# BriskStream: Scaling Data Stream Processing on Shared-Memory Multicore Architectures

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2 ADSC Illinois at Singapore Pte Ltd

3 Shenzhen University

*Work done while as research trainee at SAP Singapore.

# Importance of Data Stream Processing

Apache Storm

Twitter Heron

Apache Flink

…

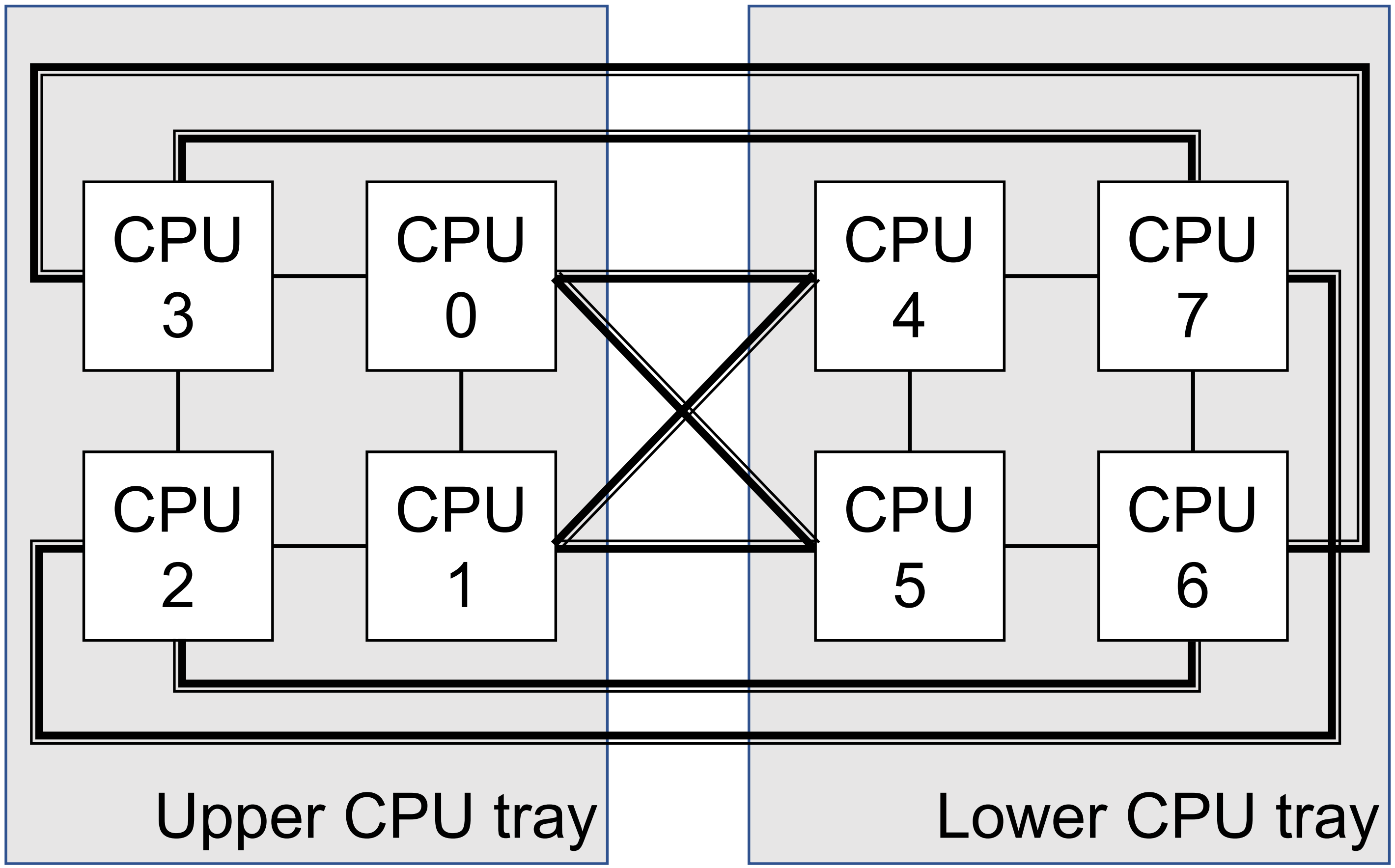
# DSPS on Modern Hardware

- **Multicore architectures are attractive platform for DSPSs.**

- **However, fully exploiting its computation power can be challenging.**

- **This work focuses on NUMA-awareness.**

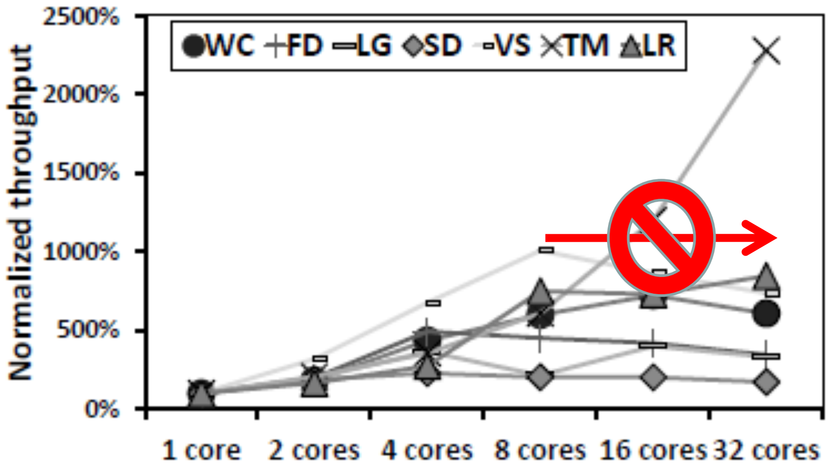
# NUMA (non- uniform-memory-access) Servers




