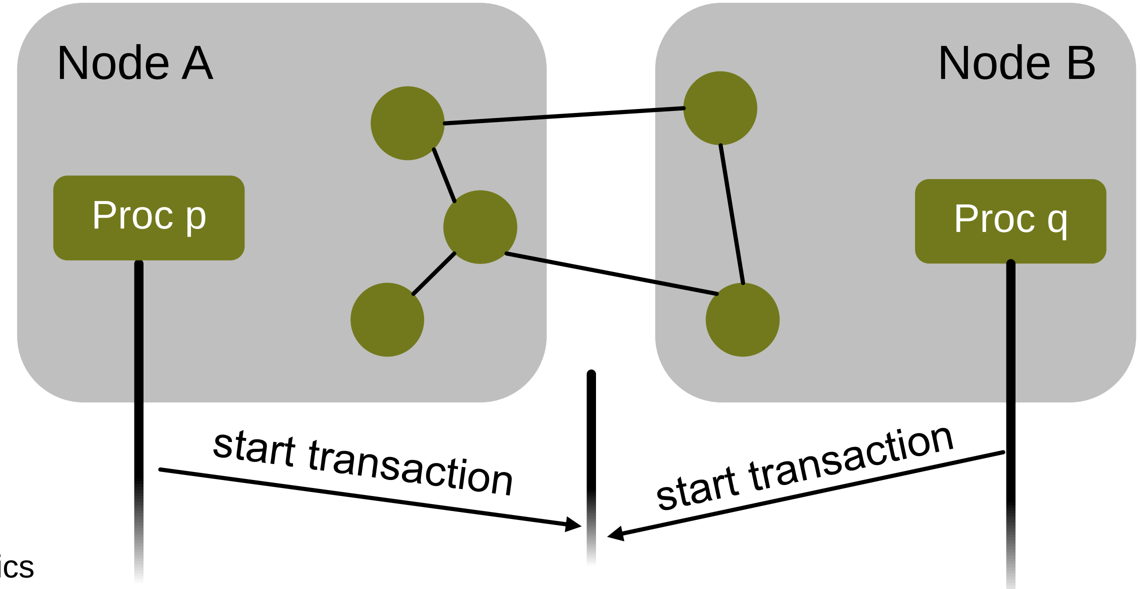

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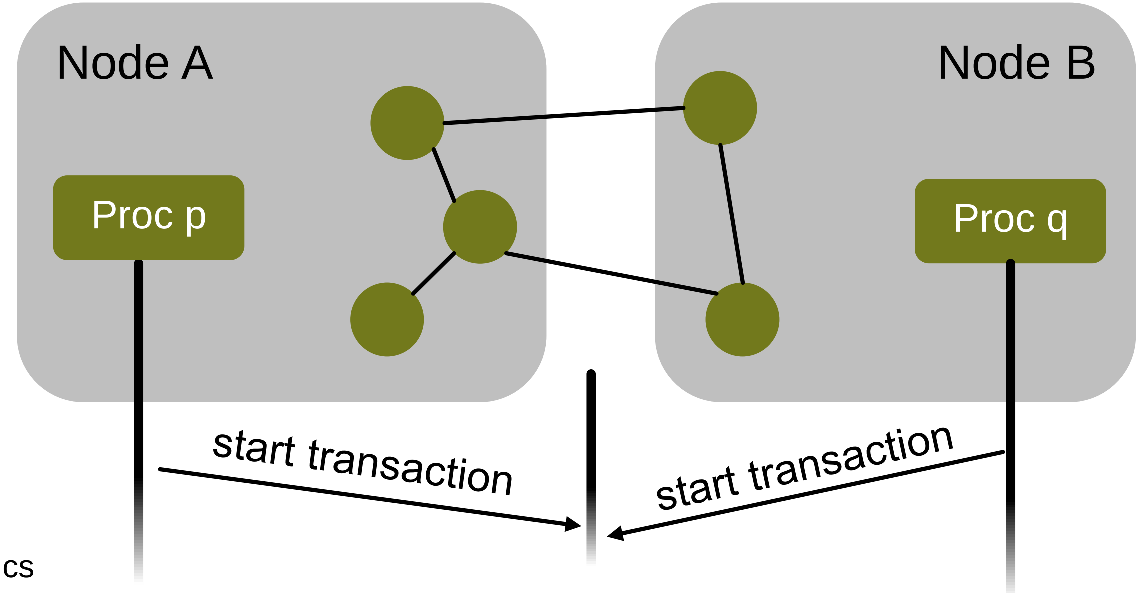
- However, some do not:



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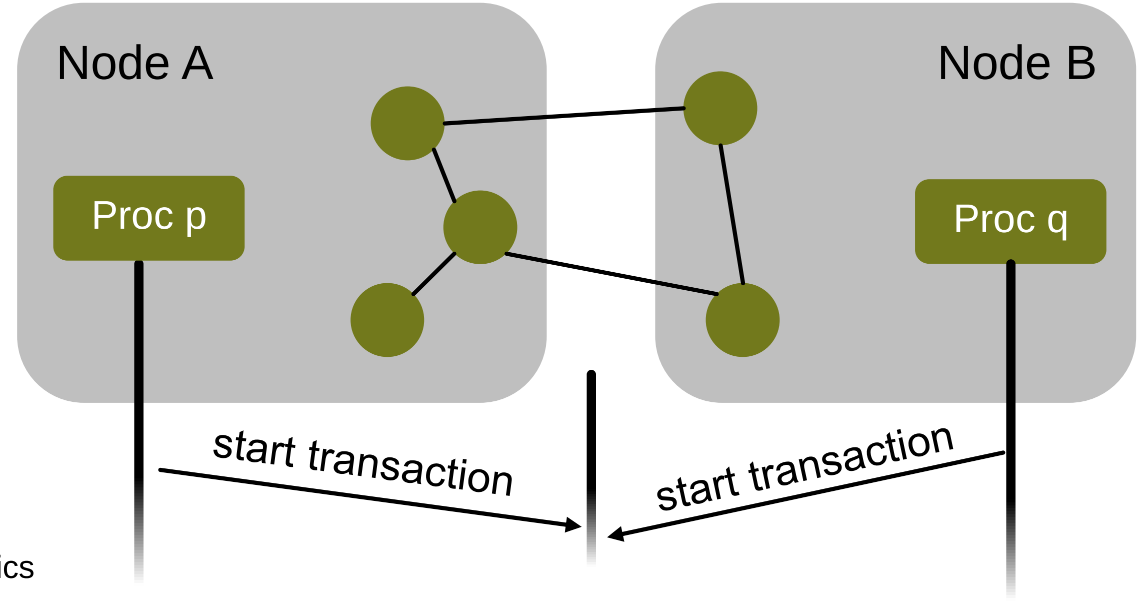

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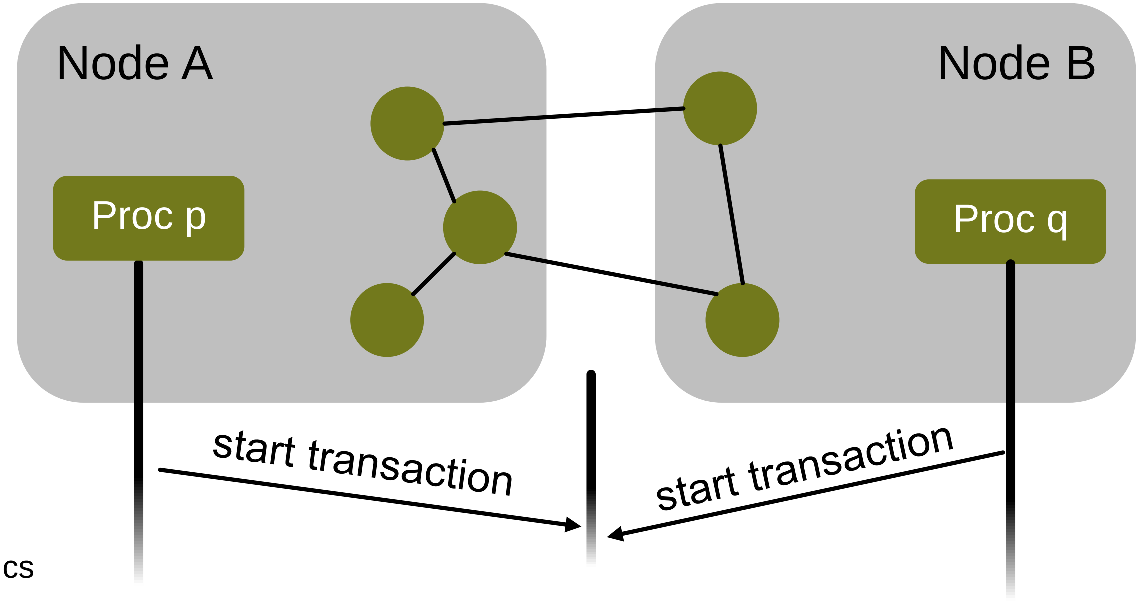
- However, some do not:
  - Very large instances
  - Rich vertex/edge data



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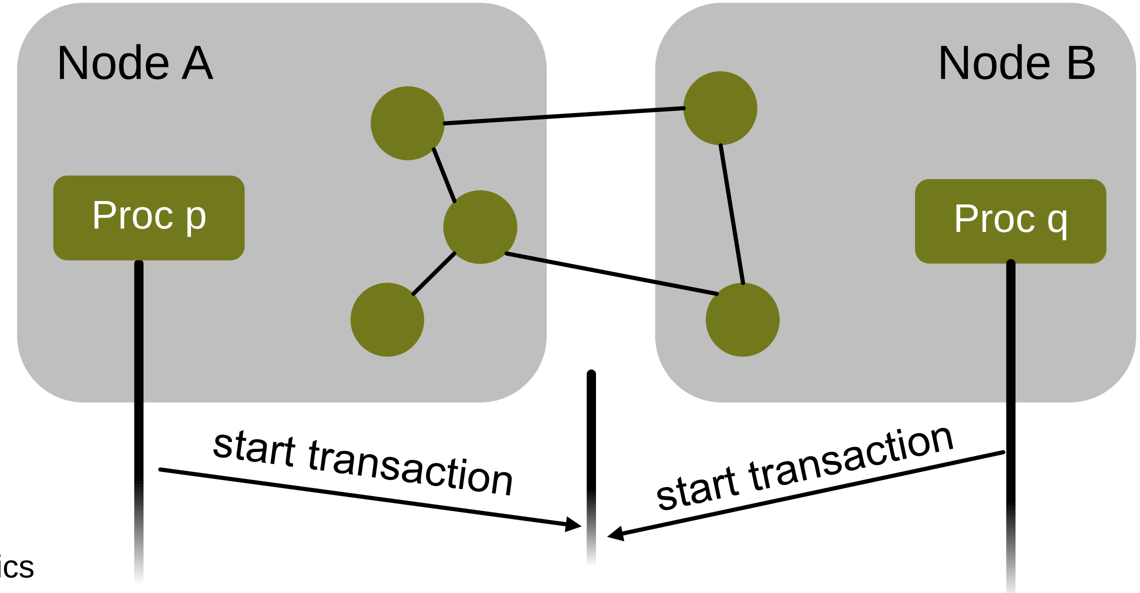
  - Most graphs fit in such machines [1]
- However, some do not:
  - Very large instances
  - Rich vertex/edge data
- Fat nodes with lots of RAM still expensive ($35K for a machine with 1TB of RAM [1])



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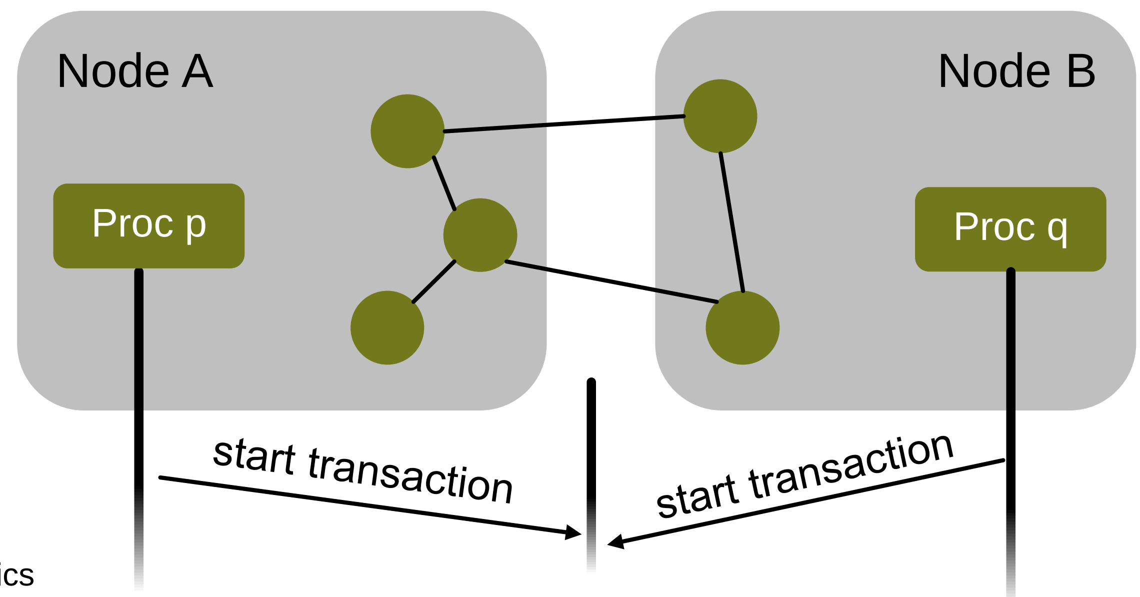
- HTM works fine for single shared-memory domains
  - Most graphs fit in such machines [1]
- However, some do not:
  - Very large instances
  - Rich vertex/edge data
- Fat nodes with lots of RAM still expensive ($35K for a machine with 1TB of RAM [1])

How to apply HTM in such a setting?



[1] Y. Perez et al. Ringo: Interactive Graph Analytics on Big-Memory Machines. SIGCOMM'14.

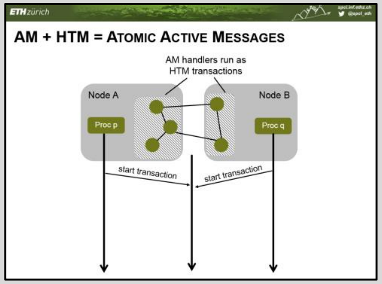
Overview of our Research

OVERVIEW OF OUR RESEARCH

HTM for graphs in SM & DM environments

Overview of our Research

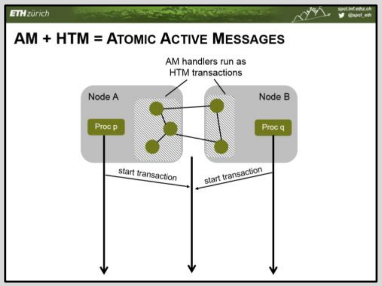
HTM for graphs in SM & DM environments



HTM + Active Messages
= Atomic Active Messages

Overview of our Research

HTM for graphs in SM & DM environments



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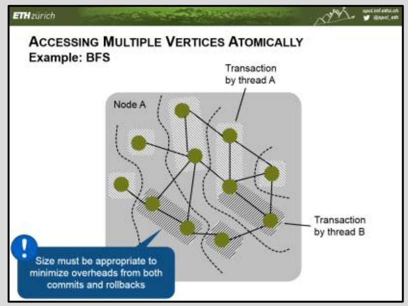
Coarsening & coalescing



Overview of our Research

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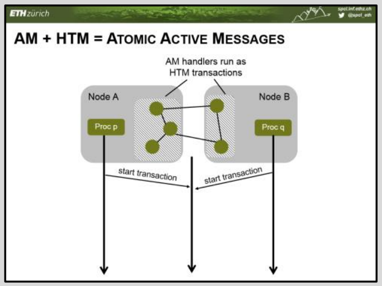

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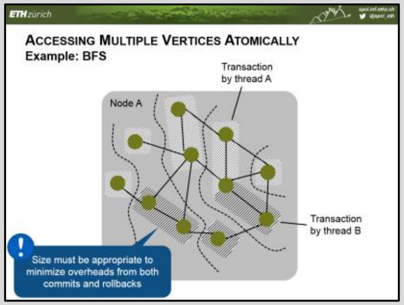
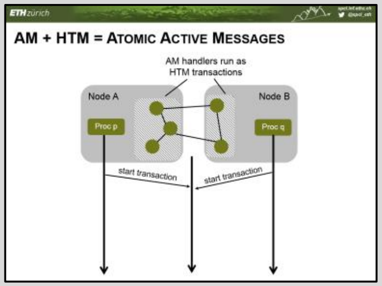


Performance Modeling & Analysis

Overview of our Research

HTM for graphs in SM & DM environments



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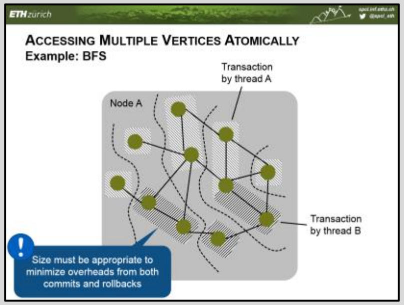
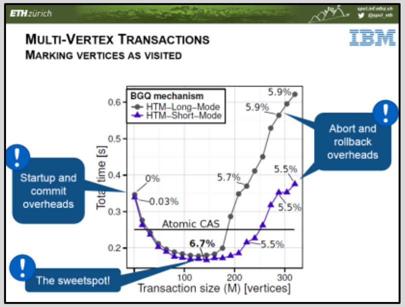


Performance Modeling & Analysis

Haswell & BG/Q Analysis



Overview of our Research

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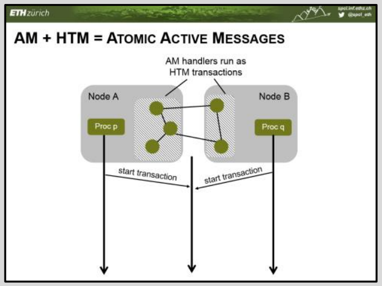

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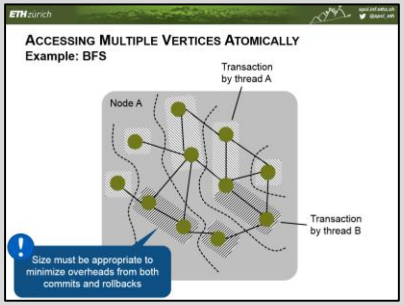

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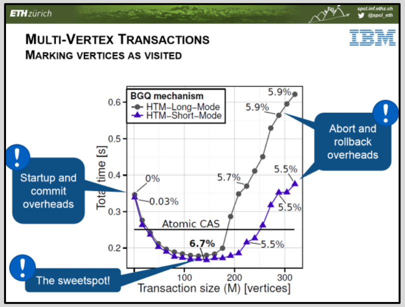
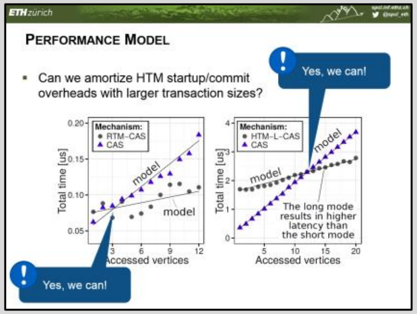
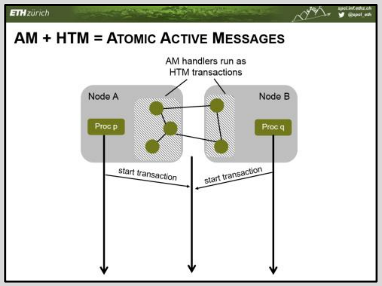




Performance model

Overview of our Research

HTM for graphs in SM & DM environments



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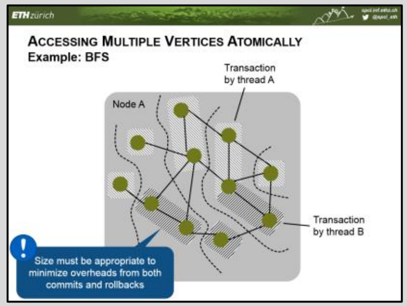
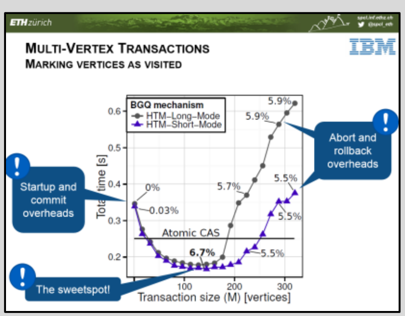
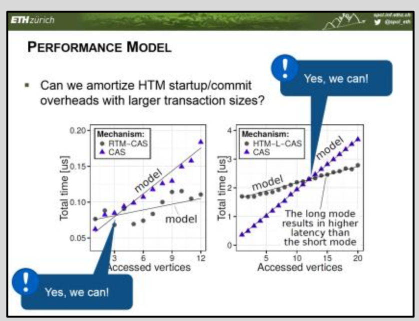


Evaluation

Performance Modeling & Analysis

Haswell & BG/Q Analysis

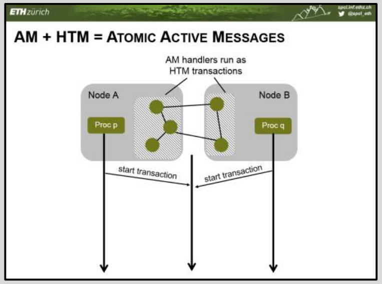




Performance model

Overview of our Research

HTM for graphs in SM & DM environments



HTM + Active Messages = Atomic Active Messages

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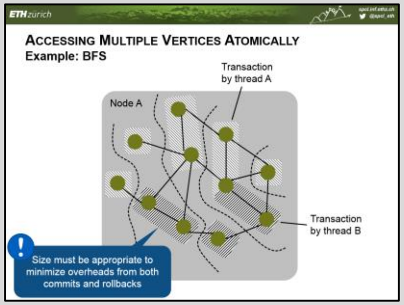
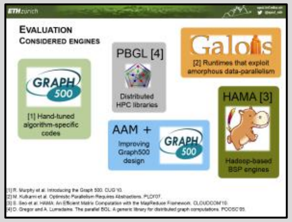
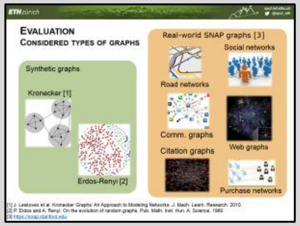


Evaluation

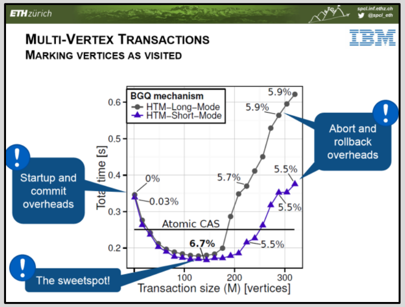


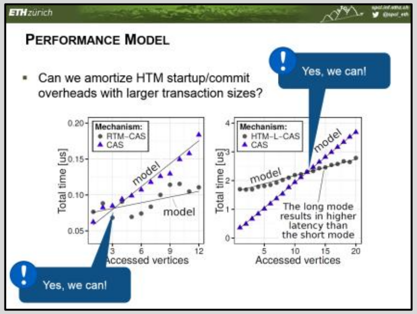


Considered engines and graphs

Performance Modeling & Analysis

Haswell & BG/Q Analysis

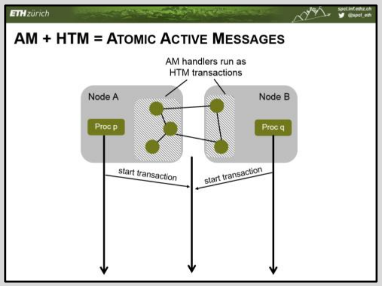




Performance model

Overview of our Research

HTM for graphs in SM & DM environments



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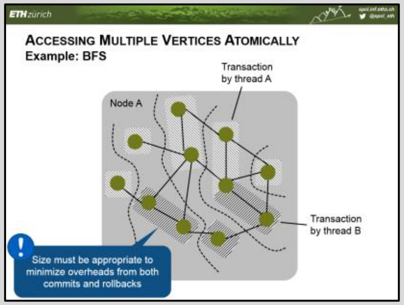

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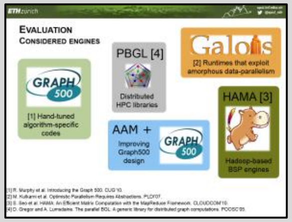

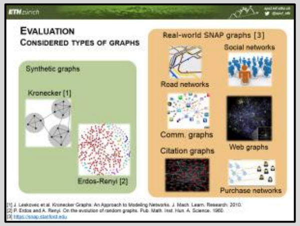

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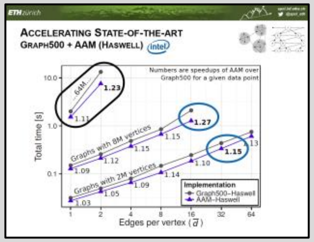
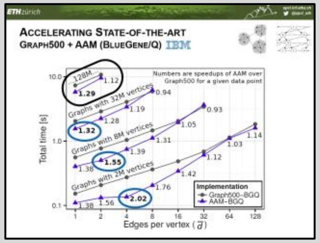
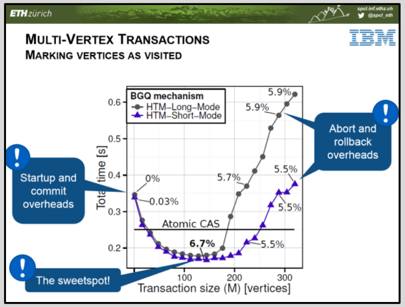


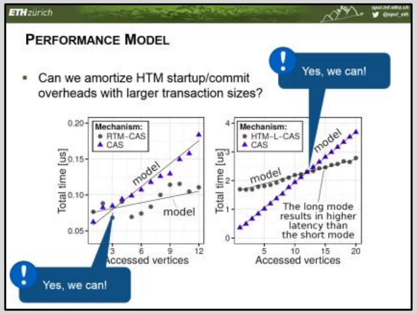


Accelerating state-of-the-art

Performance Modeling & Analysis

Haswell & BG/Q Analysis

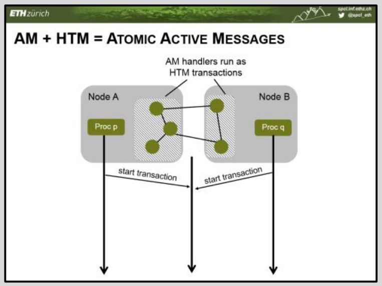




Performance model

Overview of our Research

HTM for graphs in SM & DM environments



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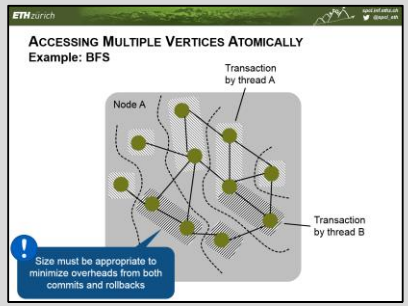

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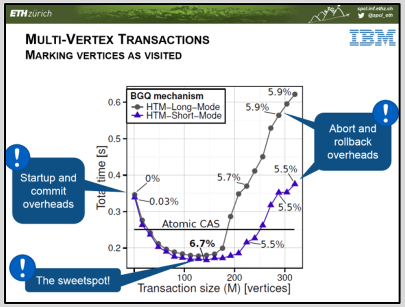

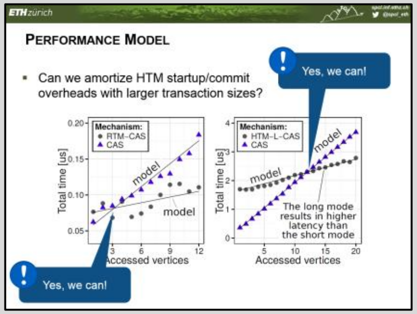

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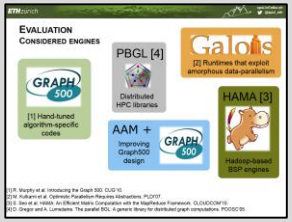
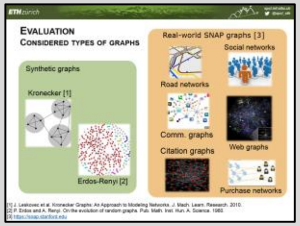
Evaluation





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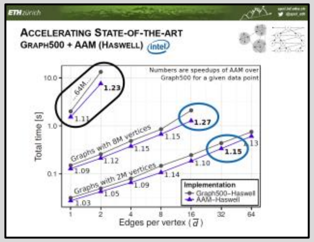

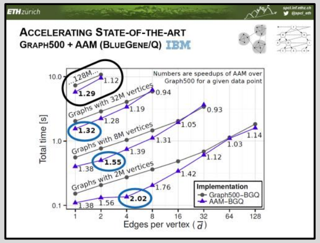

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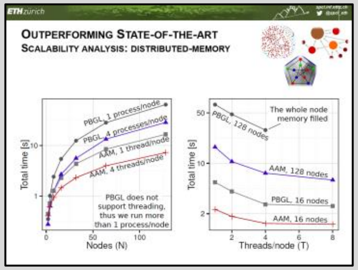
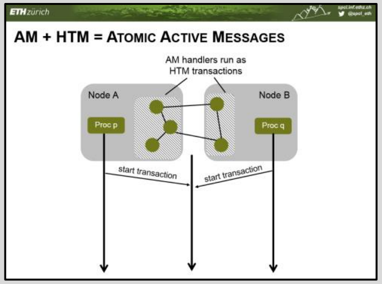


Scalability

Overview of our Research

HTM for graphs in SM & DM environments



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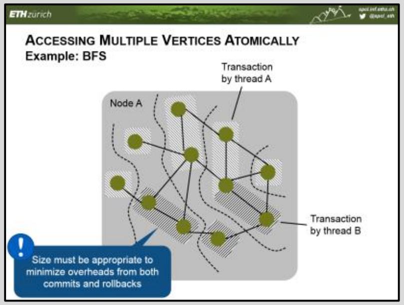
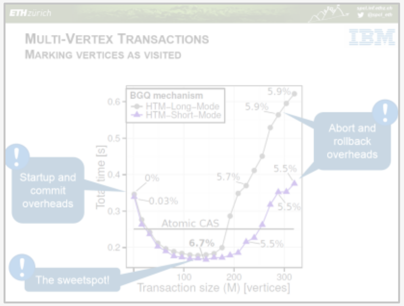
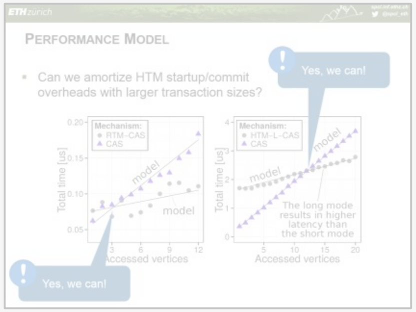


Performance Modeling & Analysis

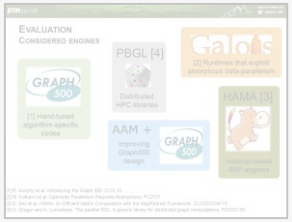
Haswell & BG/Q Analysis

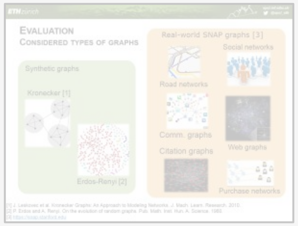




Performance model

Evaluation





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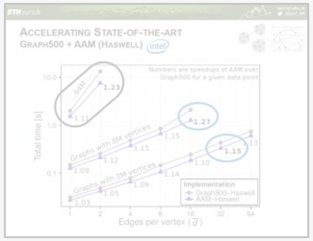
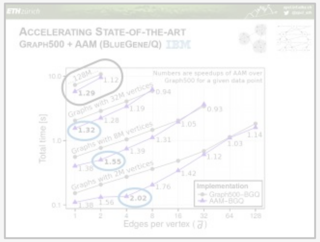
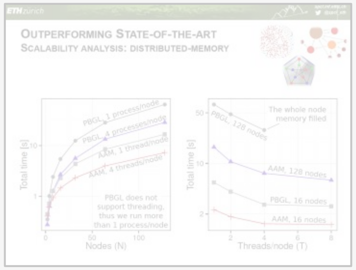




Accelerating state-of-the-art



Scalability

Active Messages (AM)

ACTIVE MESSAGES (AM)

Process p

Process q

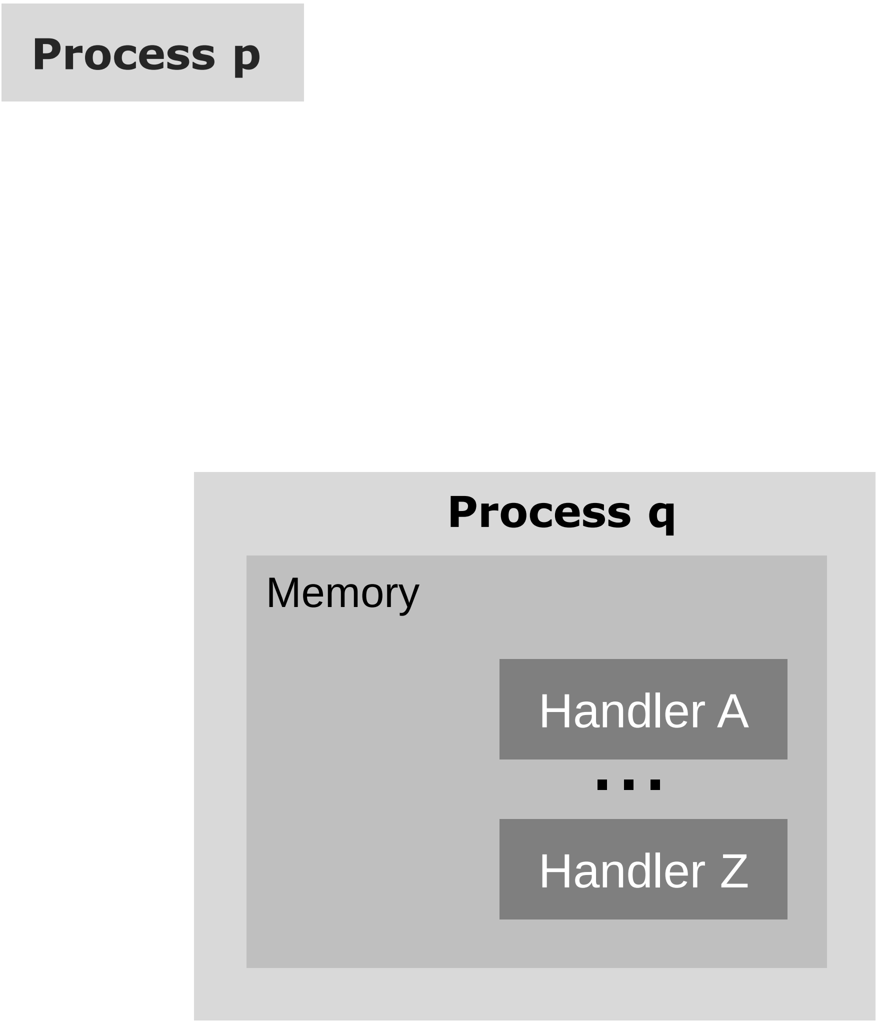
ACTIVE MESSAGES (AM)

Process p

Process q

Memory

ACTIVE MESSAGES (AM)



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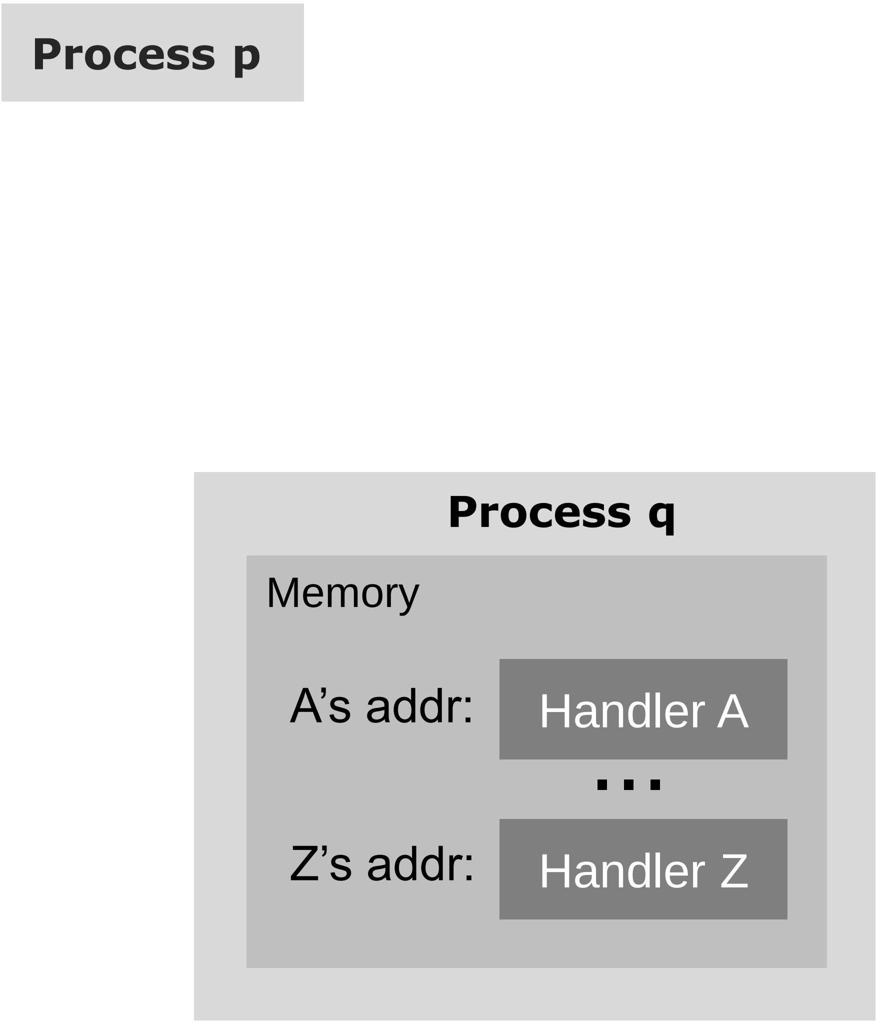

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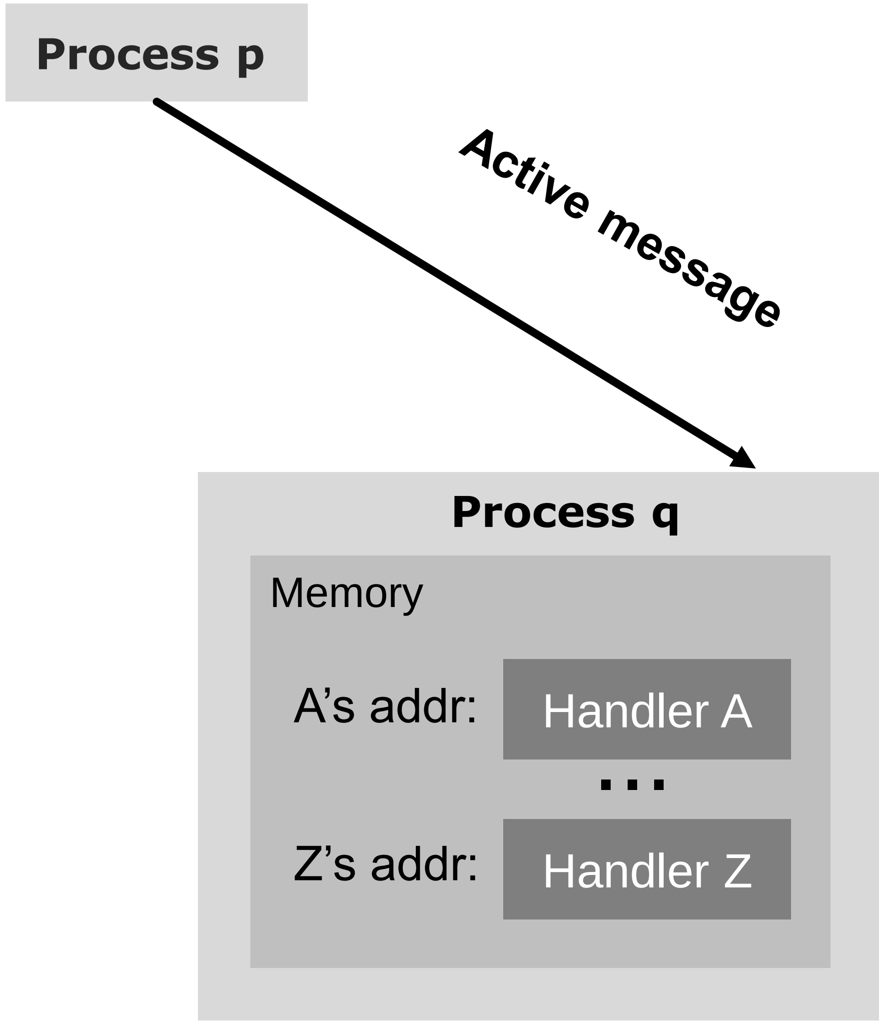

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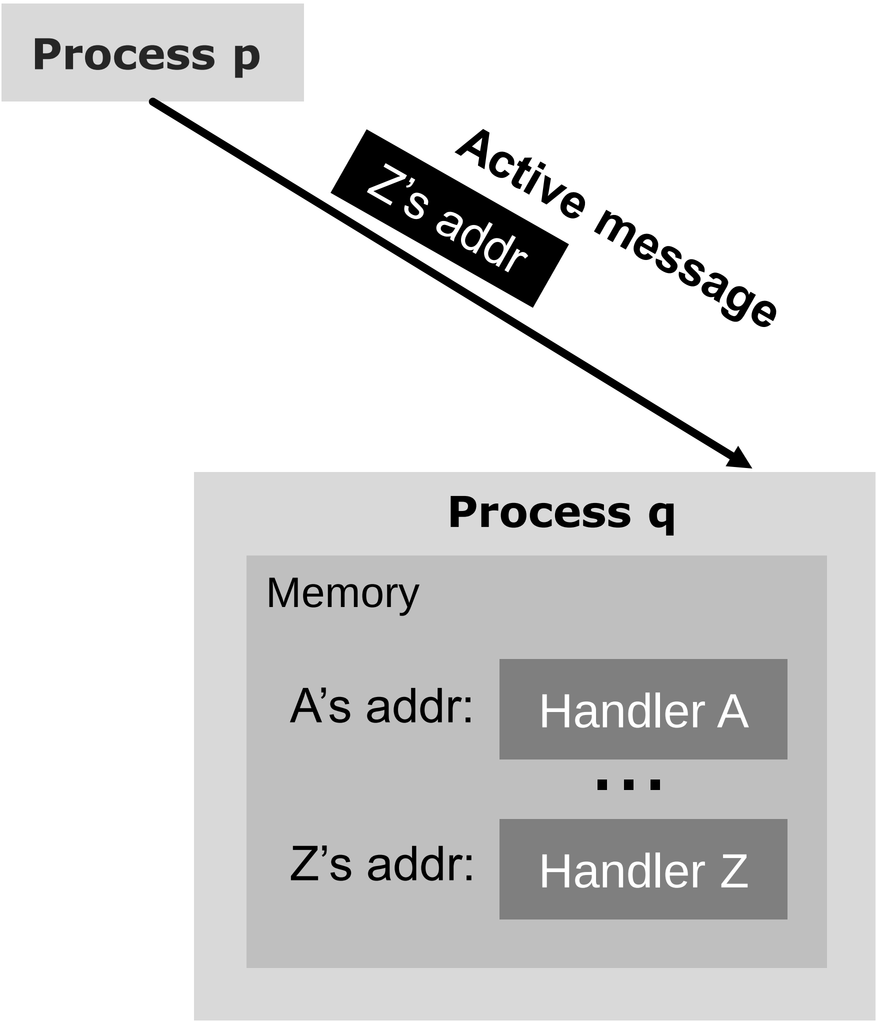

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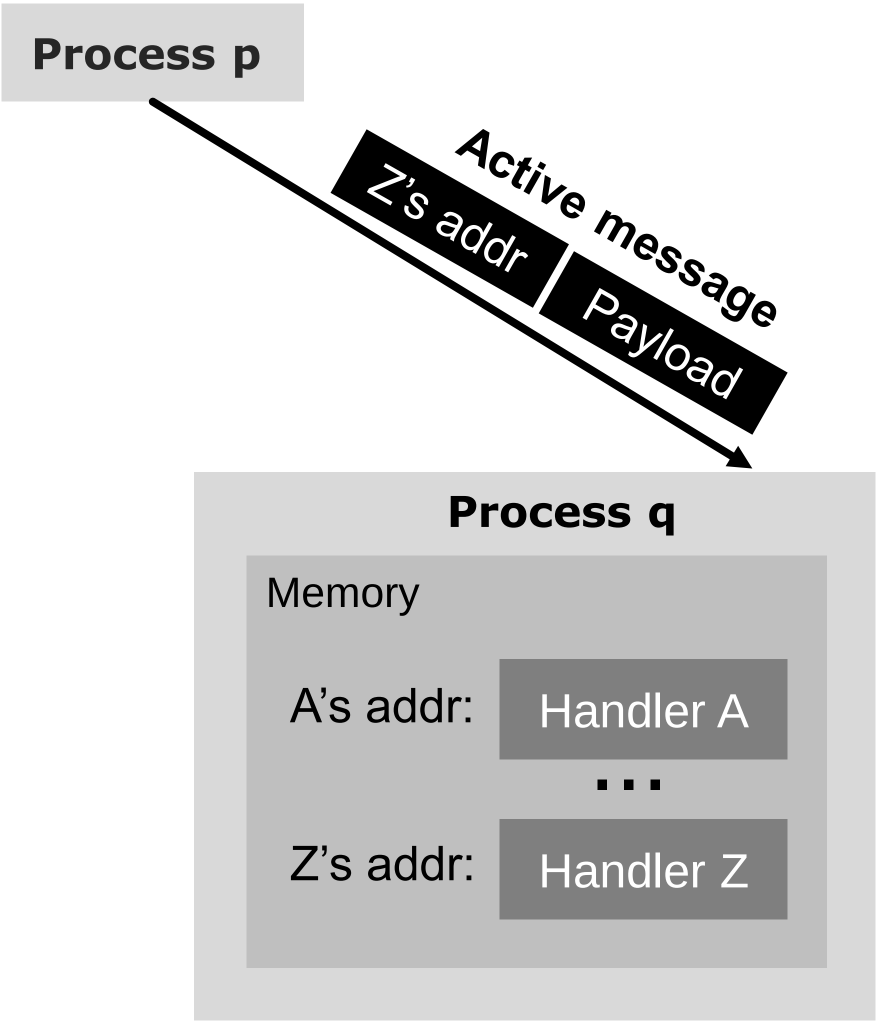

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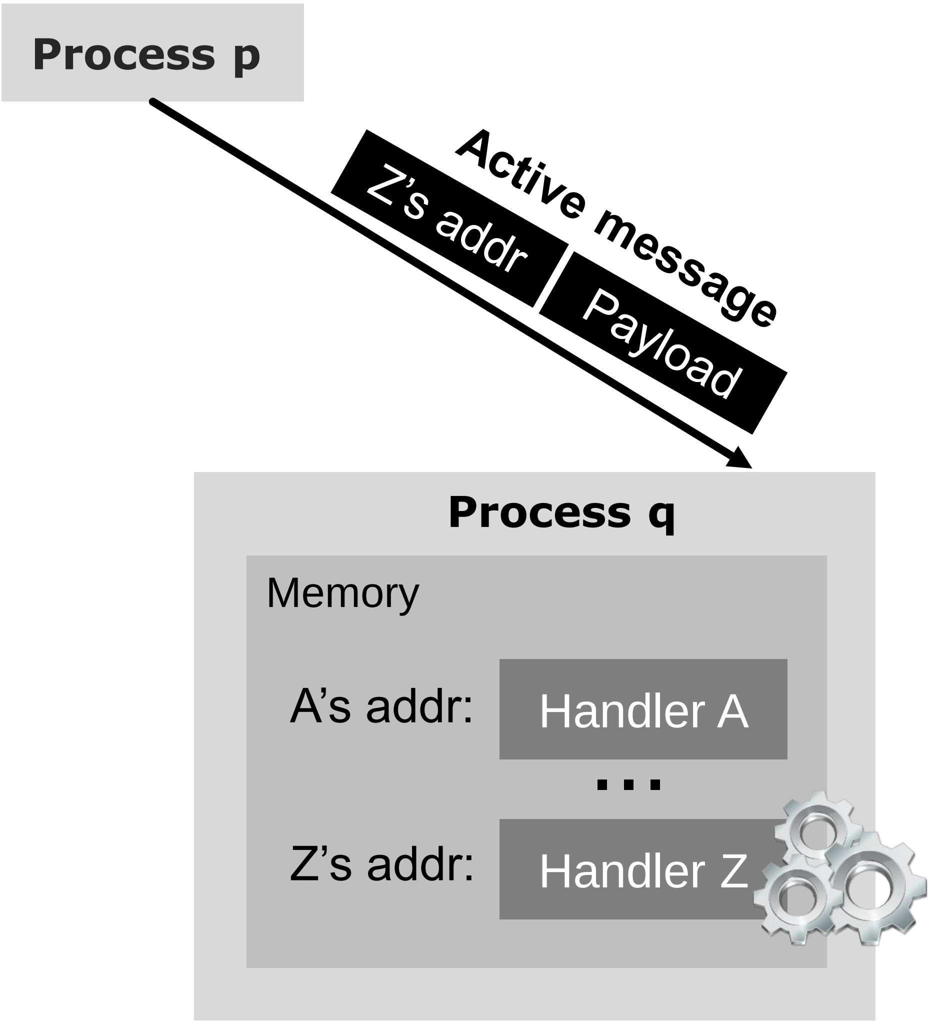