Server A: HUAWEI KunLun 8×18 Cores (w/o HT) @1.2GHz

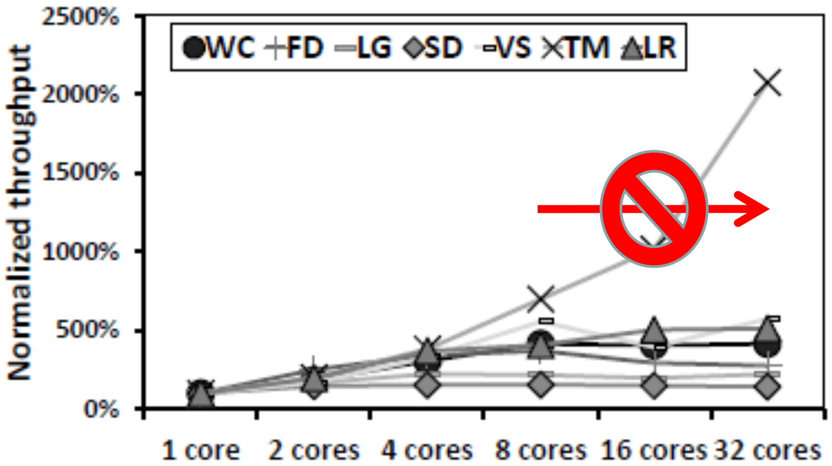
144 cores in one machine

# Scalability on varying number of cores/sockets



(2sockets)(4sockets)

(a) Storm



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Revisiting the Design of Data Stream Processing Systems on Multi-Core Processors, Zhang et al. ICDE'17

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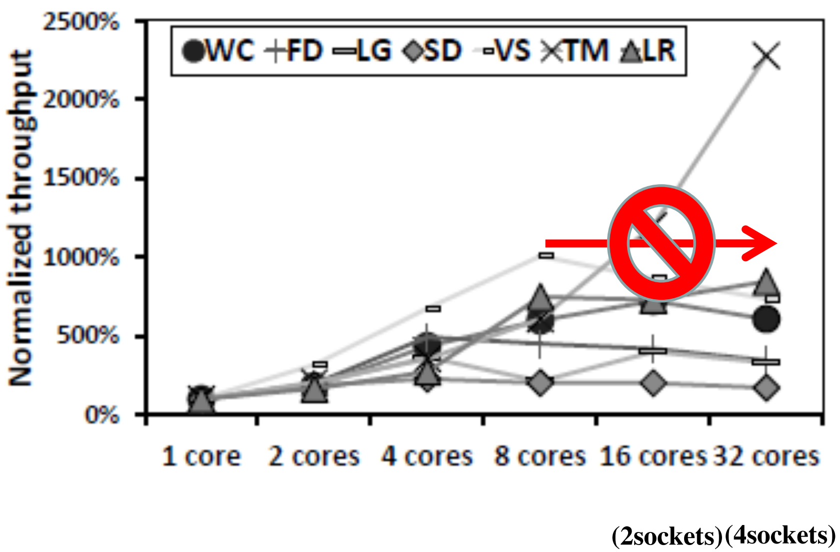


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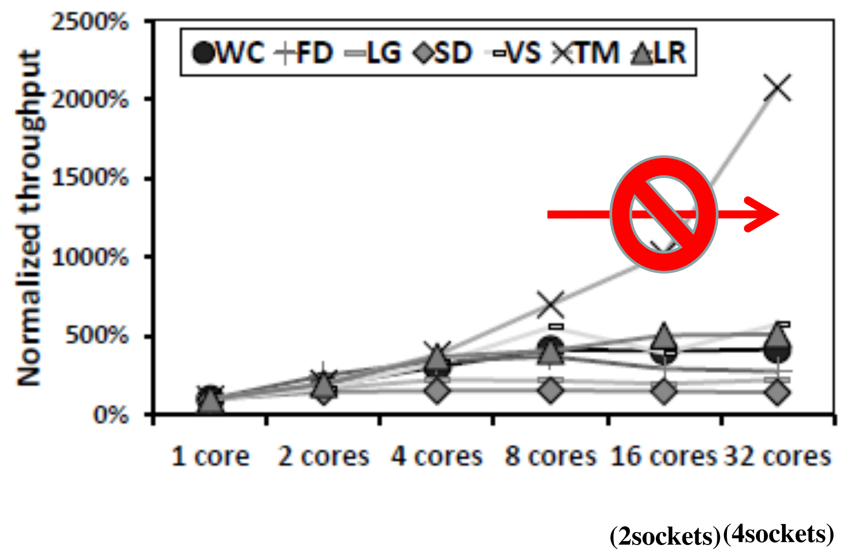


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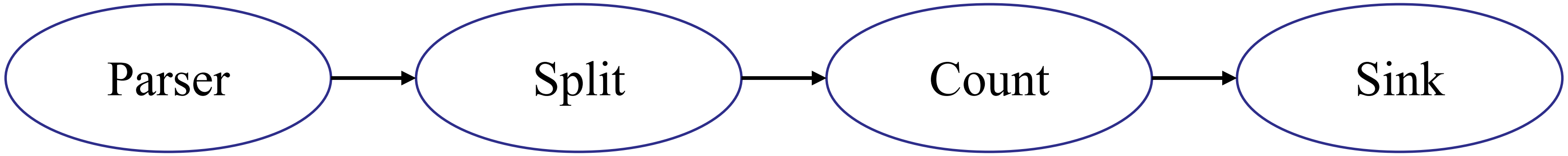
How can we maximize the throughput of a stream application on a NUMA machine (limited HW resources)?