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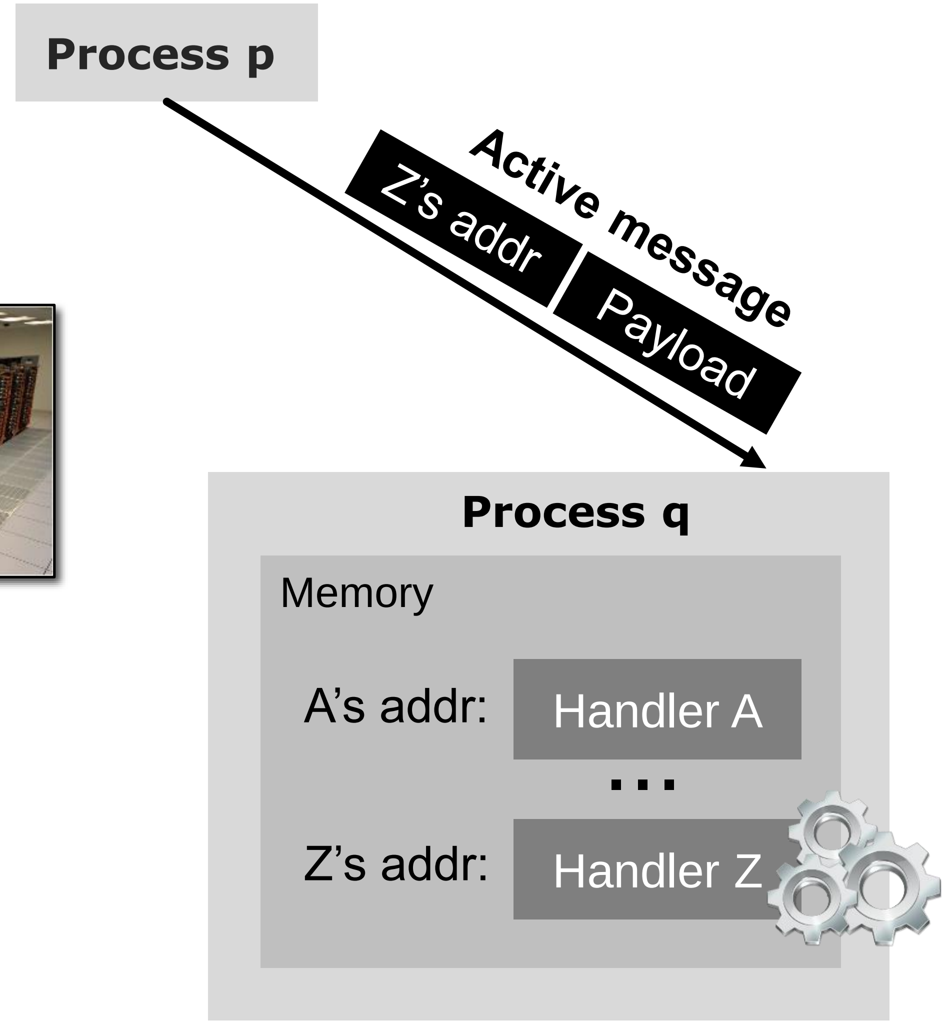
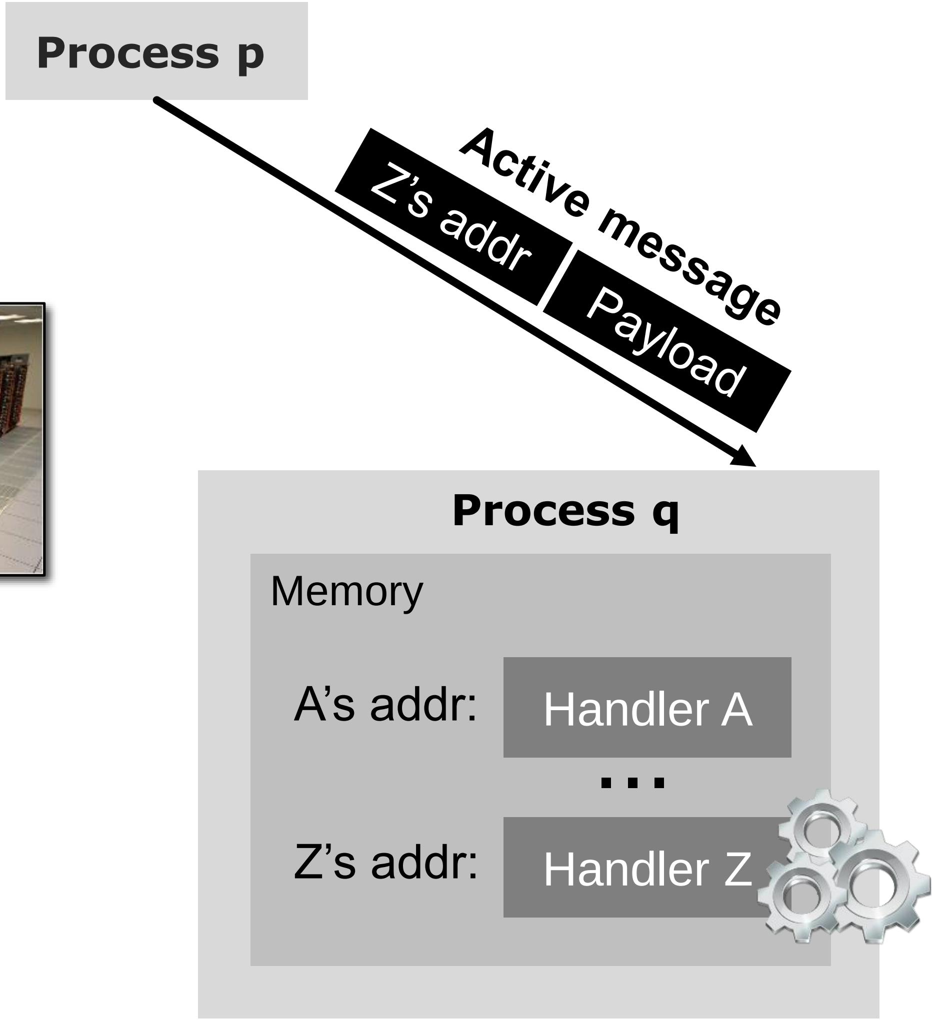


ACTIVE MESSAGES (AM)

IBM

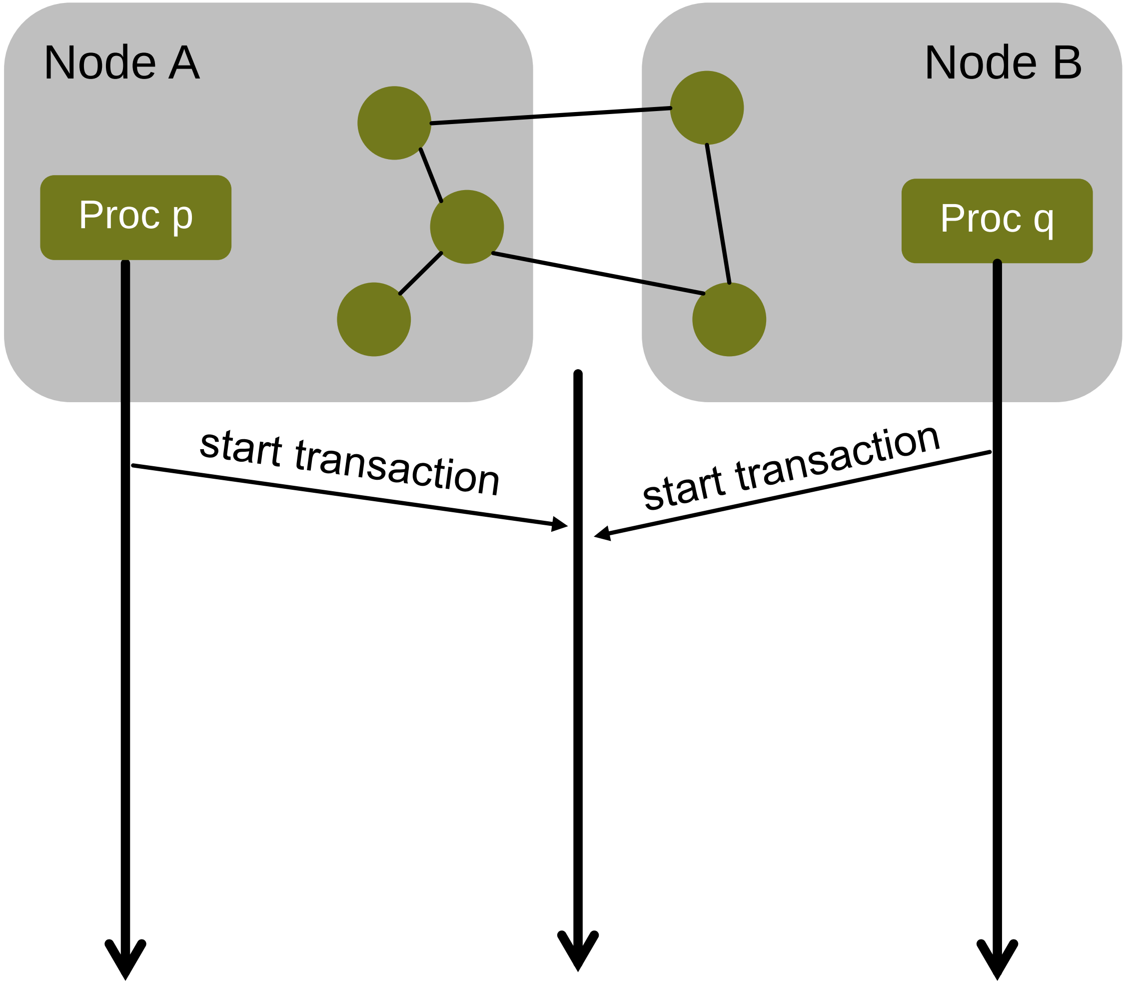
AM++[1]

GASNet [2]

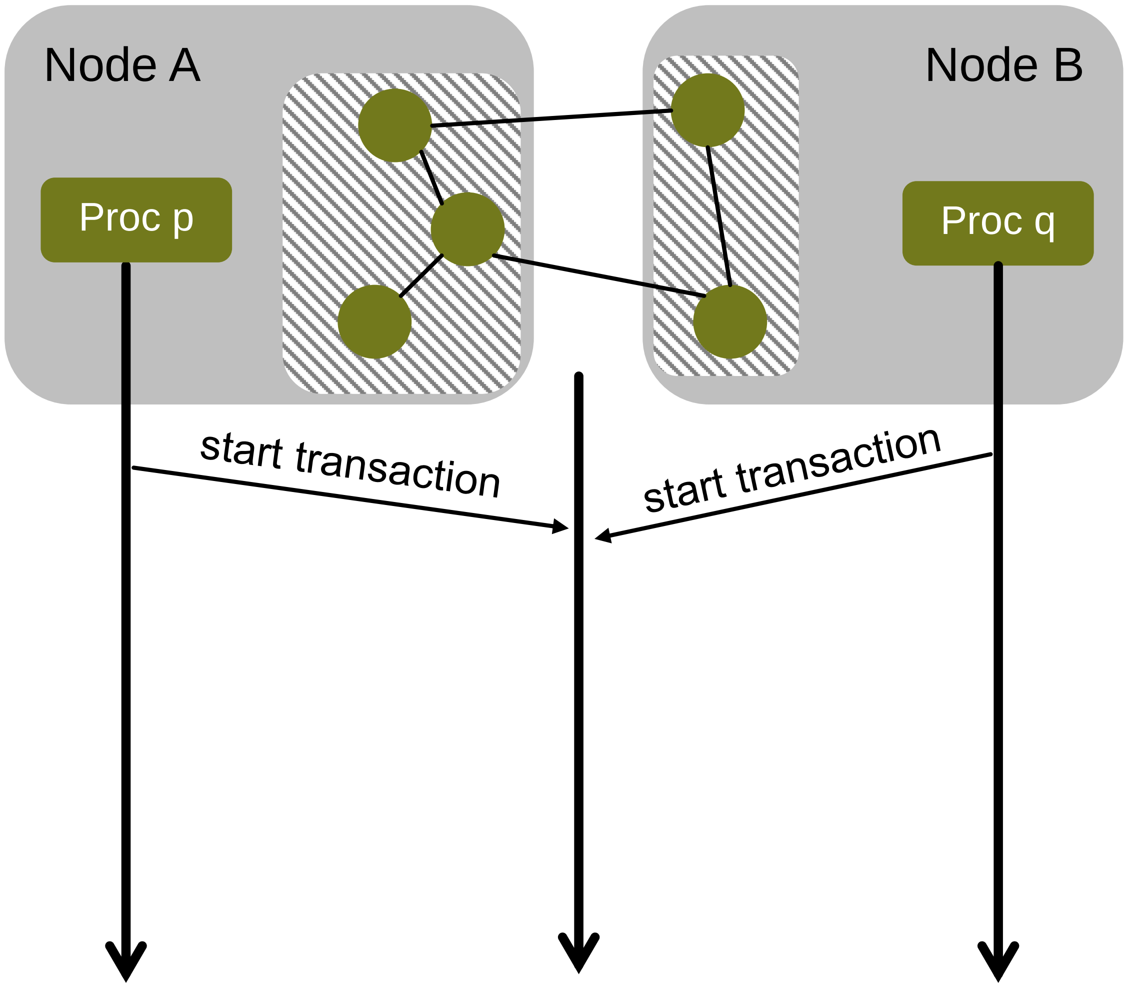


[1] J. J. Willcock et al. AM++: A generalized active message framework. PACT'10.
[2] D. Bonachea, GASNet Specification, v1.1. Berkeley Technical Report. 2002.

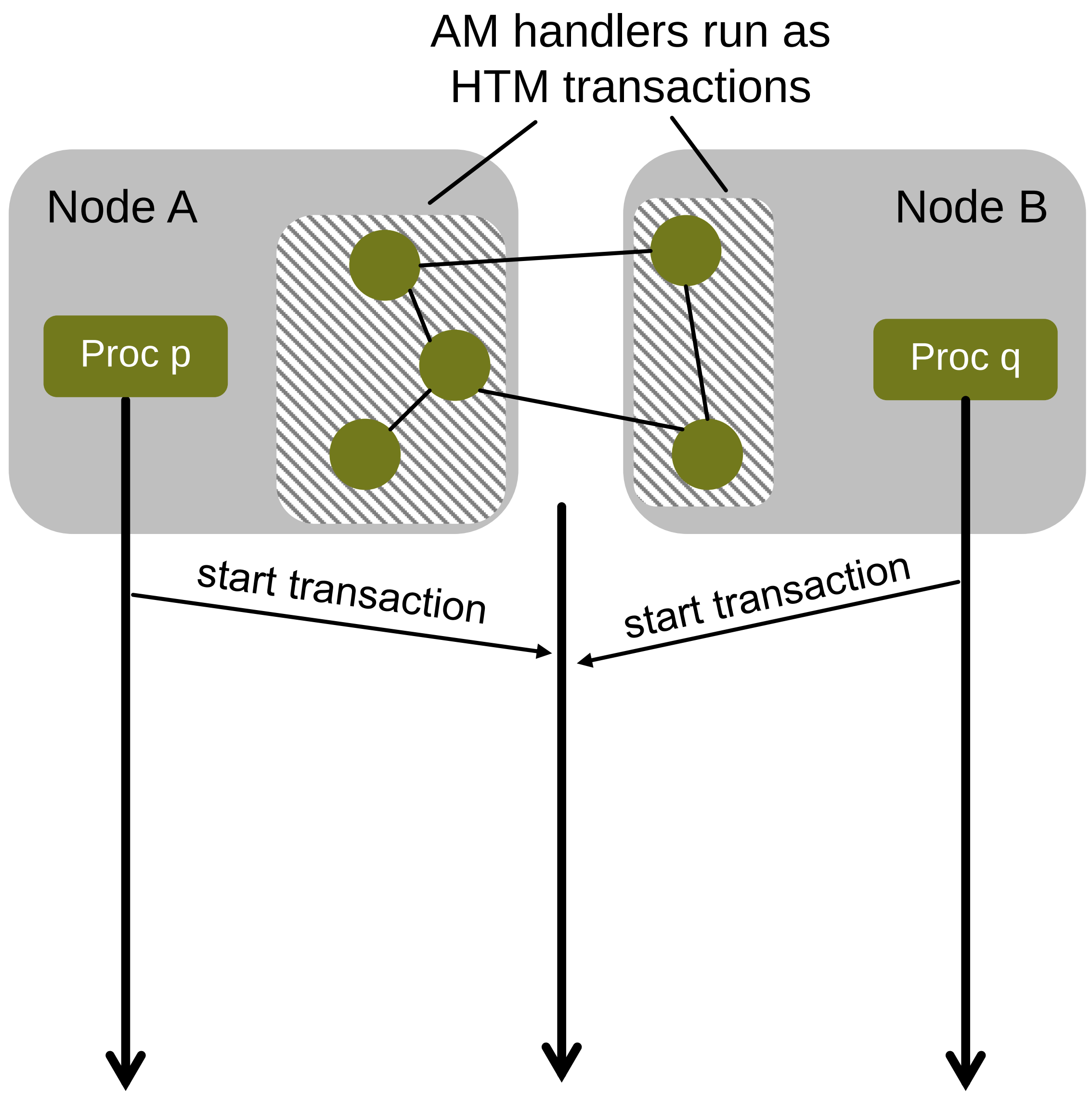
AM + HTM = ...


Node A
Node B
Proc p
Proc q
start transaction
start transaction

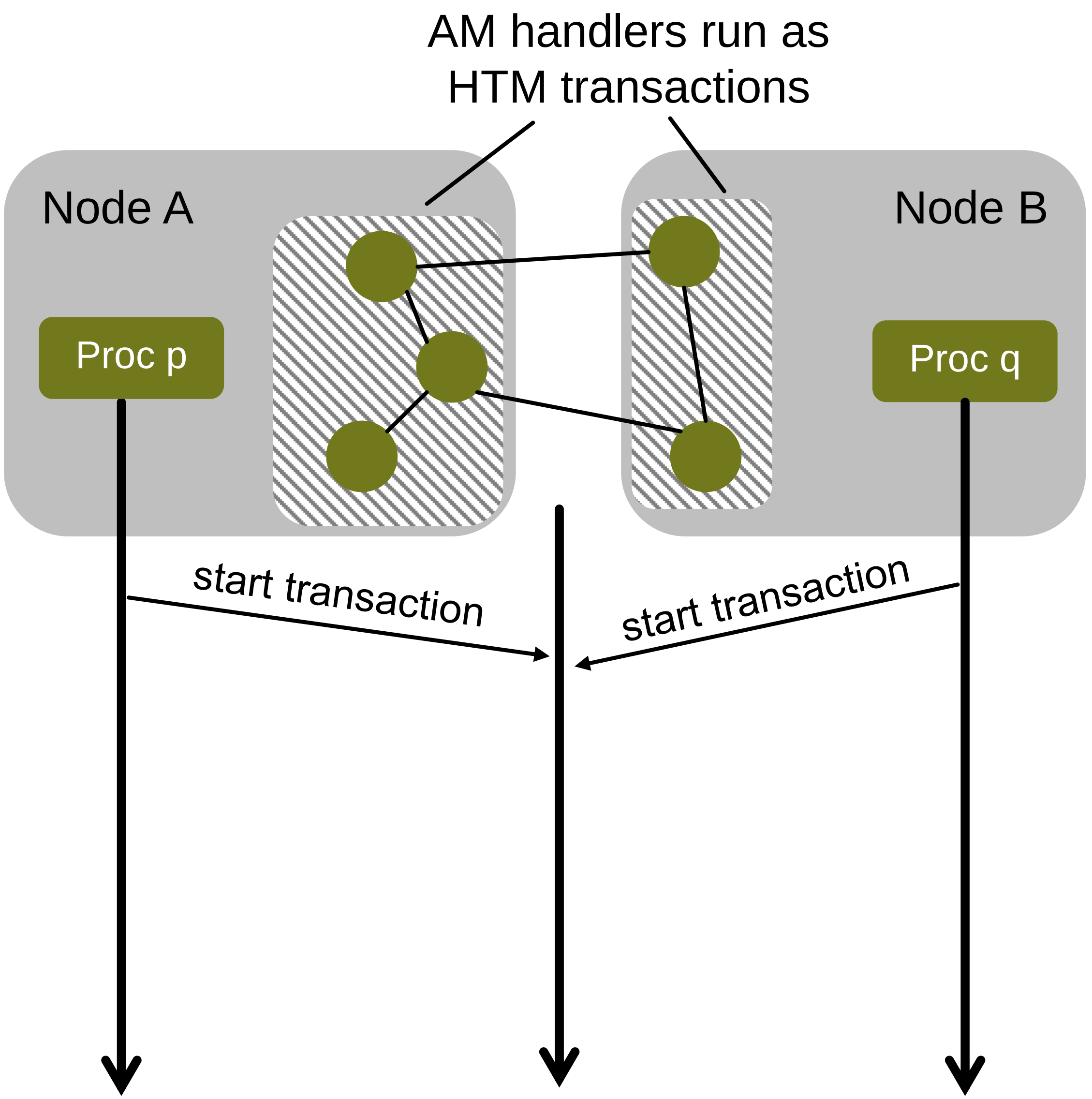
AM + HTM = ...


Node A
Node B
Proc p
Proc q
start transaction
start transaction

AM + HTM = ...

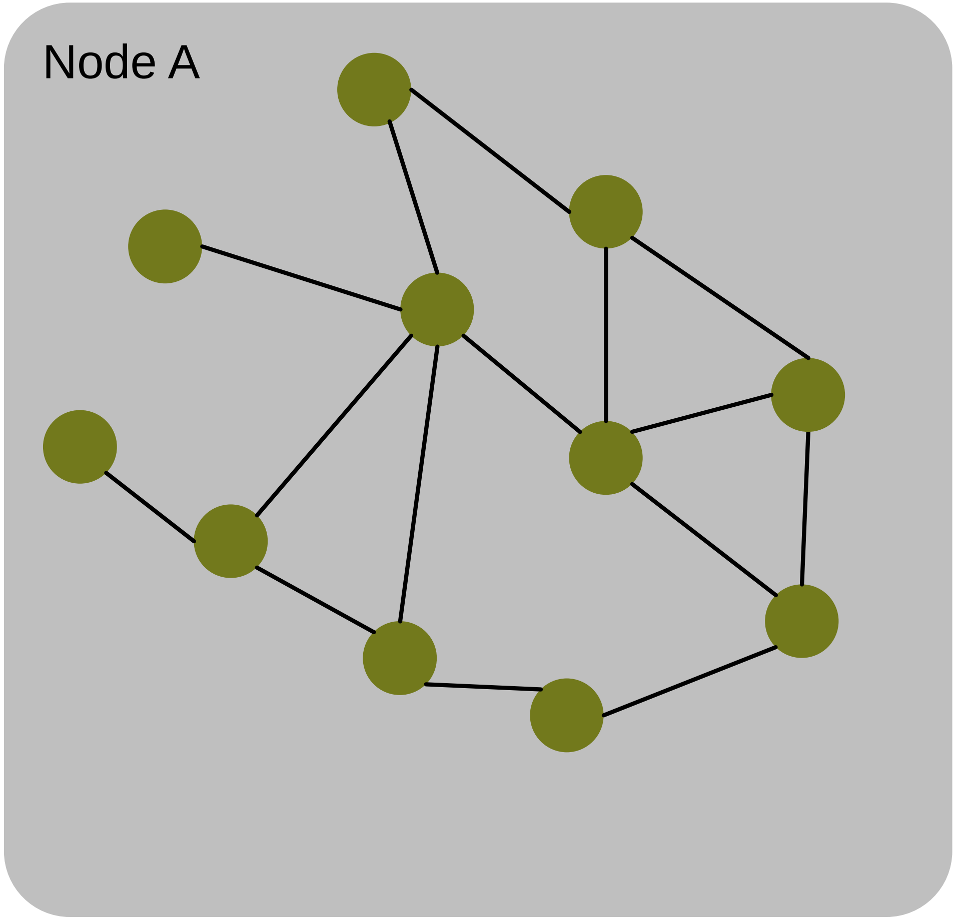

AM handlers run as
HTM transactions
Node A
Node B
Proc p
Proc q
start transaction
start transaction

AM + HTM = Atomic Active Messages

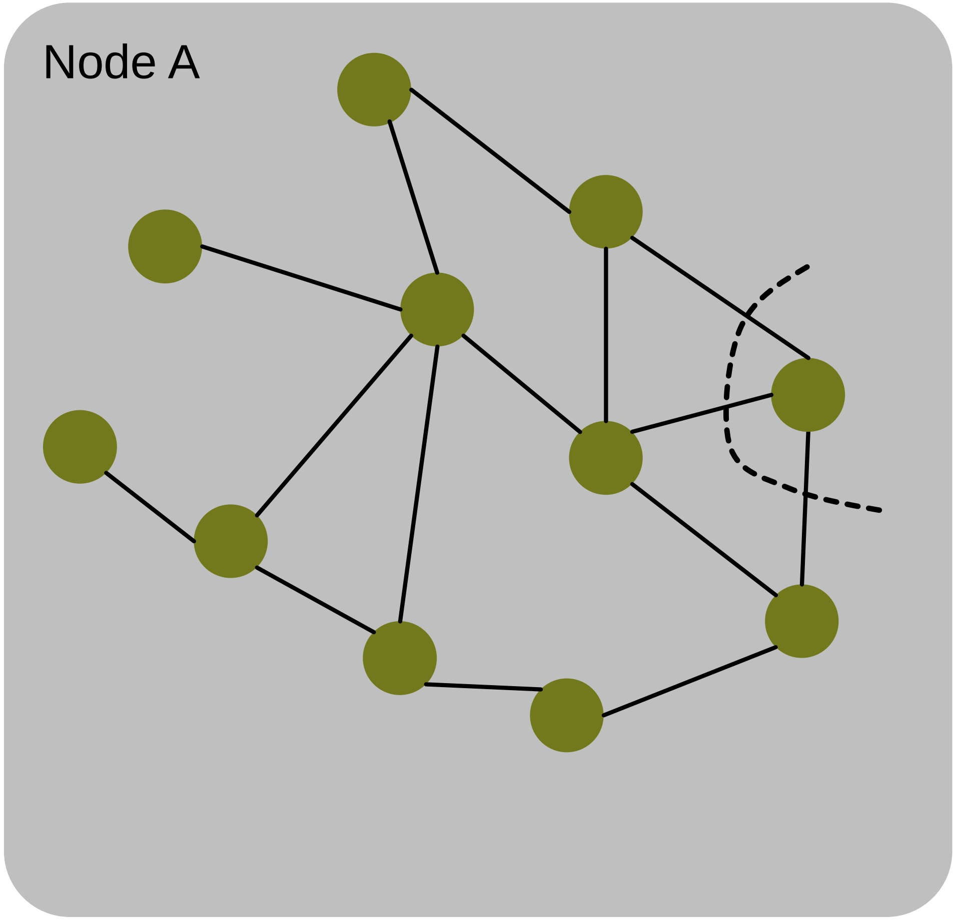


ACCESSING MULTIPLE VERTICES ATOMICALLY

Example: BFS

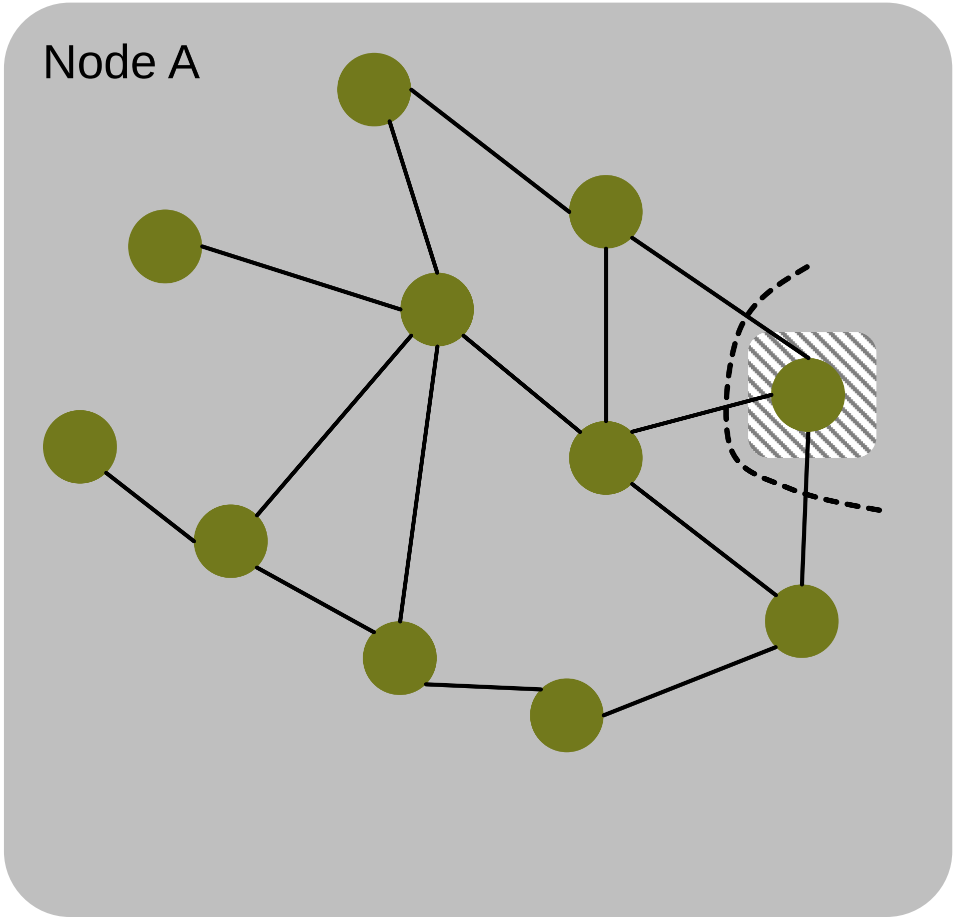


Accessing Multiple Vertices Atomically
Example: BFS



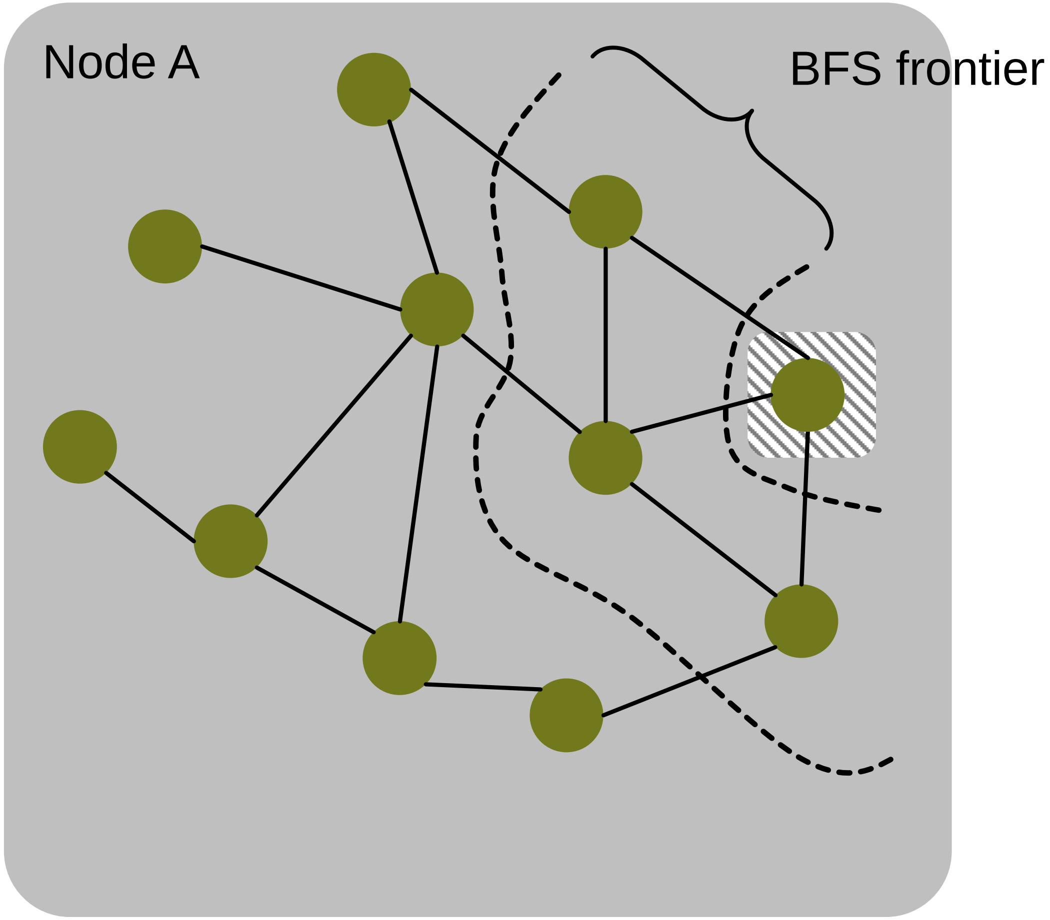
Accessing Multiple Vertices Atomically

Example: BFS



Accessing Multiple Vertices Atomically

Example: BFS



ACCESSING MULTIPLE VERTICES ATOMICALLY

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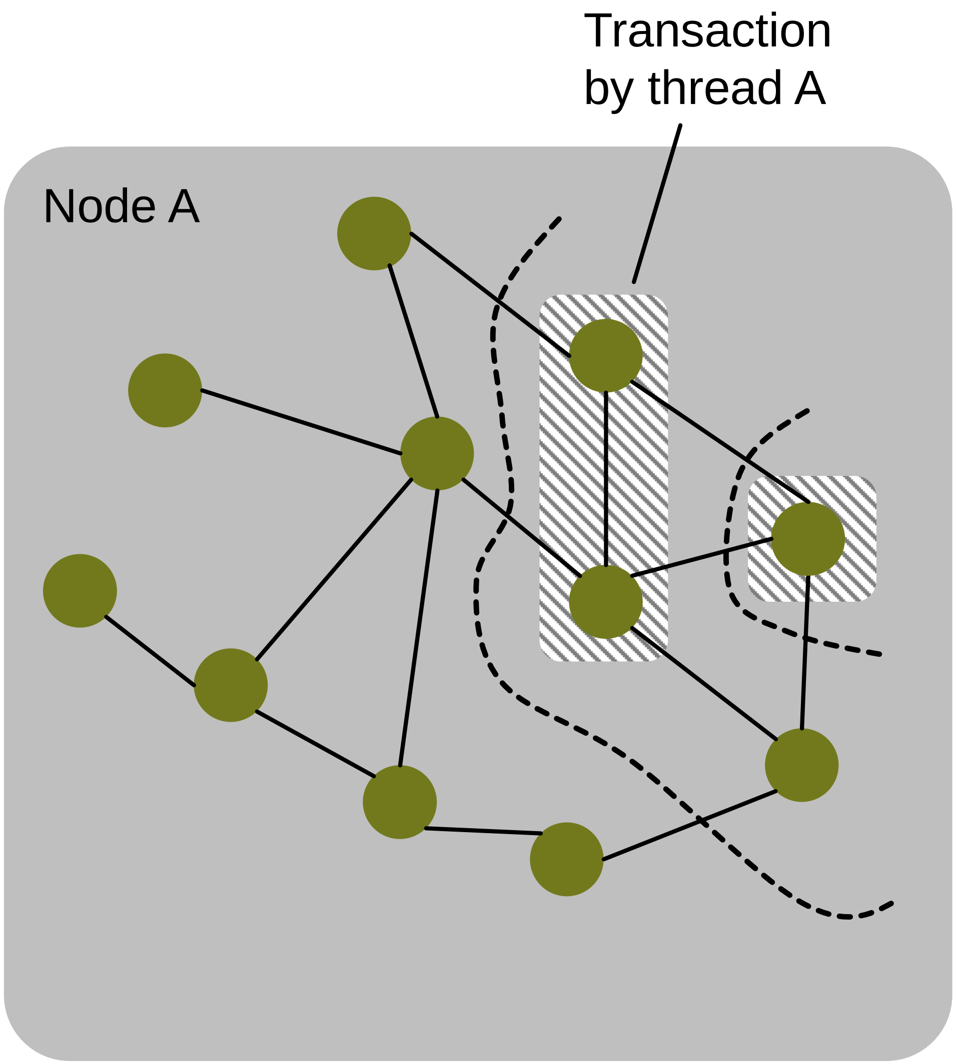

Accessing Multiple Vertices Atomically

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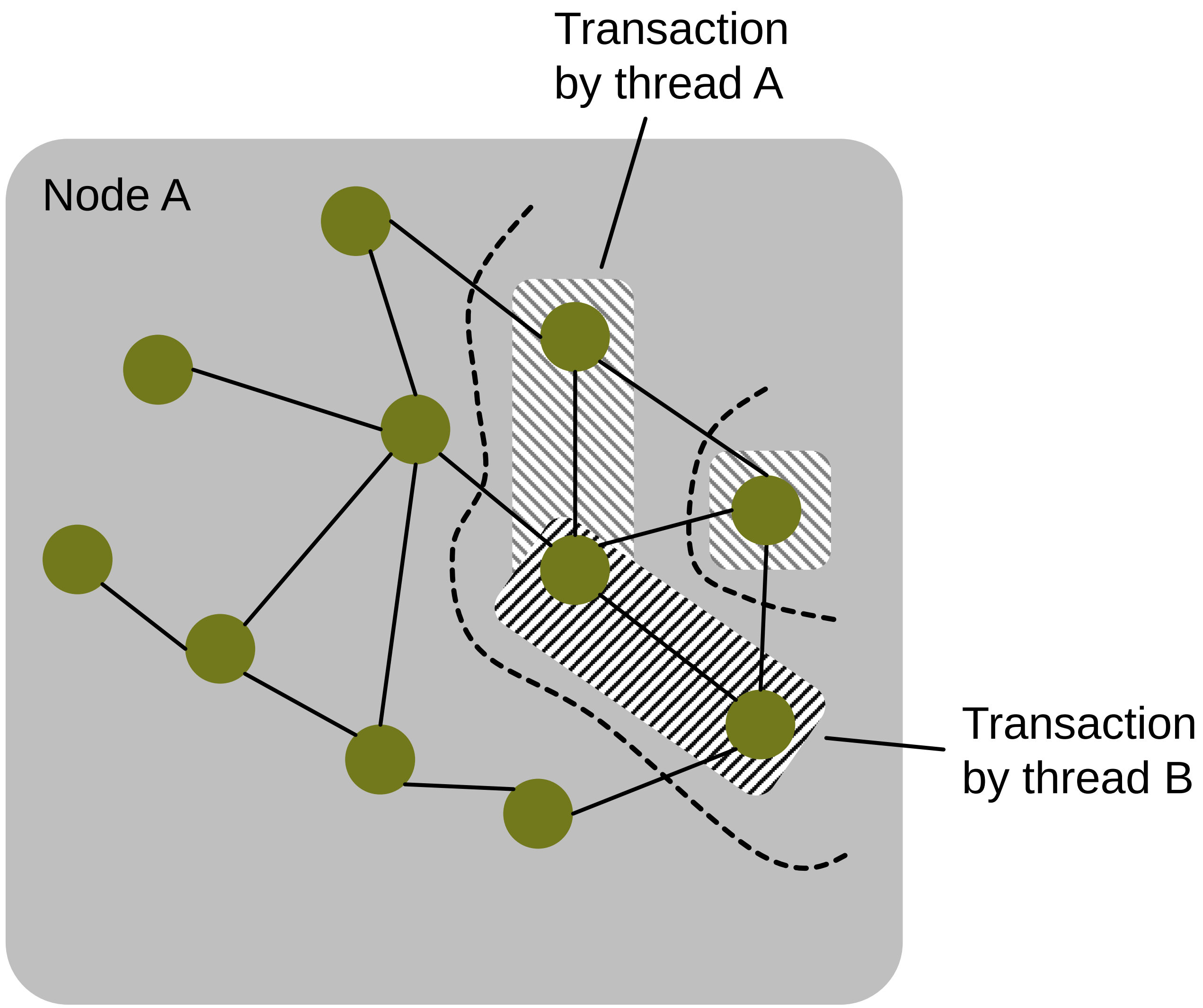
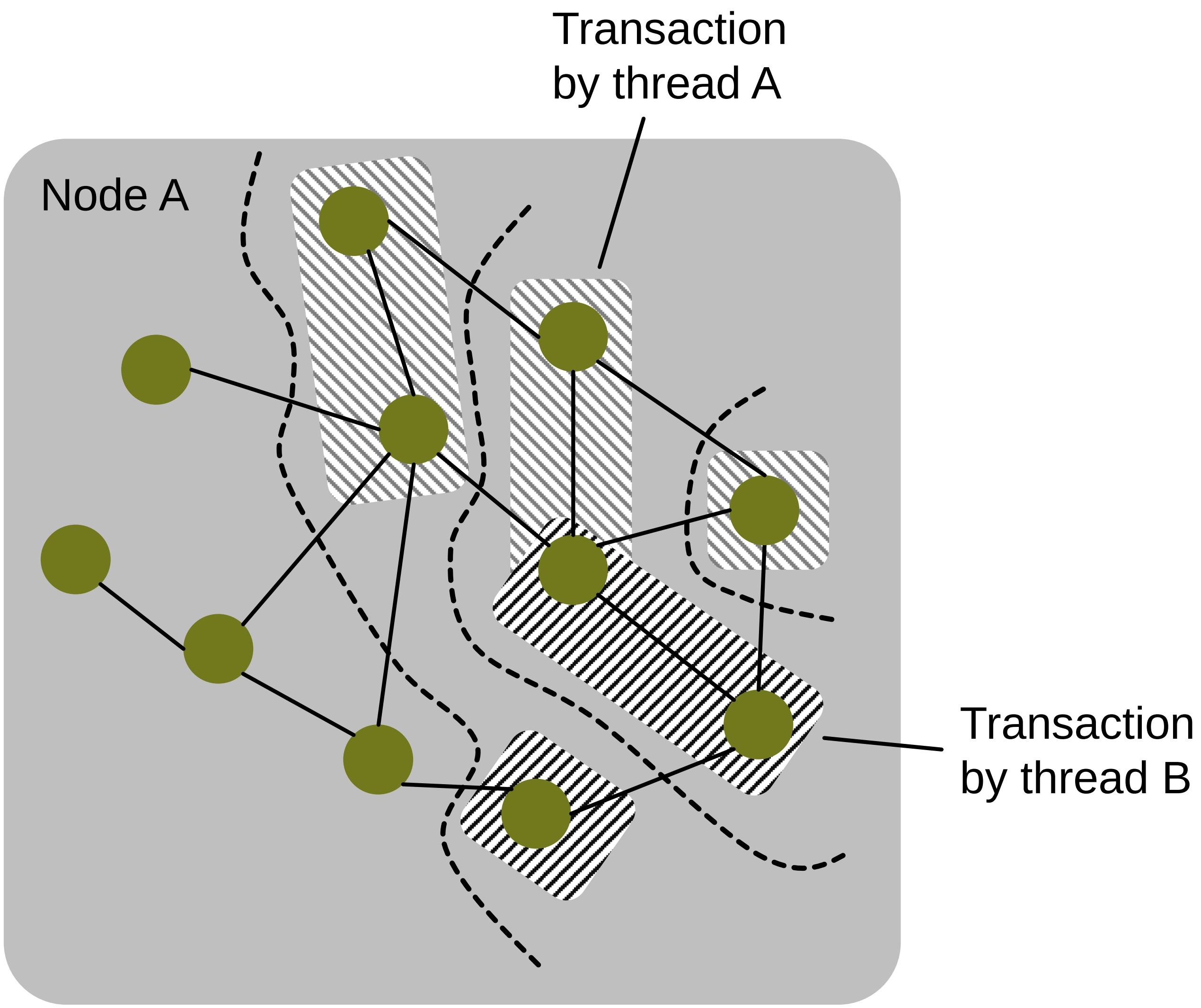
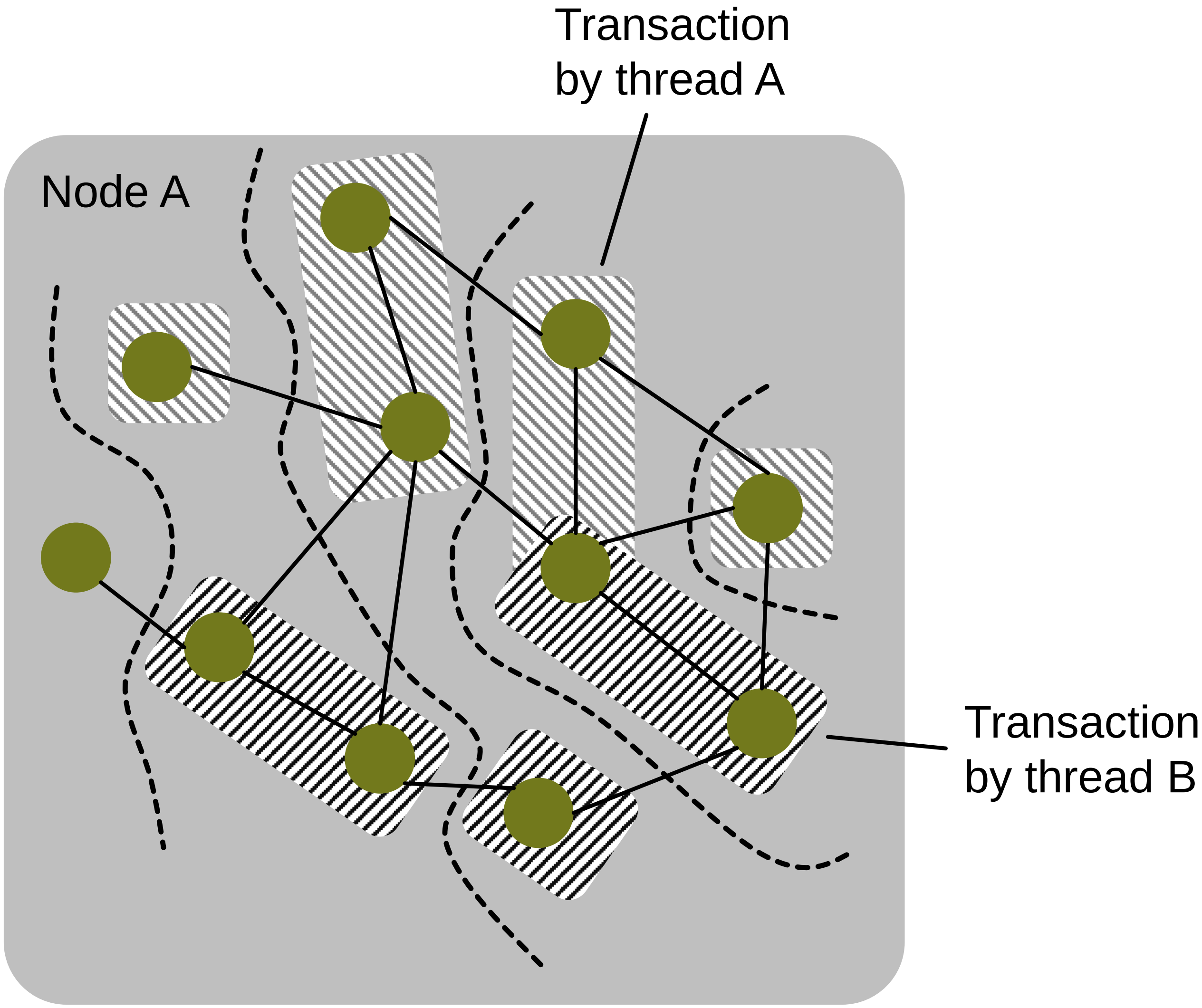


Accessing Multiple Vertices Atomically

Example: BFS



Accessing Multiple Vertices Atomically
Example: BFS



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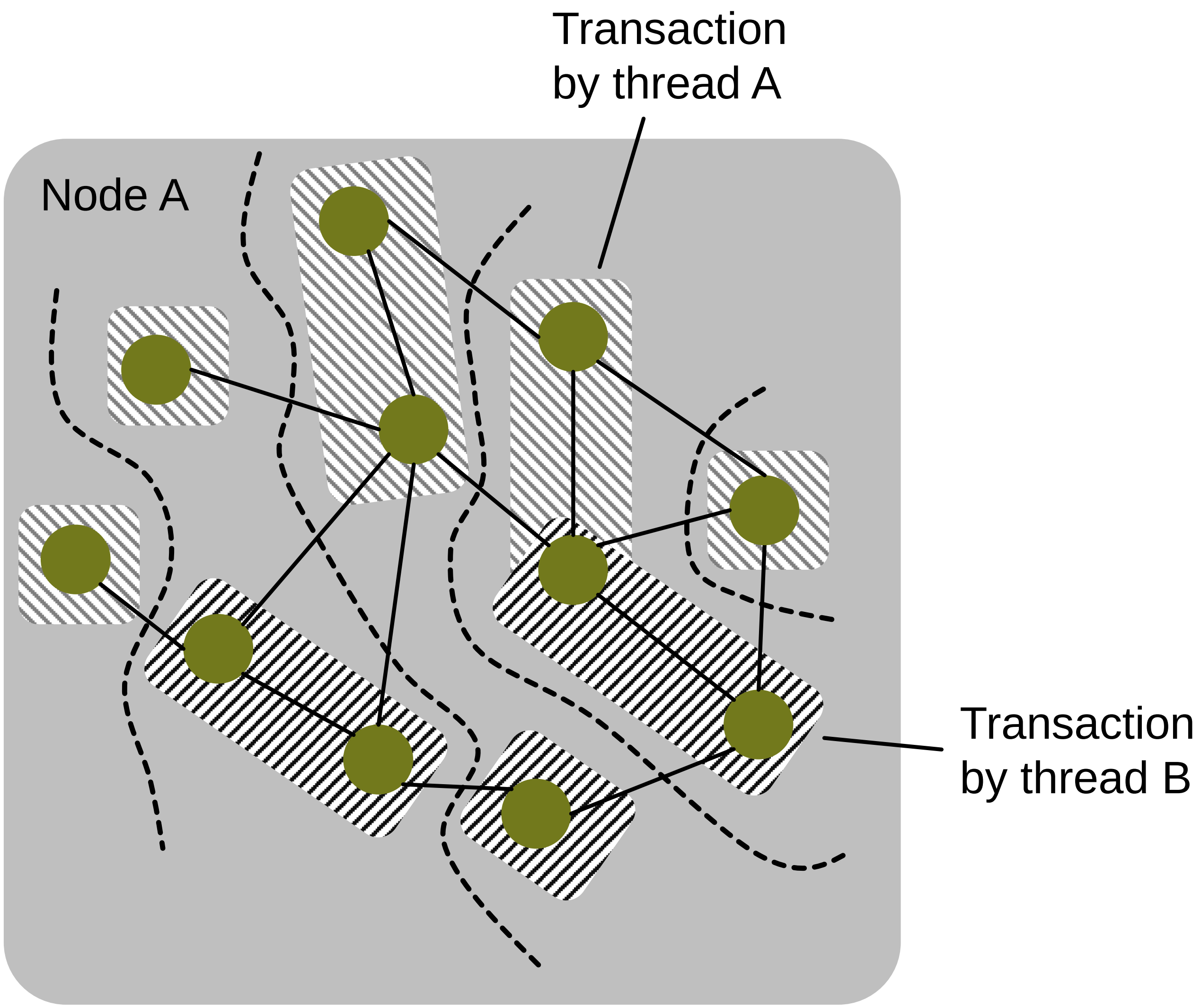
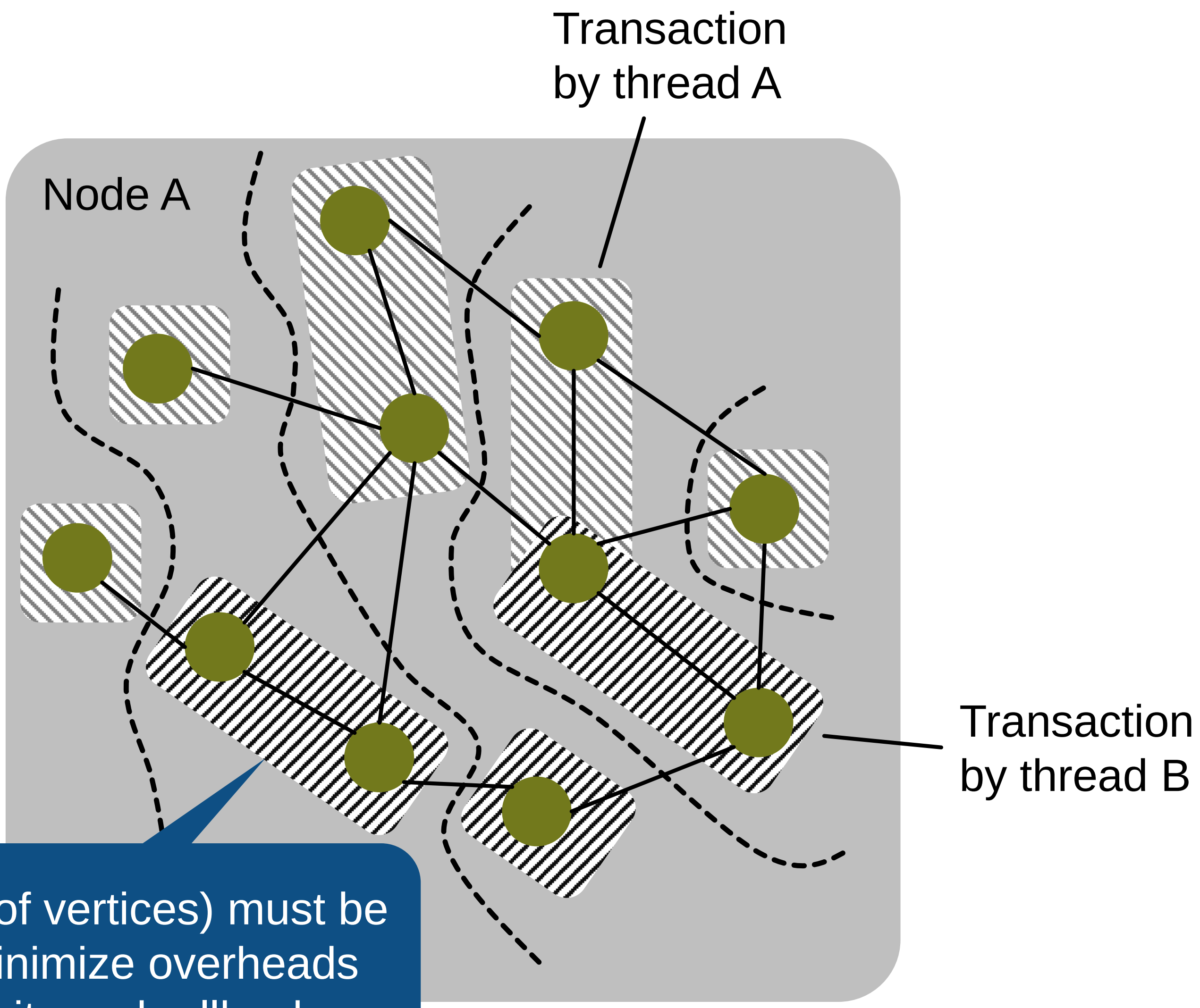