# Stream processing




Word-count (WC) application

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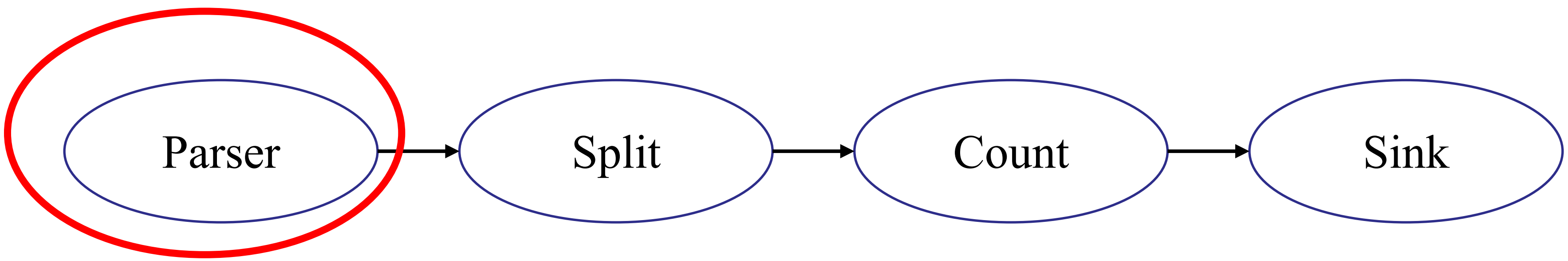

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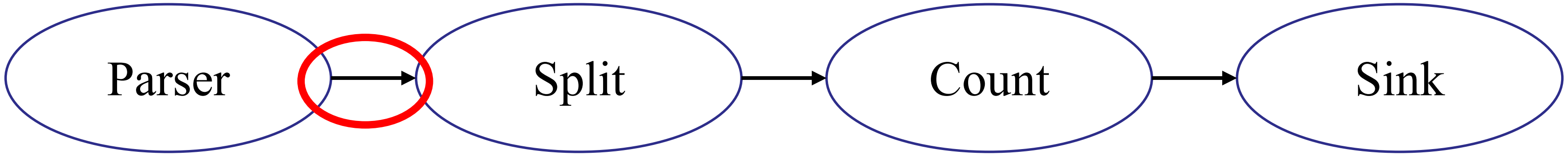

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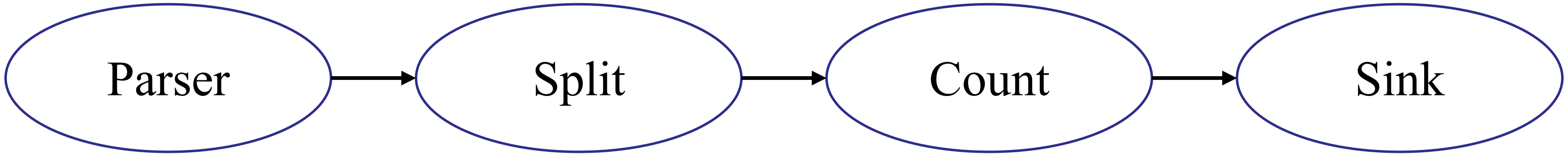

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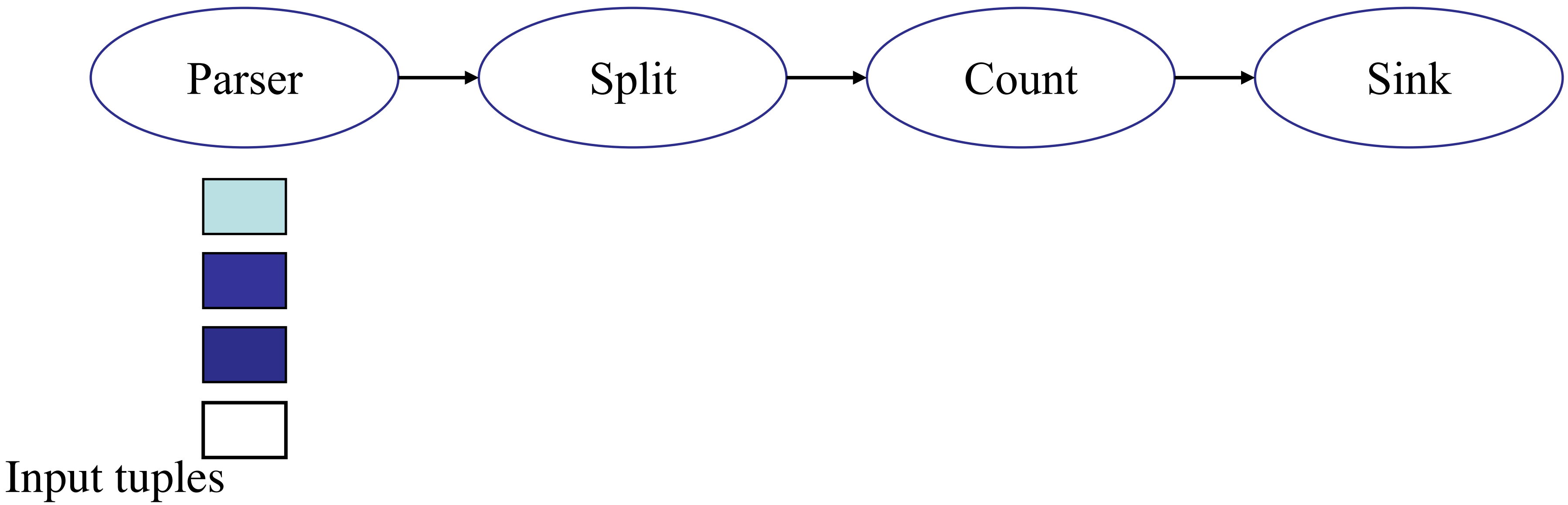

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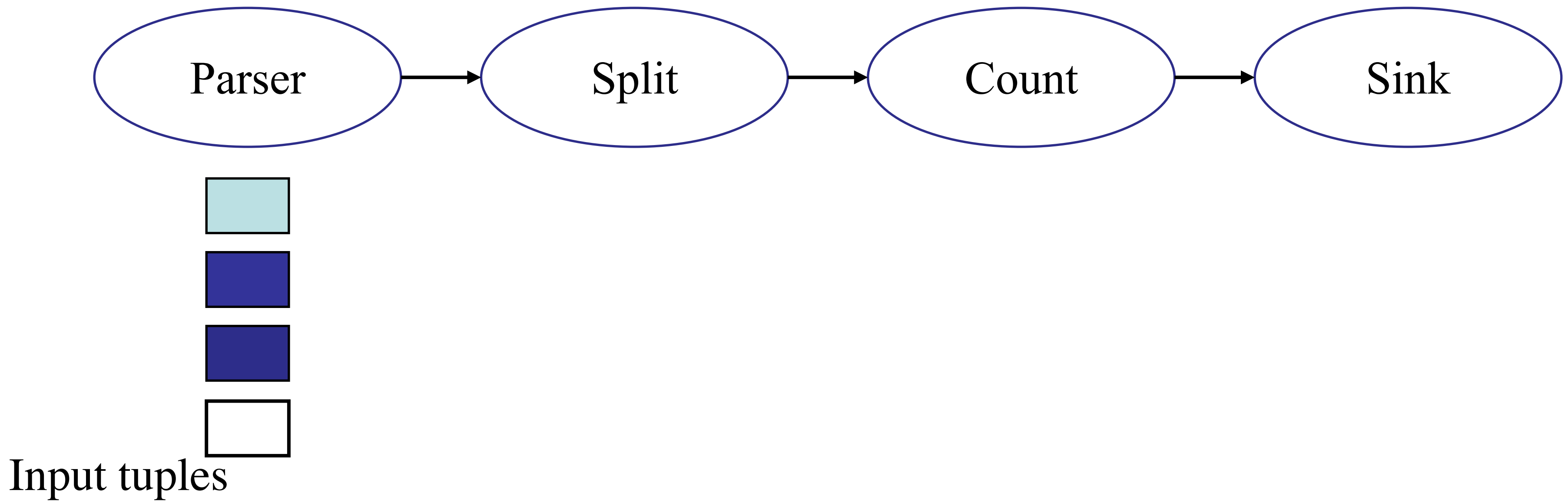

# Problem formulation

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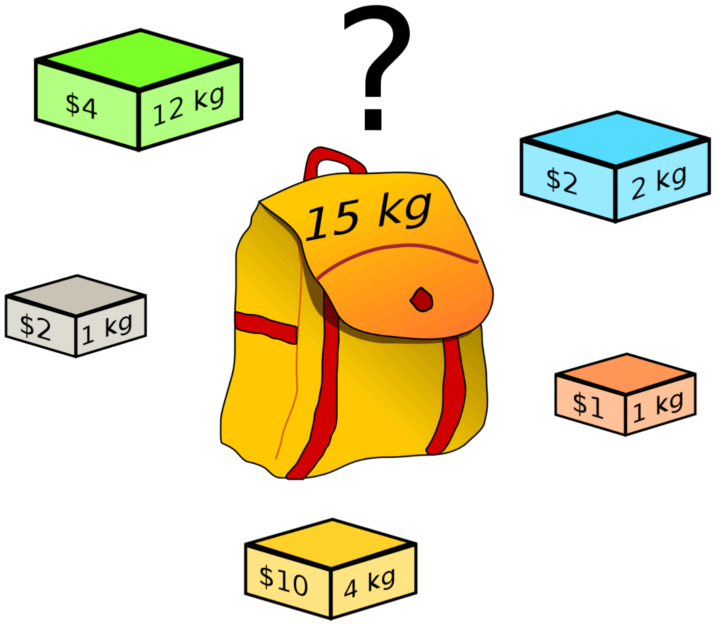
  - **Scaling optimization**: determine suitable parallelism level of each operator
  - **Placement optimization**: determine suitable placement of each thread.

# Operator placement as Knapsack?



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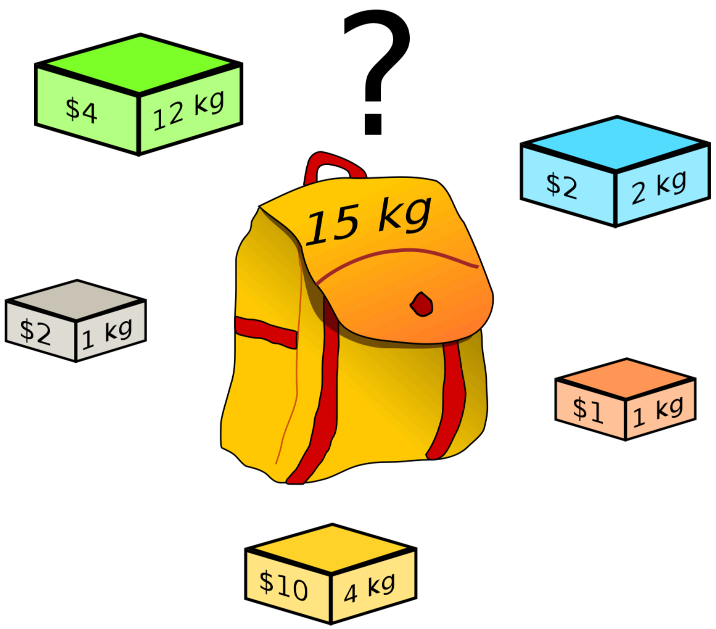


- **Bags – CPU sockets**
  - Capacity: resource availability
- **Items – operators**
  - Value: operator throughput
  - Weight: resource demand

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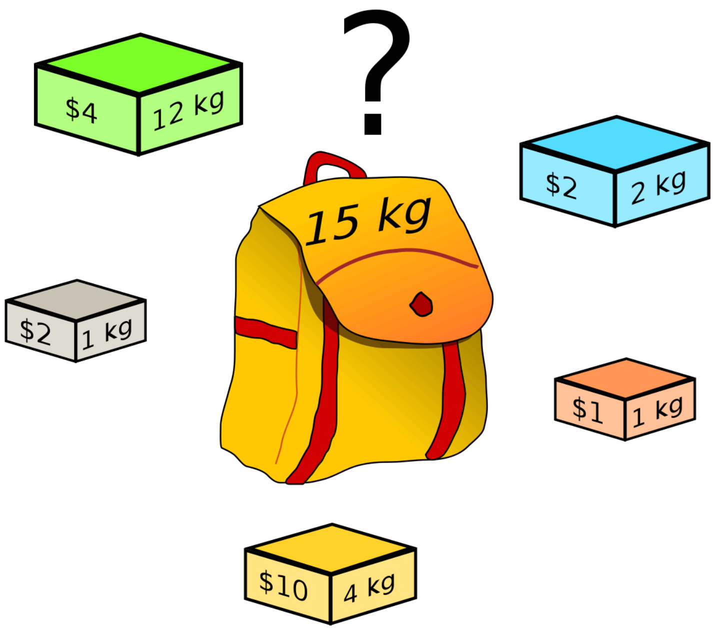