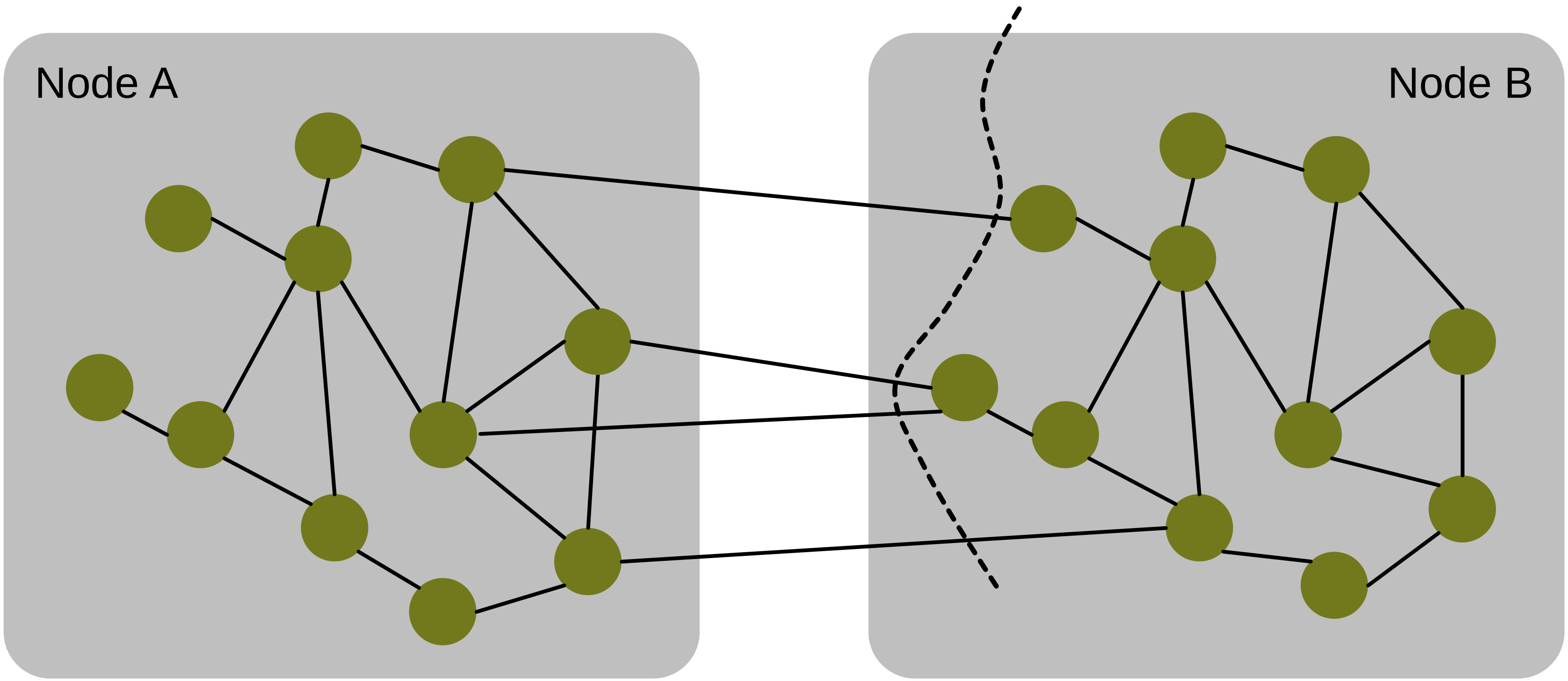
Accessing Multiple Vertices Atomically

Example: BFS



Size (the number of vertices) must be appropriate to minimize overheads from both commits and rollbacks

Transferring Transactions Across Nodes



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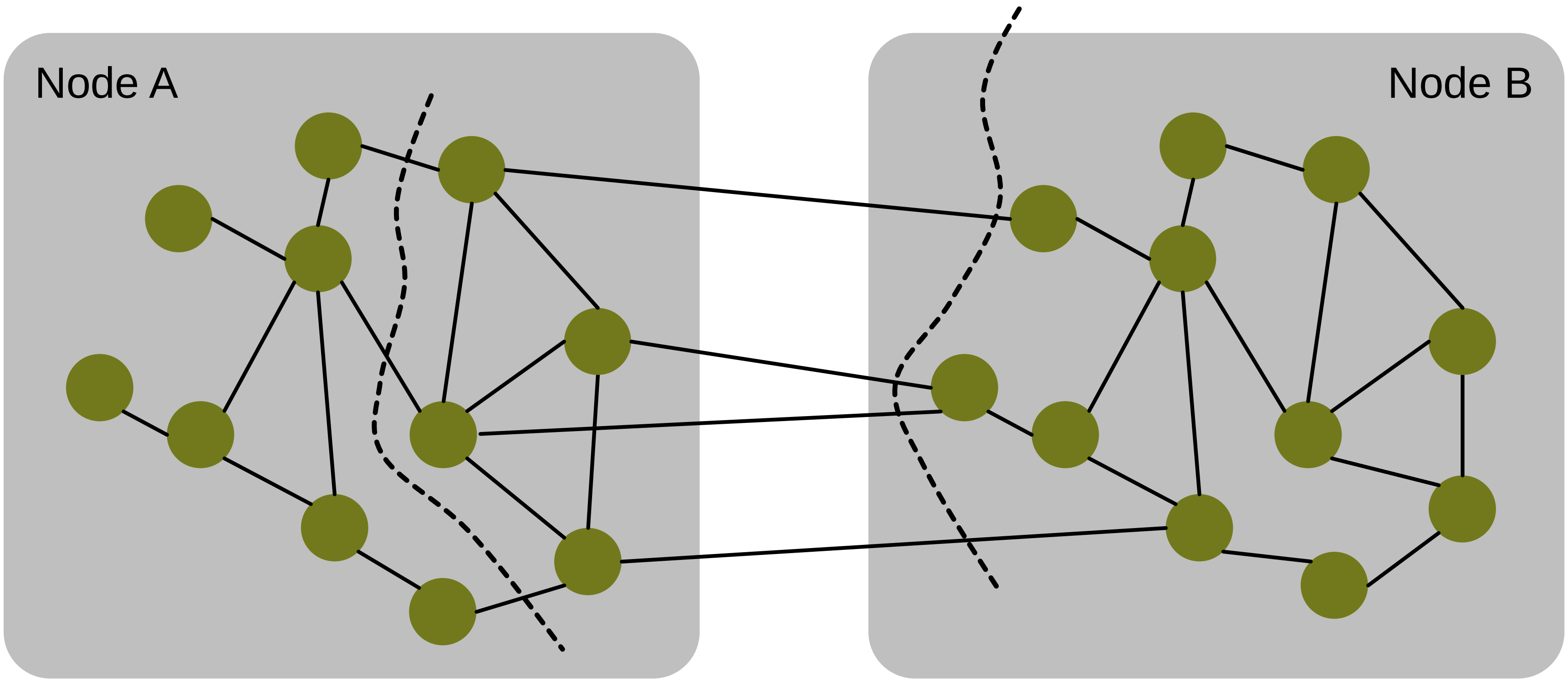
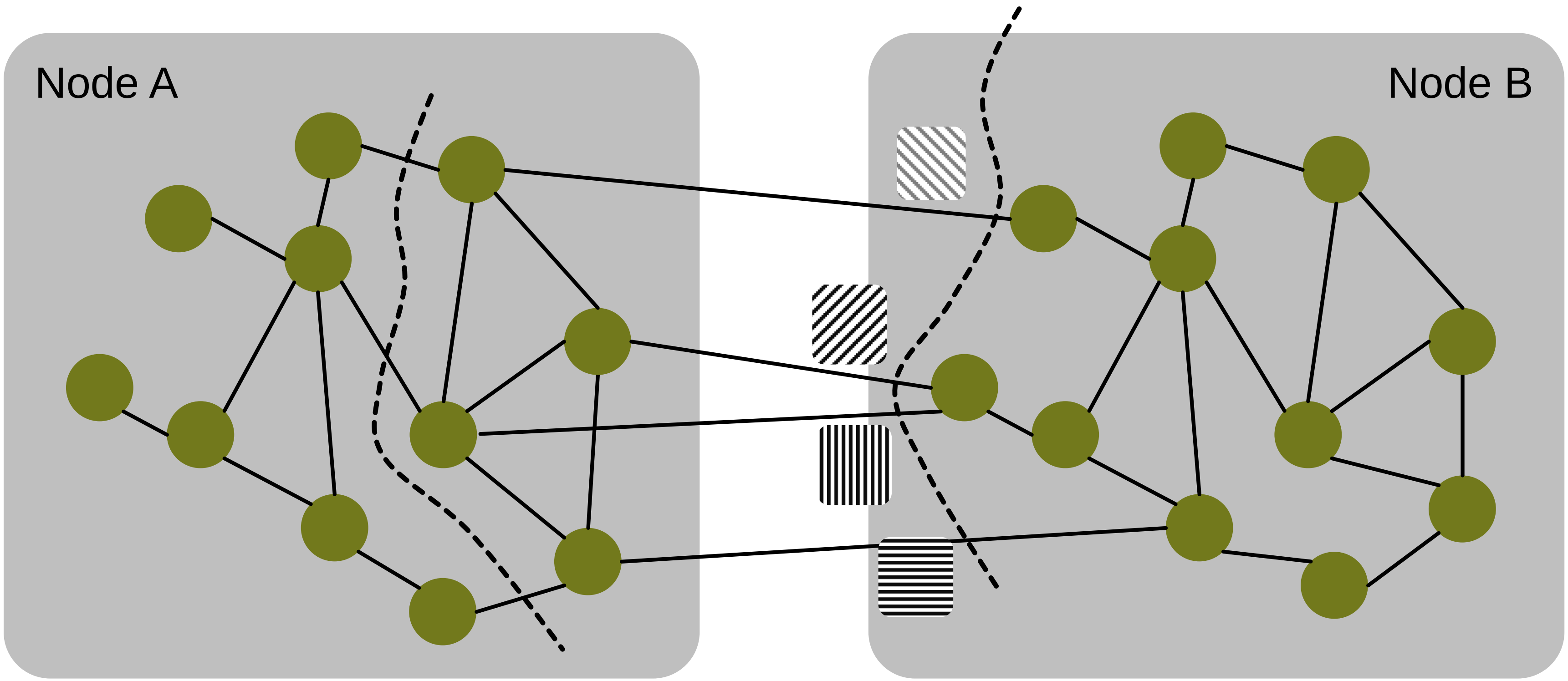
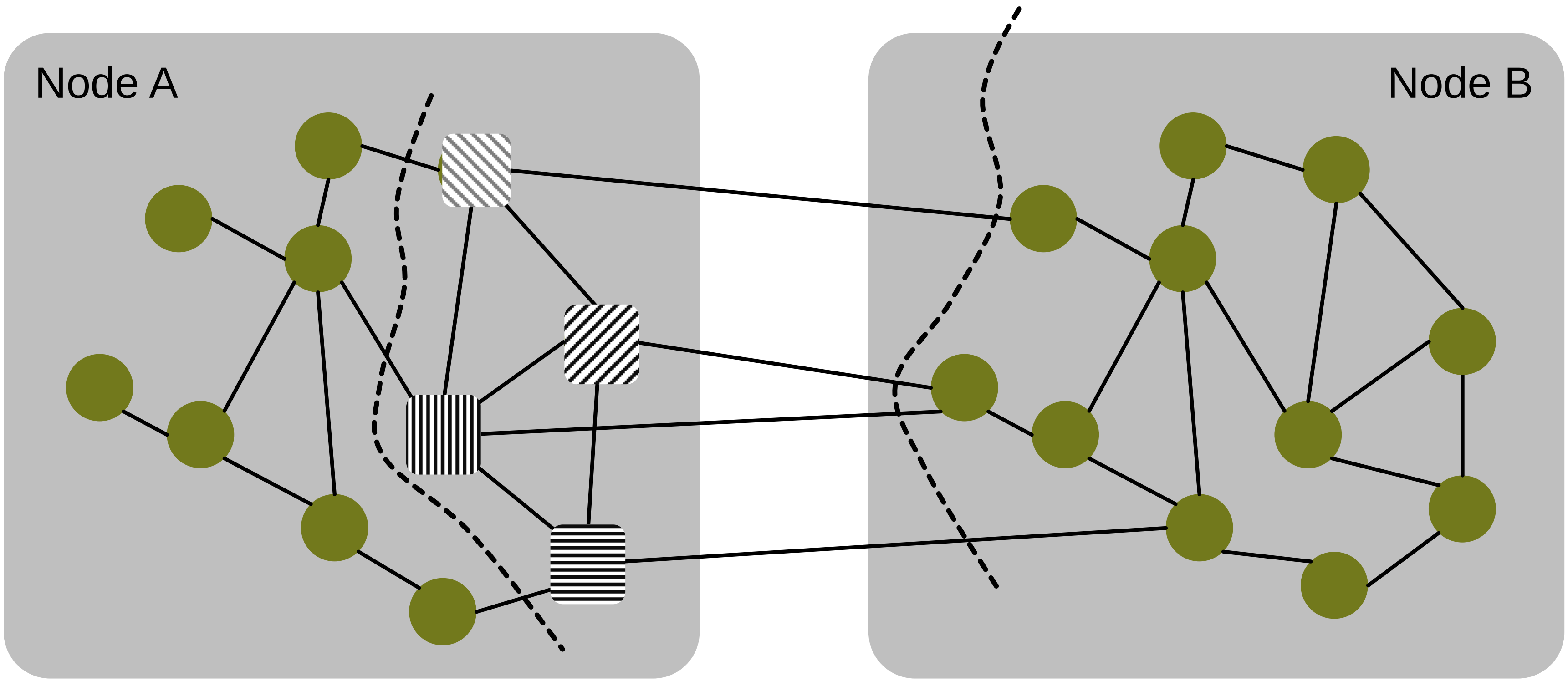


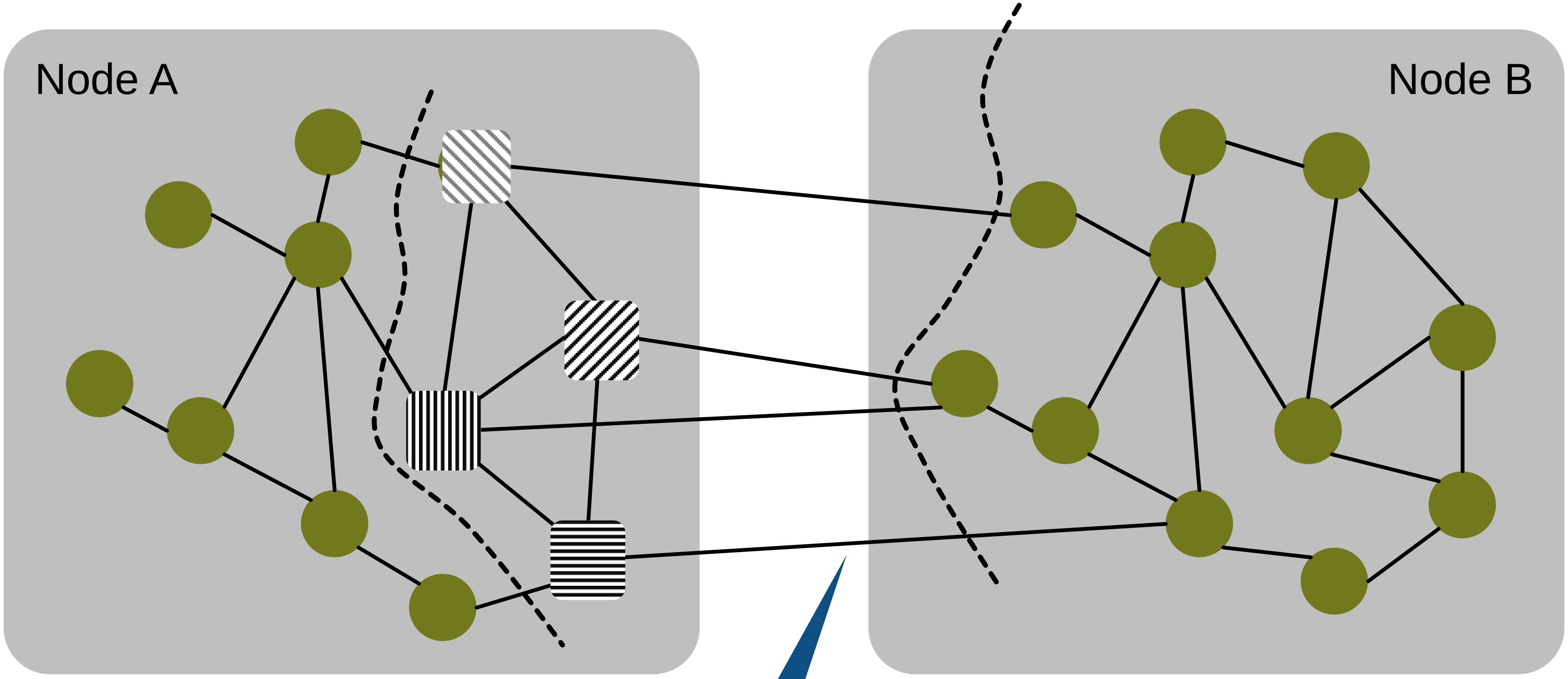
TRANSFERRING TRANSACTIONS ACROSS NODES



TRANSFERRING TRANSACTIONS ACROSS NODES

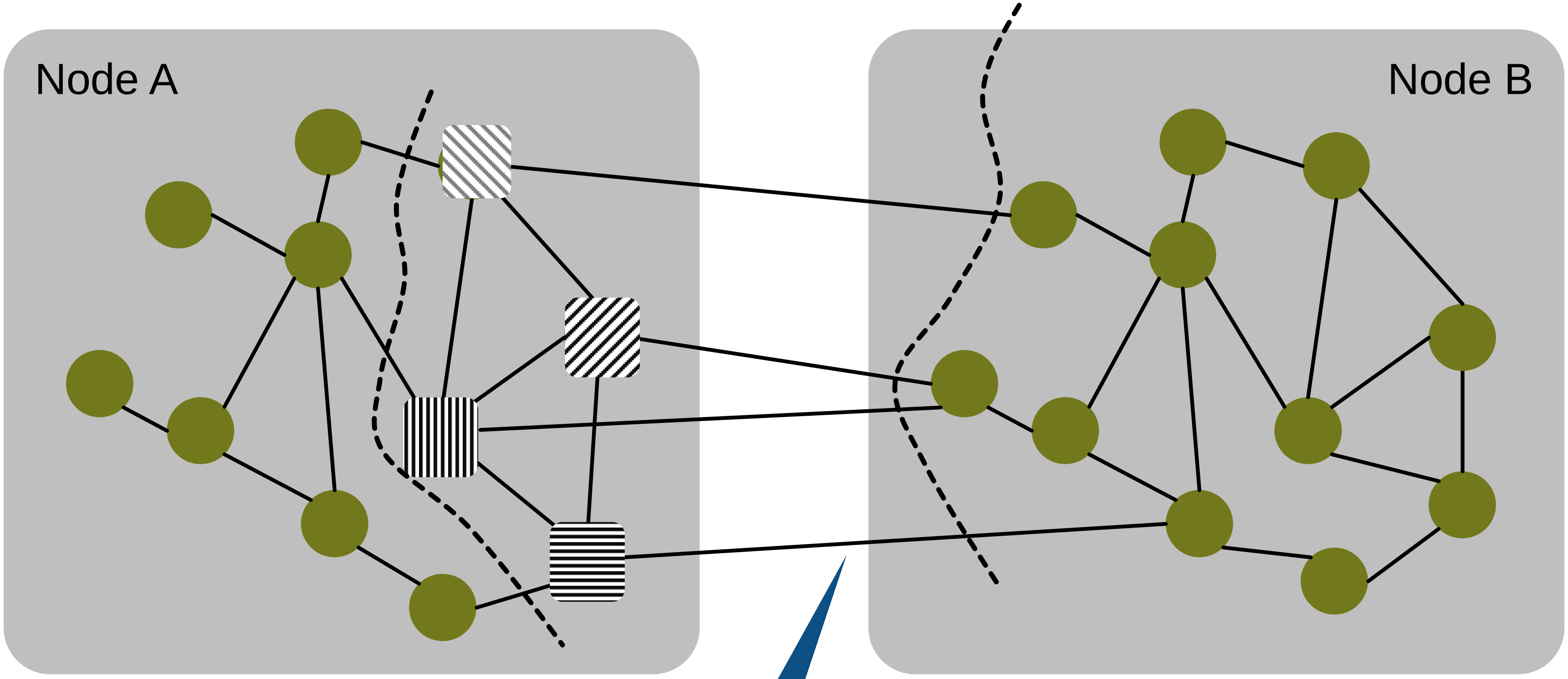


Transferring Transactions Across Nodes



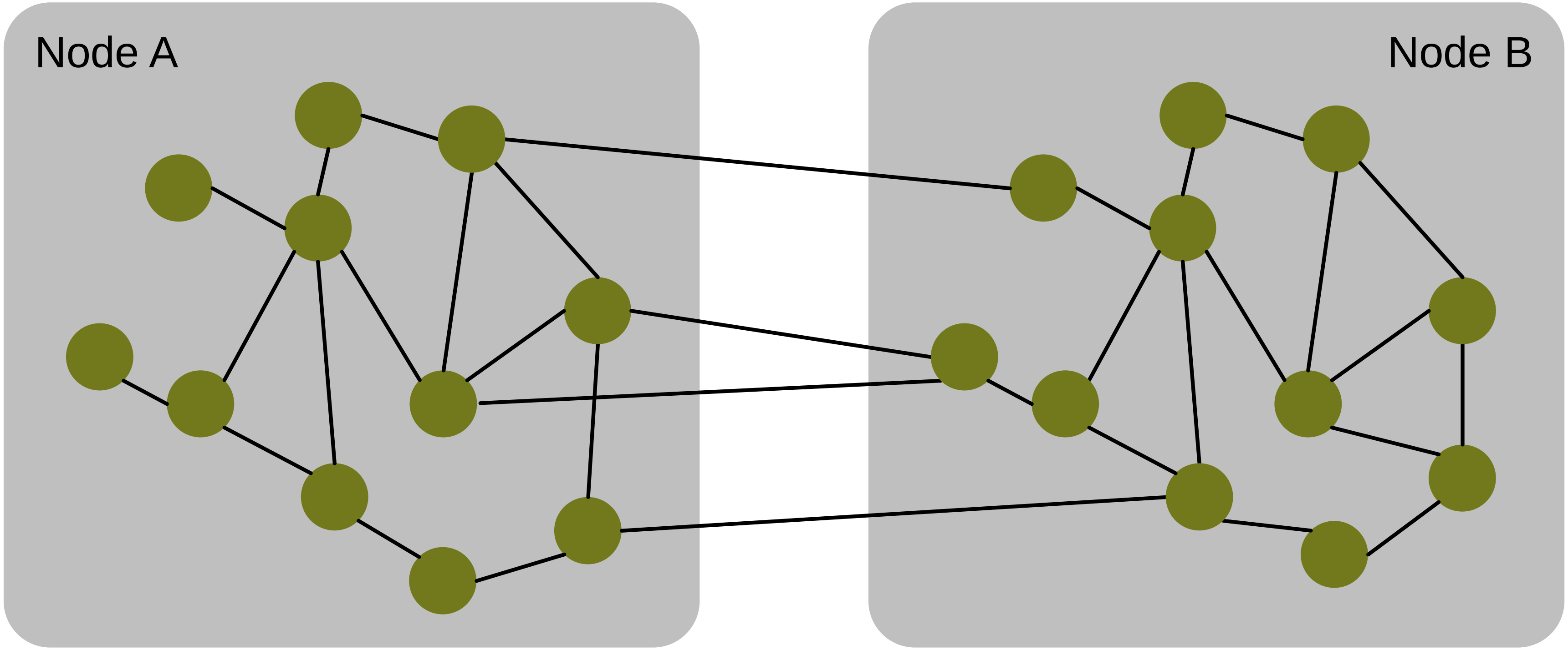
Transactions must be appropriately coalesced to minimize communication overheads

Transferring Transactions Across Nodes

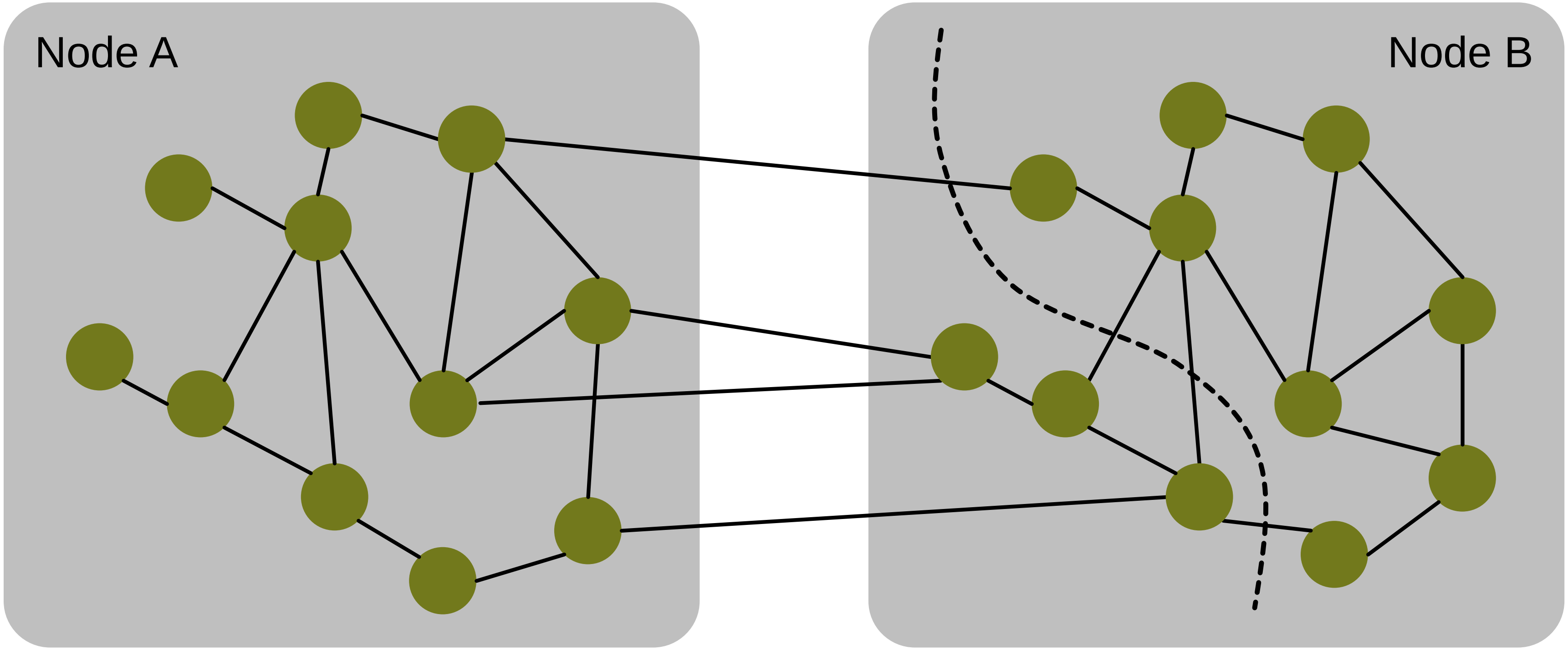


Transactions must be appropriately coalesced to minimize communication overheads

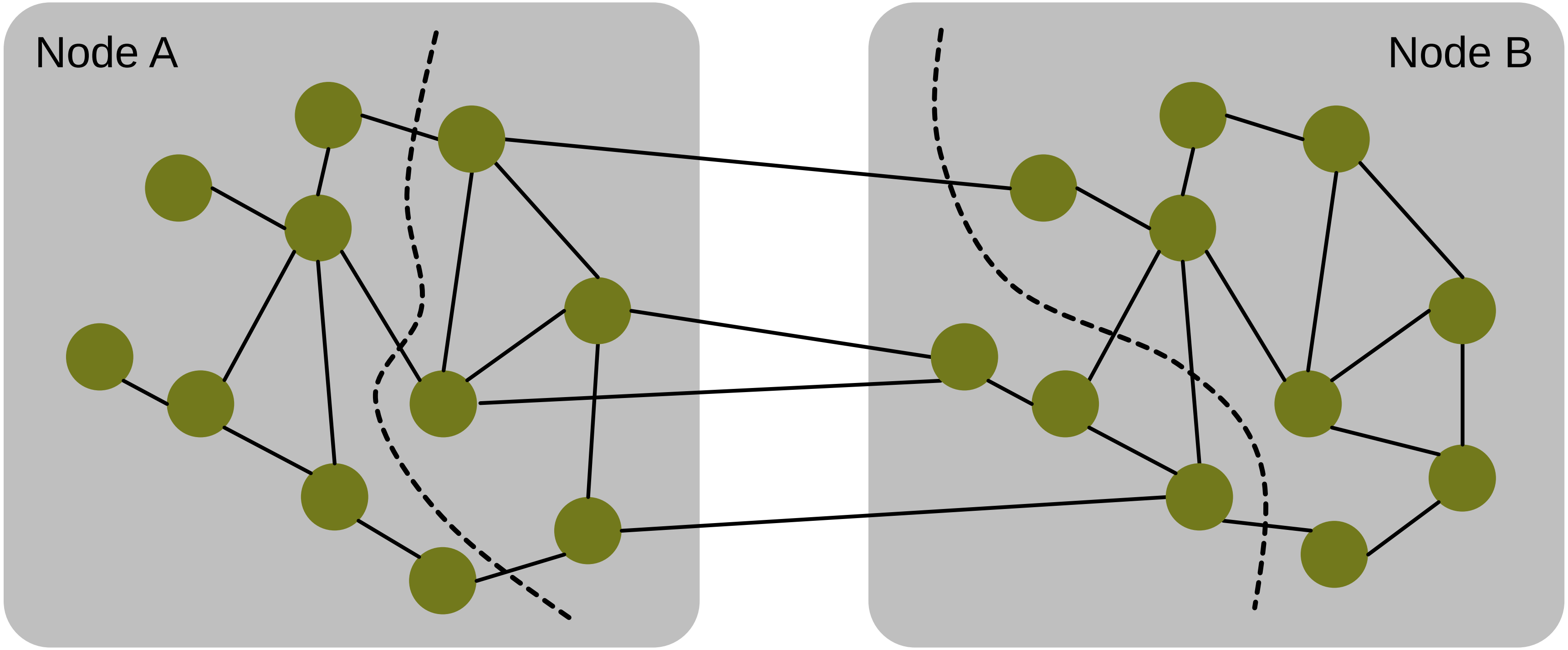
Executing Transactions on Multiple Nodes



Executing Transactions on Multiple Nodes



Executing Transactions on Multiple Nodes



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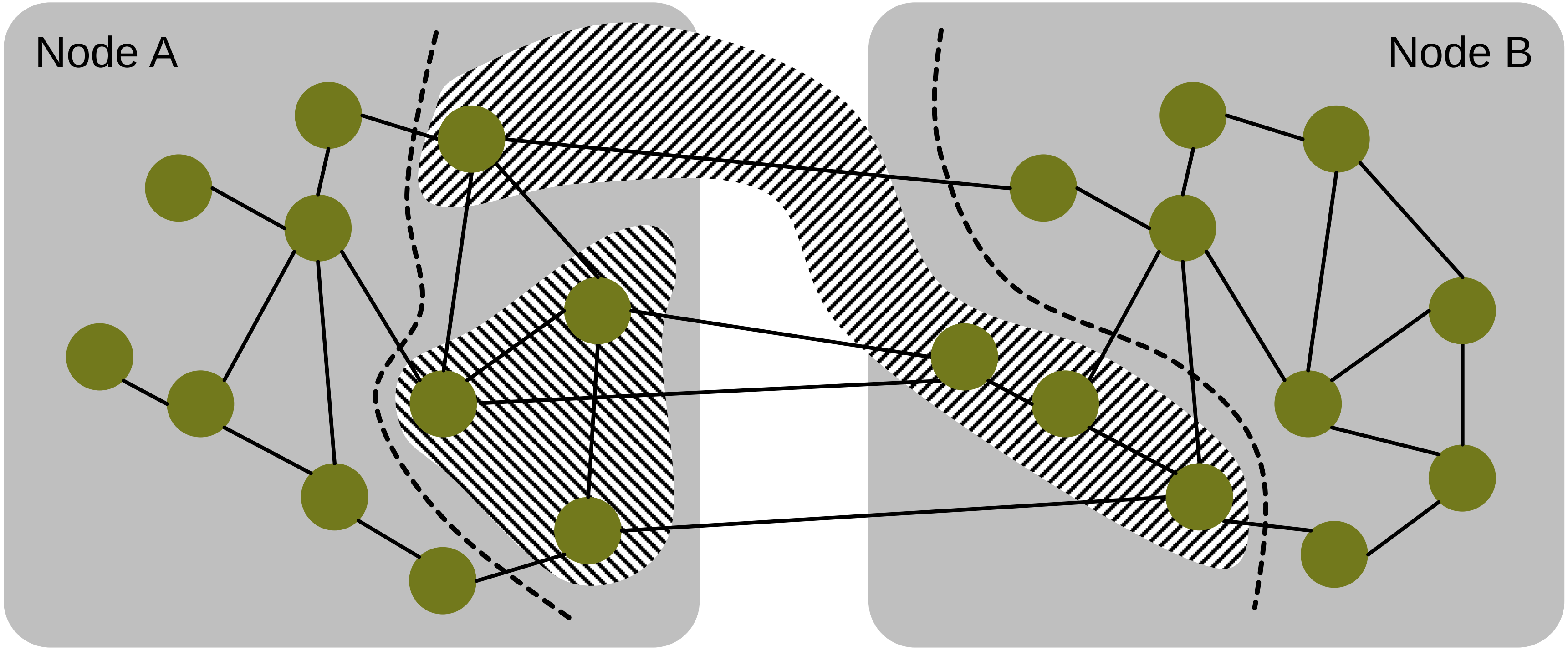

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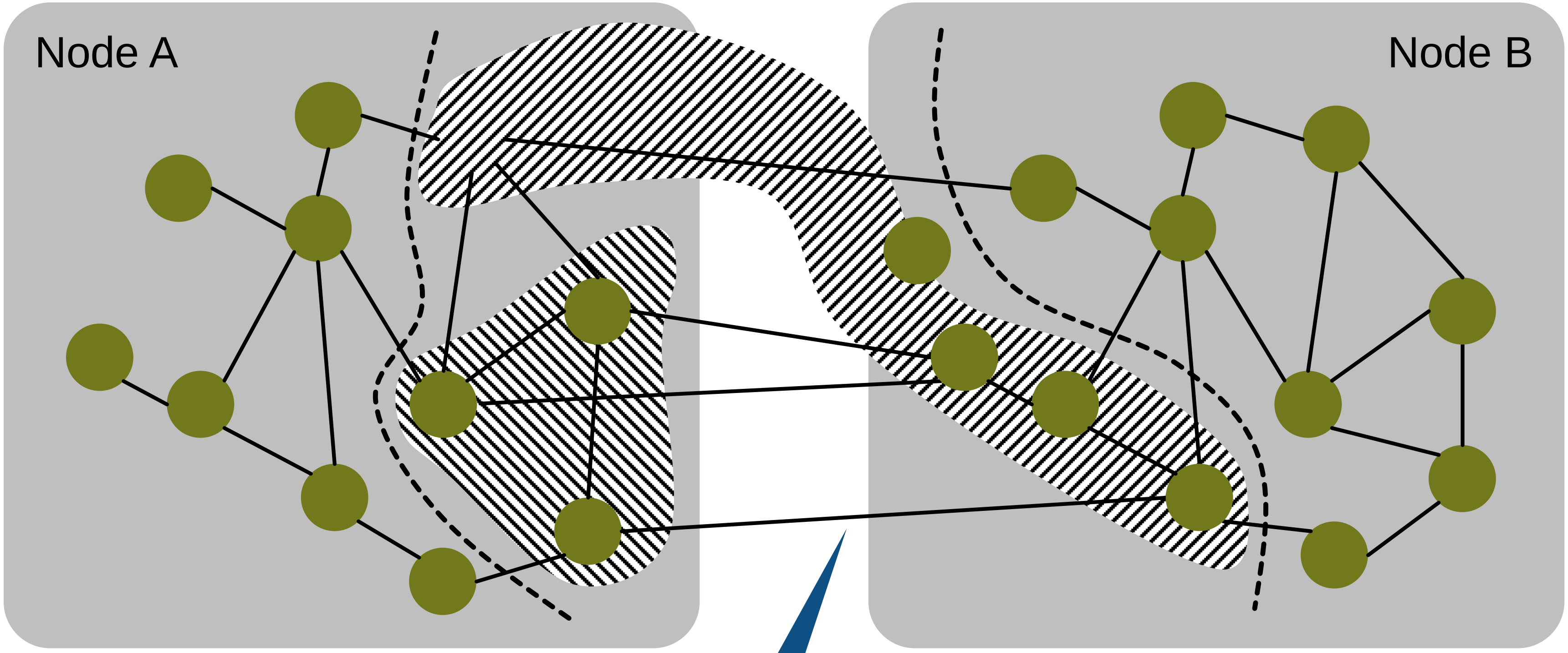
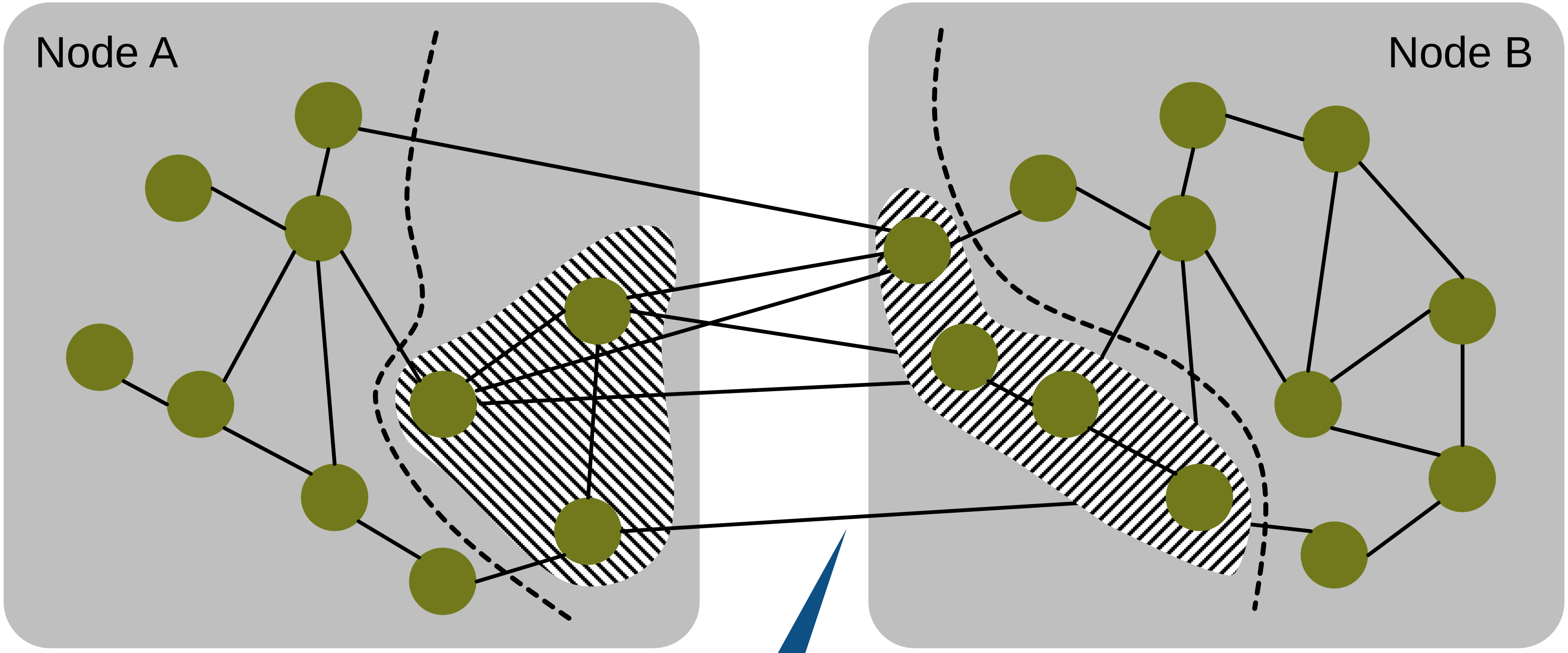


Vertices must be appropriately relocated to enable execution of a hardware transaction

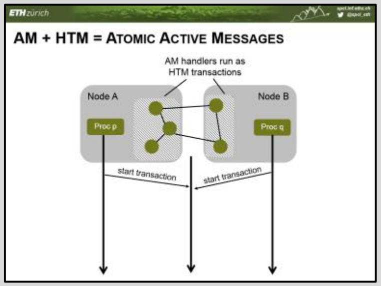
Executing Transactions on Multiple Nodes



Vertices must be appropriately relocated to enable execution of a hardware transaction

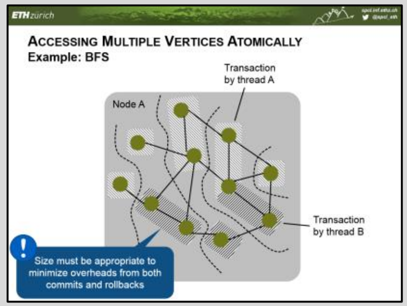
Overview of our Research

HTM for graphs in SM & DM environments

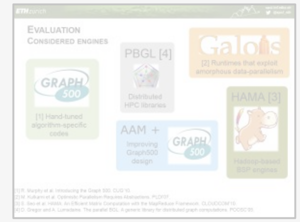


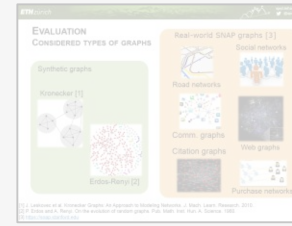
HTM + Active Messages
= Atomic Active Messages

Coarsening & coalescing



Evaluation





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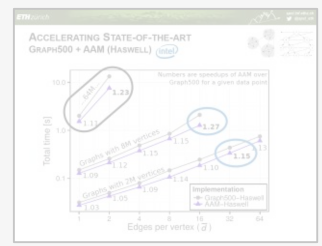

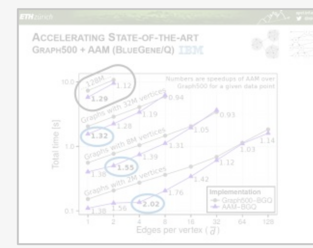

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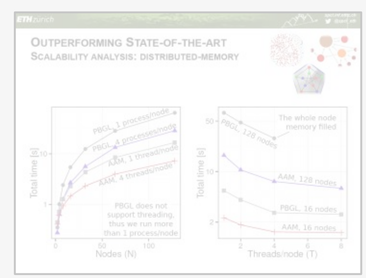
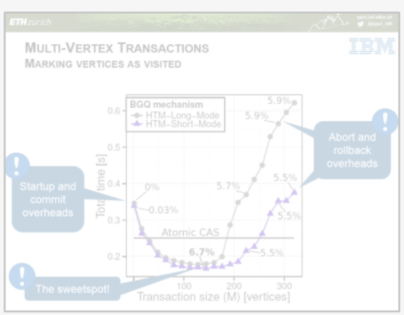
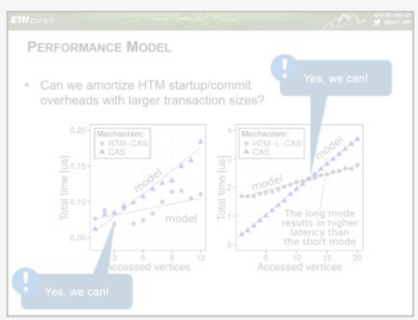


Scalability

Performance Modeling & Analysis

Haswell & BG/Q Analysis





Performance model

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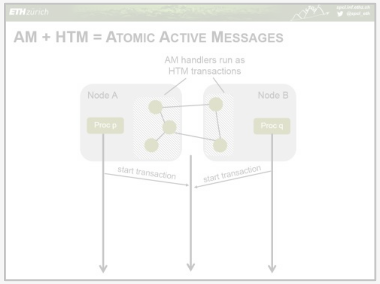

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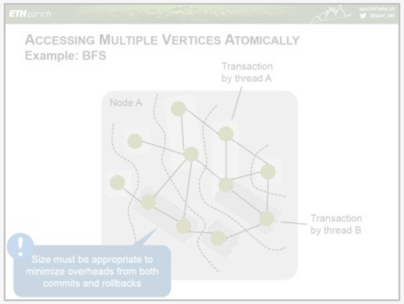

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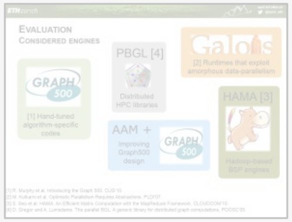

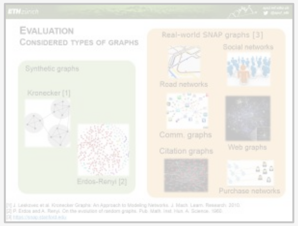

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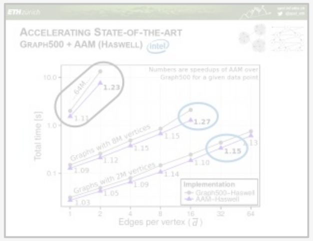

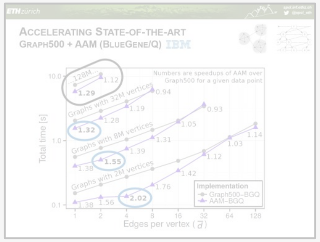

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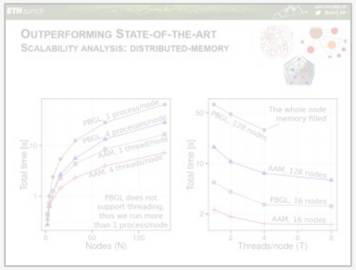

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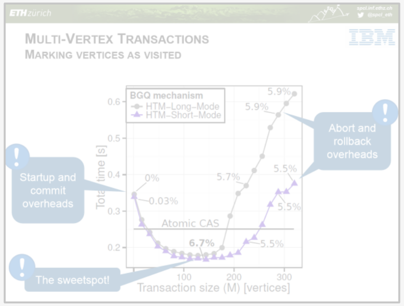

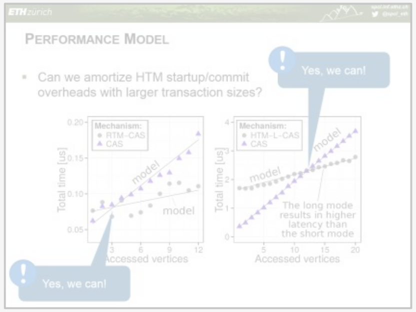

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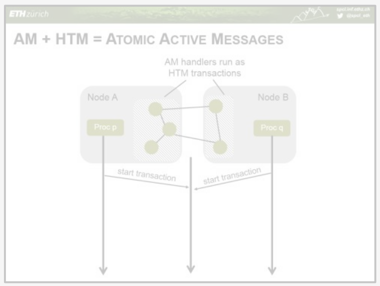

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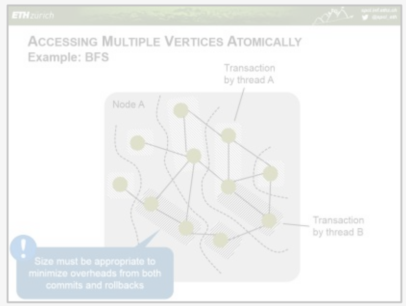

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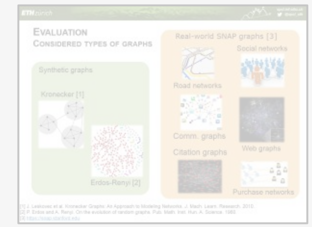

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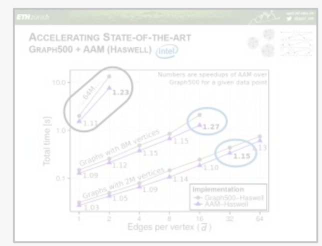

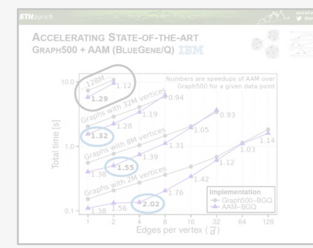

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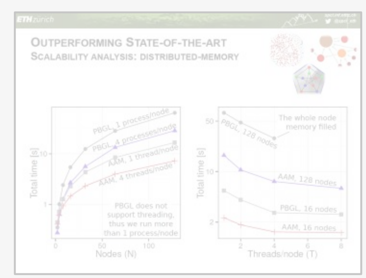

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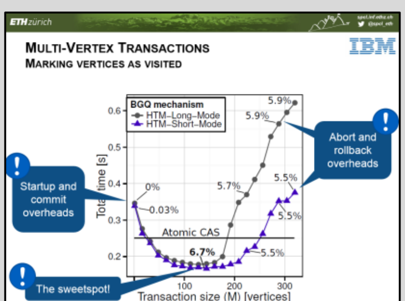

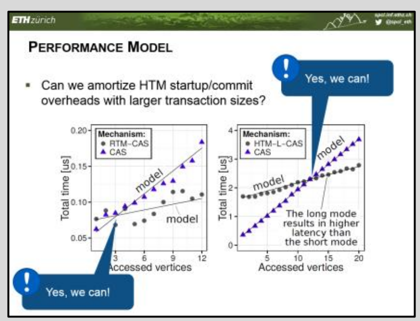

Performance model

PERFORMANCE ANALYSIS

RESEARCH QUESTIONS

Performance Analysis
Research questions

How can we implement AAM handlers to run most efficiently?

Performance Analysis

Research questions

How can we implement AAM handlers to run most efficiently?

What are performance tradeoffs related to HTM?

Performance Analysis
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What are advantages of HTM over atomics for AAM?

Performance Analysis
Research questions

How can we implement AAM handlers to run most efficiently?

What are performance tradeoffs related to HTM?

What are advantages of HTM over atomics for AAM?

What are the optimal transaction sizes? Can we amortize transaction overheads?

Performance Analysis

Types of machines

PERFORMANCE ANALYSIS
TYPES OF MACHINES

- Evaluation on 3 machines

PERFORMANCE ANALYSIS
TYPES OF MACHINES

- Evaluation on 3 machines
  - Intel Haswell server

Performance Analysis
Types of machines

- Evaluation on 3 machines
  - Intel Haswell server
  - InfiniBand cluster

HPC clusters

Commodity machines

Performance Analysis
Types of machines

- Evaluation on 3 machines
  - Intel Haswell server
  - InfiniBand cluster
  - IBM BlueGene/Q


HPC clusters

Commodity machines


Supercomputing machines

Performance Analysis

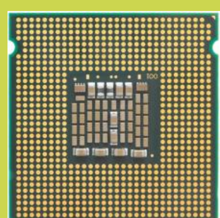
Considered mechanisms

Performance Analysis
Considered mechanisms

Haswell HTM

Performance Analysis
Considered mechanisms

Haswell HTM

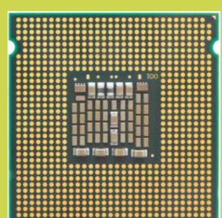


L1 L1

Deployed in L1

Performance Analysis
Considered mechanisms

Haswell HTM



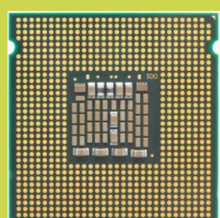
L1 L1

32KB per core

Deployed in L1

Performance Analysis
Considered mechanisms

Haswell HTM



L1 L1

32KB per core

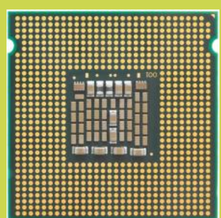
Deployed in L1

8-way associative

Performance Analysis

Considered mechanisms

Haswell HTM



L1 L1

32KB per core

Deployed in L1

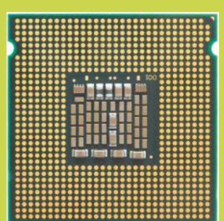
8-way associative

RTM (Restricted Transactional Memory)

HLE (Hardware Lock Elision)

Performance Analysis
Considered mechanisms

Haswell HTM



L1 L1

32KB per core

Deployed in L1

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RTM (Restricted Transactional Memory)

HLE (Hardware Lock Elision)

BlueGene/Q HTM

Performance Analysis
Considered mechanisms

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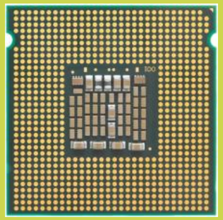


L1 L1

32KB per core

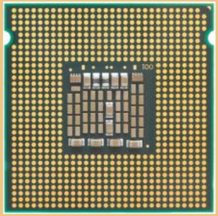
Deployed in L1

8-way associative

RTM (Restricted Transactional Memory)

HLE (Hardware Lock Elision)

BlueGene/Q HTM



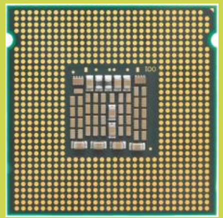
L1 L1

L2

Deployed in L2

Performance Analysis
Considered mechanisms

Haswell HTM



L1 L1

32KB per core

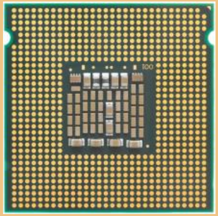
Deployed in L1

8-way associative

RTM (Restricted Transactional Memory)

HLE (Hardware Lock Elision)

BlueGene/Q HTM



L1 L1

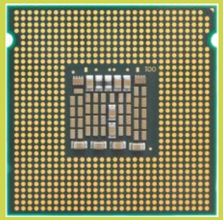
L2

2MB per core

Deployed in L2

Performance Analysis
Considered mechanisms

Haswell HTM



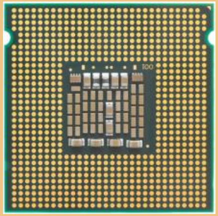
L1 | L1

- 32KB per core
- Deployed in L1
- 8-way associative

RTM (Restricted Transactional Memory)

HLE (Hardware Lock Elision)

BlueGene/Q HTM



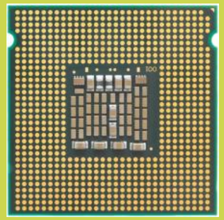
L1 | L1
L2

- 2MB per core
- Deployed in L2
- 16-way associative

Performance Analysis

Considered mechanisms

Haswell HTM



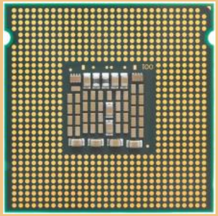
L1 L1

- 32KB per core
- Deployed in L1
- 8-way associative

RTM (Restricted Transactional Memory)

HLE (Hardware Lock Elision)

BlueGene/Q HTM



L1 L1

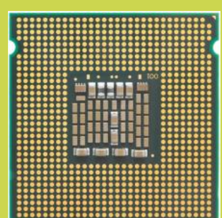
L2

- 2MB per core
- Deployed in L2
- 16-way associative

The Long Running Mode

Performance Analysis
Considered mechanisms

Haswell HTM



L1 L1

32KB per core

Deployed in L1

8-way associative

RTM (Restricted Transactional Memory)

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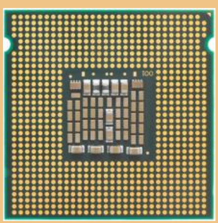
BlueGene/Q HTM



L1 L1

L2

2MB per core

Deployed in L2

16-way associative

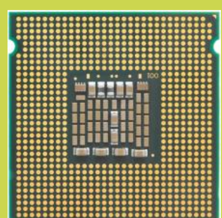
The Long Running Mode

The Short Running Mode

Performance Analysis
Considered mechanisms

Atomics

Haswell HTM



L1 L1

32KB per core

Deployed in L1

8-way associative

RTM (Restricted Transactional Memory)

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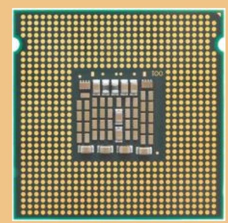

L1 L1

L2

2MB per core

Deployed in L2

16-way associative

The Long Running Mode

The Short Running Mode

SINGLE-VERTEX TRANSACTIONS
MARKING A VERTEX AS VISITED

Used in BFS, SSSP, ...

```
// start handler
if(!v.visited) {
 v.visited = 1;
}
// finish handler
```

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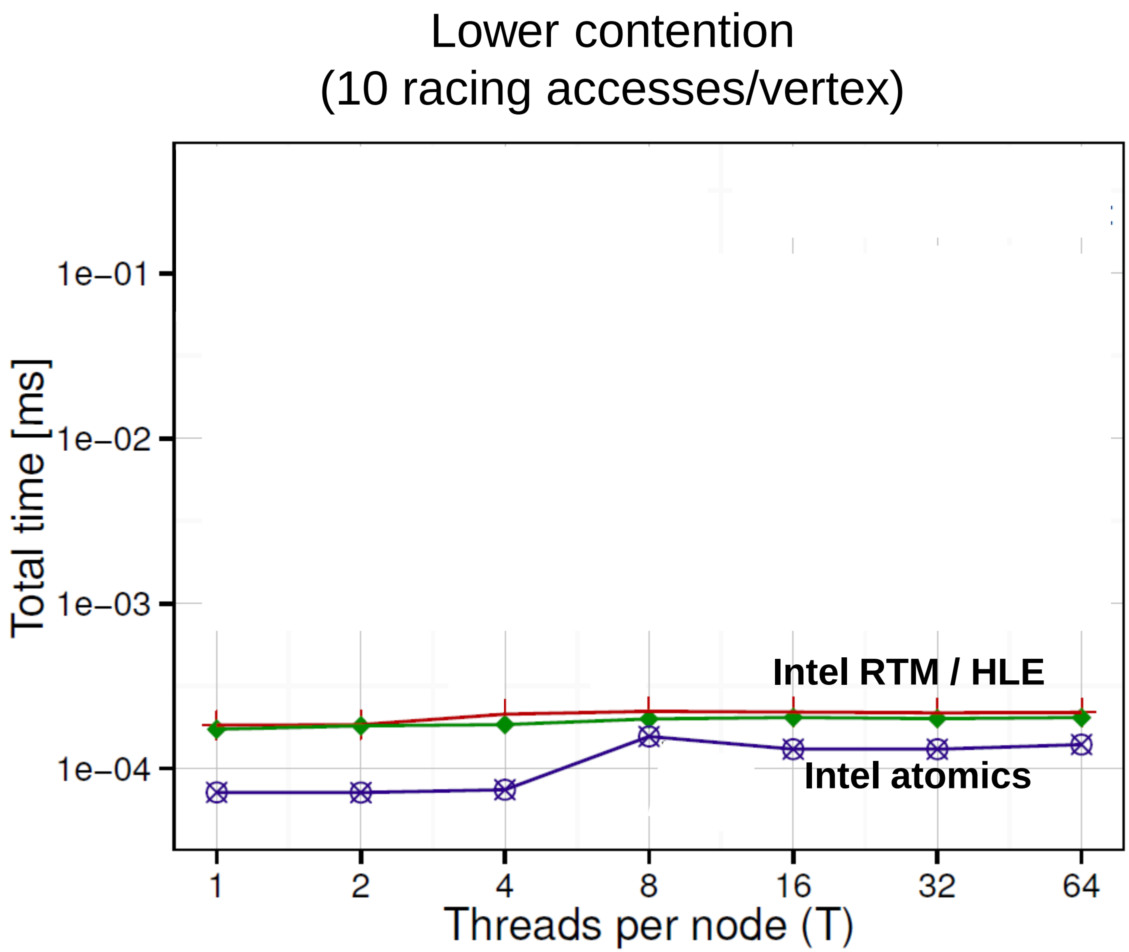


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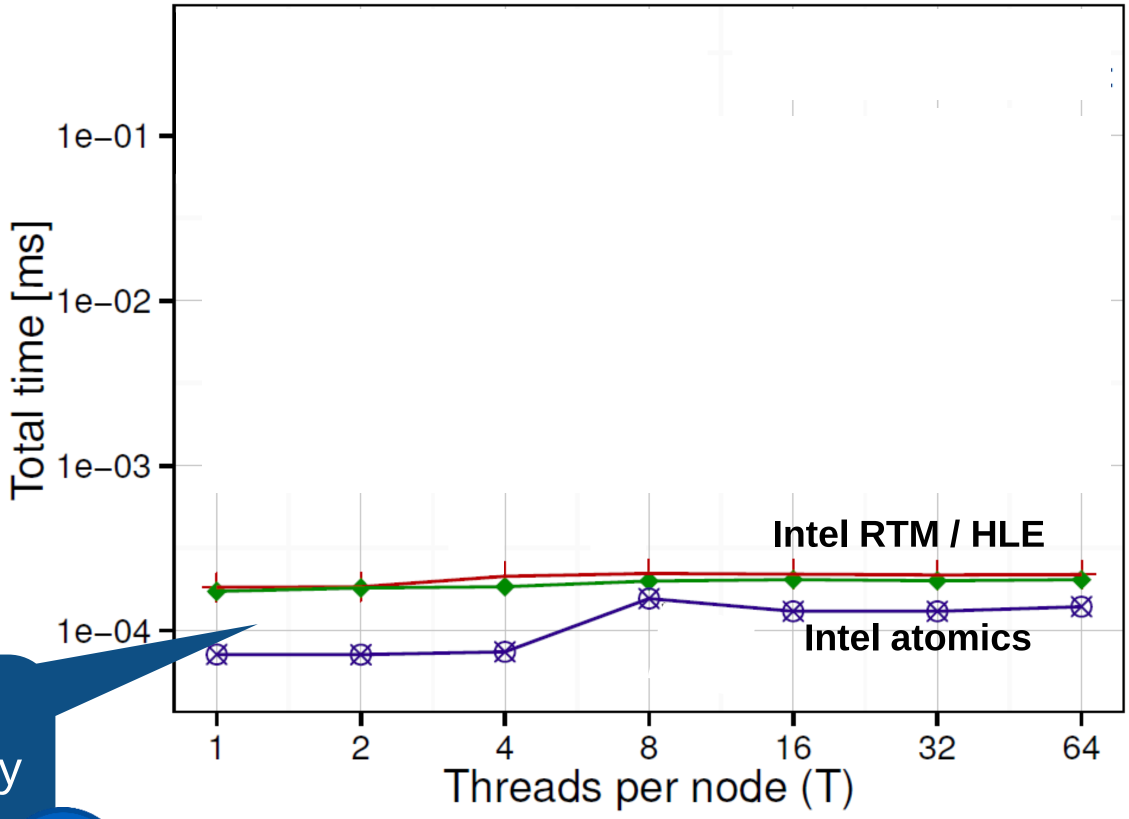
Lower contention
(10 racing accesses/vertex)



Atomics (CAS) slightly faster than HTM

Single-Vertex Transactions
Marking a vertex as visited

Used in BFS, SSSP, ...

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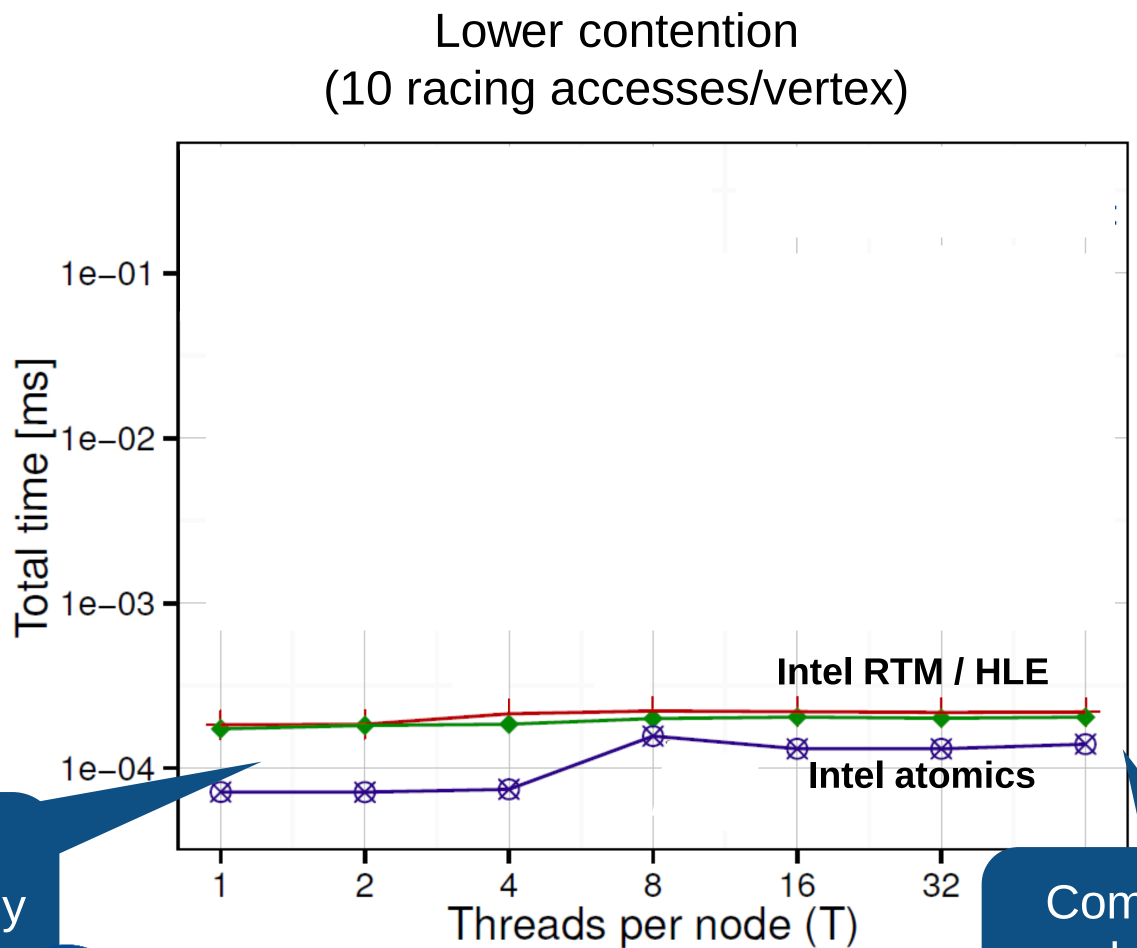

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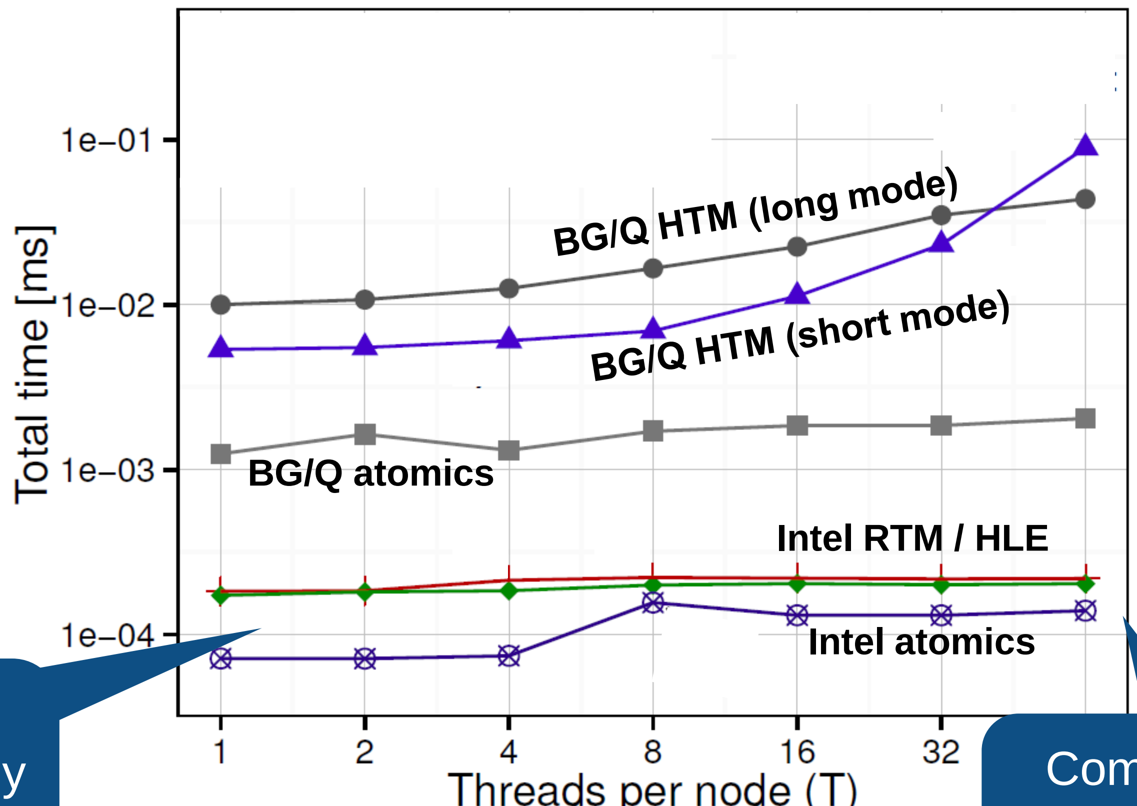

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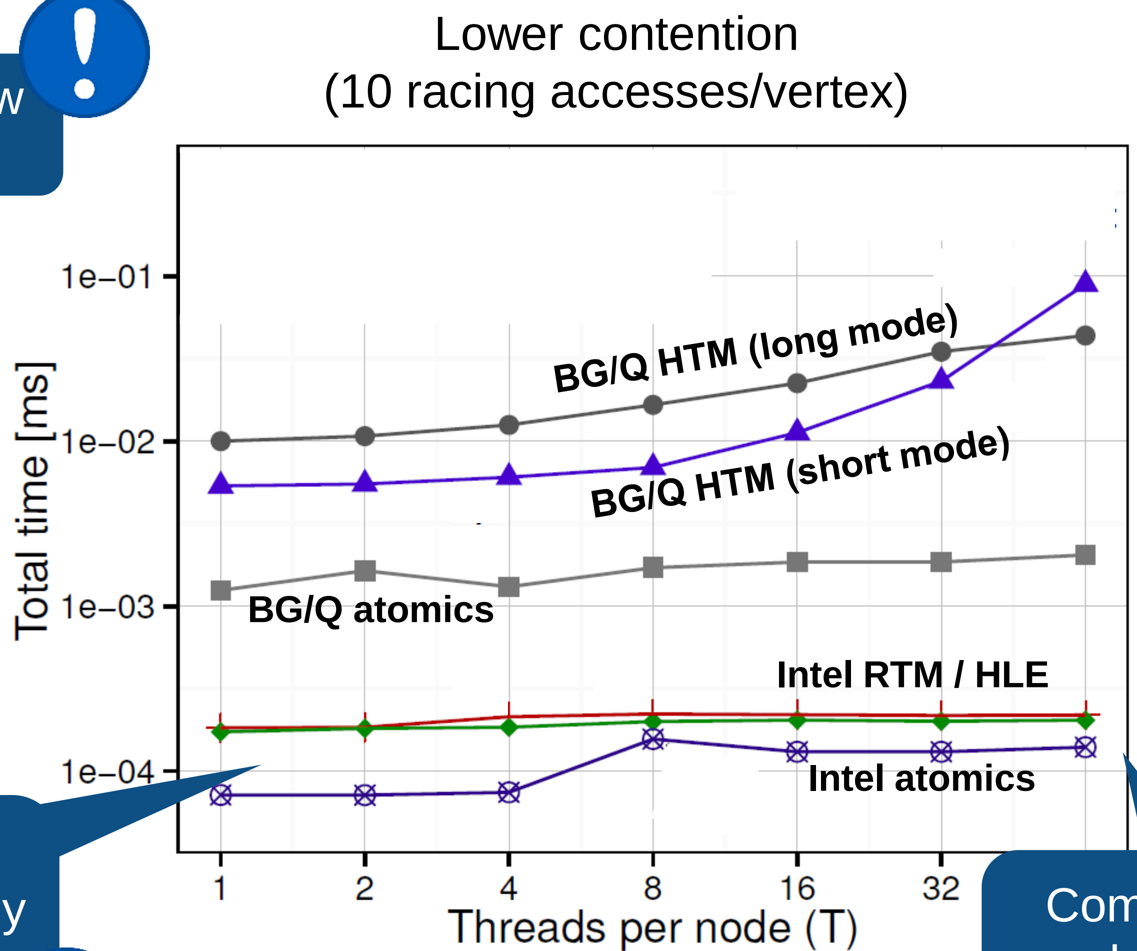

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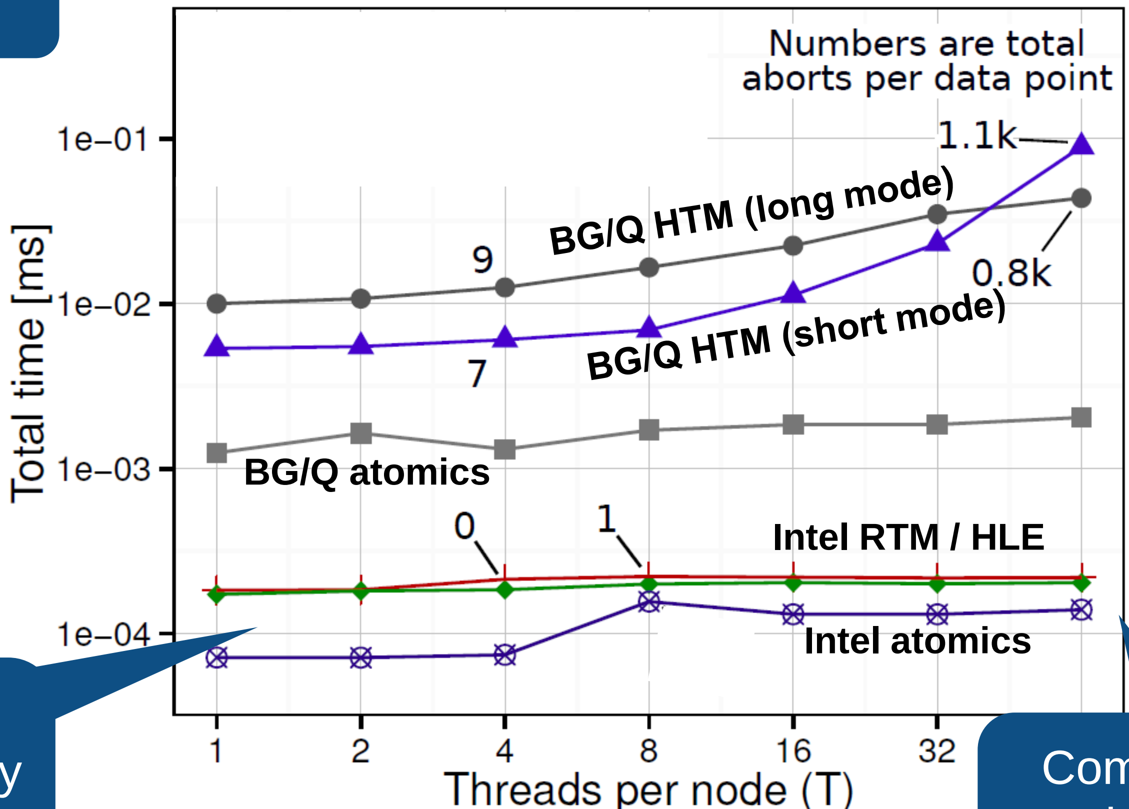

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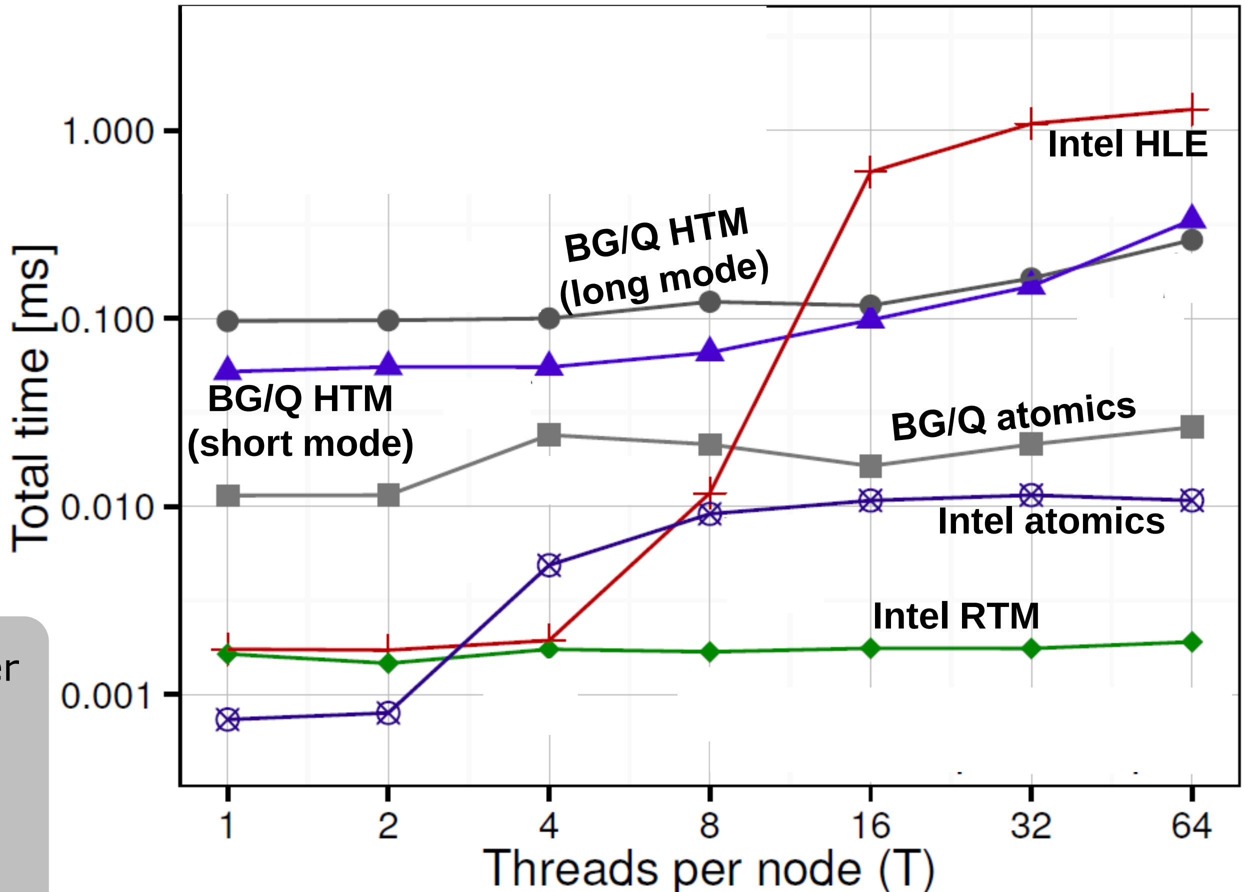


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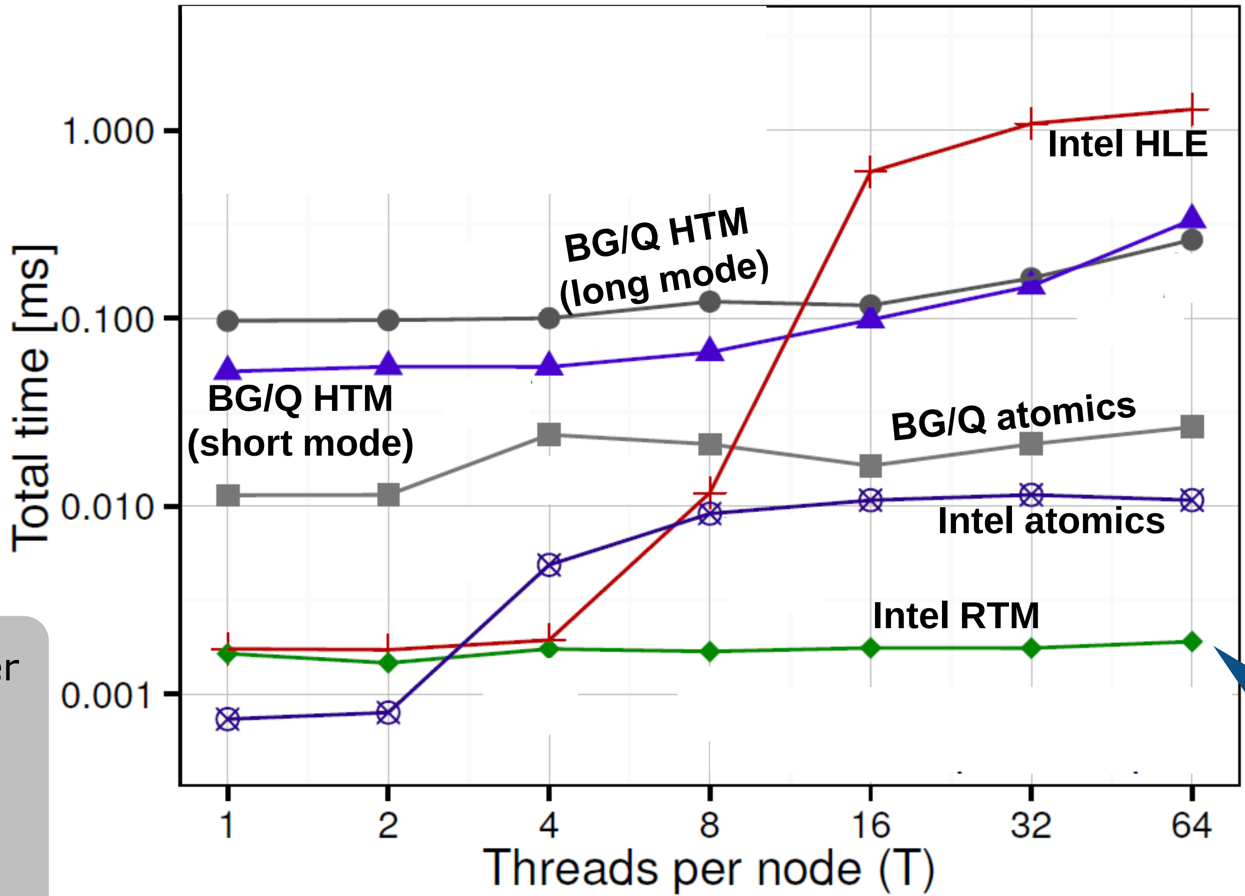


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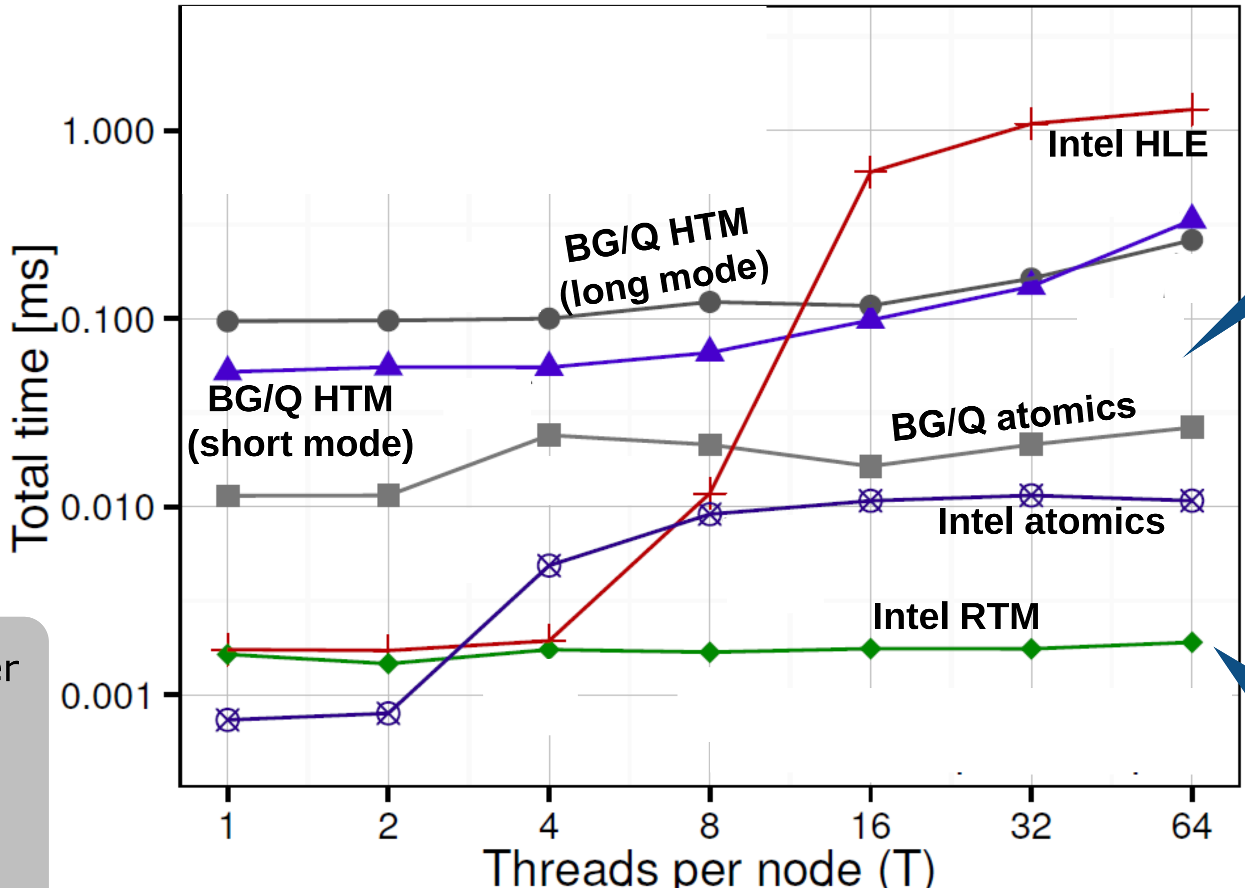


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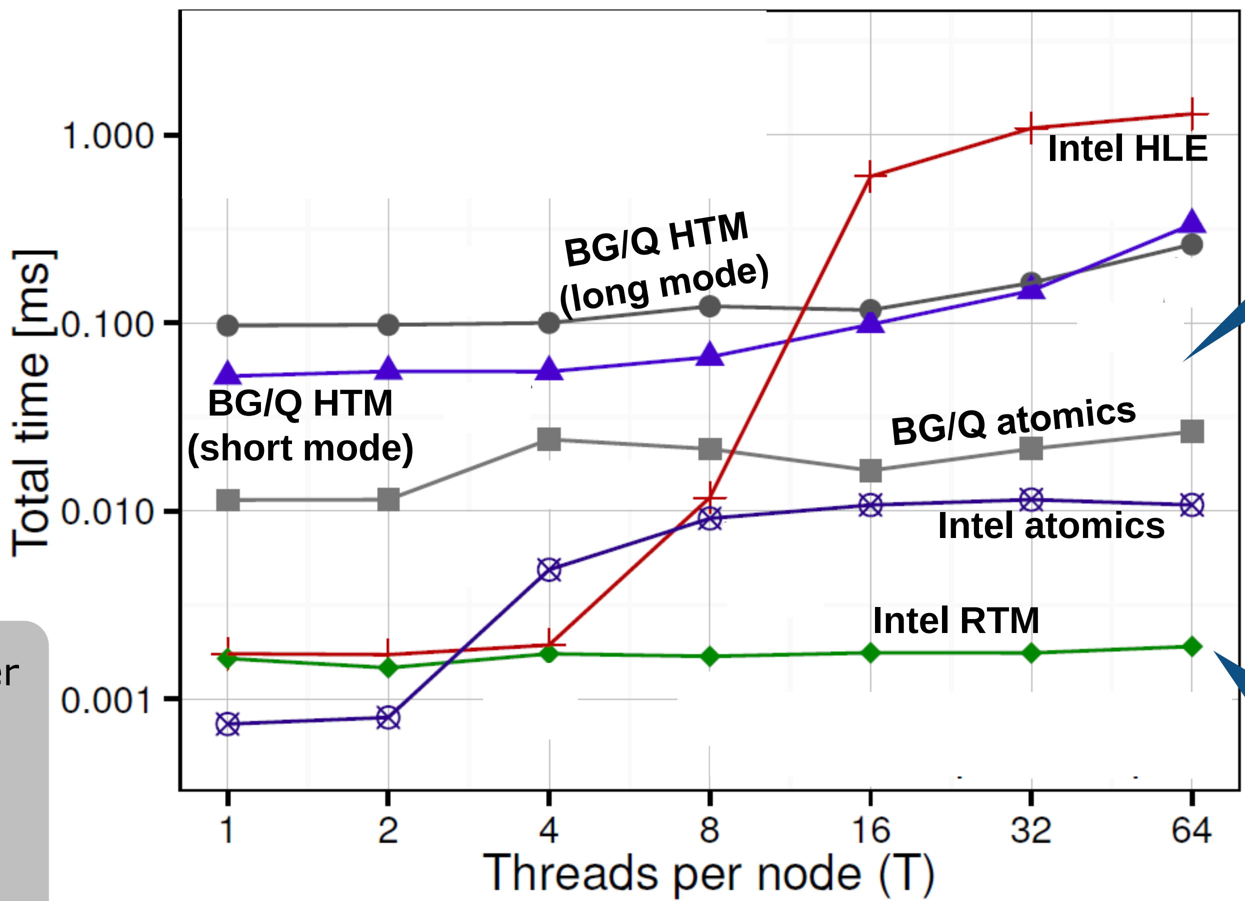

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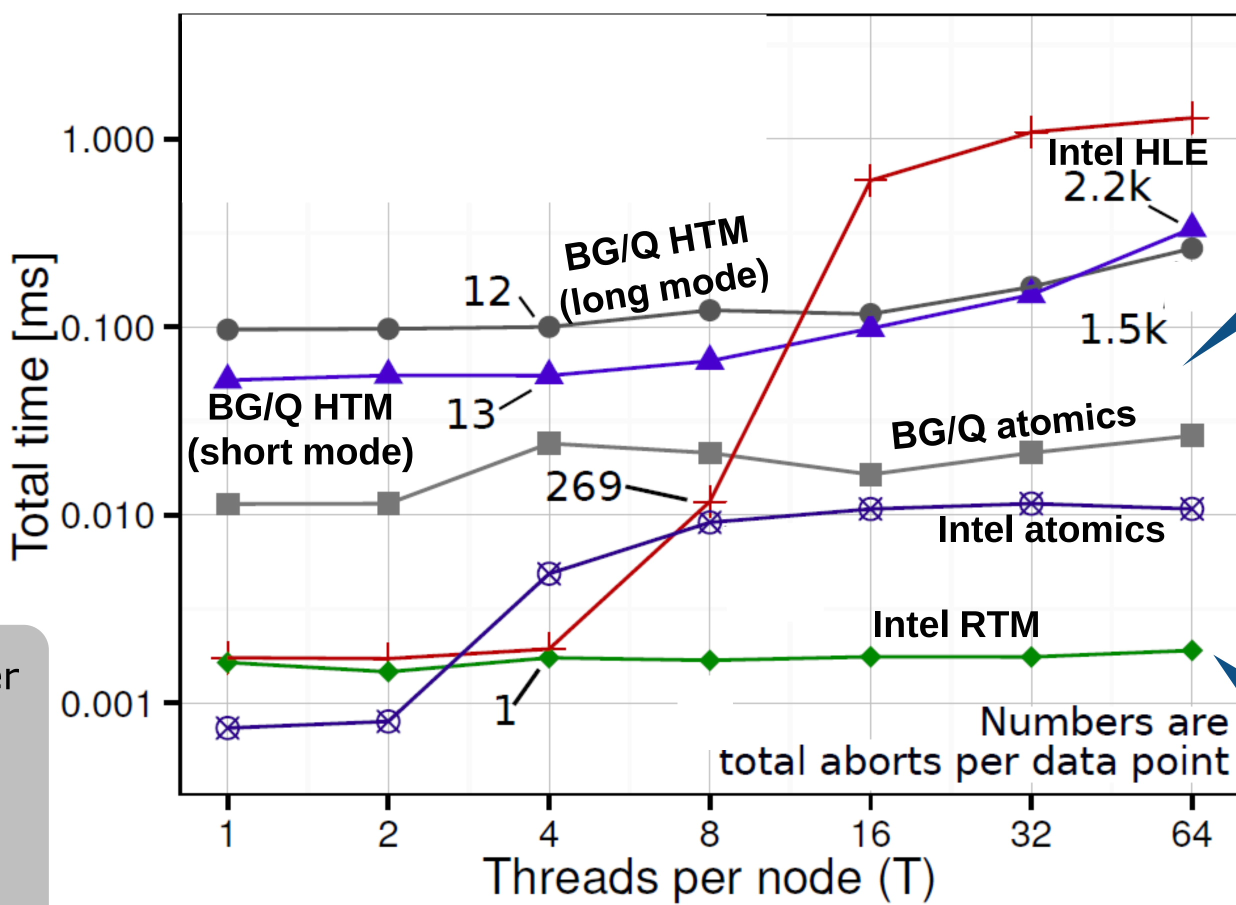

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SINGLE-VERTEX TRANSACTIONS

INCREMENTING VERTEX RANK

Used in PageRank

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// start handler
v.rank++;
// finish handler
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Single-Vertex Transactions
Incrementing vertex rank

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Atomics always outperform HTM

SINGLE-VERTEX TRANSACTIONS

INCREMENTING VERTEX RANK

Used in PageRank

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Atomics always outperform HTM

The reason: each transaction always modifies some memory cell, increasing the number of conflicts

Performance Model

Atomics vs transactions

Performance Model

Atomics vs transactions

Time to modify *N* vertices with atomics:

$$T_{AT}(N) = A_{AT}N + B_{AT}$$

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We predict that:

$$B_{AT} < B_{HTM}$$

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Transaction startup overheads dominate

PERFORMANCE MODEL
ATOMICS VS TRANSACTIONS

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Transaction startup overheads dominate

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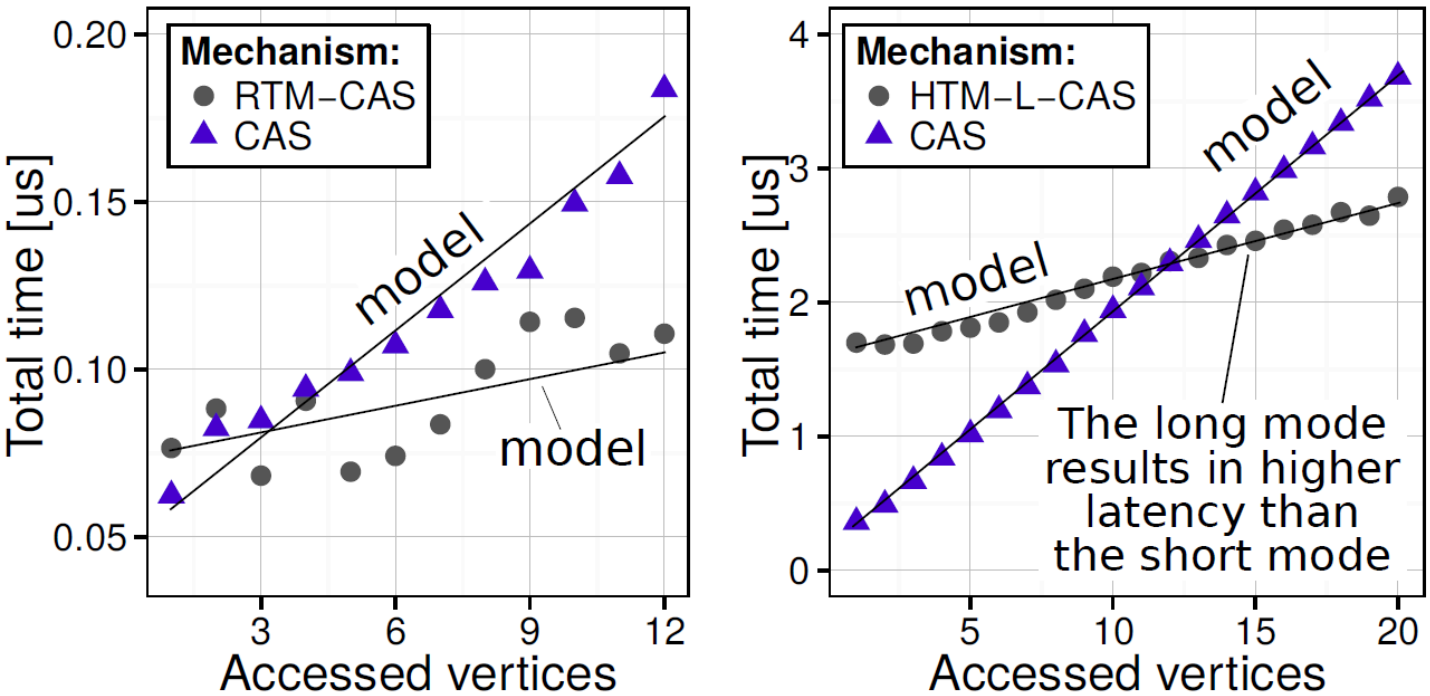

Performance Model
Atomics vs transactions

Indeed:

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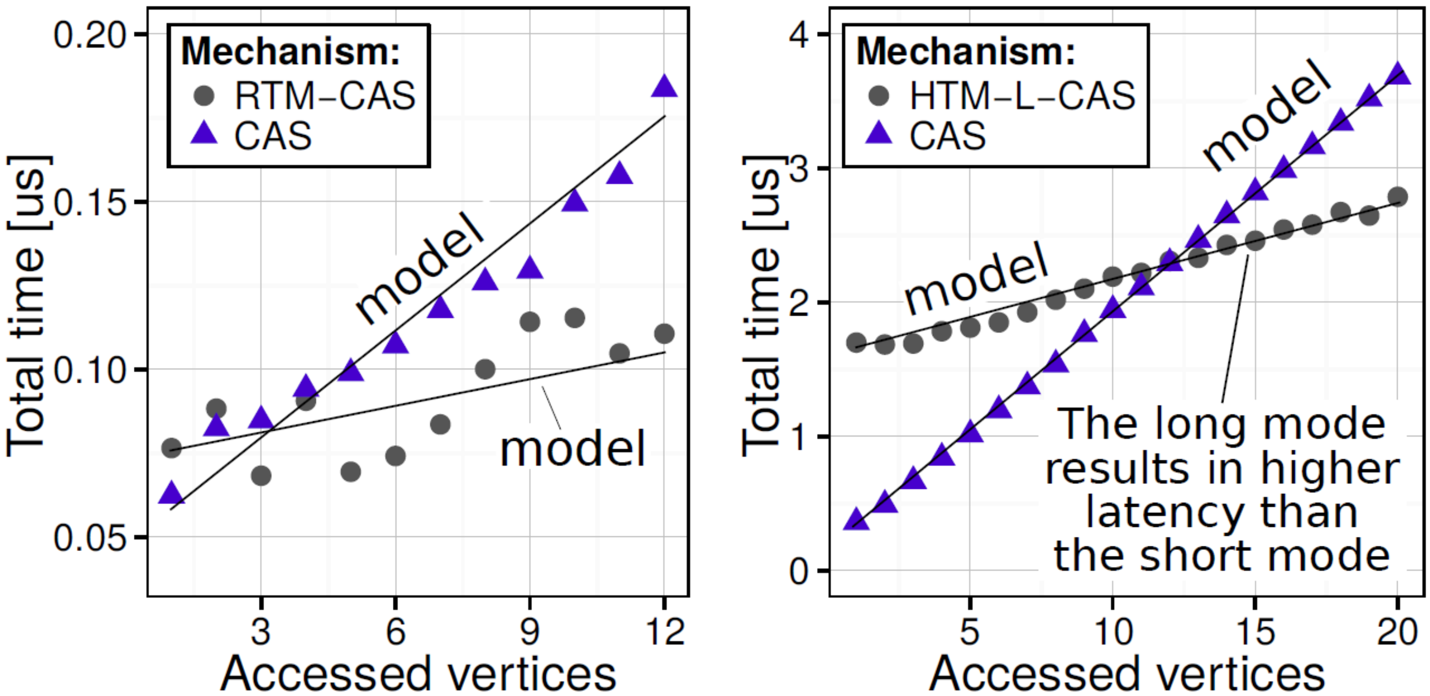

PERFORMANCE MODEL
ATOMICS VS TRANSACTIONS

- Can we amortize HTM startup/commit overheads with larger transaction sizes?