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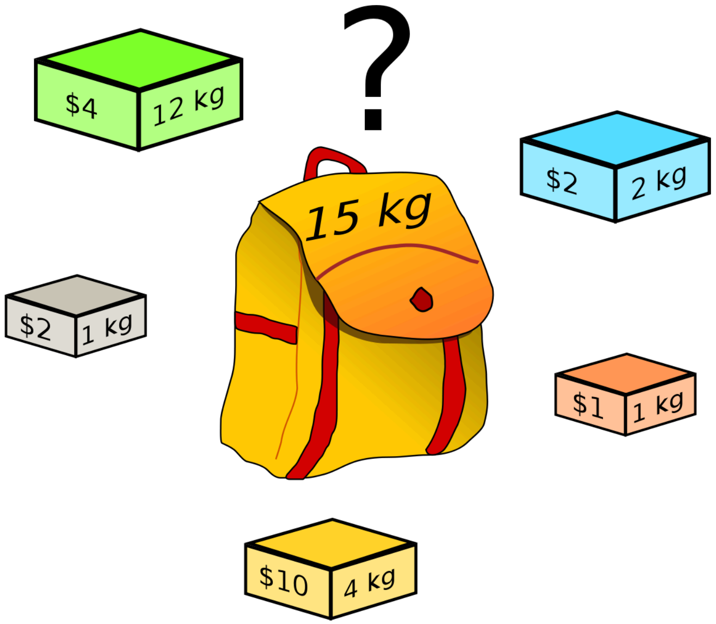


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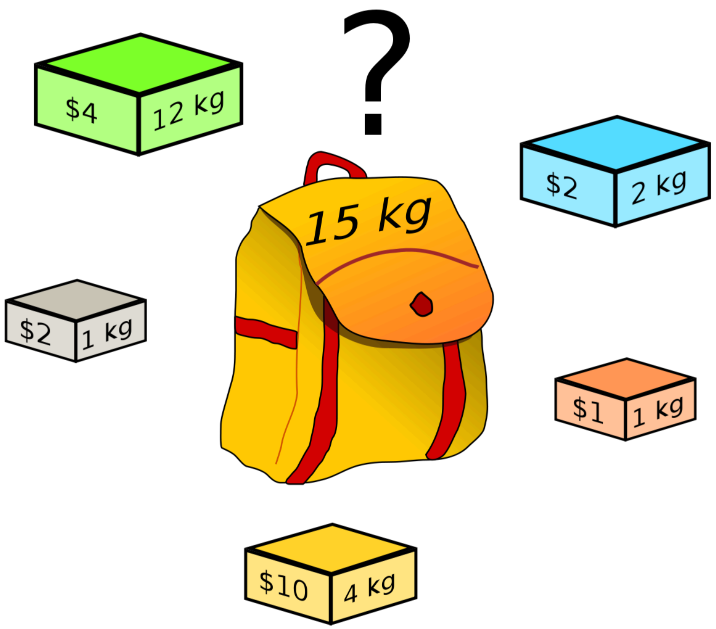


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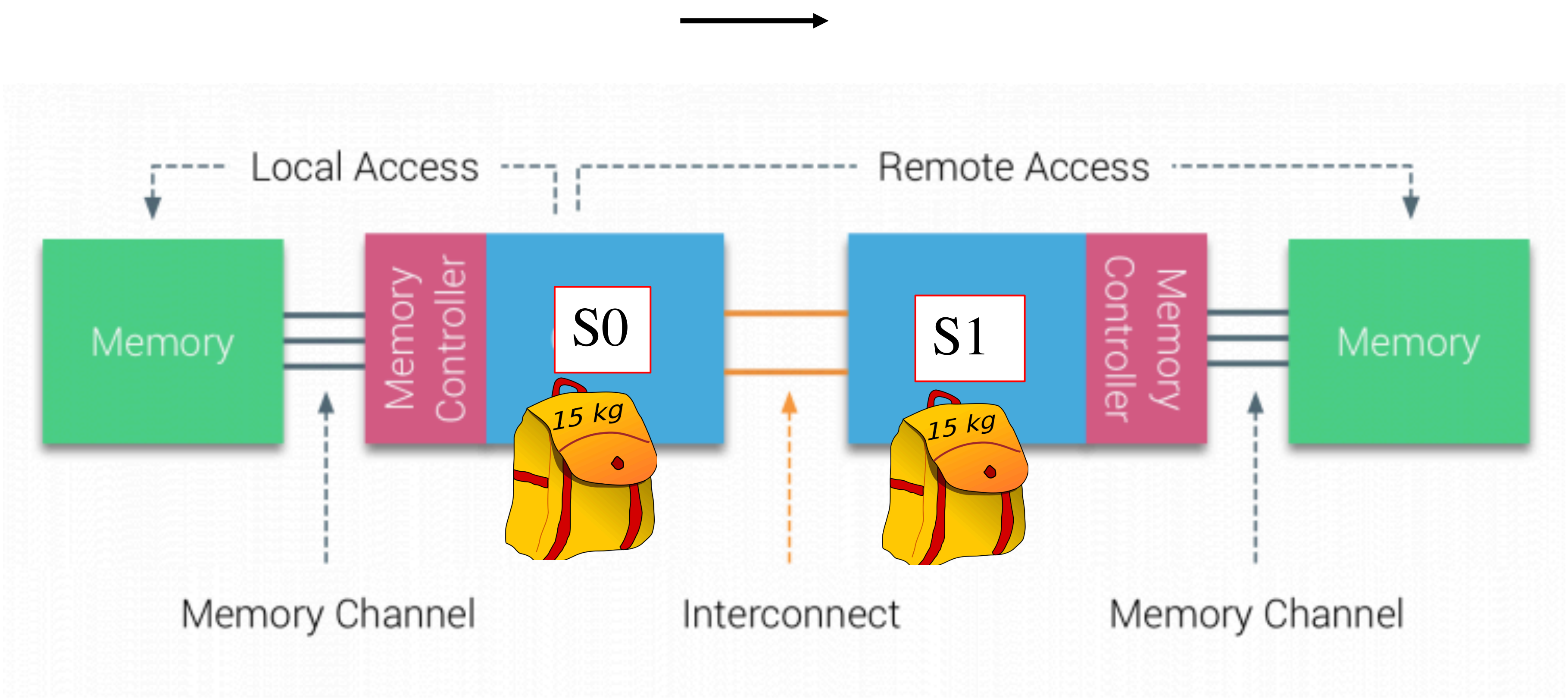