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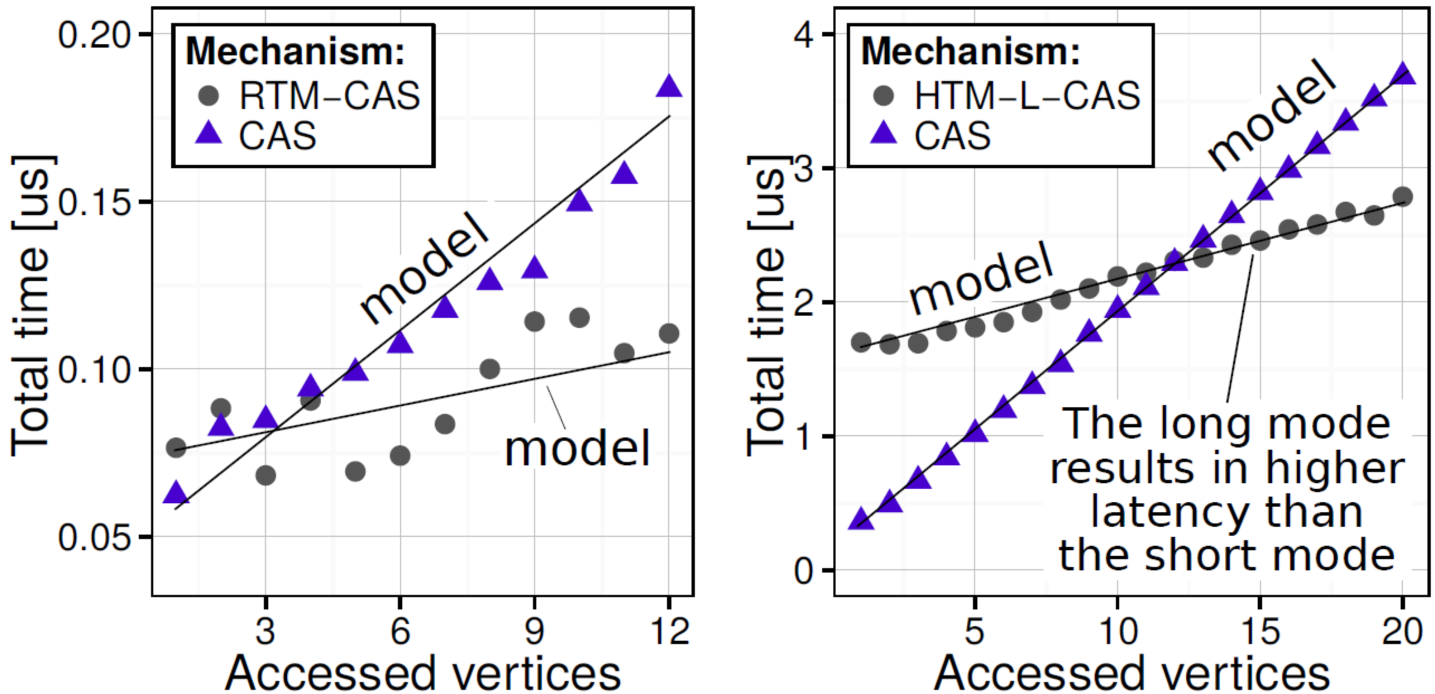

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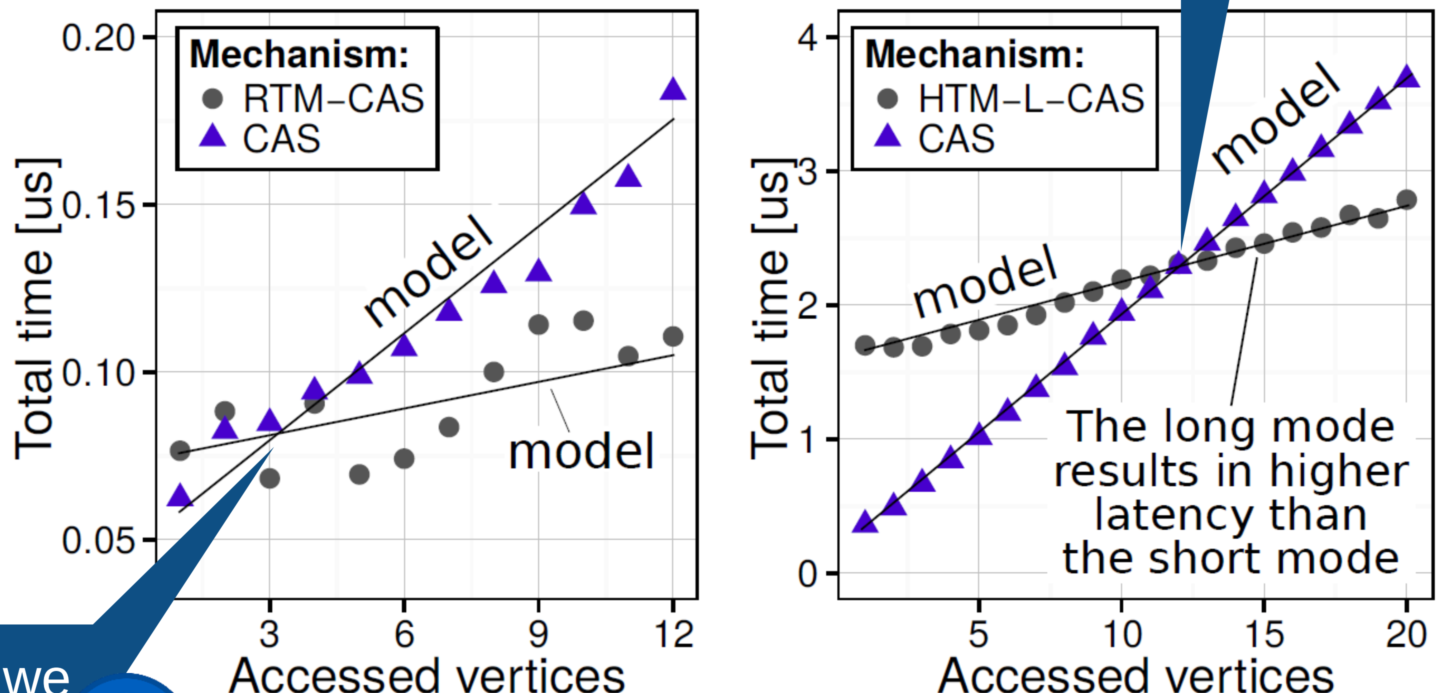
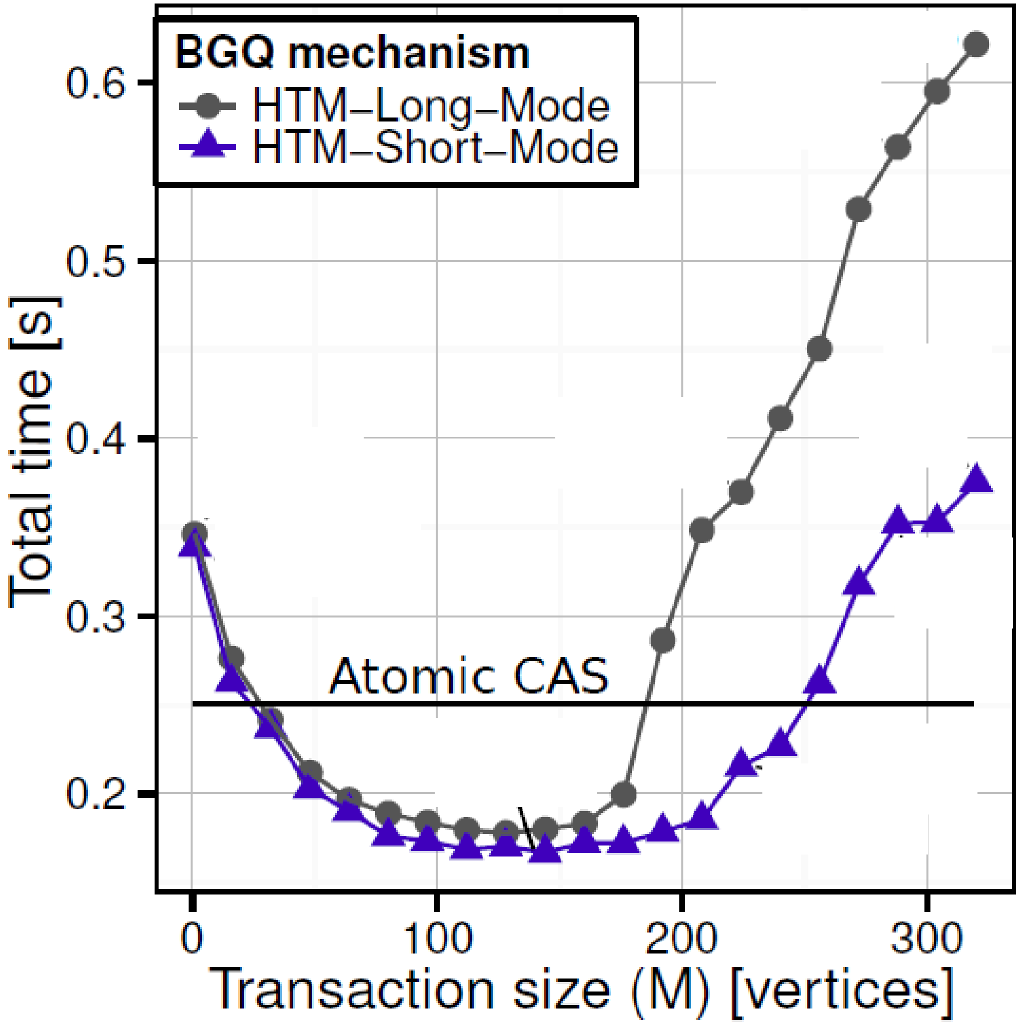


Yes, we can!

Multi-Vertex Transactions

Marking vertices as visited

MULTI-VERTEX TRANSACTIONS
MARKING VERTICES AS VISITED



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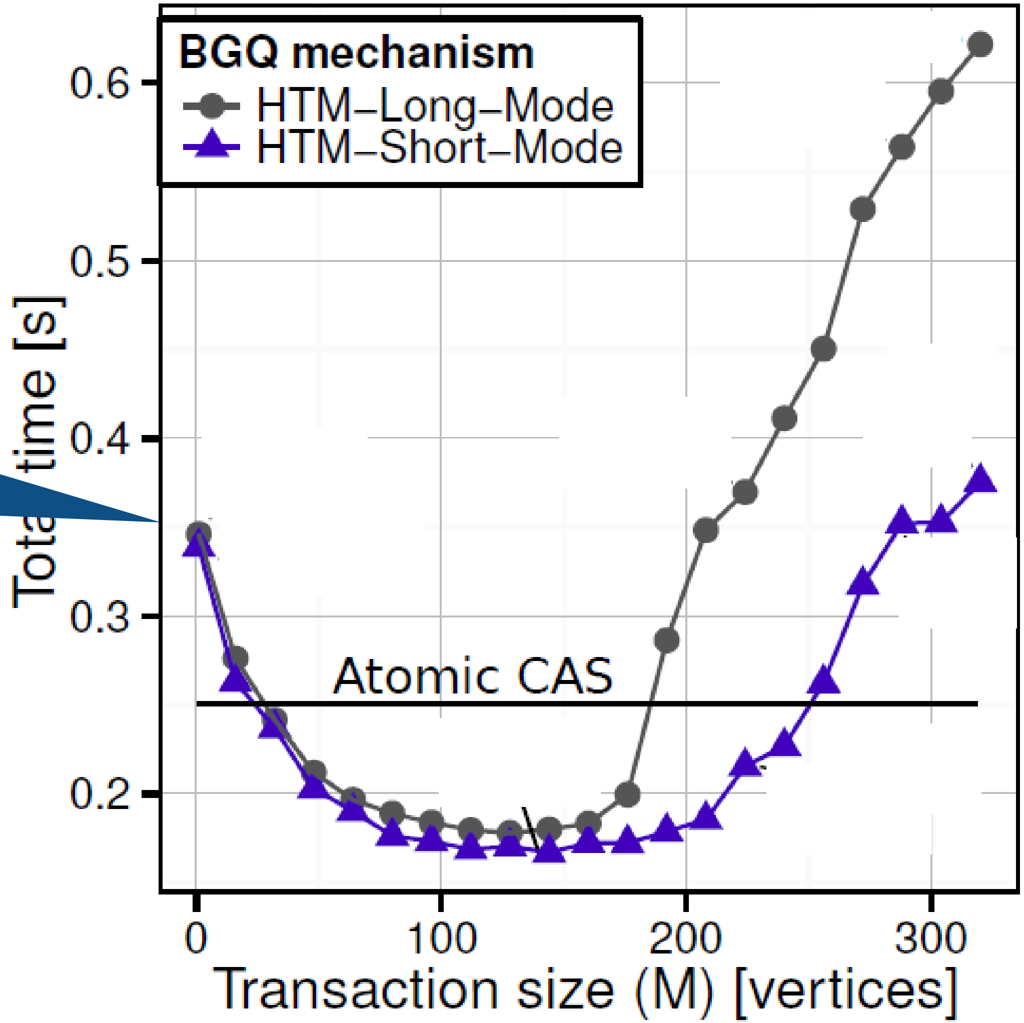

Startup and commit overheads

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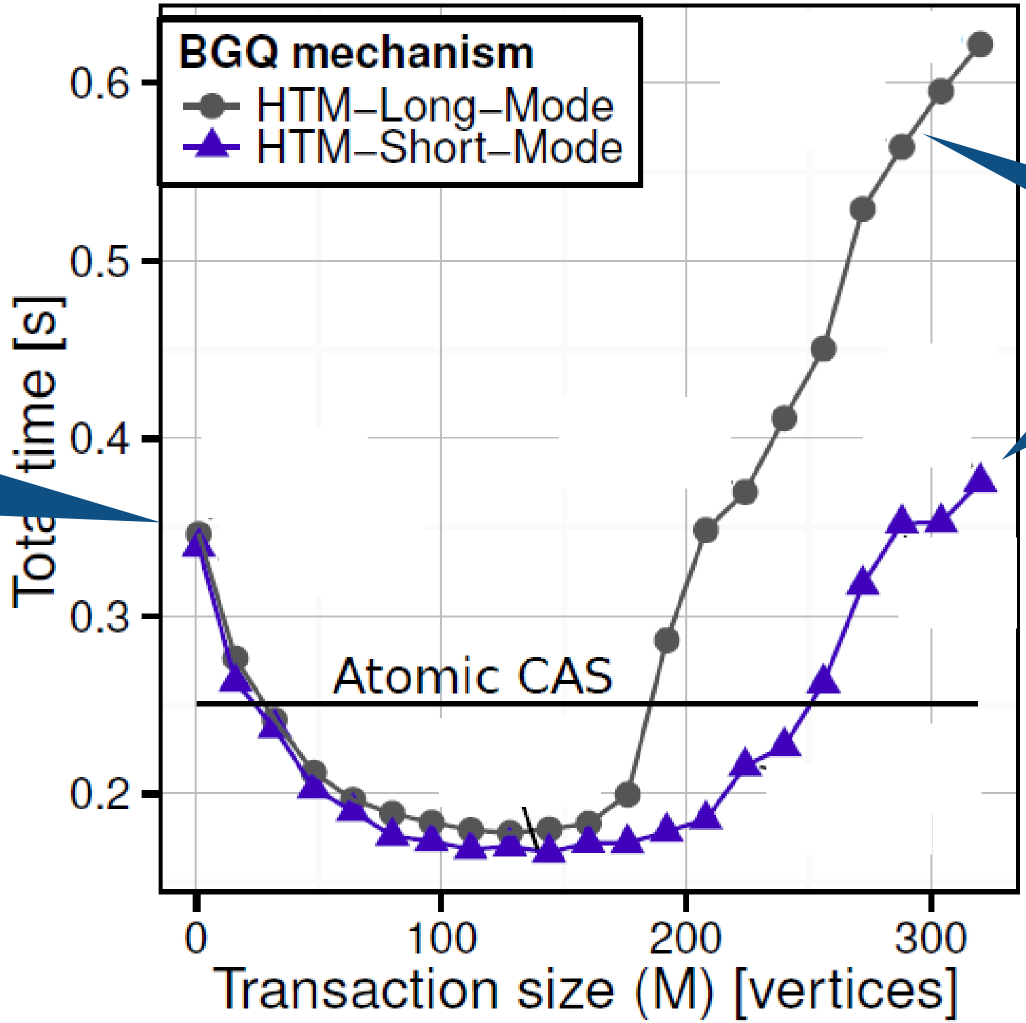

Startup and commit overheads

Abort and rollback overheads

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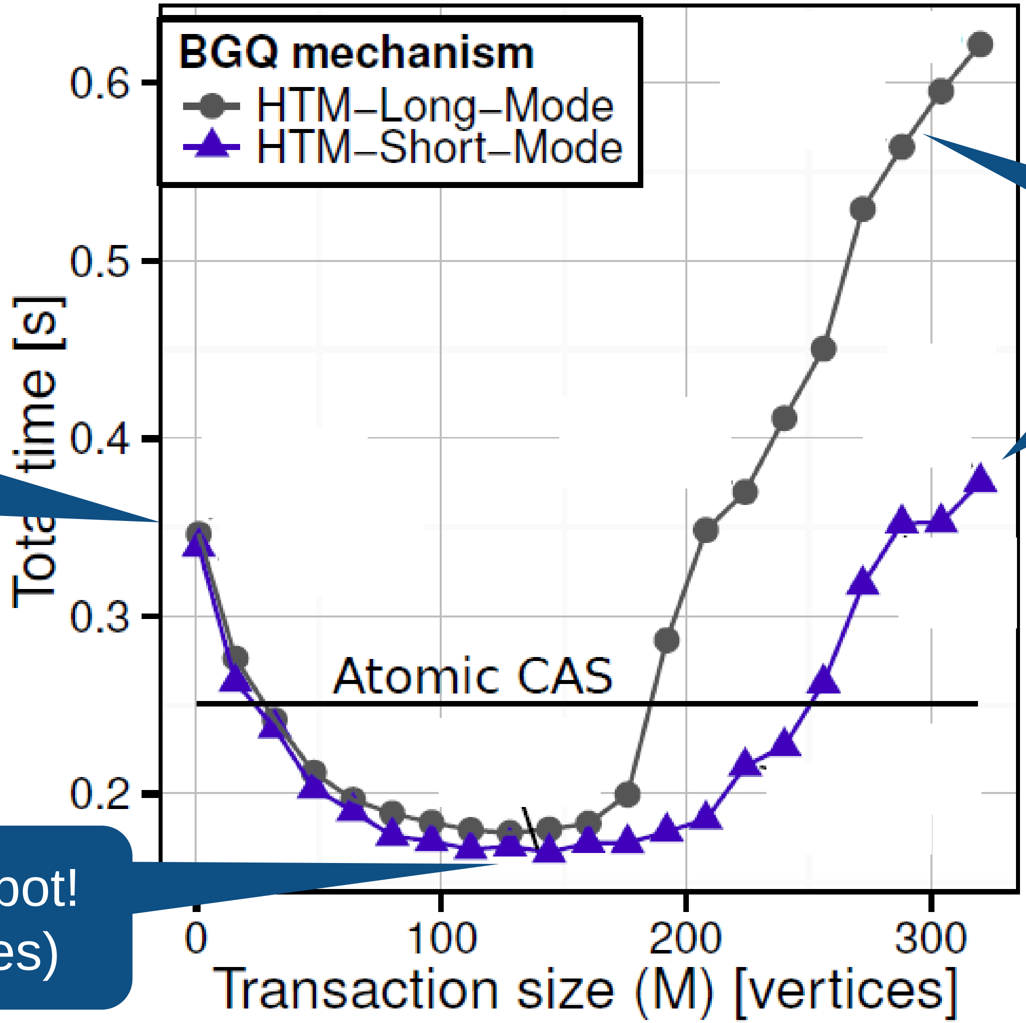

Startup and commit overheads

The sweetspot! (144 vertices)

Abort and rollback overheads

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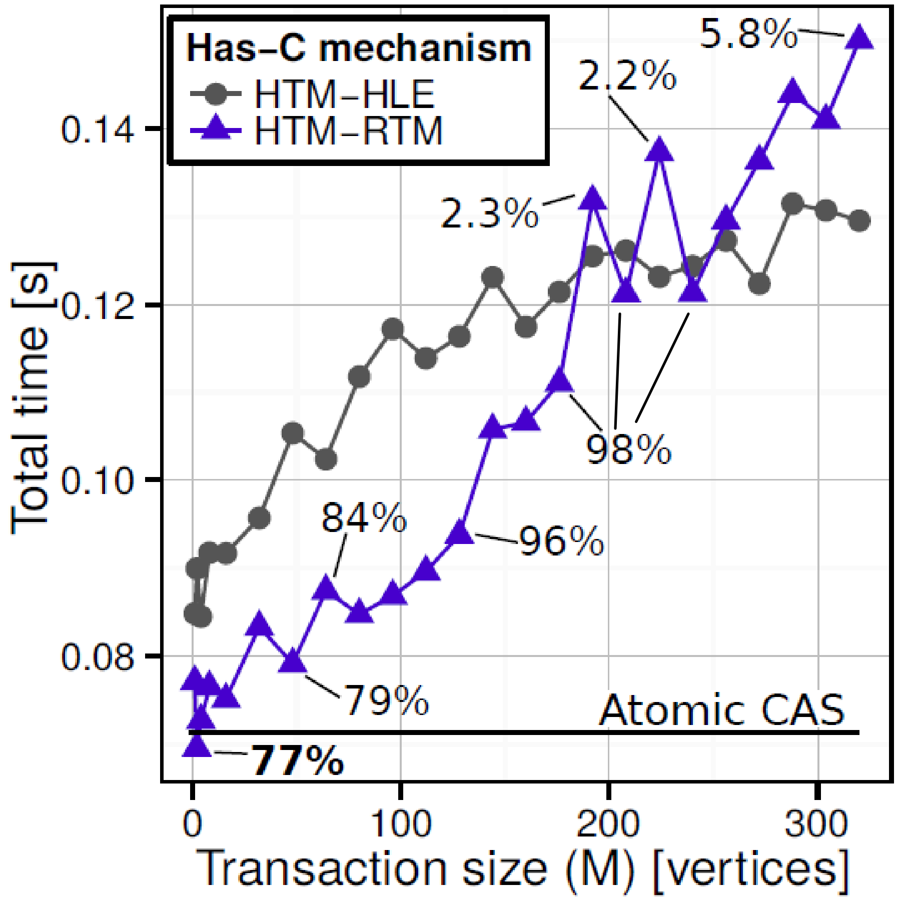

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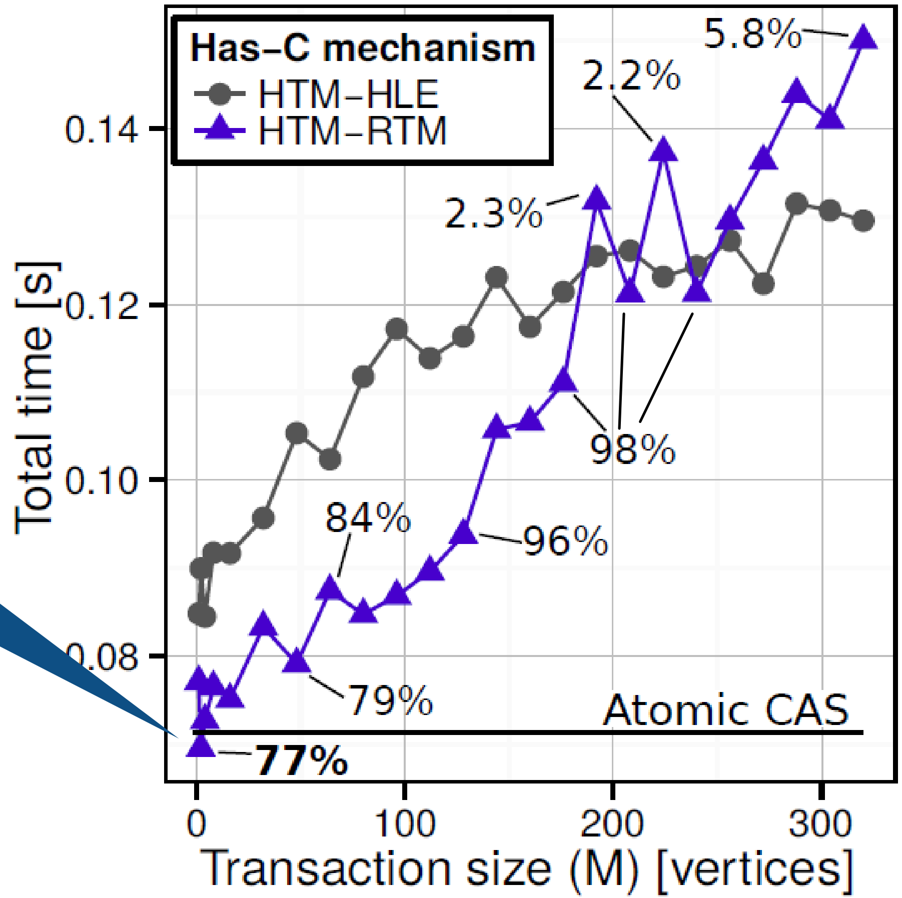

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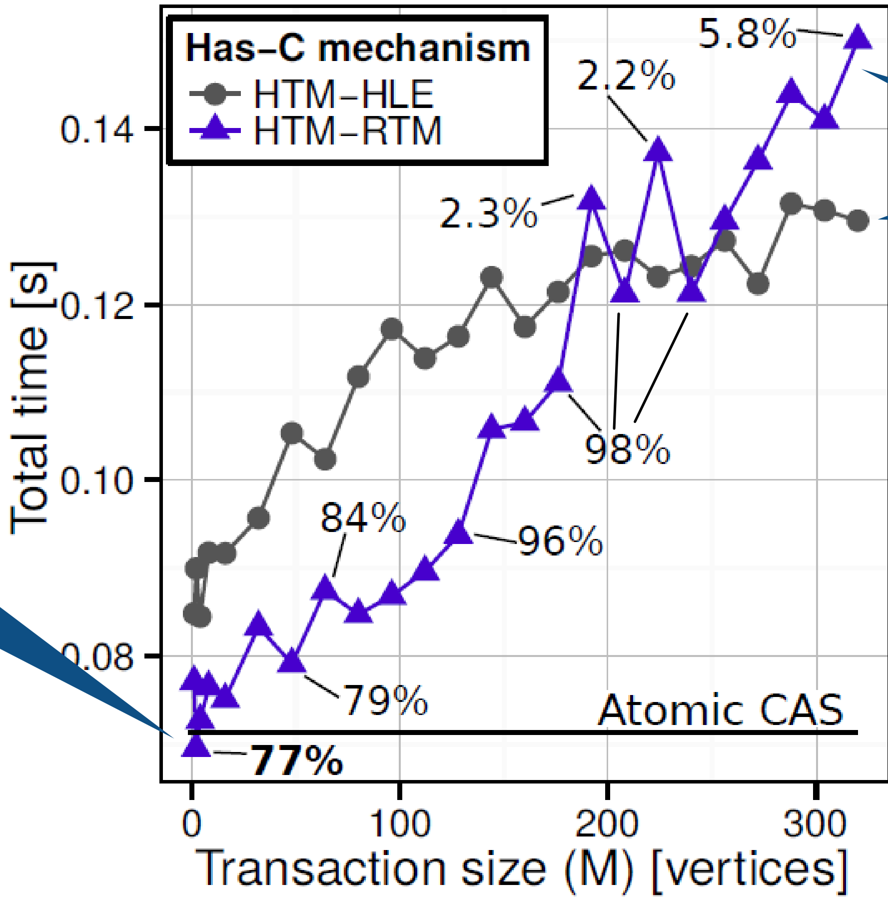

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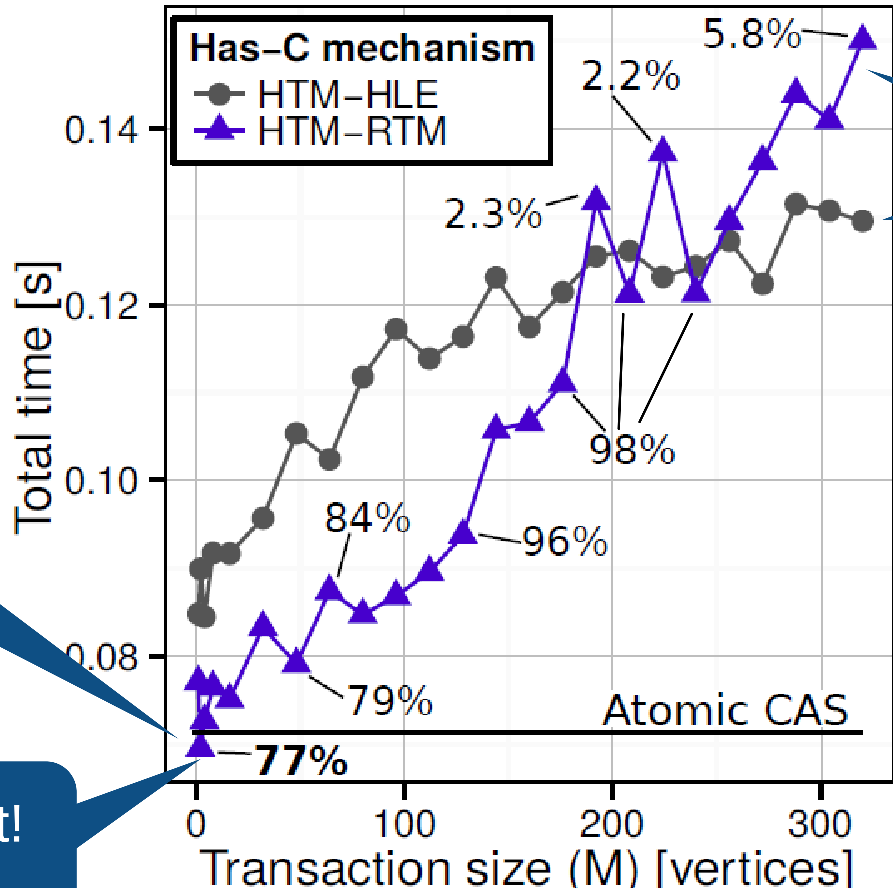

Startup and commit overheads

The sweetspot! (2 vertices)

Abort and rollback overheads

MULTI-VERTEX TRANSACTIONS
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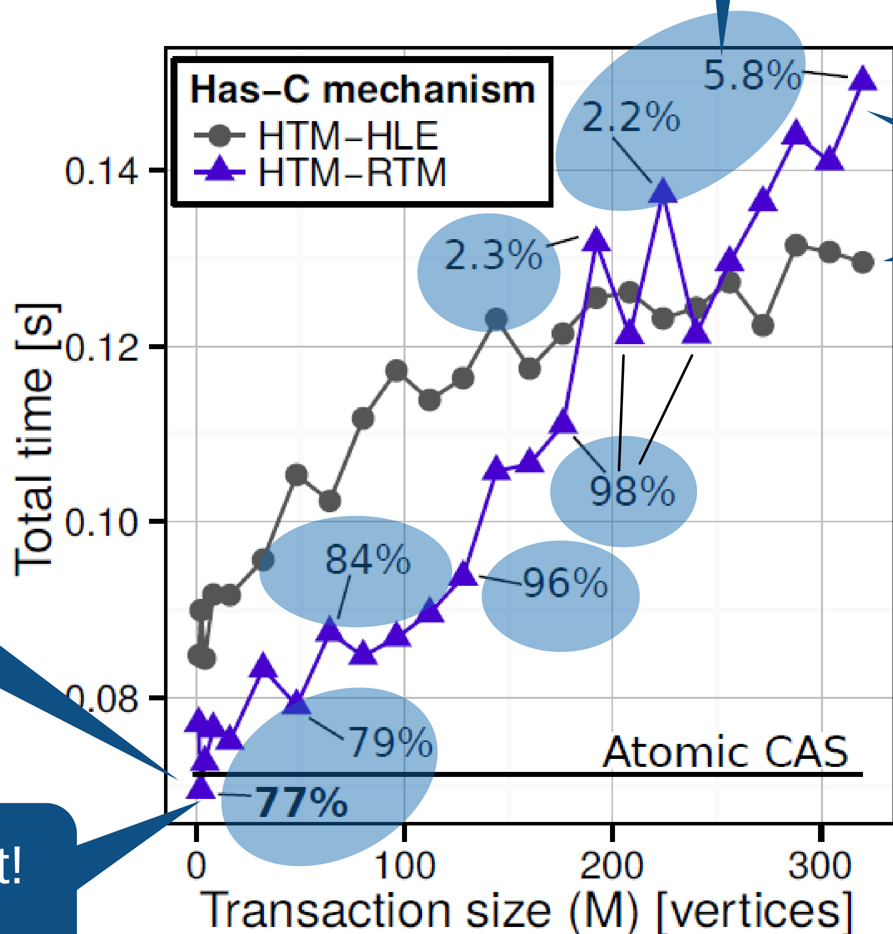
Numbers: % of aborts due to HTM capacity overflows



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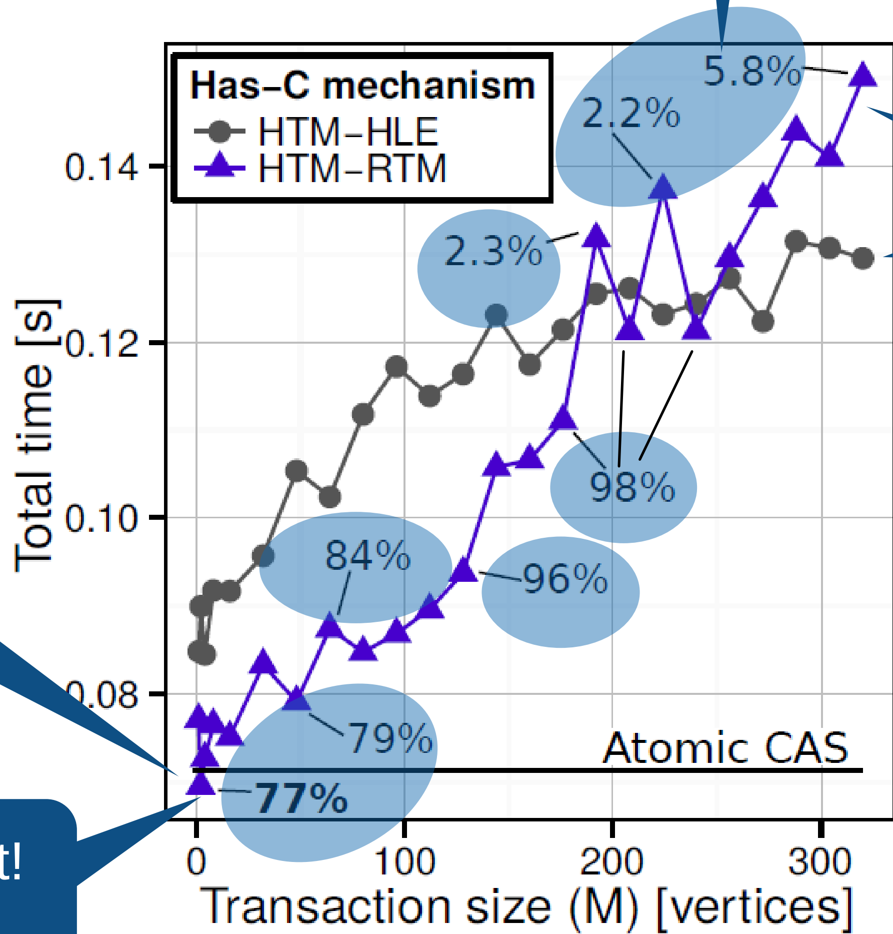

Abort and rollback overheads

Startup and commit overheads

Majority of aborts are due to HTM capacity overflows (small cache size & associativity)

The sweetspot! (2 vertices)

Performance Analysis
Questions answered

How can we implement AAM handlers most effectively?

What are performance tradeoffs related to HTM?

What are advantages of HTM over atomics for AAM?

What are the optimal transaction sizes? Can we amortize transaction overheads?

PERFORMANCE ANALYSIS
QUESTIONS ANSWERED

„It really depends” ☺. But... There are some regularities

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Same for other graphs

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Larger cache & associativity → fewer aborts & more coarsening

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Larger (L2) cache → higher latency

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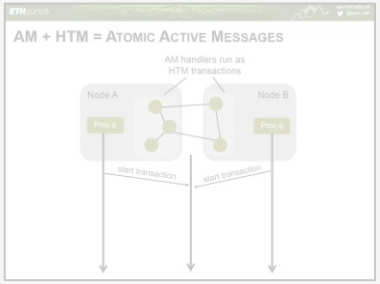
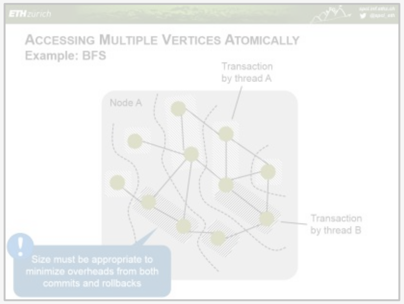
Overview of our Research

HTM for graphs in SM & DM environments



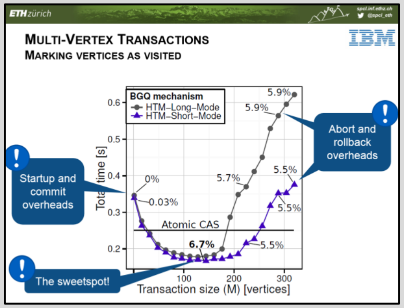
HTM + Active Messages
= Atomic Active Messages

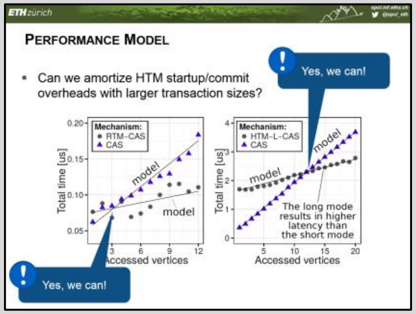
Coarsening & coalescing



Performance Modeling & Analysis

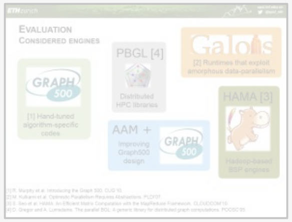
Haswell & BG/Q Analysis

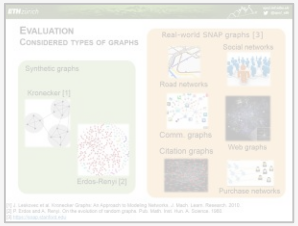




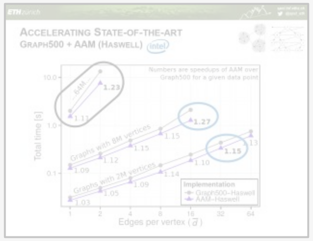
Performance model

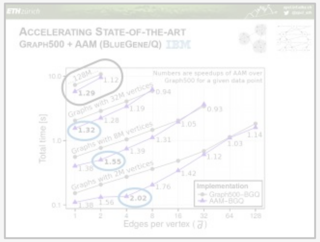
Evaluation



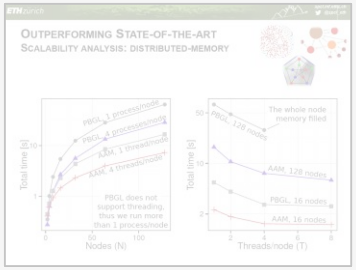


Considered engines and graphs





Accelerating state-of-the-art



Scalability

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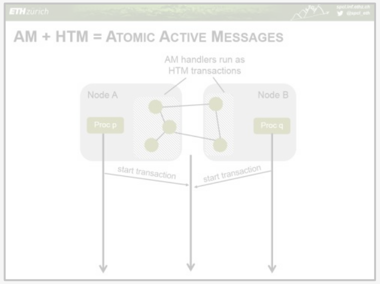

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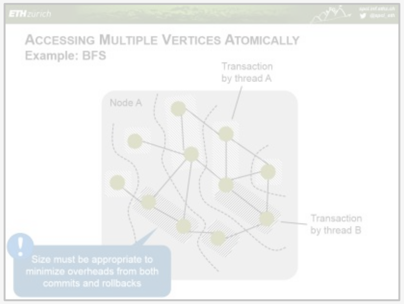

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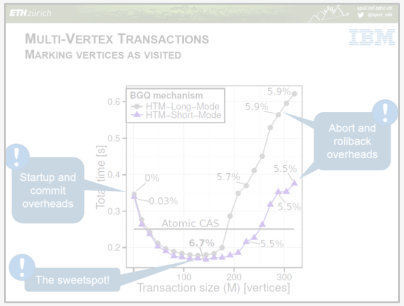
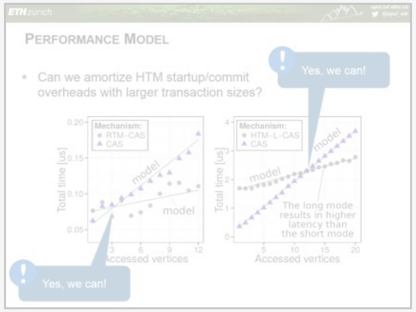
Haswell & BG/Q Analysis





Performance model

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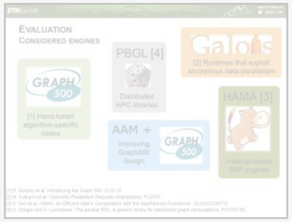

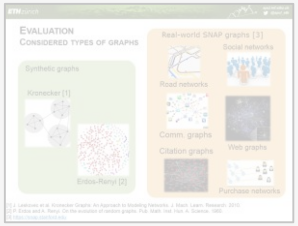

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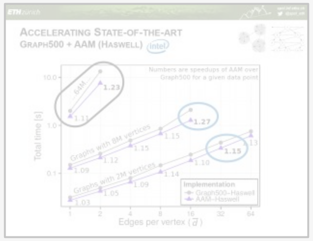
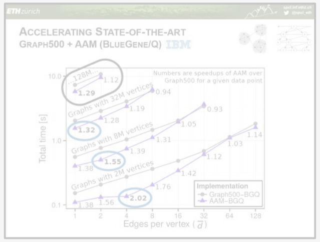
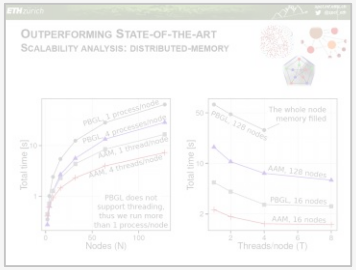




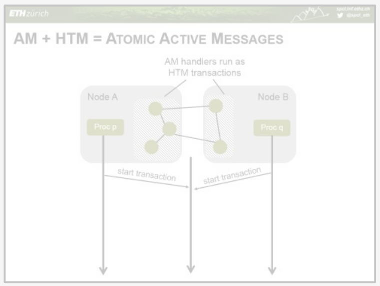
Accelerating state-of-the-art



Scalability

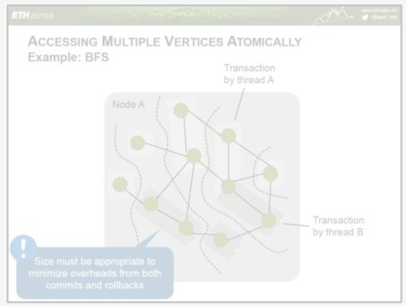
Overview of our Research

HTM for graphs in SM & DM environments



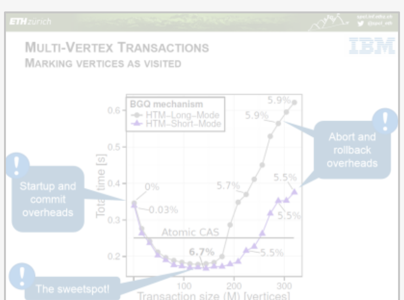
HTM + Active Messages
= Atomic Active Messages

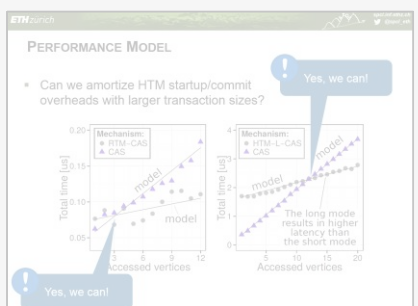
Coarsening & coalescing



Performance Modeling & Analysis

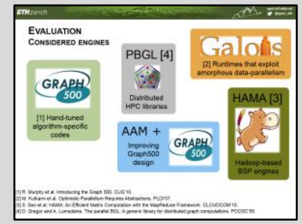
Haswell & BG/Q Analysis

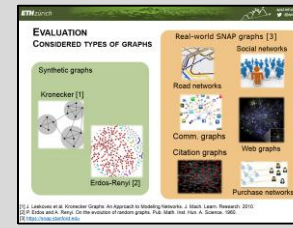




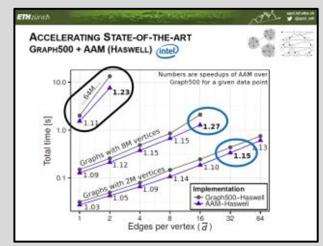
Performance model

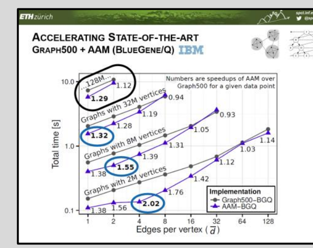
Evaluation



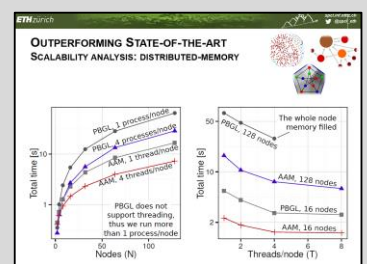


Considered engines and graphs





Accelerating state-of-the-art



Scalability

EVALUATION
CONSIDERED ENGINES

Evaluation

Considered engines

GRAPH 500

[1] Hand-tuned algorithm-specific codes

[1] R. Murphy et al. Introducing the Graph 500. CUG'10.

EVALUATION
CONSIDERED ENGINES

[1] Hand-tuned algorithm-specific codes

AAM +

Improving Graph500 design

[1] R. Murphy et al. Introducing the Graph 500. CUG'10.

EVALUATION
CONSIDERED ENGINES

Galois

[2] Runtimes that exploit amorphous data-parallelism

GRAPH 500

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AAM + GRAPH 500

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[2] M. Kulkarni et al. Optimistic Parallelism Requires Abstractions. PLDI'07.

EVALUATION
CONSIDERED ENGINES

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AAM +

Improving Graph500 design

HAMA [3]

Hadoop-based BSP engines

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[3] S. Seo et al. HAMA: An Efficient Matrix Computation with the MapReduce Framework. CLOUDCOM'10.

Evaluation
Considered engines

PBGL [4]

Distributed HPC libraries

Galois

[2] Runtimes that exploit amorphous data-parallelism

[1] Hand-tuned algorithm-specific codes

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[4] D. Gregor and A. Lumsdaine. The parallel BGL: A generic library for distributed graph computations. POOSC'05.

EVALUATION

CONSIDERED TYPES OF GRAPHS

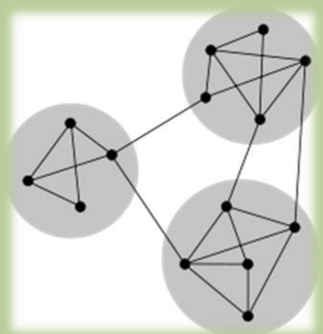
EVALUATION
CONSIDERED TYPES OF GRAPHS

Synthetic graphs

Evaluation
Considered types of graphs

Synthetic graphs

Kronecker [1]

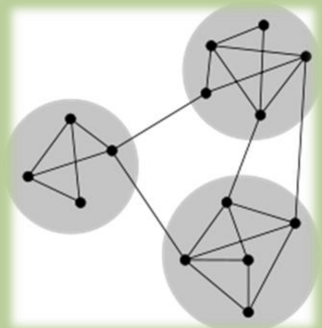


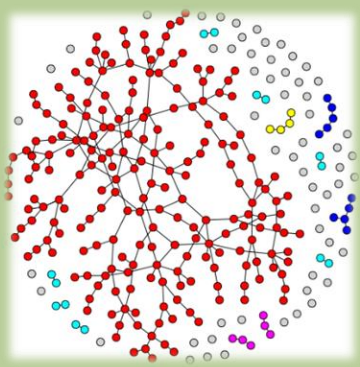
[1] J. Leskovec et al. Kronecker Graphs: An Approach to Modeling Networks. J. Mach. Learn. Research. 2010.

Evaluation
Considered types of graphs

Synthetic graphs

Kronecker [1]





Erdös-Rényi [2]

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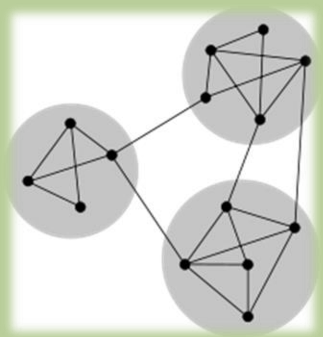
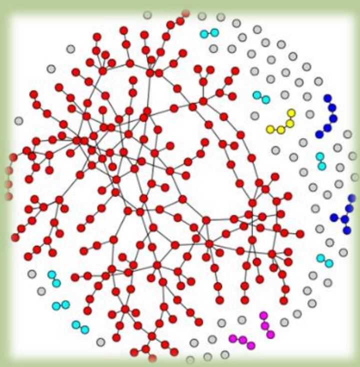
Evaluation
Considered types of graphs

Synthetic graphs

Kronecker [1]





Erdös-Rényi [2]

Real-world SNAP graphs [3]

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[3] https://snap.stanford.edu

Evaluation
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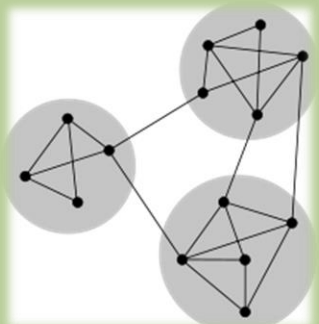
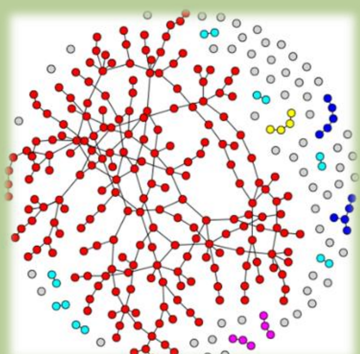
Kronecker [1]





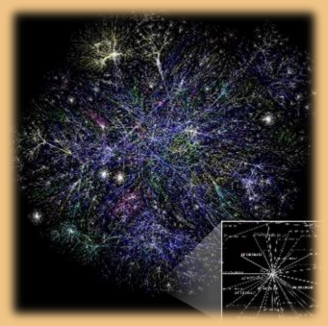
Erdös-Rényi [2]

Real-world SNAP graphs [3]

Road networks

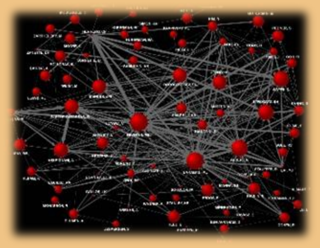
Social networks

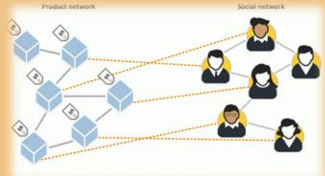
Comm. graphs



Web graphs

Citation graphs





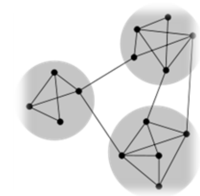
Purchase networks

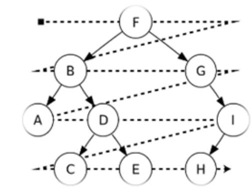
[1] J. Leskovec et al. Kronecker Graphs: An Approach to Modeling Networks. J. Mach. Learn. Research. 2010.
[2] P. Erdos and A. Renyi. On the evolution of random graphs. Pub. Math. Inst. Hun. A. Science. 1960.
[3] https://snap.stanford.edu

Accelerating State-of-the-art Graph500 + AAM (BlueGene/Q)

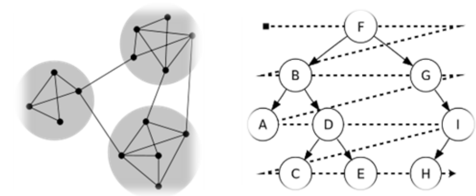
ACCELERATING STATE-OF-THE-ART

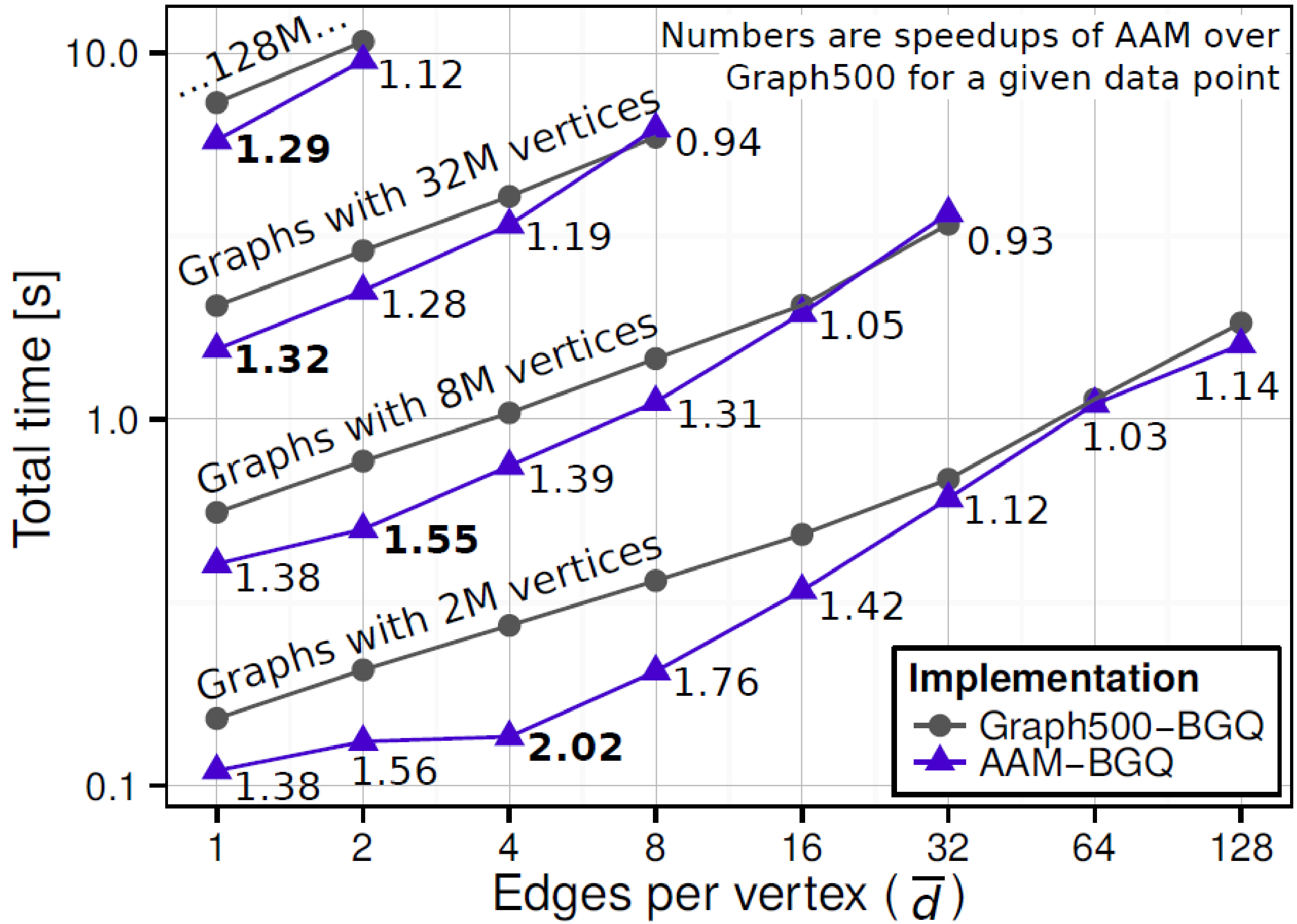
GRAPH500 + AAM (BLUEGENE/Q) IBM



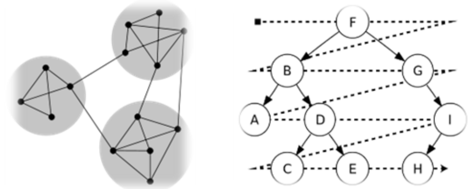


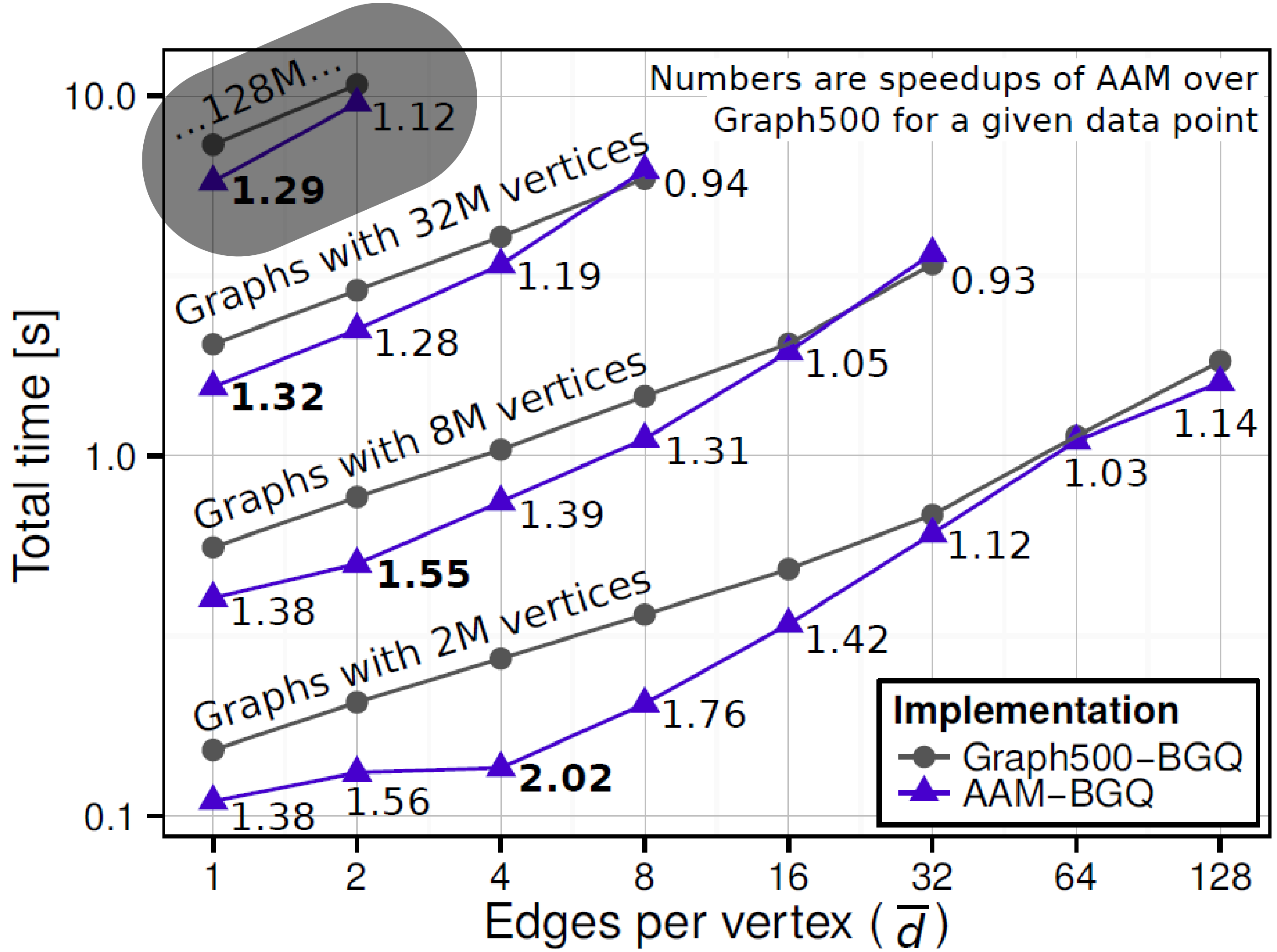
ACCELERATING STATE-OF-THE-ART GRAPH500 + AAM (BLUEGENE/Q) IBM





ACCELERATING STATE-OF-THE-ART GRAPH500 + AAM (BLUEGENE/Q)





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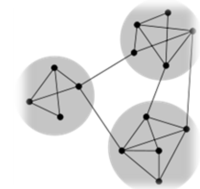
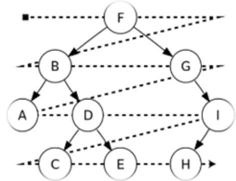
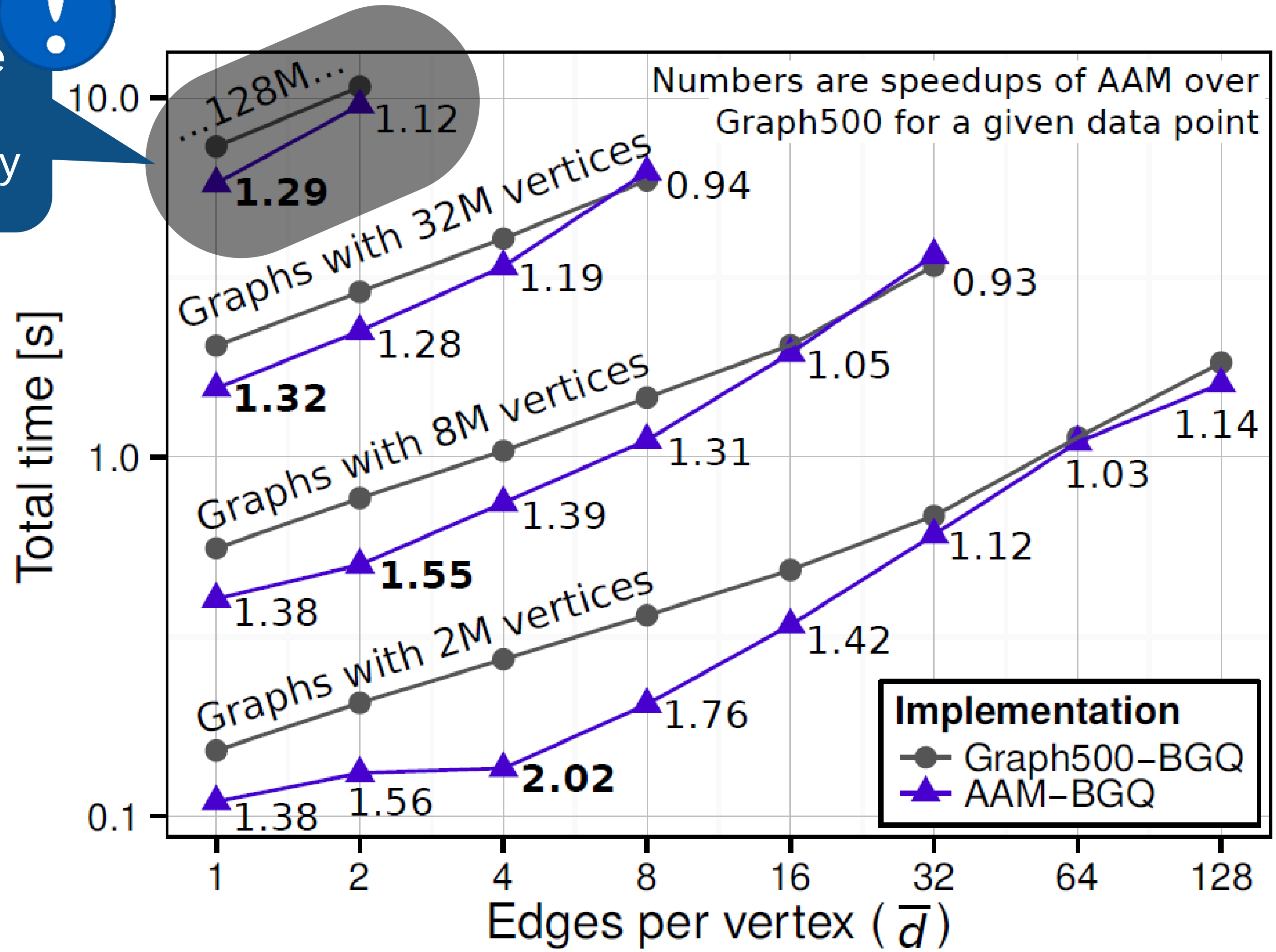
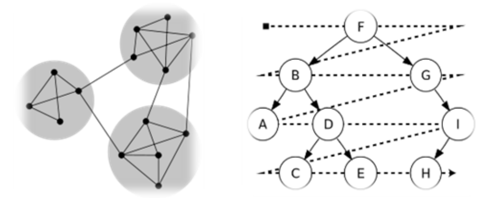




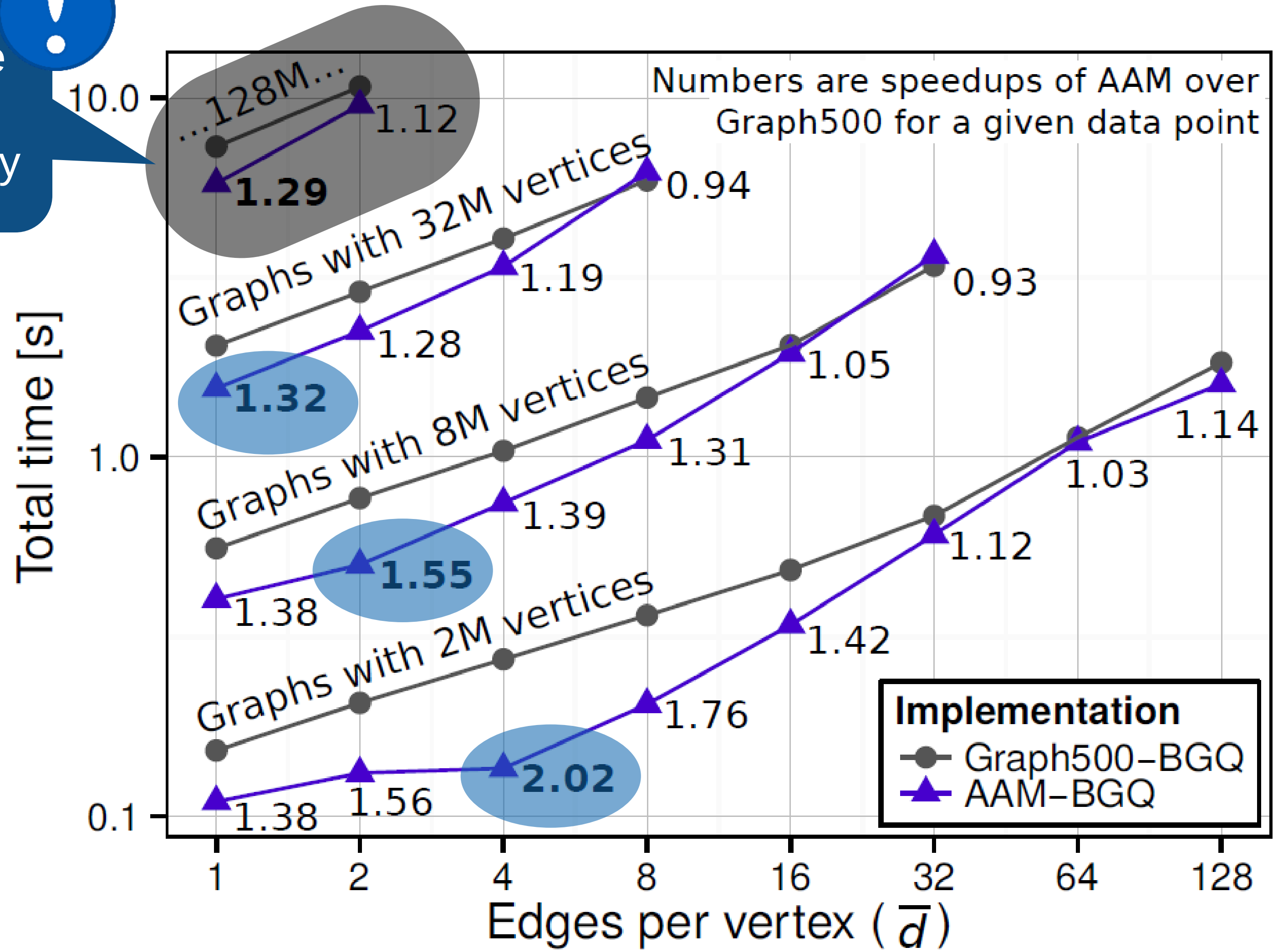
Fill the whole memory



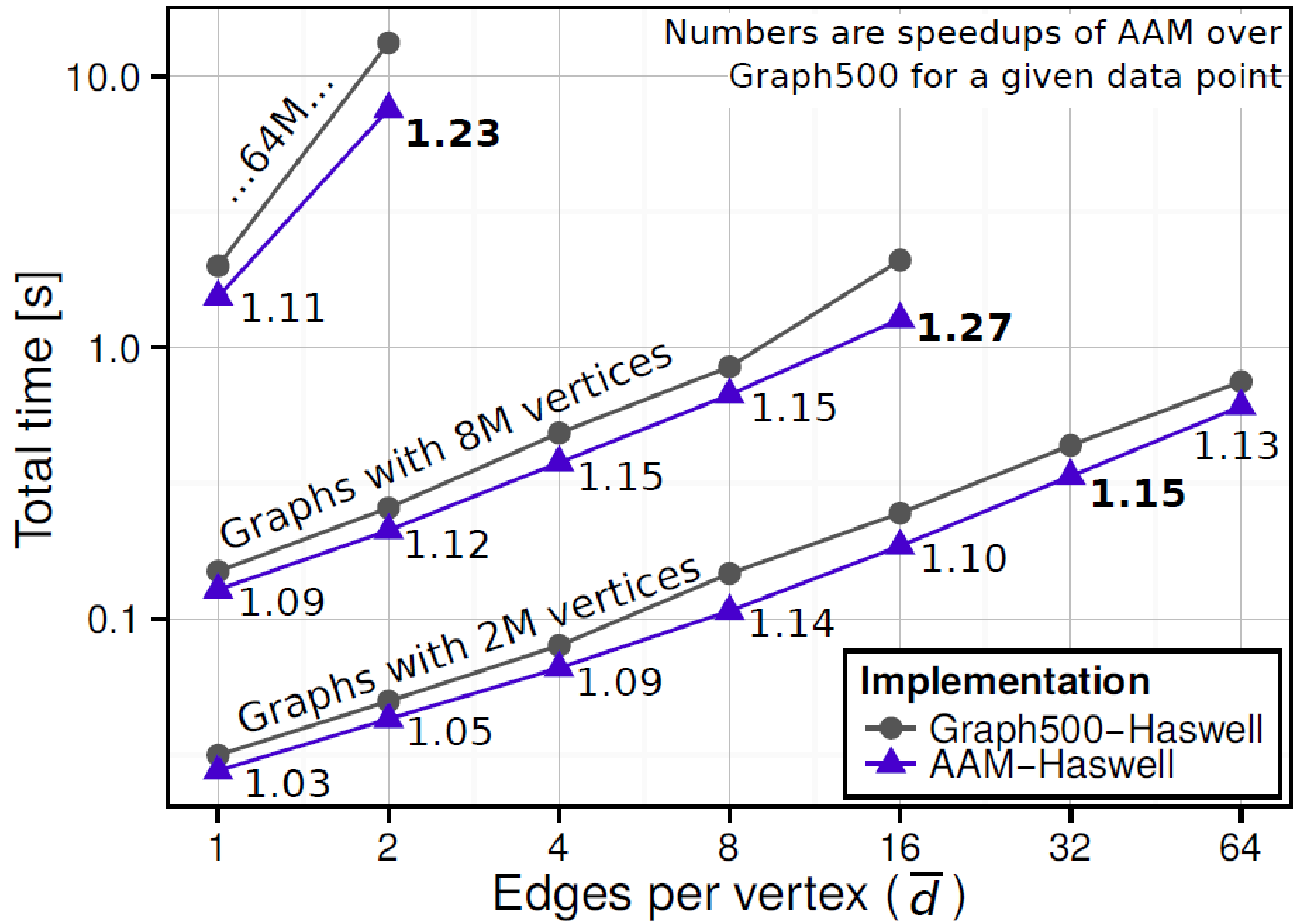
ACCELERATING STATE-OF-THE-ART GRAPH500 + AAM (BLUEGENE/Q) IBM



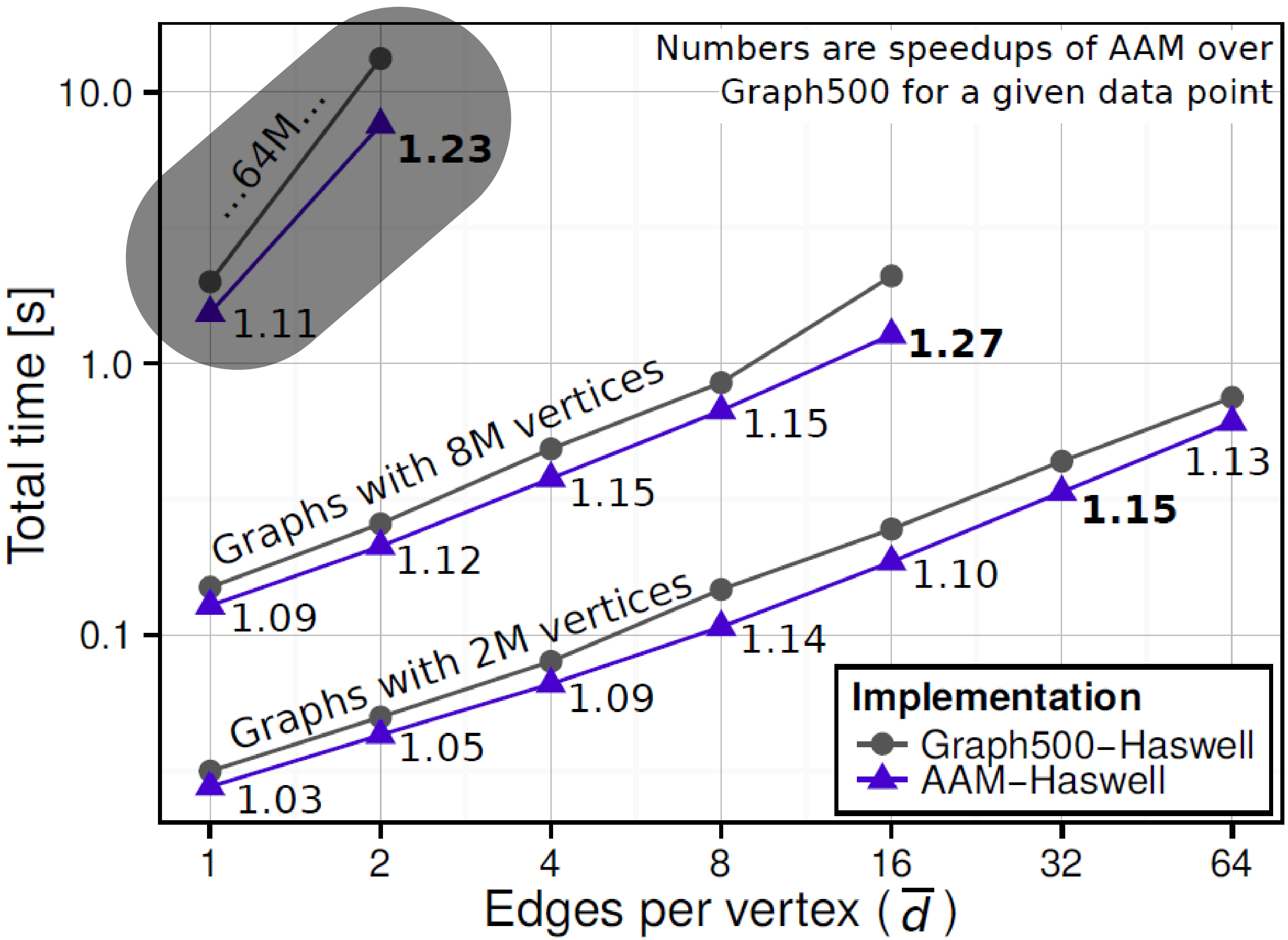
Fill the whole memory



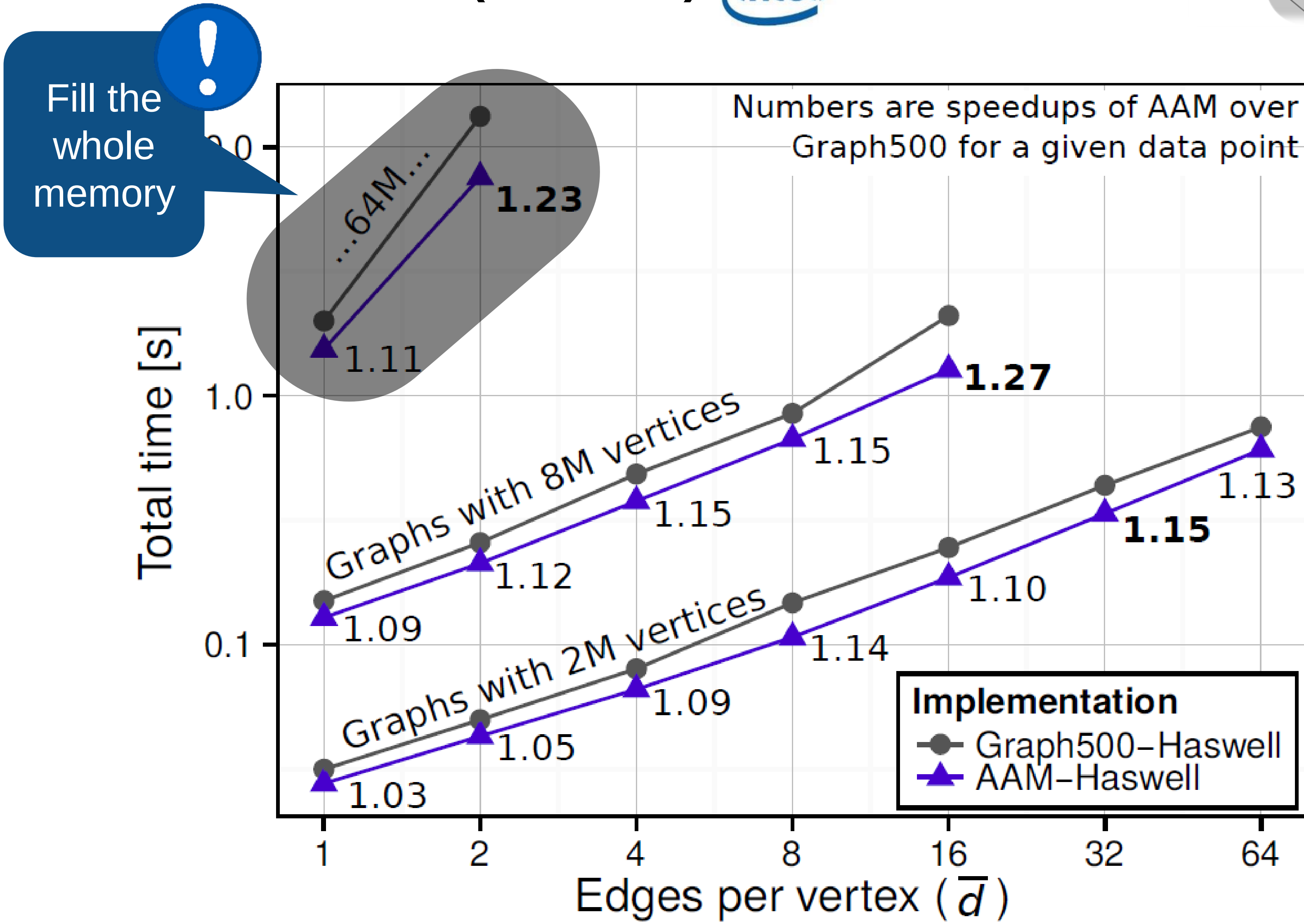
ACCELERATING STATE-OF-THE-ART GRAPH500 + AAM (HASWELL)



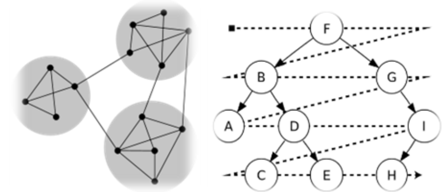
ACCELERATING STATE-OF-THE-ART GRAPH500 + AAM (HASWELL)

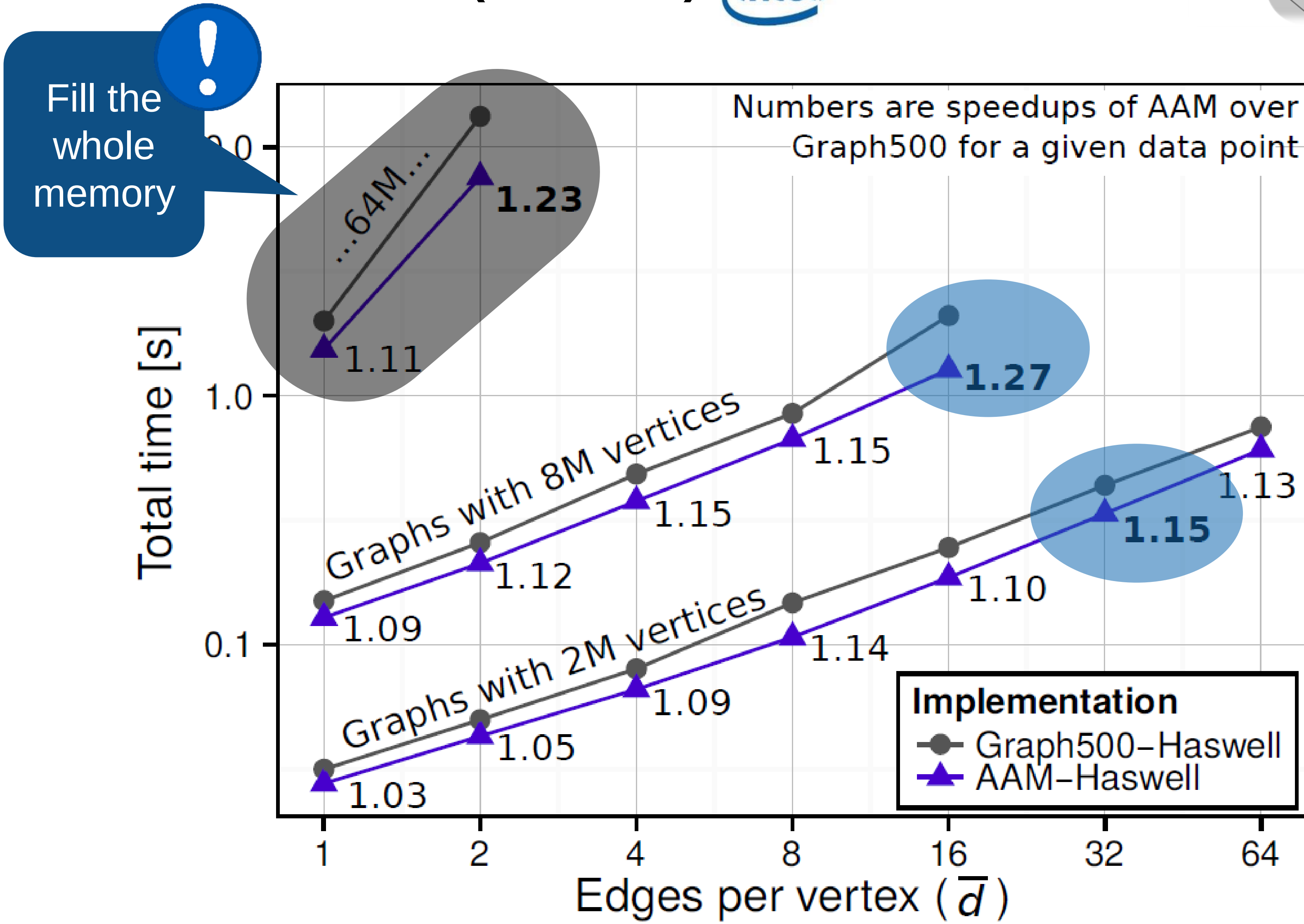


ACCELERATING STATE-OF-THE-ART GRAPH500 + AAM (HASWELL)



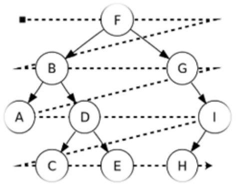
ACCELERATING STATE-OF-THE-ART GRAPH500 + AAM (HASWELL)



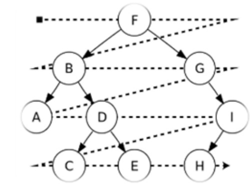


OUTPERFORMING STATE-OF-THE-ART

SNAP

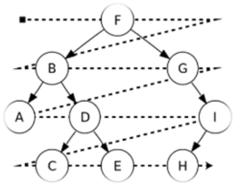


OUTPERFORMING STATE-OF-THE-ART



Input graph properties					BG/Q analysis			Haswell analysis					
Type	ID	Name	$\|V\|$	$\|E\|$	S over g500 ($M = 24$)	M	S over g500	S over g500 ($M = 2$)	S over Galois ($M = 2$)	M	S over g500	S over Galois	S over HAMA
Comm. networks (CNs)	cWT	wiki-Talk	2.4M	5M	2.82	48	3.35	0.91	1.22	6	0.96	1.28	344
	cEU	email-EuAll	265k	420k	3.67	32	4.36	0.76	0.88	4	0.97	1.12	1448
Social networks (SNs)	sLV	soc-LiveJ.	4.8M	69M	1.44	12	1.56	1.05	1.1	3	1.07	1.12	$> 10^4$
	sOR	com-orkut	3M	117M	1.22	20	1.27	1.06	0.69	4	1.13	0.74	$> 10^4$
	sLJ	com-lj	4M	34M	1.44	12	1.54	1.03	1.03	4	1.04	1.04	603
	sYT	com-youtube	1.1M	2.9M	1.67	8	1.84	0.96	1.1	5	0.98	1.11	670
	sDB	com-dblp	317k	1M	1.33	8	1.80	≈ 1	2.5	2	≈ 1	2.53	2160
	sAM	com-amazon	334k	925k	1.14	8	1.62	1.04	1.64	2	1.04	1.64	1426
Purchase network (PNs)	pAM	amazon0601	403k	3.3M	1.45	8	1.91	≈ 1	1.25	3	1.03	1.30	618
Road networks (RNs)	rCA	roadNet-CA	1.9M	5.5M	≈ 1	2	1.59	1.33	1.74	8	1.38	1.80	$> 10^4$
	rTX	roadNet-TX	1.3M	3.8M	≈ 1	2	1.53	1.29	1.89	6	1.42	2.08	$> 10^4$
	rPA	roadNet-PA	1M	3M	≈ 1	2	1.52	≈ 1	2.00	9	1.07	2.16	$> 10^4$
Citation graphs (CGs)	ciP	cit-Patents	3.7M	16.5M	1.16	8	1.57	1.01	1.26	2	1.01	1.26	1875
Web graphs (WGs)	wGL	web-Google	875k	5.1M	1.78	12	2.08	0.98	1.26	6	1.06	1.35	365
	wBS	web-BerkStan	685k	7.6M	1.91	24	1.91	0.93	1.31	5	1.07	1.40	755
	wSF	web-Stanford	281k	2.3M	1.89	24	1.89	0.98	1.54	5	1.07	1.58	1077

OUTPERFORMING STATE-OF-THE-ART



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	sOR	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.06	[illegible]	[illegible]	1.12	[illegible]	$> 10^4$
	sLJ	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
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	sAM	[illegible]	[illegible]	[illegible]	1.14	8	[illegible]	1.04	1.64	2	1.04	1.64	1426
Purchase network (PNs)	pAM	amazon0601	[illegible]	[illegible]	1.45	8	[illegible]	≈1	1.25	3	1.03	1.50	618
Road networks (RNs)	rCA	roadNet-CA	1.9M	5.5M	≈1	2	1.59	1.33	1.74	8	1.38	1.80	$> 10^4$
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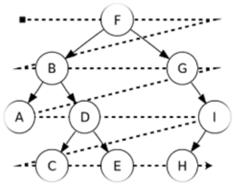
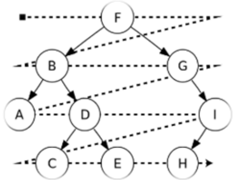
☺ No, you don't have to read it. All details are in the paper. Here: just a summary.

OUTPERFORMING STATE-OF-THE-ART
HASWELL



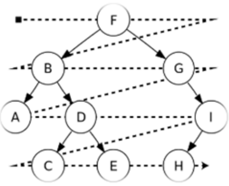
OUTPERFORMING STATE-OF-THE-ART
HASWELL



Average overall speedup (geometric mean) over Graph500: 1.07, Galois: 1.40, HAMA ~1000

Outperforming State-of-the-Art
Haswell (intel)

SNAP



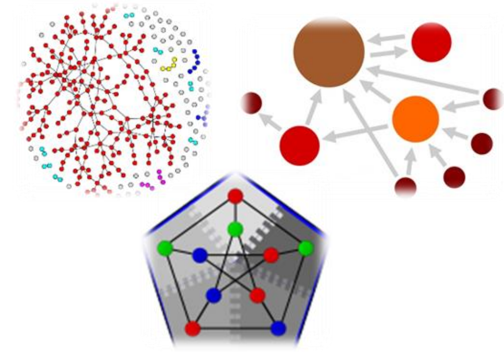
Average overall speedup (geometric mean) over Graph500: 1.07, Galois: 1.40, HAMA ~1000

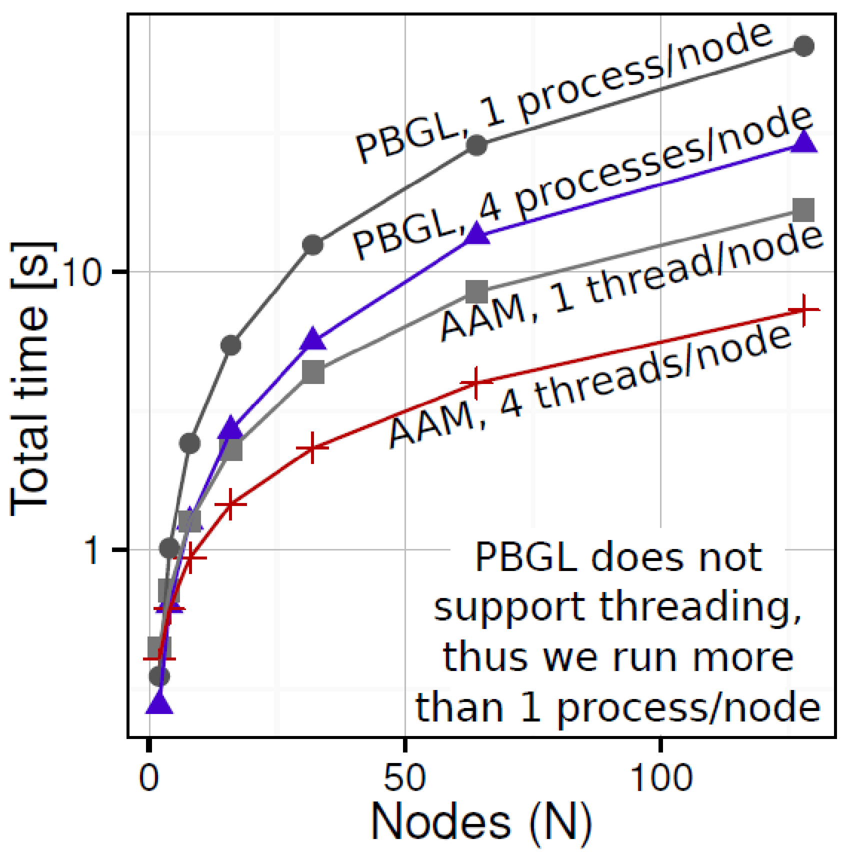
1.85x on average, up to 4.3x

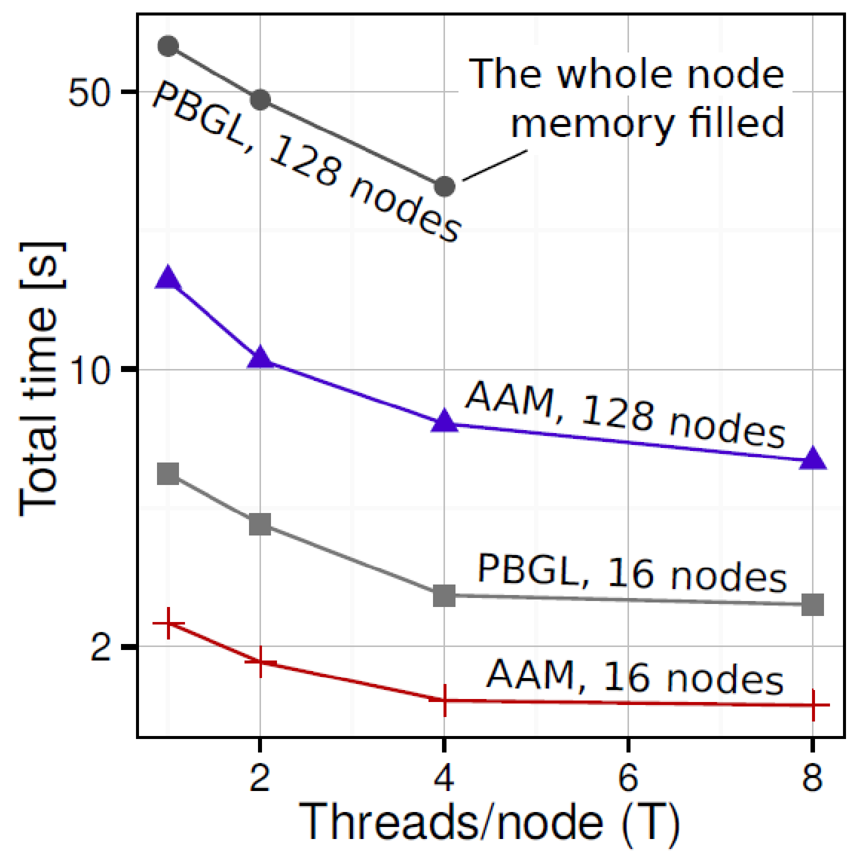
IBM

GRAPH 500

OUTPERFORMING STATE-OF-THE-ART
SCALABILITY ANALYSIS: DISTRIBUTED-MEMORY







OTHER ANALYSES

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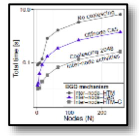
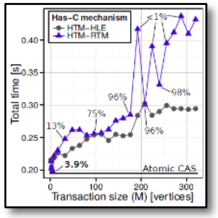
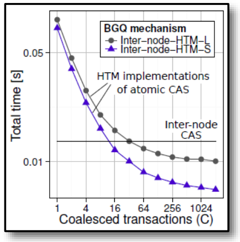
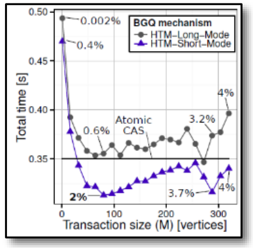
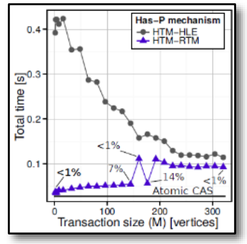
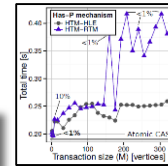


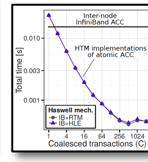


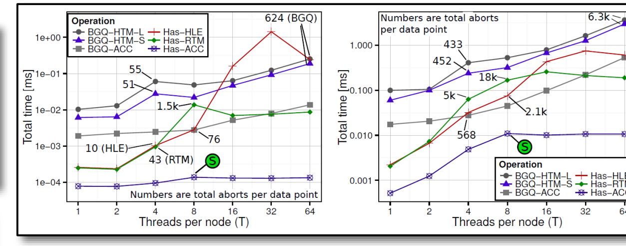


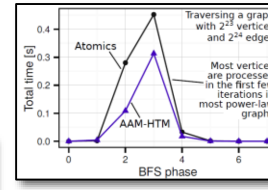


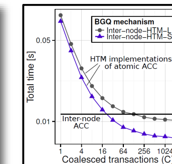


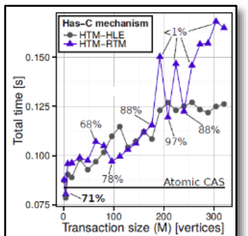


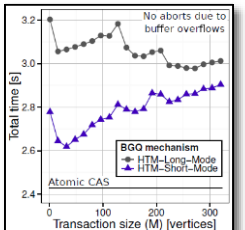


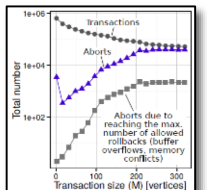


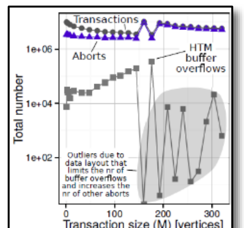


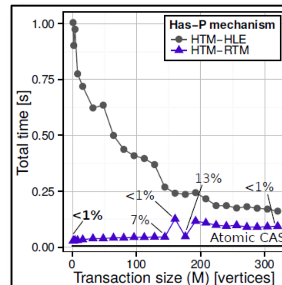






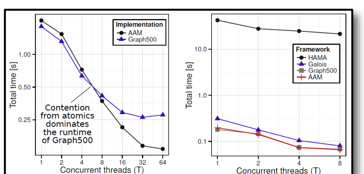


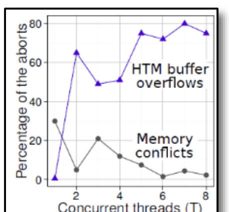


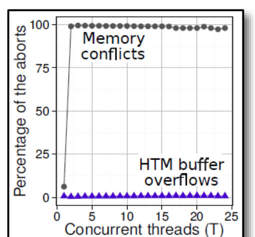


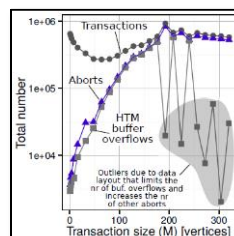
		Memory conflicts	Buffer overflows	Other reasons
10 ops	Has-RTM	1,520	1	0
	BGQ-HTM-L	624	62	614
	BGQ-HTM-S	623	62	613
100 ops	Has-RTM	18,952	33	0
	BGQ-HTM-L	6,374	637	6,360
	BGQ-HTM-S	6,392	639	6,380

Aborts due to:



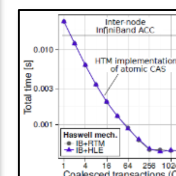


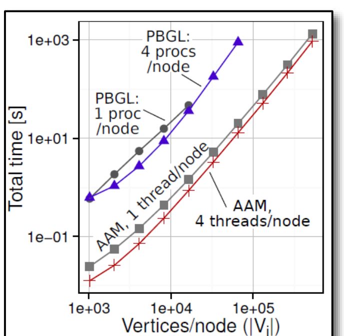


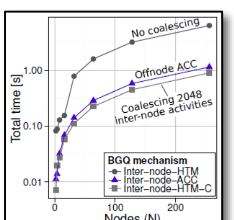


		Memory conflicts	Buffer overflows	Other reasons
10 ops	Has-RTM	2	2	0
	BGQ-HTM-L	802	3	1
	BGQ-HTM-S	1,118	46	180
100 ops	Has-RTM	2	2	0
	BGQ-HTM-L	1,539	5	1
	BGQ-HTM-S	2,242	13	2

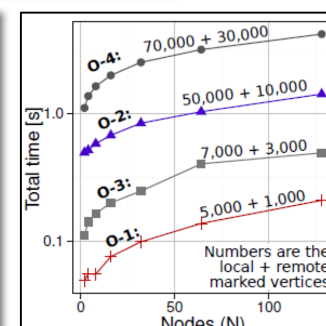
Aborts due to:







Input graph properties					BG/Q analysis			Haswell analysis					
Type	ID	Name	$\|V\|$	$\|E\|$	S over g500 ($M = 24$)	M	S over g500	S over g500 ($M = 2$)	S over Galois ($M = 2$)	M	S over g500	S over Galois	S over HAMA
Comm. networks (CNs)	cWT	wiki-Talk	2.4M	5M	2.82	48	3.35	0.91	1.22	6	0.96	1.28	344
	cEU	email-EuAll	265k	420k	3.67	32	4.36	0.76	0.88	4	0.97	1.12	1448
Social networks (SNs)	sLV	soc-LiveJ.	4.8M	69M	1.44	12	1.56	1.05	1.1	3	1.07	1.12	$> 10^4$
	sOR	com-orkut	3M	117M	1.22	20	1.27	1.06	0.69	4	1.13	0.74	$> 10^4$
	sLJ	com-lj	4M	34M	1.44	12	1.54	1.03	1.03	4	1.04	1.04	603
	sYT	com-youtube	1.1M	2.9M	1.67	8	1.84	0.96	1.1	5	0.98	1.11	670
	sDB	com-dblp	317k	1M	1.33	8	1.80	≈1	2.5	2	≈1	2.53	2160
	sAM	com-amazon	334k	925k	1.14	8	1.62	1.04	1.64	2	1.04	1.64	1426
Purchase network (PNs)	pAM	amazon0601	403k	3.3M	1.45	8	1.91	≈1	1.25	3	1.03	1.30	618
Road networks (RNs)	rCA	roadNet-CA	1.9M	5.5M	≈1	2	1.59	1.33	1.74	8	1.38	1.80	$> 10^4$
	rTX	roadNet-TX	1.3M	3.8M	≈1	2	1.53	1.29	1.89	6	1.42	2.08	$> 10^4$
	rPA	roadNet-PA	1M	3M	≈1	2	1.52	≈1	2.00	9	1.07	2.16	$> 10^4$
Citation graphs (CGs)	ciP	cit-Patents	3.7M	16.5M	1.16	8	1.57	1.01	1.26	2	1.01	1.26	1875
Web graphs (WGs)	wGL	web-Google	875k	5.1M	1.78	12	2.08	0.98	1.26	6	1.06	1.35	365
	wBS	web-BerkStan	685k	7.6M	1.91	24	1.91	0.93	1.31	5	1.07	1.40	755
	wSF	web-Stanford	281k	2.3M	1.89	24	1.89	0.98	1.54	5	1.07	1.58	1077



CONCLUSIONS

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HTM for graphs in SM & DM environments

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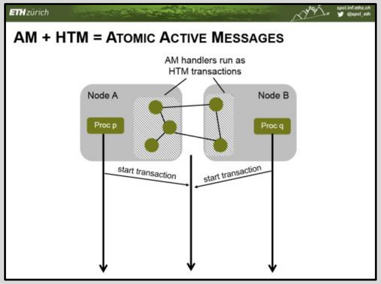
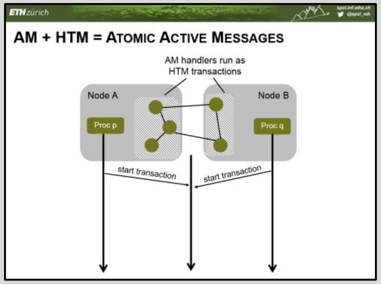


AAM: Combine the advantages of HTM and Active Messages

CONCLUSIONS

HTM for graphs in SM & DM environments



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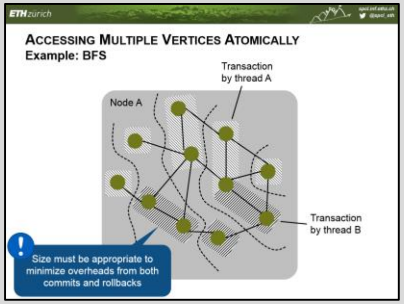

Illustrate HTM's advantages in performance, next to programmability

CONCLUSIONS

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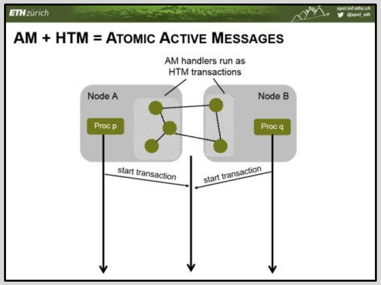

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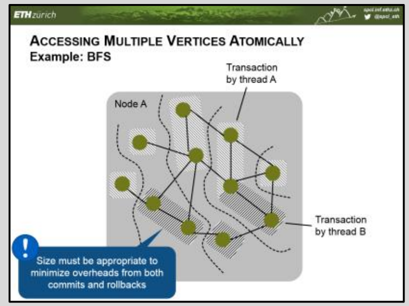

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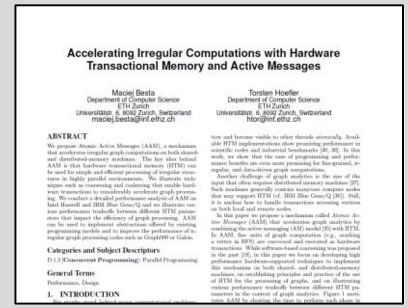
Accelerating Irregular Computations with Hardware Transactional Memory and Active Messages

Maciej Besta
Department of Computer Science
ETH Zurich

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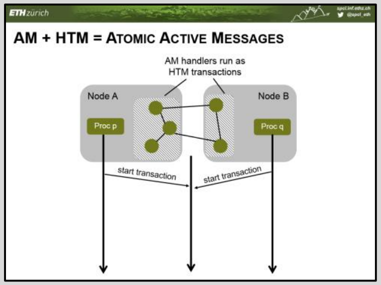
ABSTRACT

Deliver the of hierarchy of atomic messages that covers various graph algorithms

CONCLUSIONS

HTM for graphs in SM & DM environments



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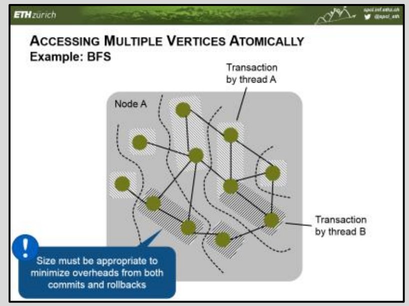

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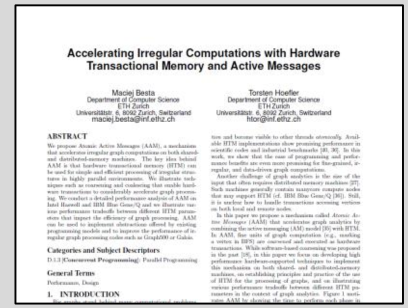
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General Terms

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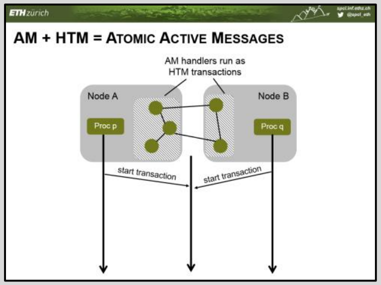
Deliver the of hierarchy of atomic messages that covers various graph algorithms

Detailed performance analysis

CONCLUSIONS

HTM for graphs in SM & DM environments



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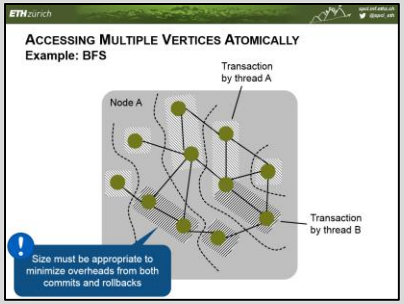

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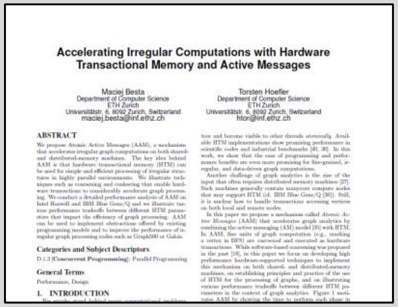
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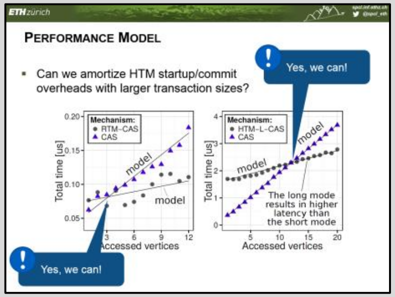
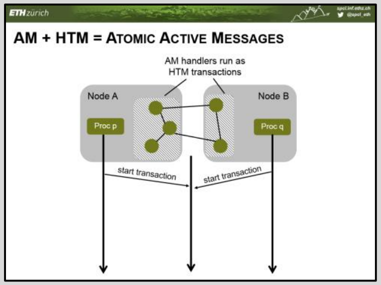


Model & analyze performance tradeoffs

Conclusions

HTM for graphs in SM & DM environments



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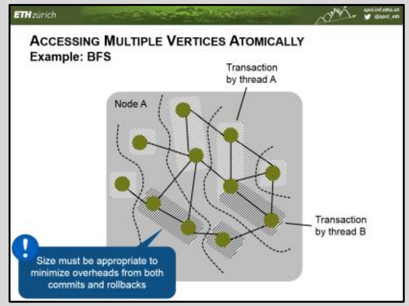