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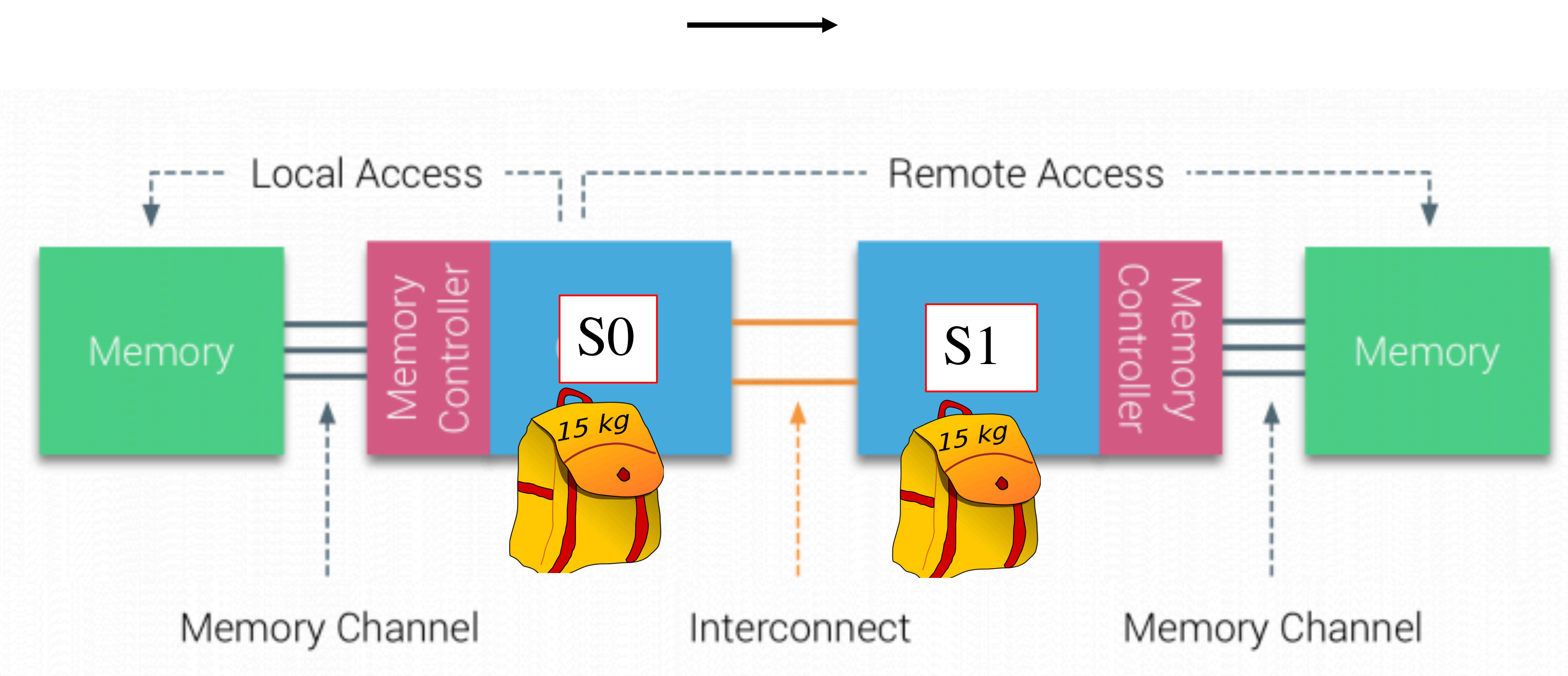


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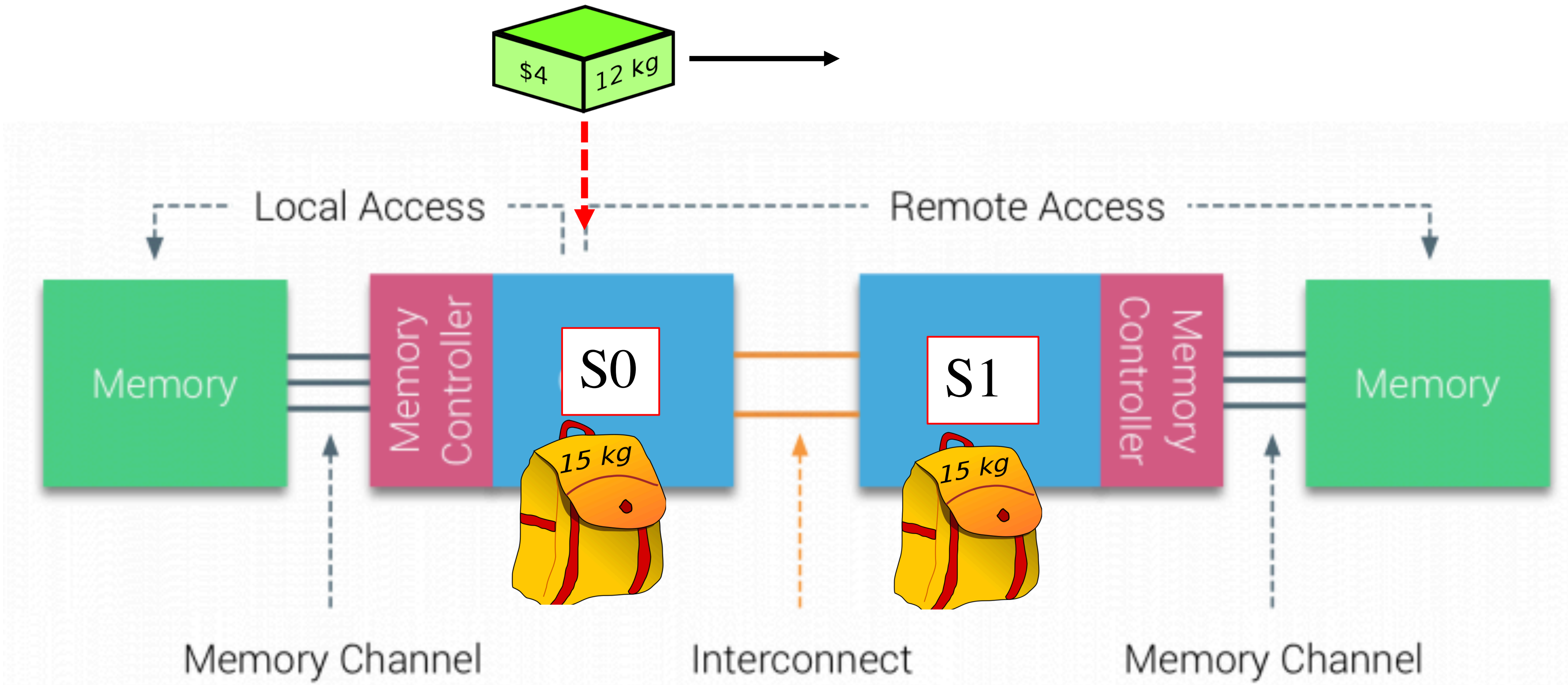