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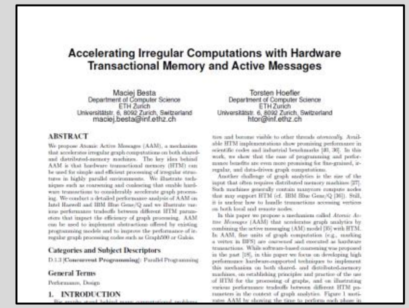
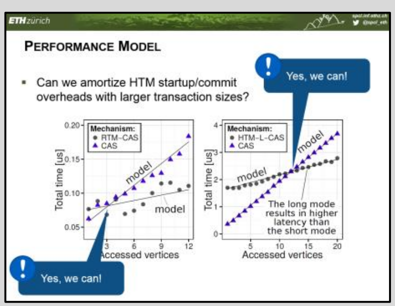


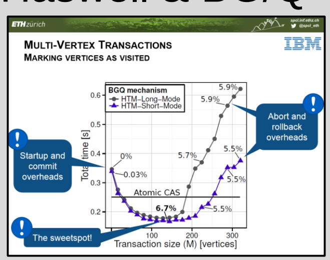
Deliver the of hierarchy of atomic messages that covers various graph algorithms

Detailed performance analysis



Model & analyze performance tradeoffs

Derive close-to-optimal transaction sizes for Haswell & BG/Q



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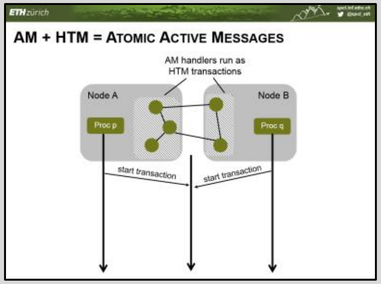

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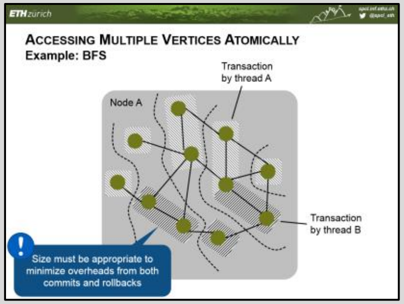

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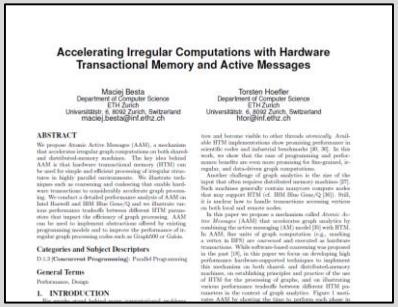
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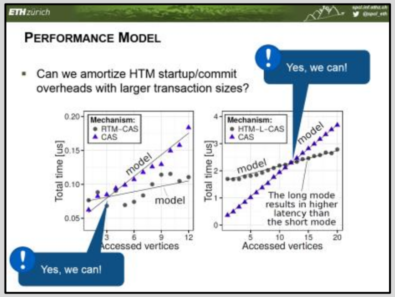

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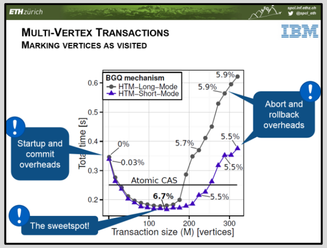
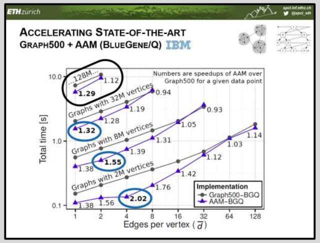
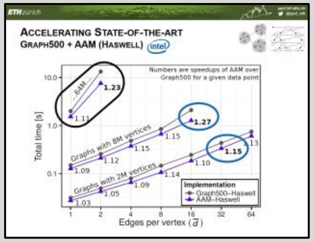


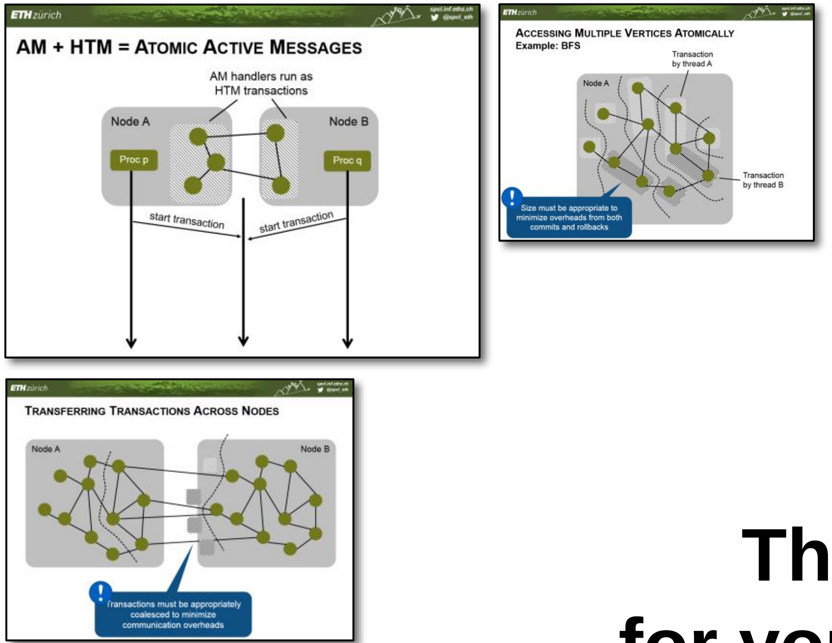
Accelerating state-of-the-art

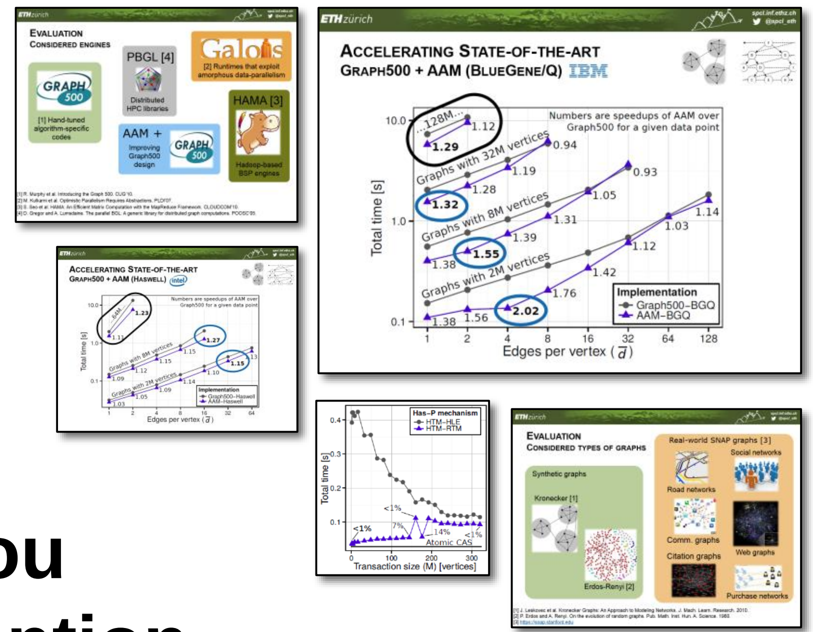




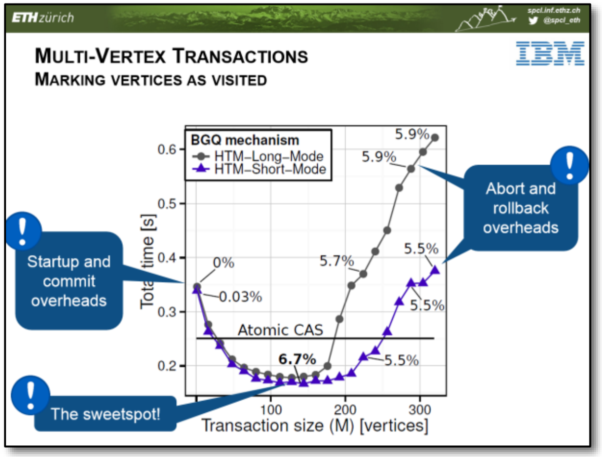
Average speedup 1.85x

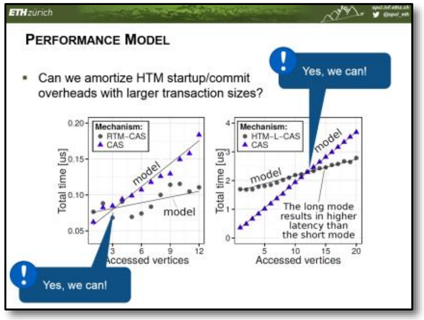
Up to 4x

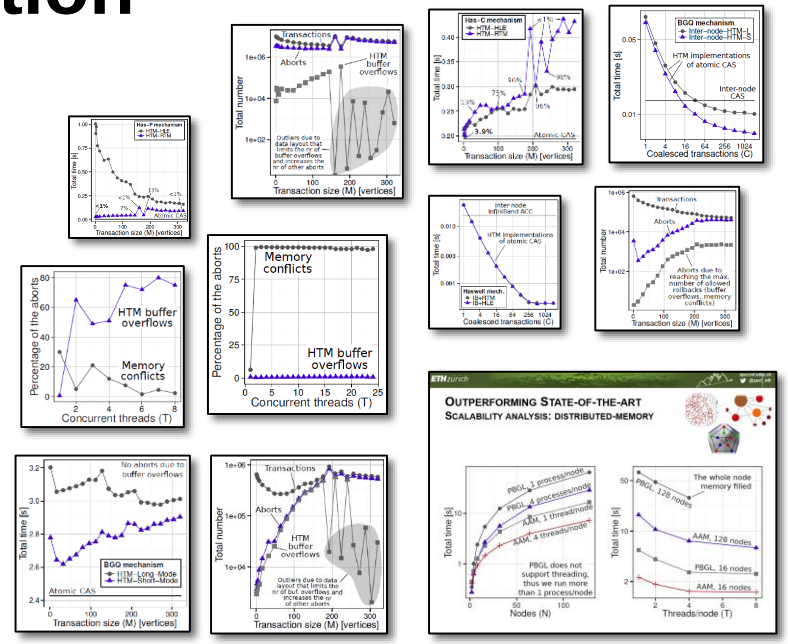




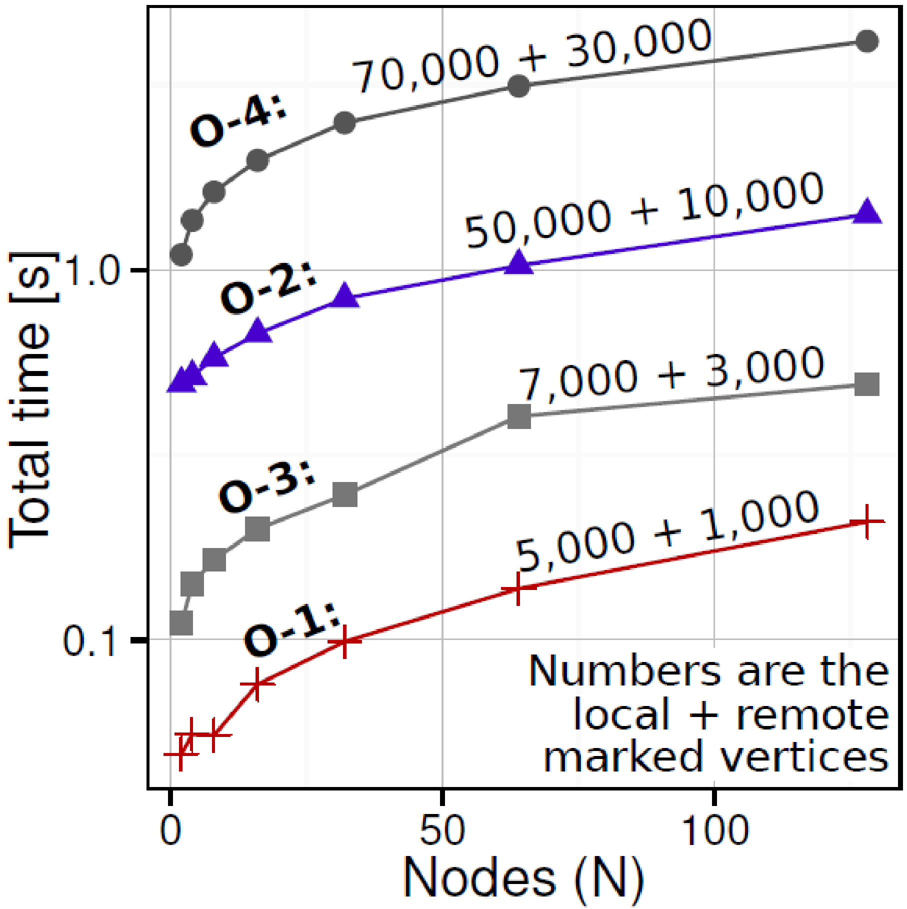
Thank you for your attention



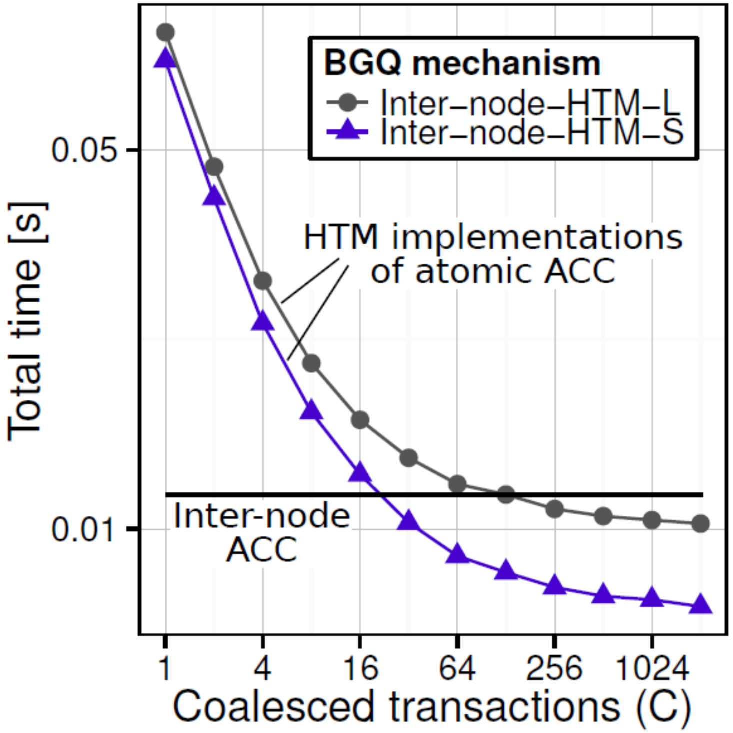


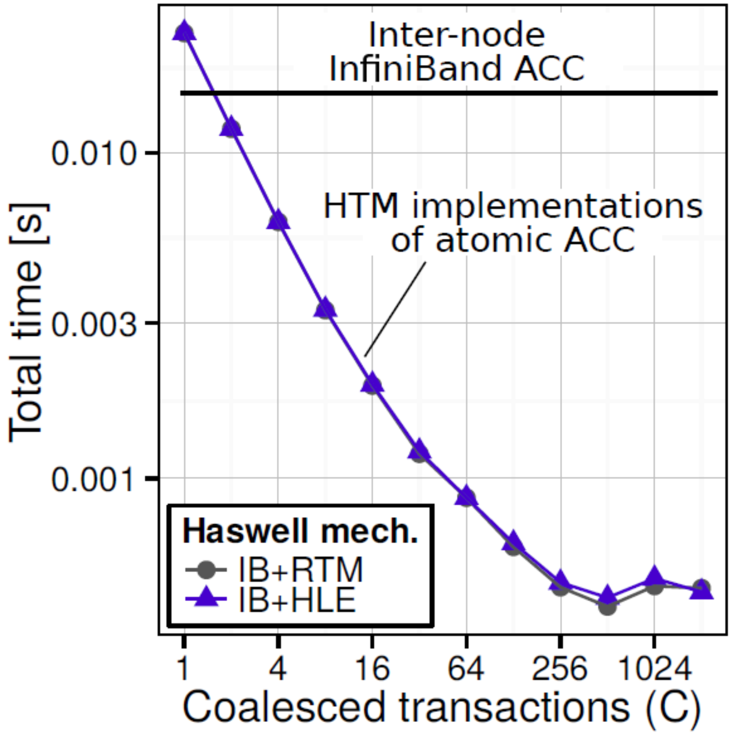


DISTRIBUTED HTM TRANSACTIONS



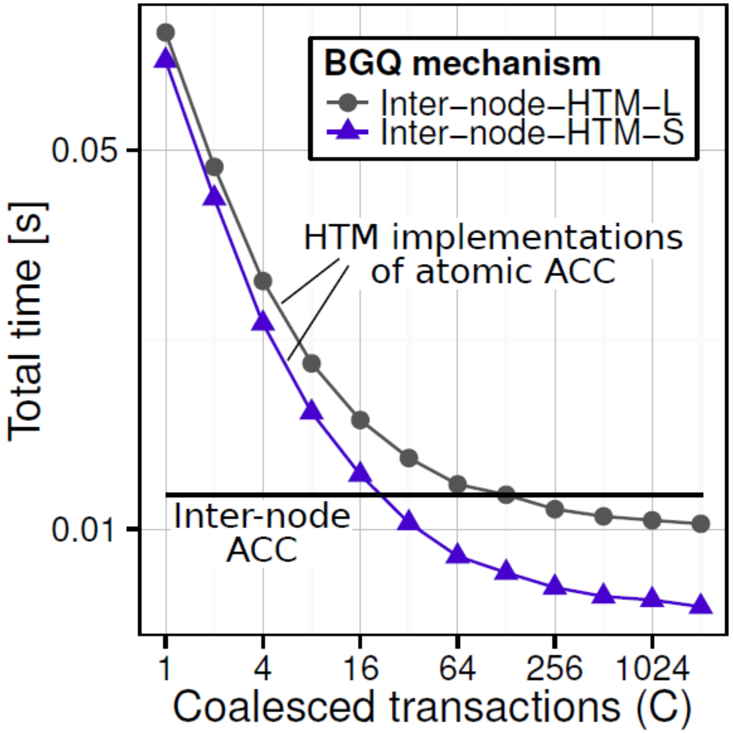
Transferring Transactions
Incrementing ranks of vertices

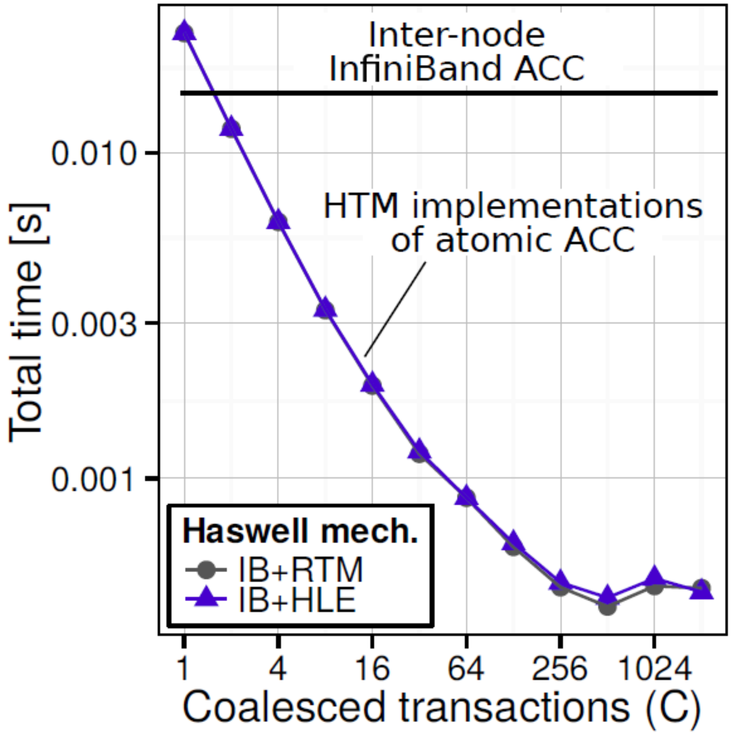




TRANSFERRING TRANSACTIONS
INCREMENTING RANKS OF VERTICES

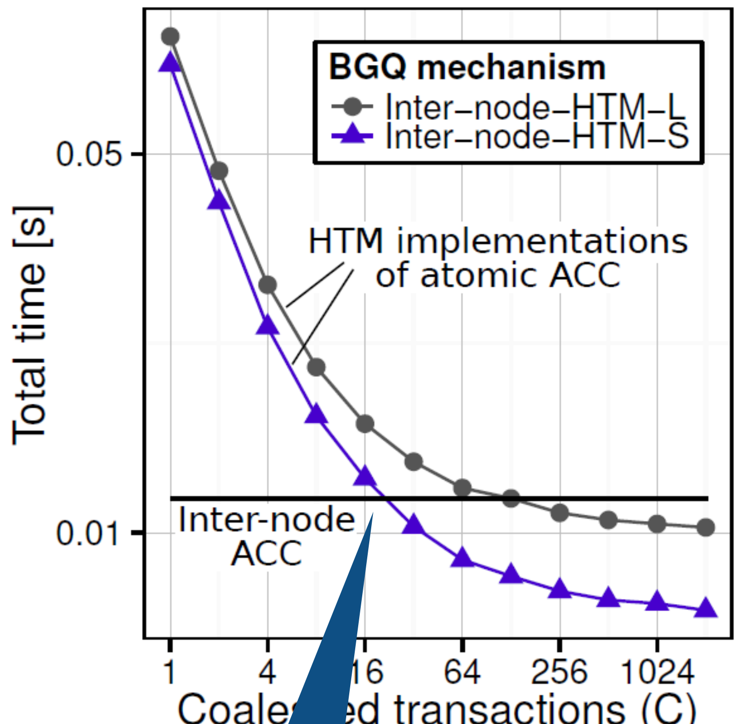
- Can we amortize HTM transactions' transfer overheads with coalescing?

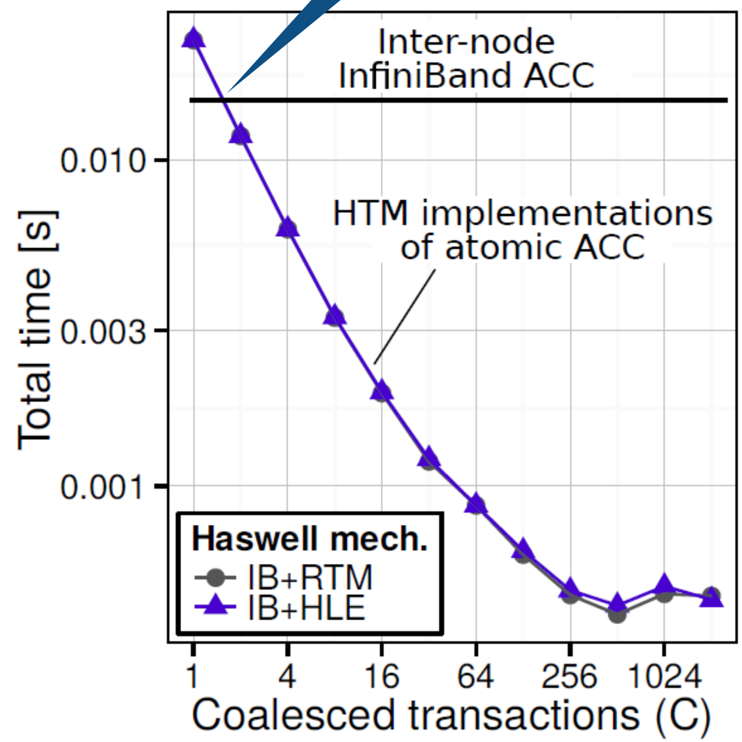




Transferring Transactions
Incrementing ranks of vertices

- Can we amortize HTM transactions' transfer overheads with coalescing?





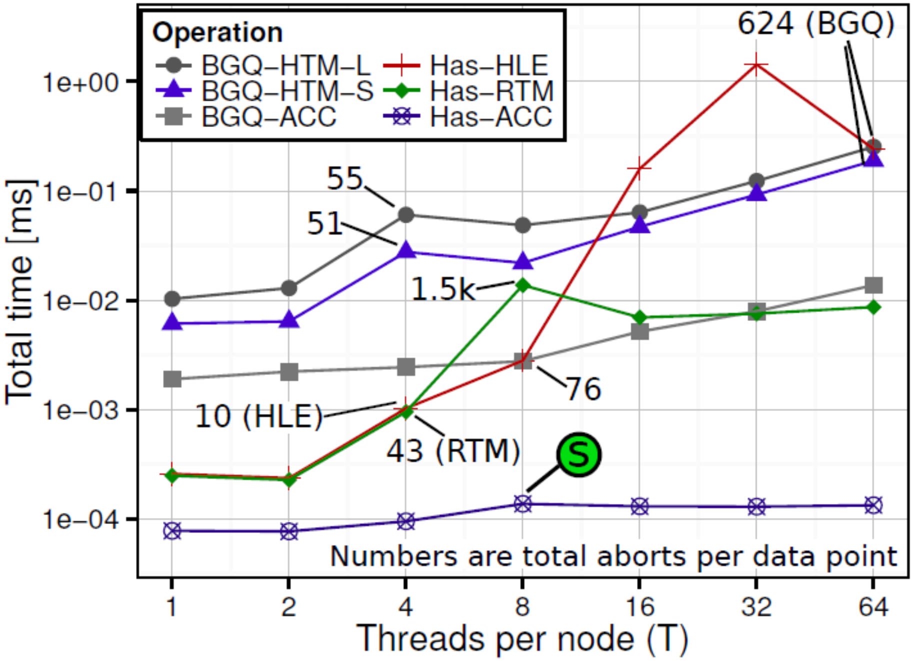
Yes, we can!

Yes, we can!

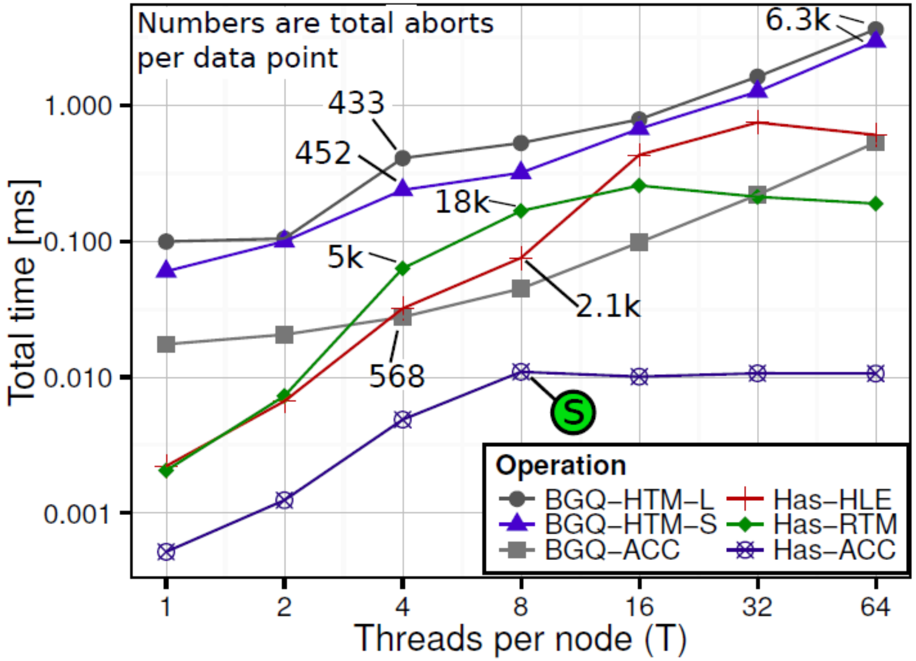
SINGLE-VERTEX TRANSACTIONS
INCREMENTING VERTEX RANK

Used in PageRank

Lower contention
(10 accesses/vertex)



Higher contention
(100 accesses/vertex)



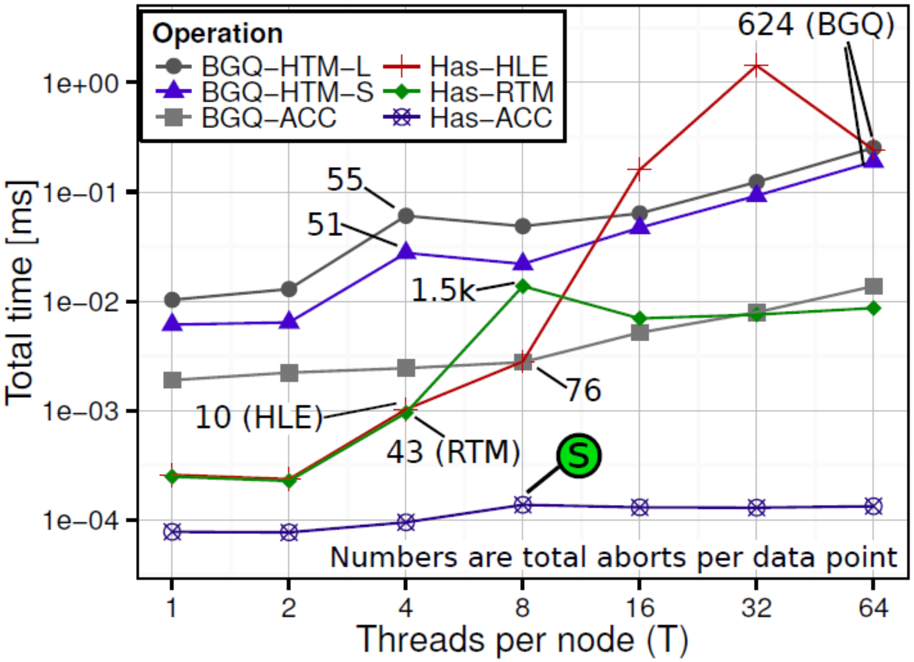
SINGLE-VERTEX TRANSACTIONS
INCREMENTING VERTEX RANK

Used in PageRank

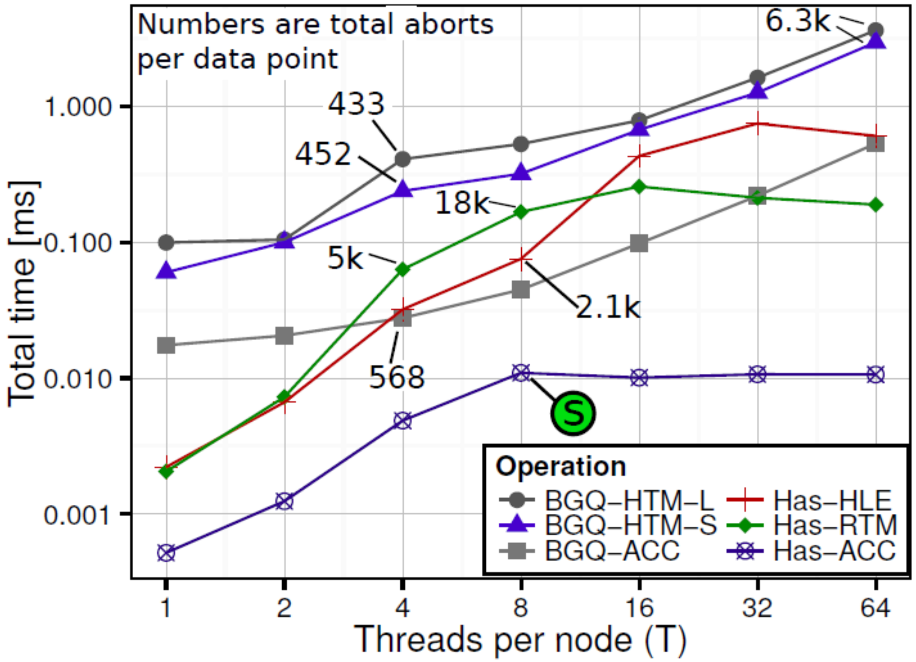
IBM intel

Atomics always outperform HTM

Lower contention (10 accesses/vertex)



Higher contention (100 accesses/vertex)

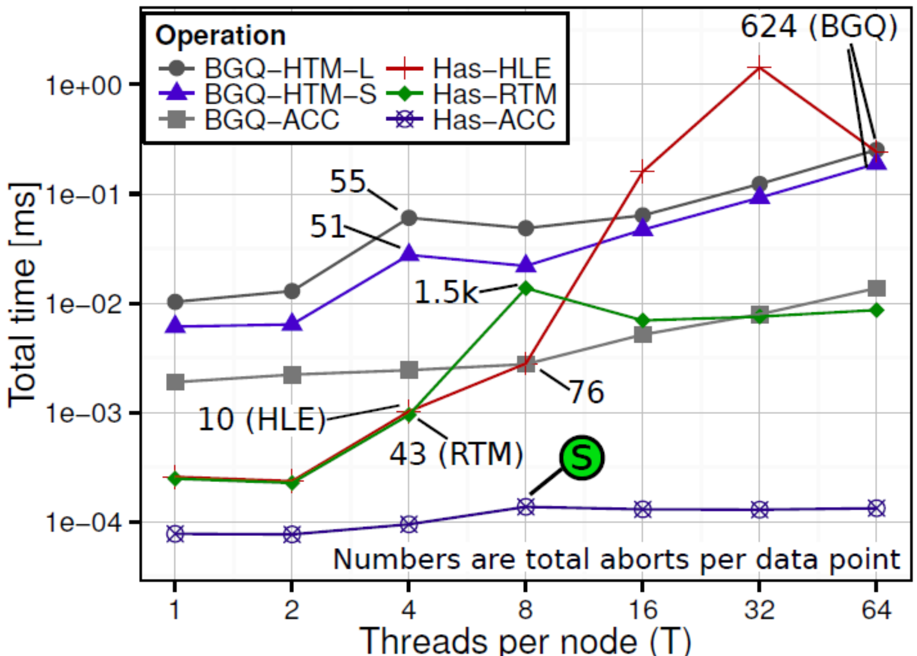


SINGLE-VERTEX TRANSACTIONS
INCREMENTING VERTEX RANK

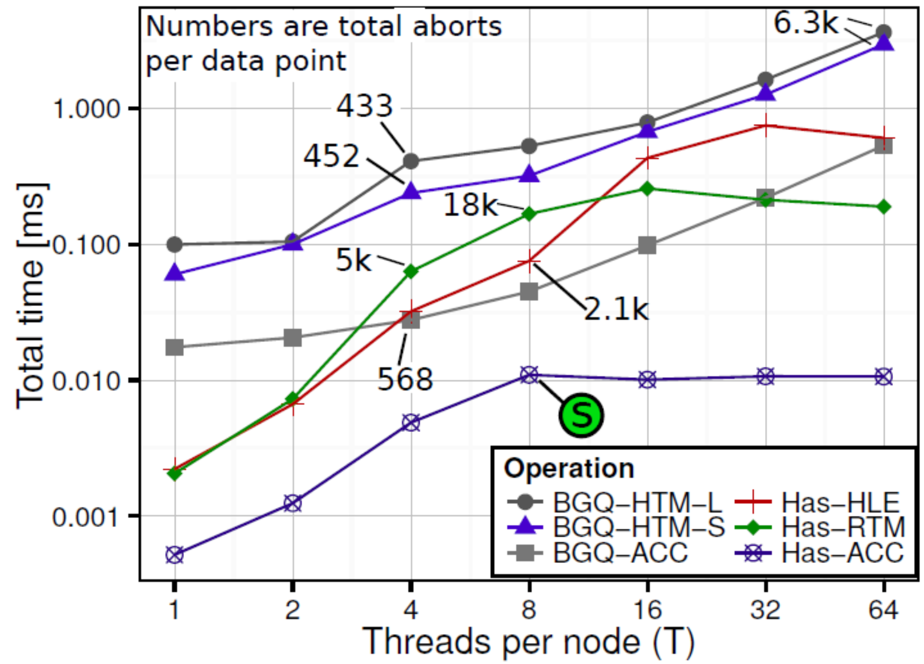
Used in PageRank

Atomics always outperform HTM

Lower contention (10 accesses/vertex)



Higher contention (100 accesses/vertex)



The reason: each transaction always modifies some memory cell, increasing the number of conflicts

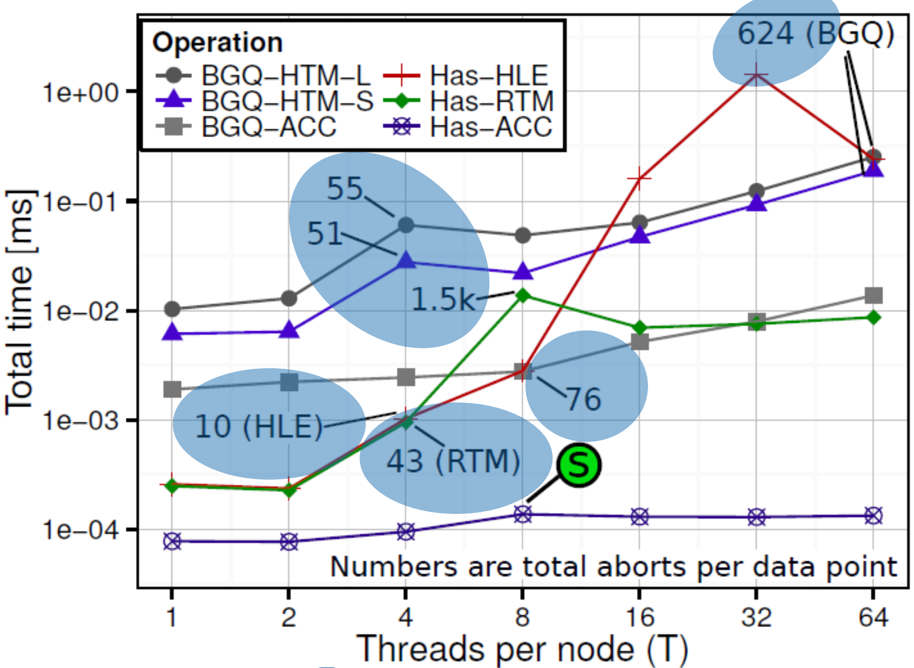
Single-Vertex Transactions
Incrementing vertex rank

Used in PageRank

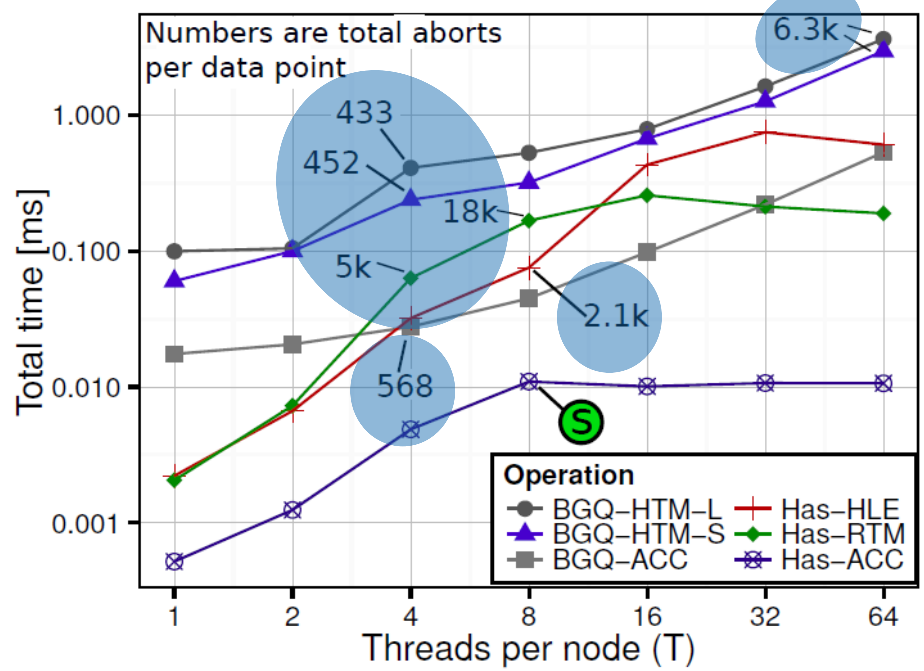
More aborts

Atomics always outperform HTM

Lower contention (10 accesses/vertex)



Higher contention (100 accesses/vertex)

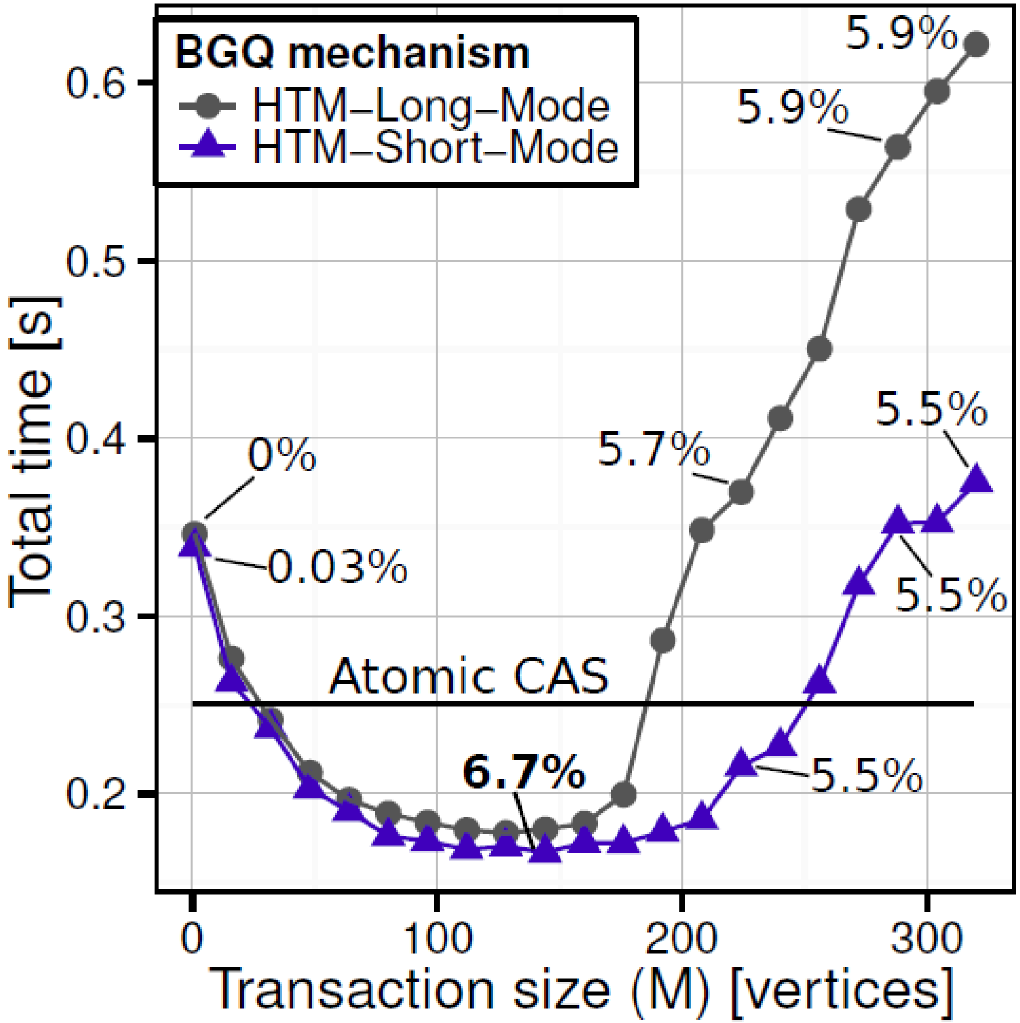


The reason: each transaction always modifies some memory cell, increasing the number of conflicts

MULTI-VERTEX TRANSACTIONS

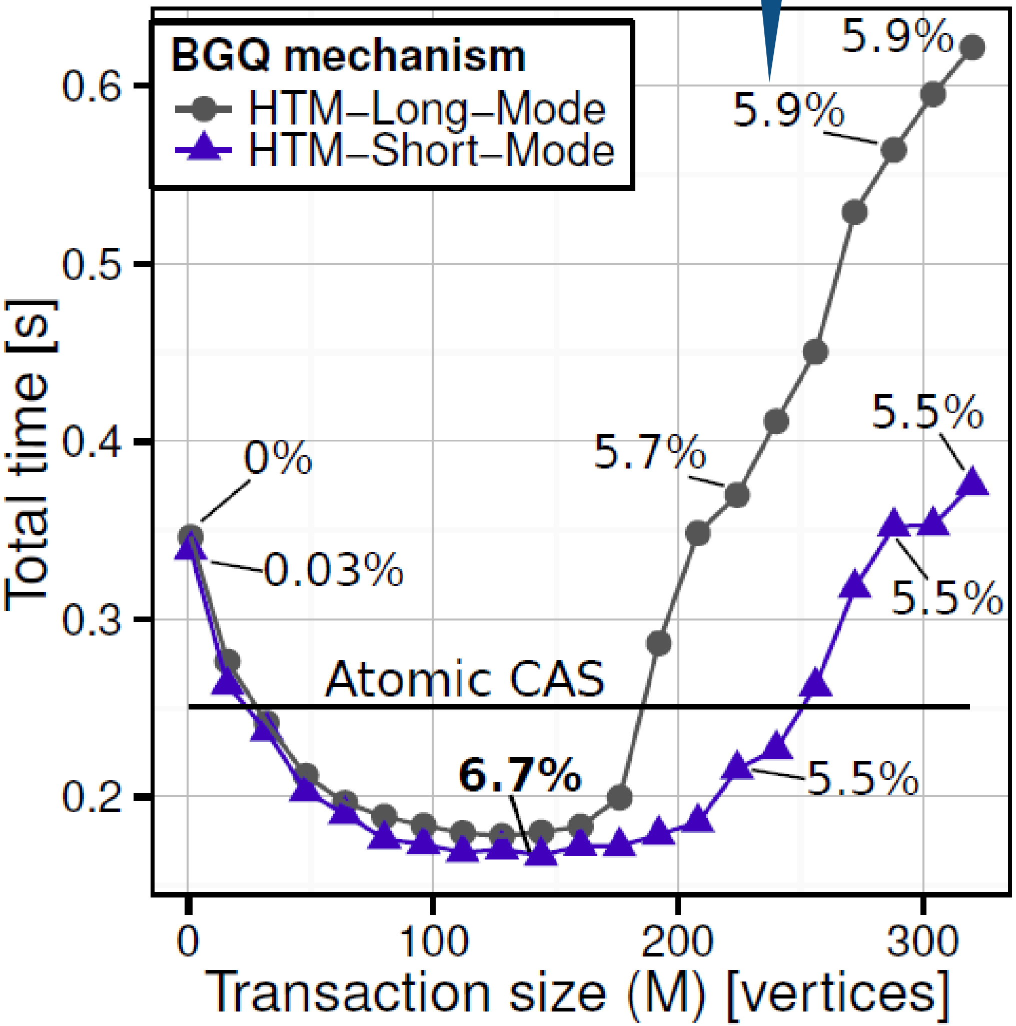
MARKING VERTICES AS VISITED

MULTI-VERTEX TRANSACTIONS
MARKING VERTICES AS VISITED



Multi-Vertex Transactions
Marking vertices as visited

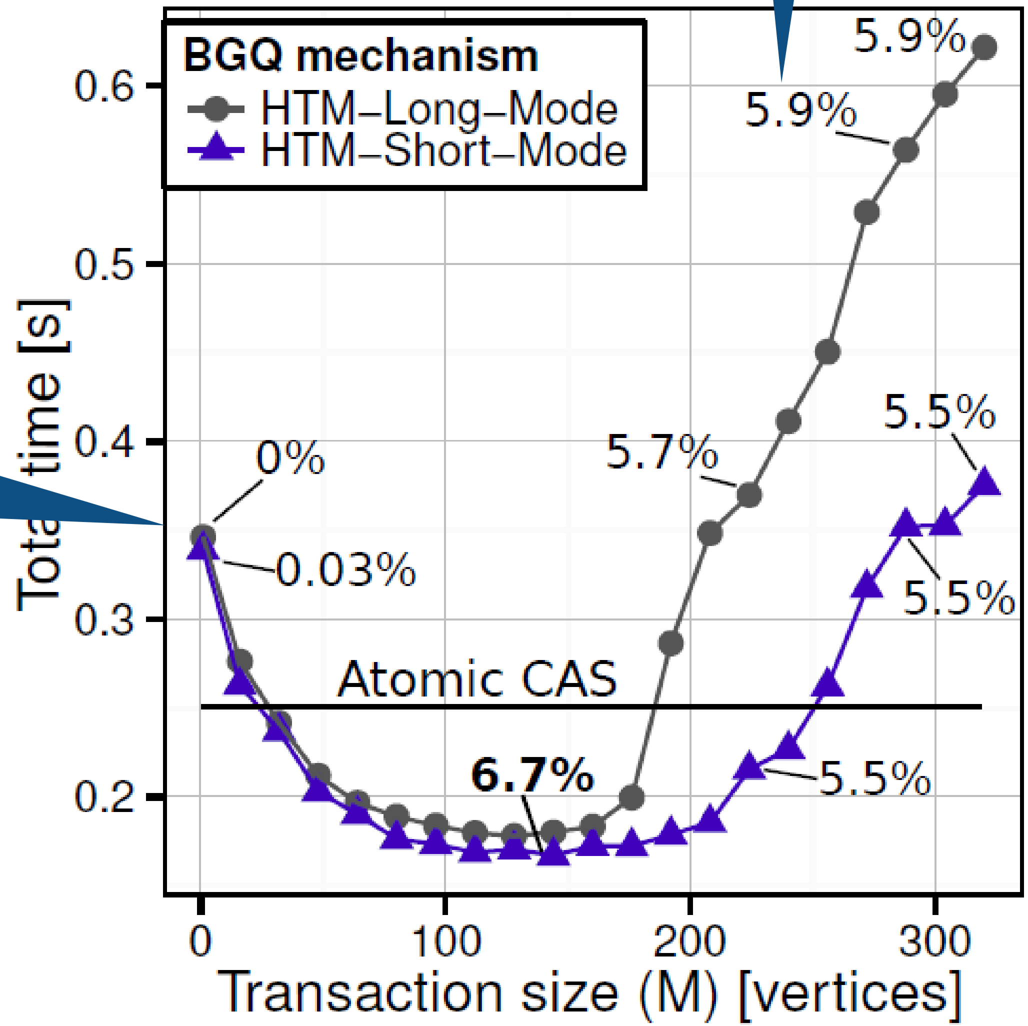
Numbers: % of aborts due to the lack of HTM resources + memory conflicts



MULTI-VERTEX TRANSACTIONS
MARKING VERTICES AS VISITED

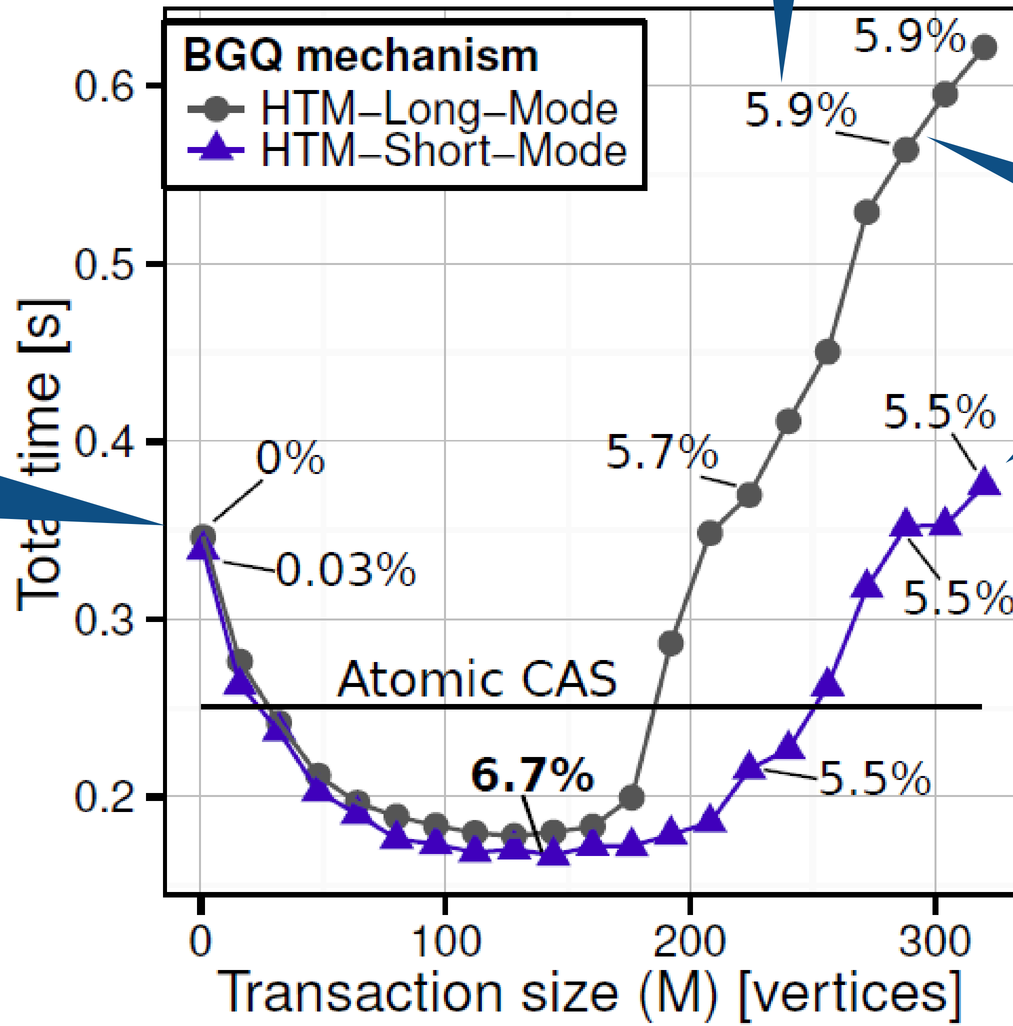
Numbers: % of aborts due to the lack of HTM resources + memory conflicts

Startup and commit overheads



MULTI-VERTEX TRANSACTIONS
MARKING VERTICES AS VISITED

Numbers: % of aborts due to the lack of HTM resources + memory conflicts

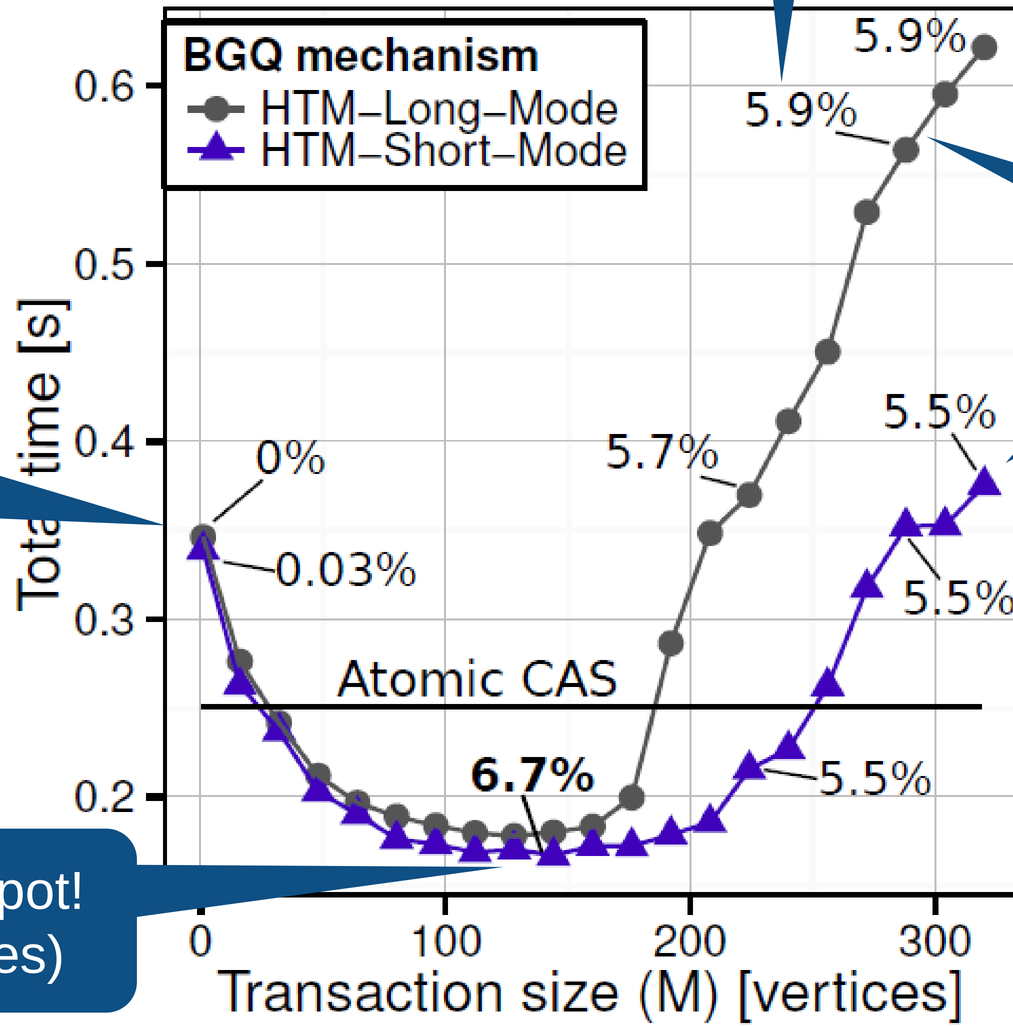


Startup and commit overheads

Abort and rollback overheads

MULTI-VERTEX TRANSACTIONS
MARKING VERTICES AS VISITED

Numbers: % of aborts due to the lack of HTM resources + memory conflicts



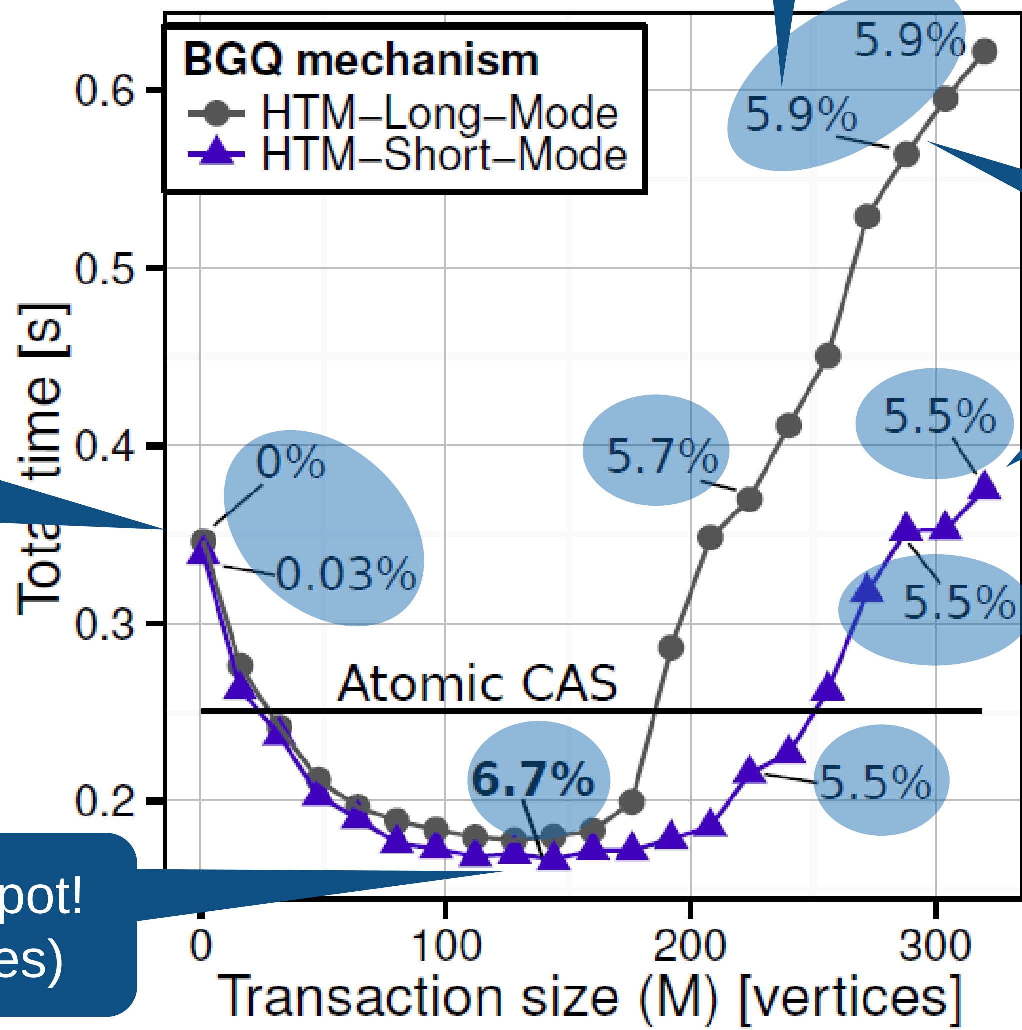
Abort and rollback overheads

Startup and commit overheads

The sweetspot! (144 vertices)

MULTI-VERTEX TRANSACTIONS
MARKING VERTICES AS VISITED

Numbers: % of aborts due to the lack of HTM resources + memory conflicts



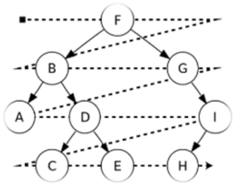
Abort and rollback overheads

Startup and commit overheads

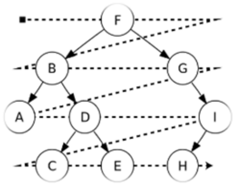
Not too many aborts due to the lack of HW resources (large cache size & associativity)

The sweetspot! (144 vertices)

Outperforming State-of-the-art BlueGene/Q



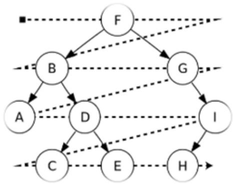
OUTPERFORMING STATE-OF-THE-ART
BLUEGENE/Q IBM



Average overall speedup over Graph500 (geometric mean): 1.51 (1.85)

Outperforming State-of-the-Art

BlueGene/Q IBM





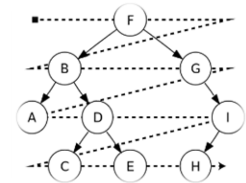


Average overall speedup over Graph500 (geometric mean): 1.51 (1.85)

OUTPERFORMING STATE-OF-THE-ART

BLUEGENE/Q IBM

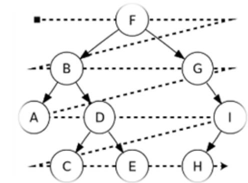
SNAP



Average overall speedup over Graph500 (geometric mean): 1.51 (1.85)

The same transaction size for all graphs

Outperforming State-of-the-Art
BlueGene/Q IBM

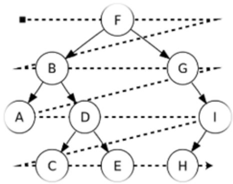


Average overall speedup over Graph500 (geometric mean): 1.51 (1.85)

The same transaction size for all graphs

The same transaction sizes for each graph separately

OUTPERFORMING STATE-OF-THE-ART
BLUEGENE/Q IBM



Average speedup: 1

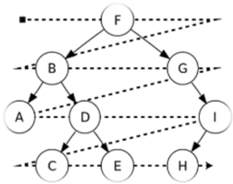
Average overall speedup over Graph500 (geometric mean): 1.51 (1.85)

The same transaction size for all graphs

The same transaction sizes for each graph separately

Outperforming State-of-the-Art

BlueGene/Q IBM



Average speedup: 1

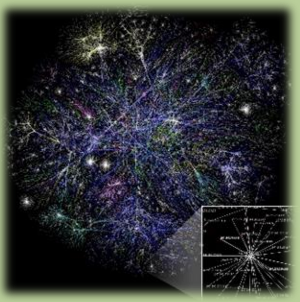




Average overall speedup over Graph500 (geometric mean): 1.51 (1.85)

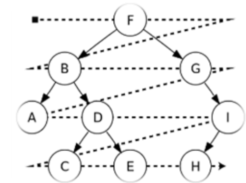
The same transaction size for all graphs

The same transaction sizes for each graph separately

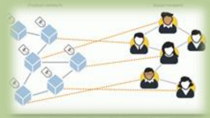


Average speedup: 1.85

Outperforming State-of-the-Art
BlueGene/Q IBM



Average speedup: 1

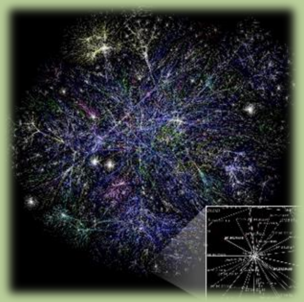


Average overall speedup over Graph500 (geometric mean): 1.51 (1.85)

The same transaction size for all graphs

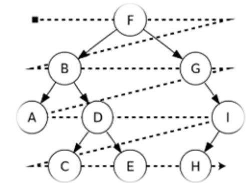
The same transaction sizes for each graph separately

Average speedup: 3.20



Average speedup: 1.85

Outperforming State-of-the-Art
BlueGene/Q IBM

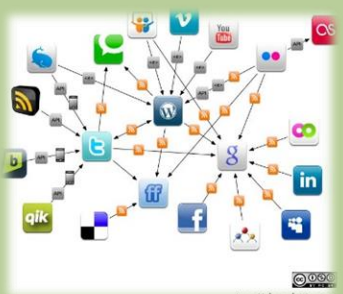


Average speedup: 1

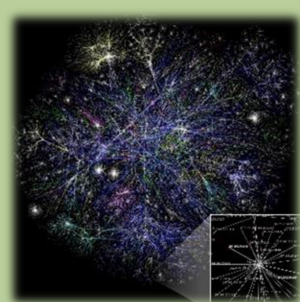
Average overall speedup over Graph500 (geometric mean): 1.51 (1.85)

The same transaction size for all graphs

The same transaction sizes for each graph separately



Average speedup: 3.20



Average speedup: 1.85

!

Best transaction size: ~24-100 vertices accessed

SINGLE-VERTEX TRANSACTIONS

MARKING A VERTEX AS VISITED

Single-Vertex Transactions

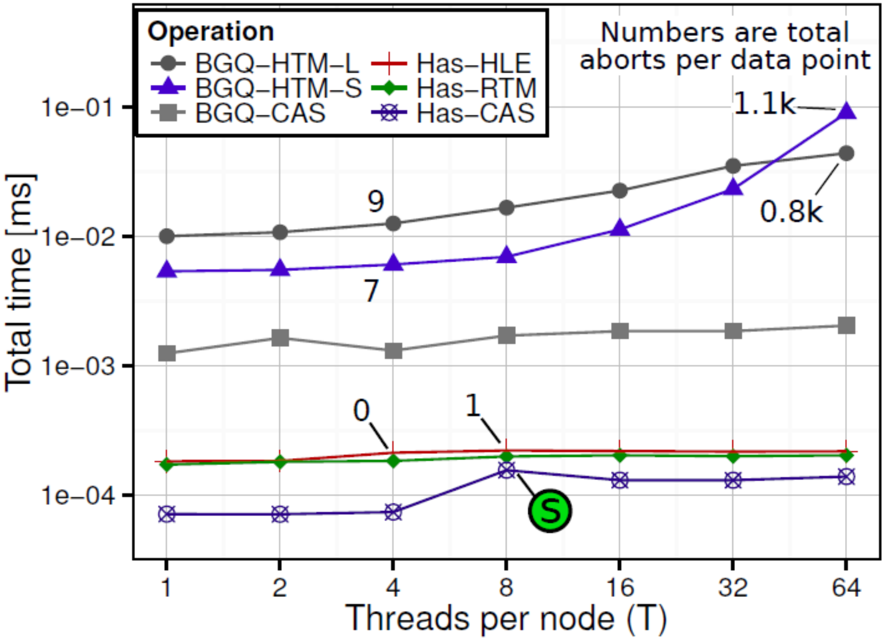
Marking a vertex as visited

Used in BFS, SSSP, ...

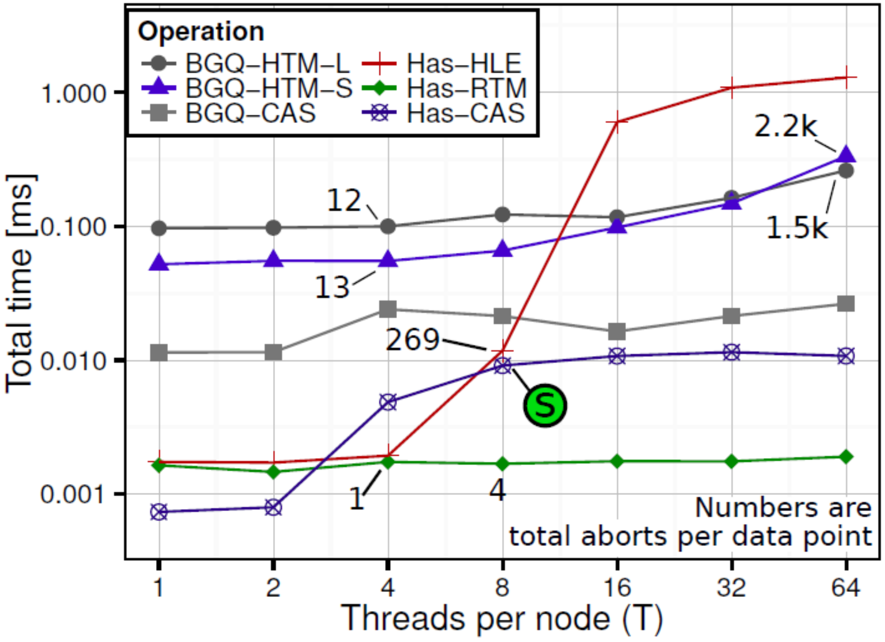
SINGLE-VERTEX TRANSACTIONS
MARKING A VERTEX AS VISITED

Used in BFS, SSSP, ...

Lower contention
(10 accesses/vertex)



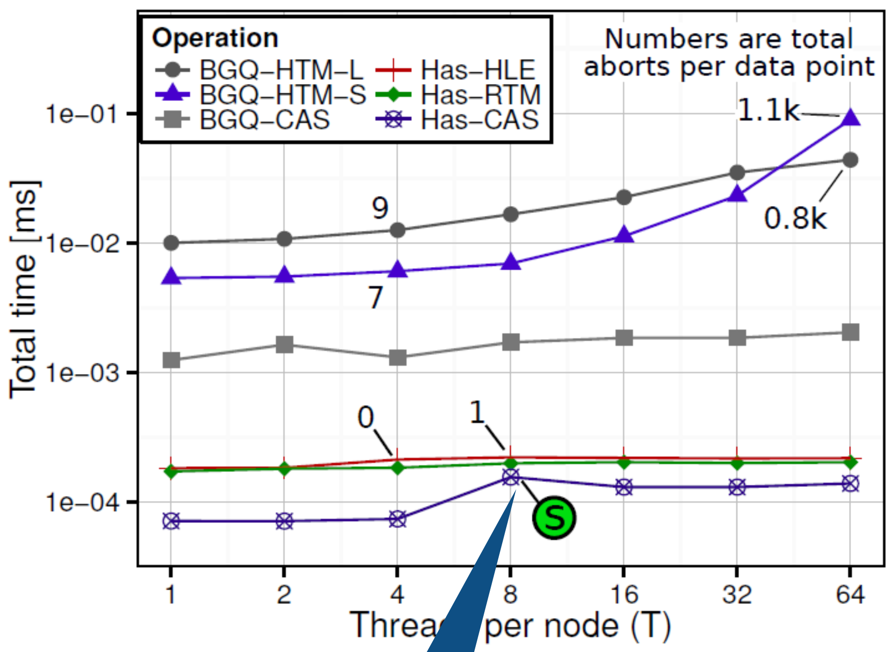
Higher contention
(100 accesses/vertex)



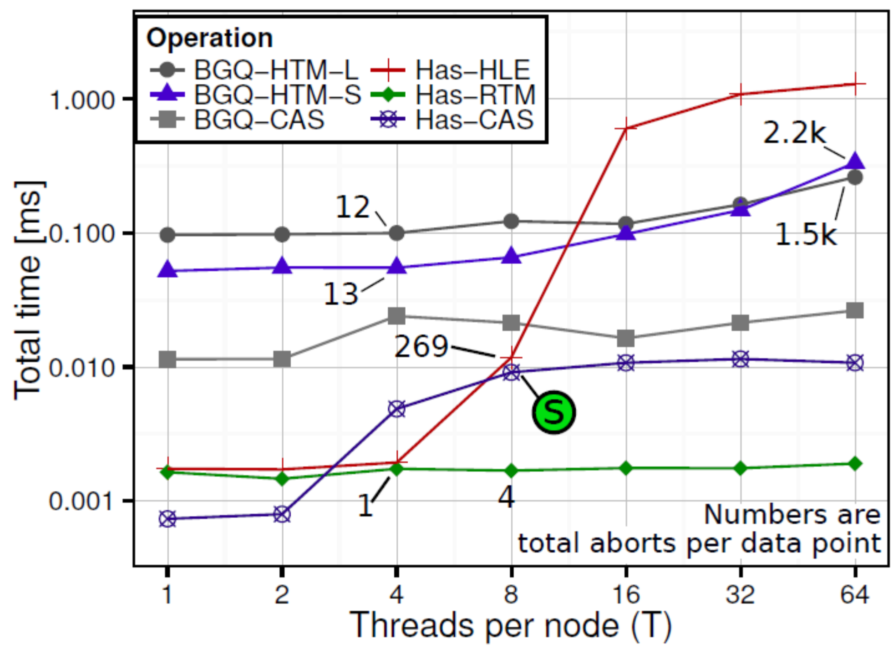
Single-Vertex Transactions
Marking a vertex as visited

Used in BFS, SSSP, ...

Lower contention (10 accesses/vertex)



Higher contention (100 accesses/vertex)

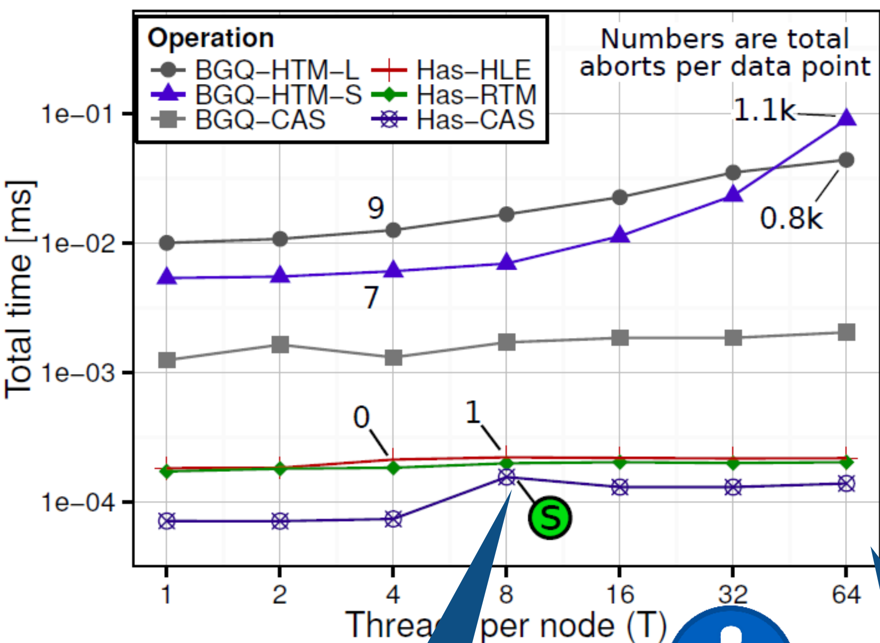


Atomics (CAS) slightly faster than HTM

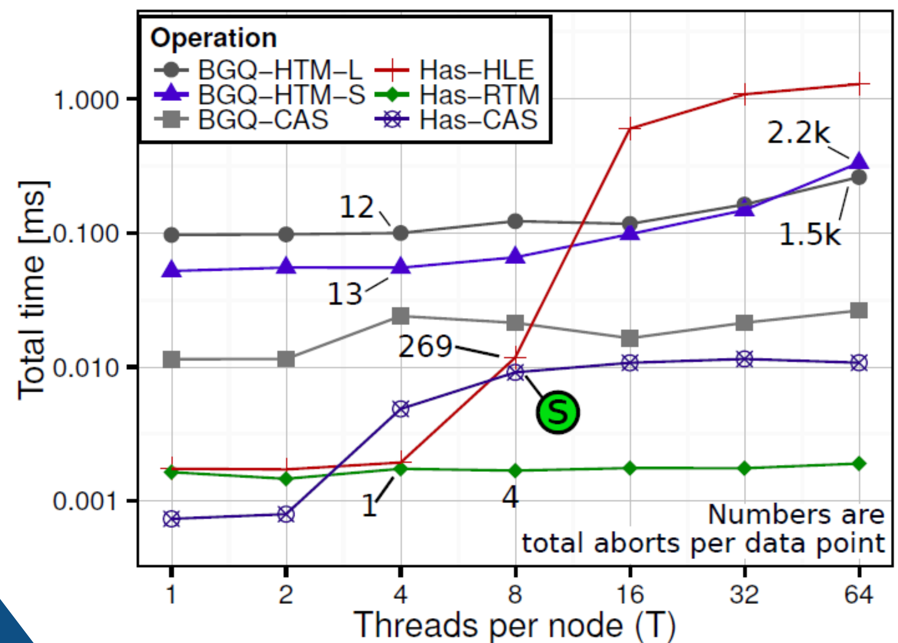
SINGLE-VERTEX TRANSACTIONS
MARKING A VERTEX AS VISITED

Used in BFS, SSSP, ...

Lower contention
(10 accesses/vertex)



Higher contention
(100 accesses/vertex)



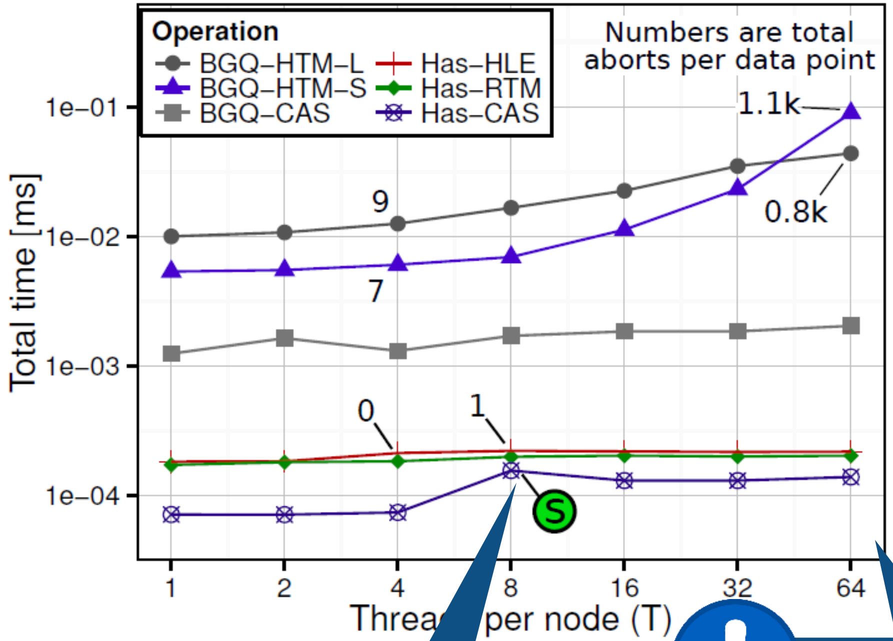
Atomics (CAS) slightly faster than HTM

Commit overheads dominate

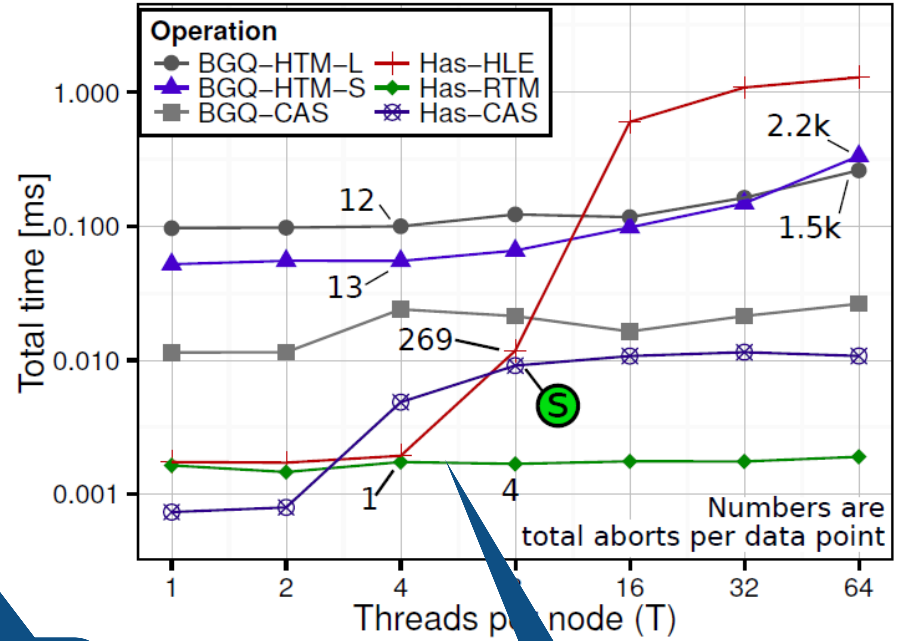
SINGLE-VERTEX TRANSACTIONS
MARKING A VERTEX AS VISITED

Used in BFS, SSSP, ...

Lower contention
(10 accesses/vertex)



Higher contention
(100 accesses/vertex)



Atomics (CAS) slightly faster than HTM

Commit overheads dominate

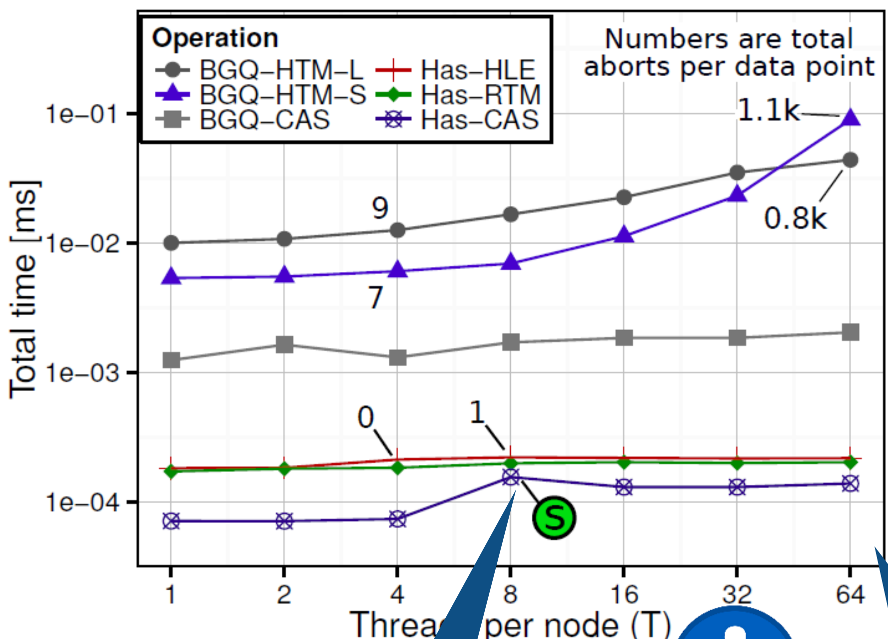
RTM outperforms other (overcontended) targets

SINGLE-VERTEX TRANSACTIONS
MARKING A VERTEX AS VISITED

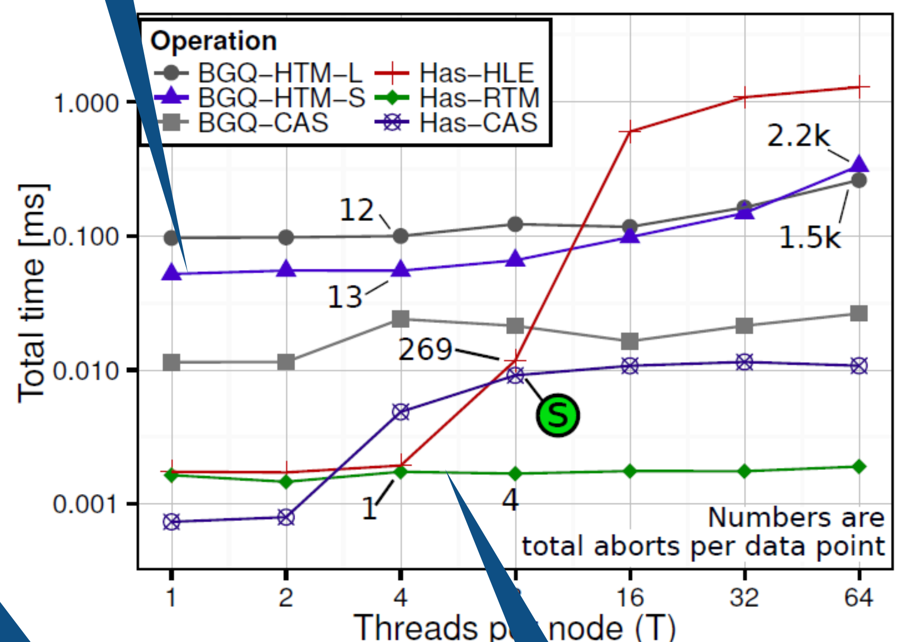
Used in BFS, SSSP, ...

BG/Q HTM still worse (L1 vs L2 matters!)

Lower contention (10 accesses/vertex)



Higher contention (100 accesses/vertex)



Atomics (CAS) slightly faster than HTM

Commit overheads dominate

RTM outperforms other (overcontended) targets

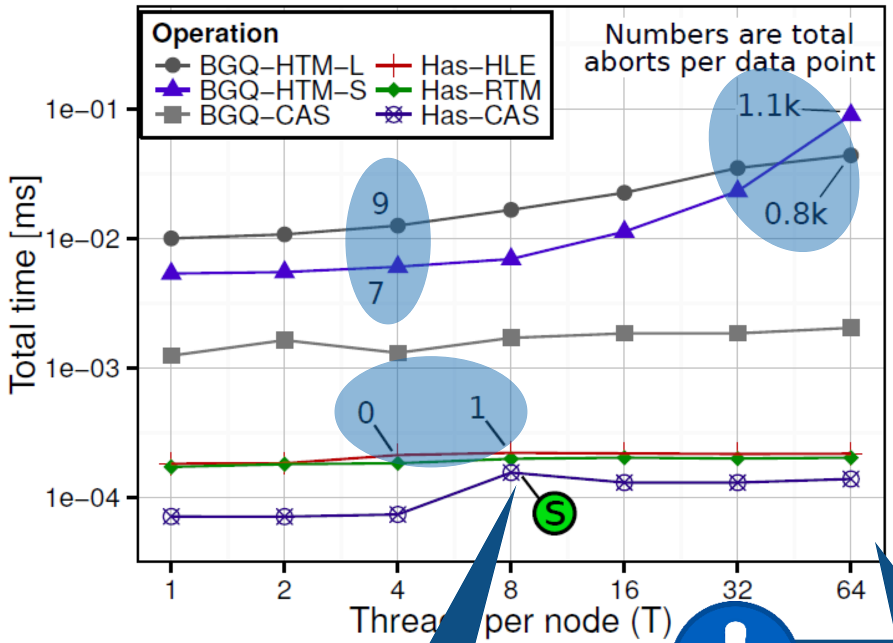
Single-Vertex Transactions
Marking a vertex as visited

Used in BFS, SSSP, ...

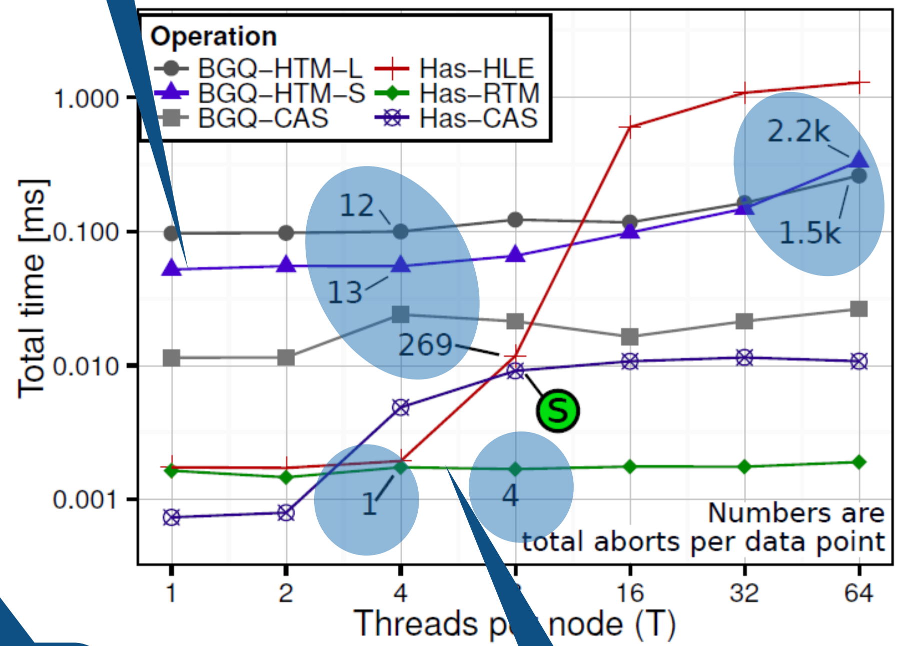
Very few aborts

BG/Q HTM still worse (L1 vs L2 matters!)

Lower contention (10 accesses/vertex)



Higher contention (100 accesses/vertex)

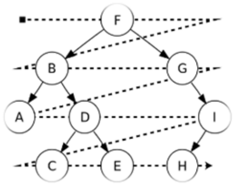


Atomics (CAS) slightly faster than HTM

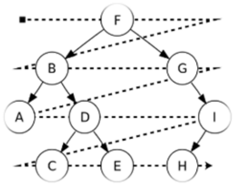
Commit overheads dominate

RTM outperforms other (overcontended) targets

OUTPERFORMING STATE-OF-THE-ART
HASWELL



Outperforming State-of-the-art
Haswell

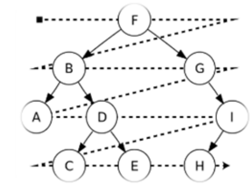


Average overall speedup (geometric mean) over Graph500: 1.07, Galois: 1.40, HAMA ~1000

OUTPERFORMING STATE-OF-THE-ART

HASWELL

SNAP

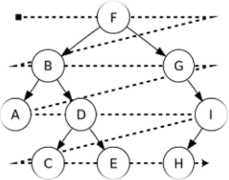


Average overall speedup (geometric mean) over Graph500: 1.07, Galois: 1.40, HAMA ~1000

IBM

Outperforming State-of-the-Art

Haswell



Average speedup: 1

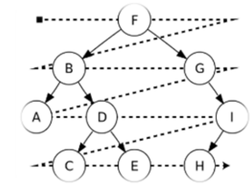




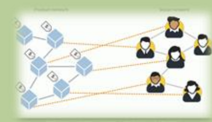
Average overall speedup (geometric mean) over Graph500: 1.07, Galois: 1.40, HAMA ~1000

OUTPERFORMING STATE-OF-THE-ART

HASWELL

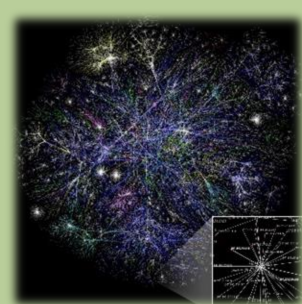


Average speedup: 1



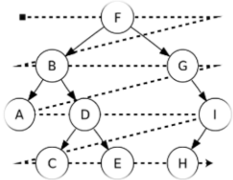
Average overall speedup (geometric mean) over Graph500: 1.07, Galois: 1.40, HAMA ~1000



Average speedup: 1.85

OUTPERFORMING STATE-OF-THE-ART

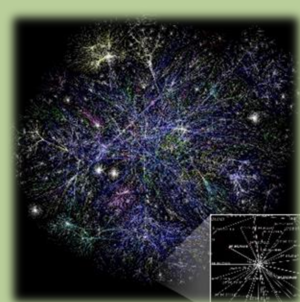
HASWELL



Average speedup: 1

Average overall speedup (geometric mean) over Graph500: 1.07, Galois: 1.40, HAMA ~1000

Average speedup: 3.20

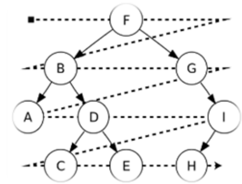


Average speedup: 1.85

OUTPERFORMING STATE-OF-THE-ART

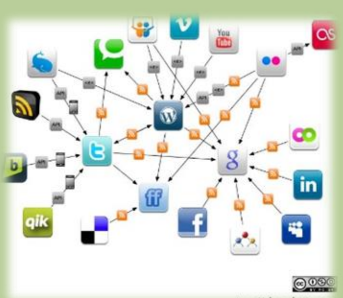
HASWELL

SNAP

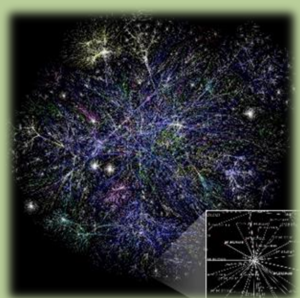


Average speedup: 1

Average overall speedup (geometric mean) over Graph500: 1.07, Galois: 1.40, HAMA ~1000



Average speedup: 3.20

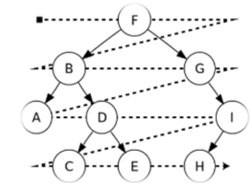


Average speedup: 1.85

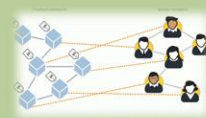
1.85x on average, up to 4.3x

Best transaction size: ~2-9 vertices accessed

OUTPERFORMING STATE-OF-THE-ART
HASWELL intel

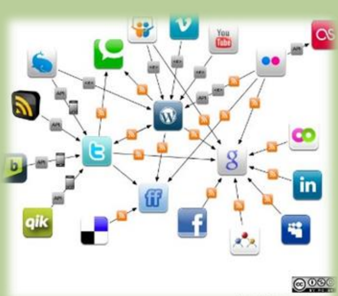


Average speedup: 1

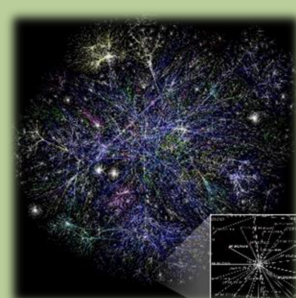





Average overall speedup (geometric mean) over Graph500: 1.07, Galois: 1.40, HAMA ~1000



Average speedup: 3.20



Average speedup: 1.85

! 1.85x on average, up to 4.3x

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! Best transaction size: ~2-9 vertices accessed

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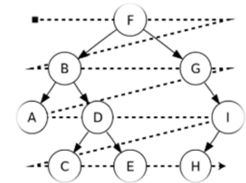


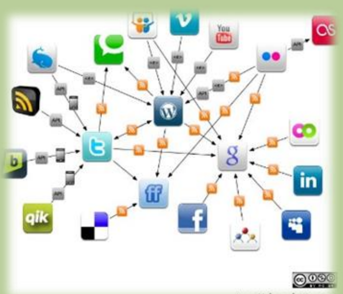
Average speedup: 1



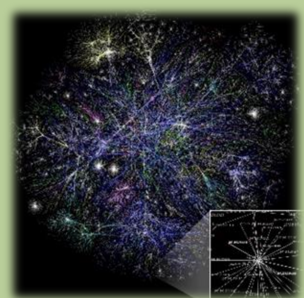



Average overall speedup (geometric mean) over Graph500: 1.07, Galois: 1.40, HAMA ~1000

1.85x on average, up to 4.3x



Average speedup: 3.20

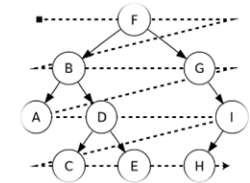


Average speedup: 1.85

Best transaction size: ~2-9 vertices accessed

OUTPERFORMING STATE-OF-THE-ART

HASWELL



Best transaction size:
~4 vertices
~14 vertices

OUTPERFORMING STATE-OF-THE-ART

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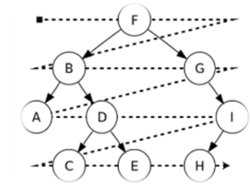


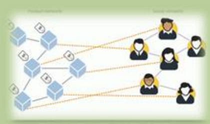



Average overall speedup (geometric mean) over Graph500: 1.07, Galois: 1.40, HAMA ~1000

!

Best transaction size:
~4 vertices
~14 vertices

OUTPERFORMING STATE-OF-THE-ART
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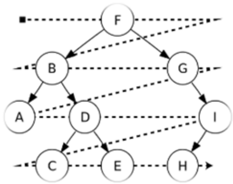
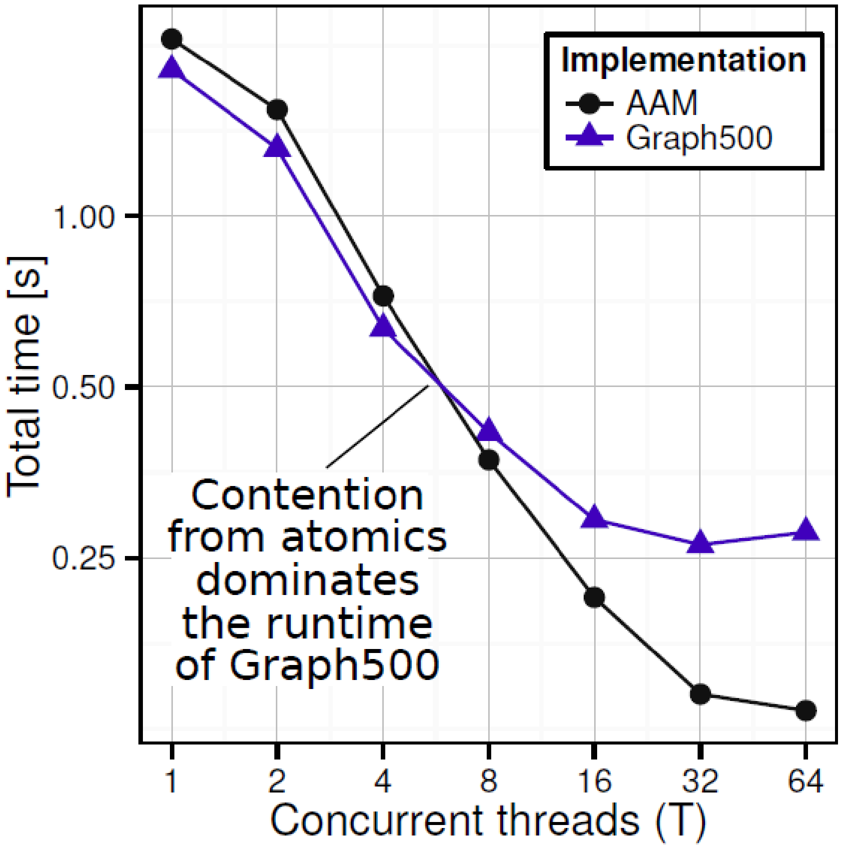


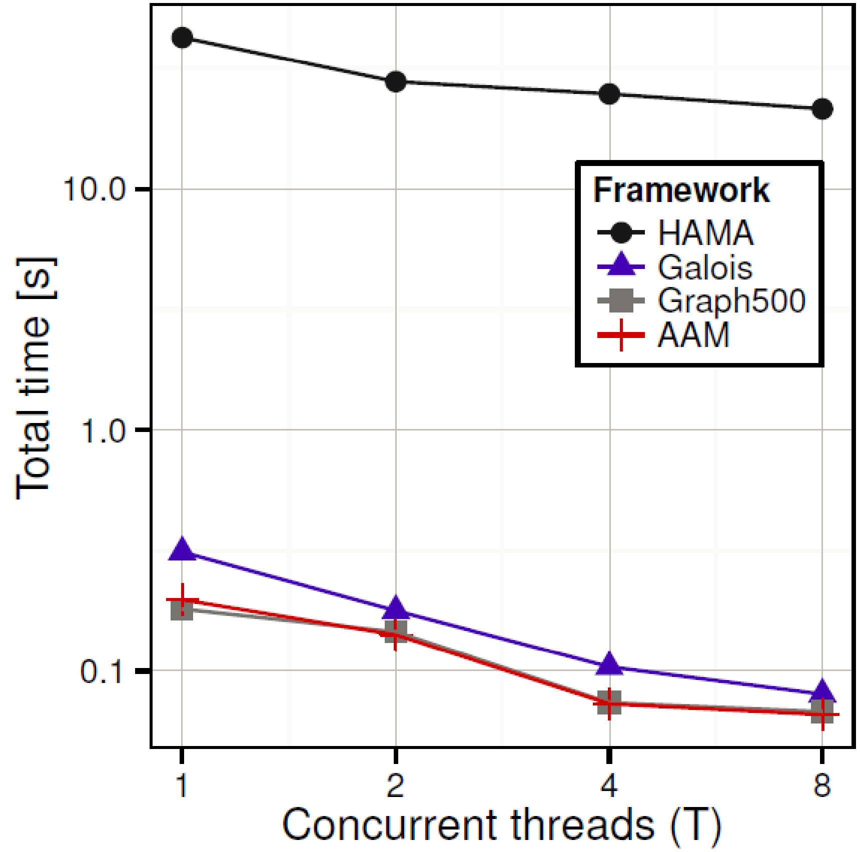
Average overall speedup (geometric mean) over Graph500: 1.07, Galois: 1.40, HAMA ~1000

1.85x on average, up to 4.3x

Best transaction size:
~4 vertices
~14 vertices

OUTPERFORMING STATE-OF-THE-ART
SCALABILITY ANALYSIS: SHARED-MEMORY





OUTPERFORMING STATE-OF-THE-ART
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Input graph properties					BG/Q analysis		
Type	ID	Name	$\|V\|$	$\|E\|$	S over g500 ($M = 24$)	M	S over g500
Comm. networks (CNs)	cWT	wiki-Talk	2.4M	5M	2.82	48	3.35
	cEU	email-EuAll	265k	420k	3.67	32	4.36
Social networks (SNs)	sLV	soc-LiveJ.	4.8M	69M	1.44	12	1.56
	sOR	com-orkut	3M	117M	1.22	20	1.27
	sLJ	com-lj	4M	34M	1.44	12	1.54
	sYT	com-youtube	1.1M	2.9M	1.67	8	1.84
	sDB	com-dblp	317k	1M	1.33	8	1.80
	sAM	com-amazon	334k	925k	1.14	8	1.62
Purchase network (PNs)	pAM	amazon0601	403k	3.3M	1.45	8	1.91
Road networks (RNs)	rCA	roadNet-CA	1.9M	5.5M	≈1	2	1.59
	rTX	roadNet-TX	1.3M	3.8M	≈1	2	1.53
	rPA	roadNet-PA	1M	3M	≈1	2	1.52
Citation graphs (CGs)	ciP	cit-Patents	3.7M	16.5M	1.16	8	1.57
Web graphs (WGs)	wGL	web-Google	875k	5.1M	1.78	12	2.08
	wBS	web-BerkStan	685k	7.6M	1.91	24	1.91
	wSF	web-Stanford	281k	2.3M	1.89	24	1.89

OUTPERFORMING STATE-OF-THE-ART
HASWELL

Input graph properties					Haswell analysis					
Type	ID	Name	$\|V\|$	$\|E\|$	S over g500 ($M=2$)	S over Galois ($M=2$)	M	S over g500	S over Galois	S over HAMA
Comm. networks (CNs)	cWT	wiki-Talk	2.4M	5M	0.91	1.22	6	0.96	1.28	344
	cEU	email-EuAll	265k	420k	0.76	0.88	4	0.97	1.12	1448
Social networks (SNs)	sLV	soc-LiveJ.	4.8M	69M	1.05	1.1	3	1.07	1.12	$> 10^4$
	sOR	com-orkut	3M	117M	1.06	0.69	4	1.13	0.74	$> 10^4$
	sLJ	com-lj	4M	34M	1.03	1.03	4	1.04	1.04	603
	sYT	com-youtube	1.1M	2.9M	0.96	1.1	5	0.98	1.11	670
	sDB	com-dblp	317k	1M	≈ 1	2.5	2	≈ 1	2.53	2160
	sAM	com-amazon	334k	925k	1.04	1.64	2	1.04	1.64	1426
Purchase network (PNs)	pAM	amazon0601	403k	3.3M	≈ 1	1.25	3	1.03	1.30	618
Road networks (RNs)	rCA	roadNet-CA	1.9M	5.5M	1.33	1.74	8	1.38	1.80	$> 10^4$
	rTX	roadNet-TX	1.3M	3.8M	1.29	1.89	6	1.42	2.08	$> 10^4$
	rPA	roadNet-PA	1M	3M	≈ 1	2.00	9	1.07	2.16	$> 10^4$
Citation graphs (CGs)	ciP	cit-Patents	3.7M	16.5M	1.01	1.26	2	1.01	1.26	1875
Web graphs (WGs)	wGL	web-Google	875k	5.1M	0.98	1.26	6	1.06	1.35	365
	wBS	web-BerkStan	685k	7.6M	0.93	1.31	5	1.07	1.40	755
	wSF	web-Stanford	281k	2.3M	0.98	1.54	5	1.07	1.58	1077