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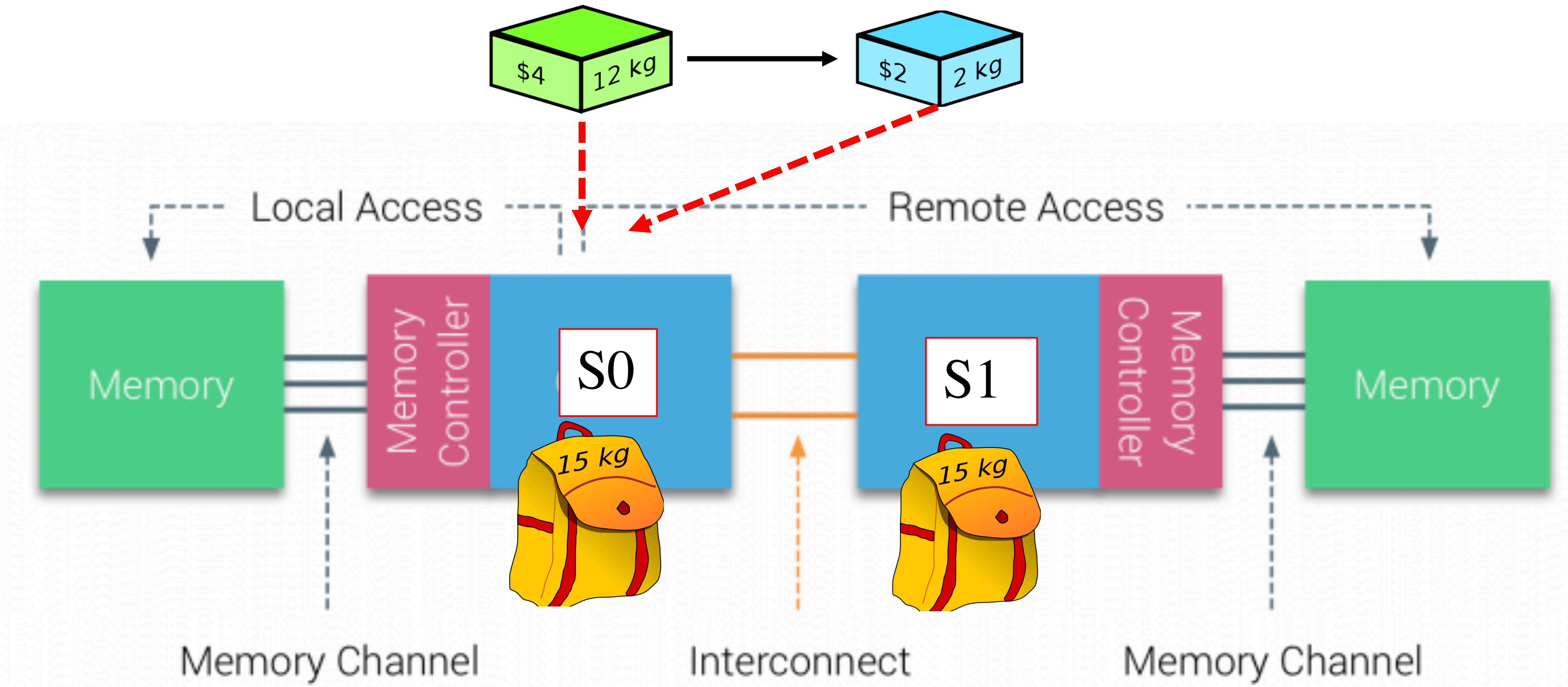


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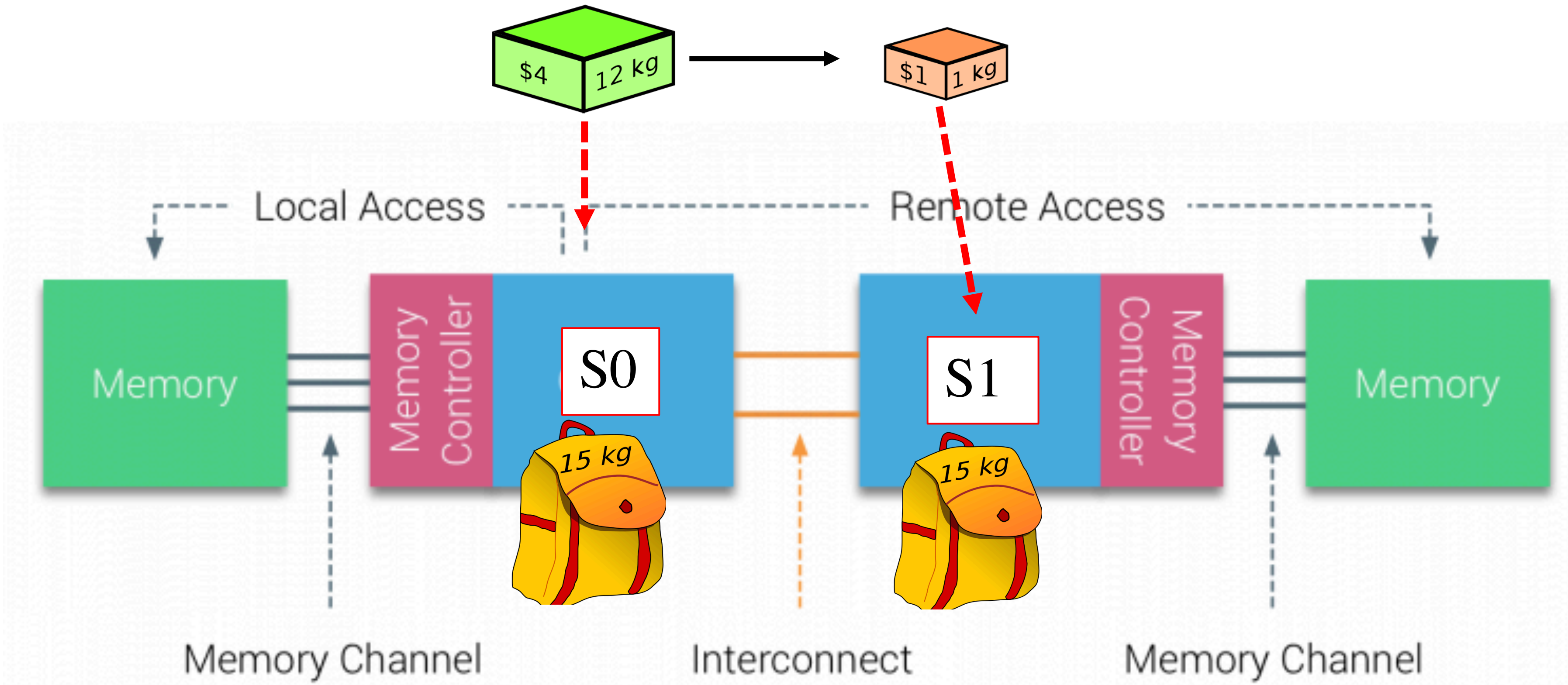


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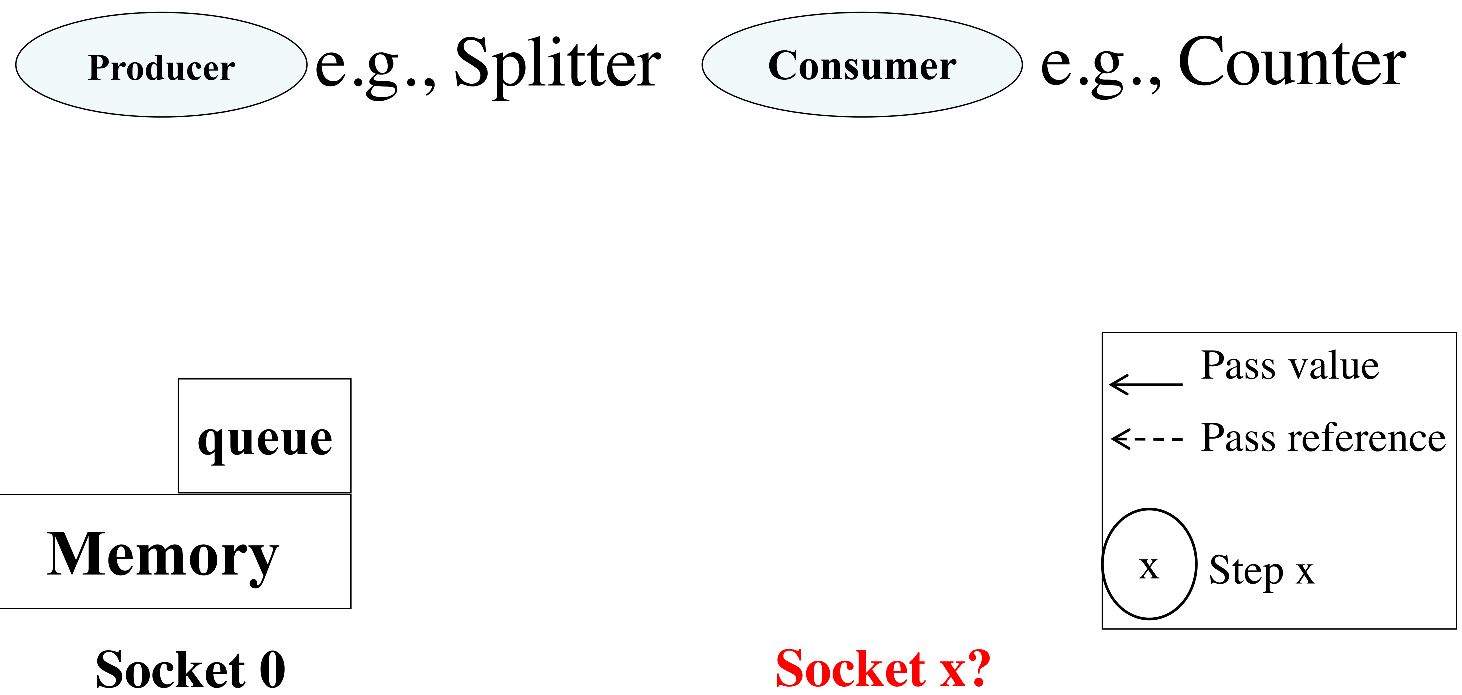
# Zoom into the current system design



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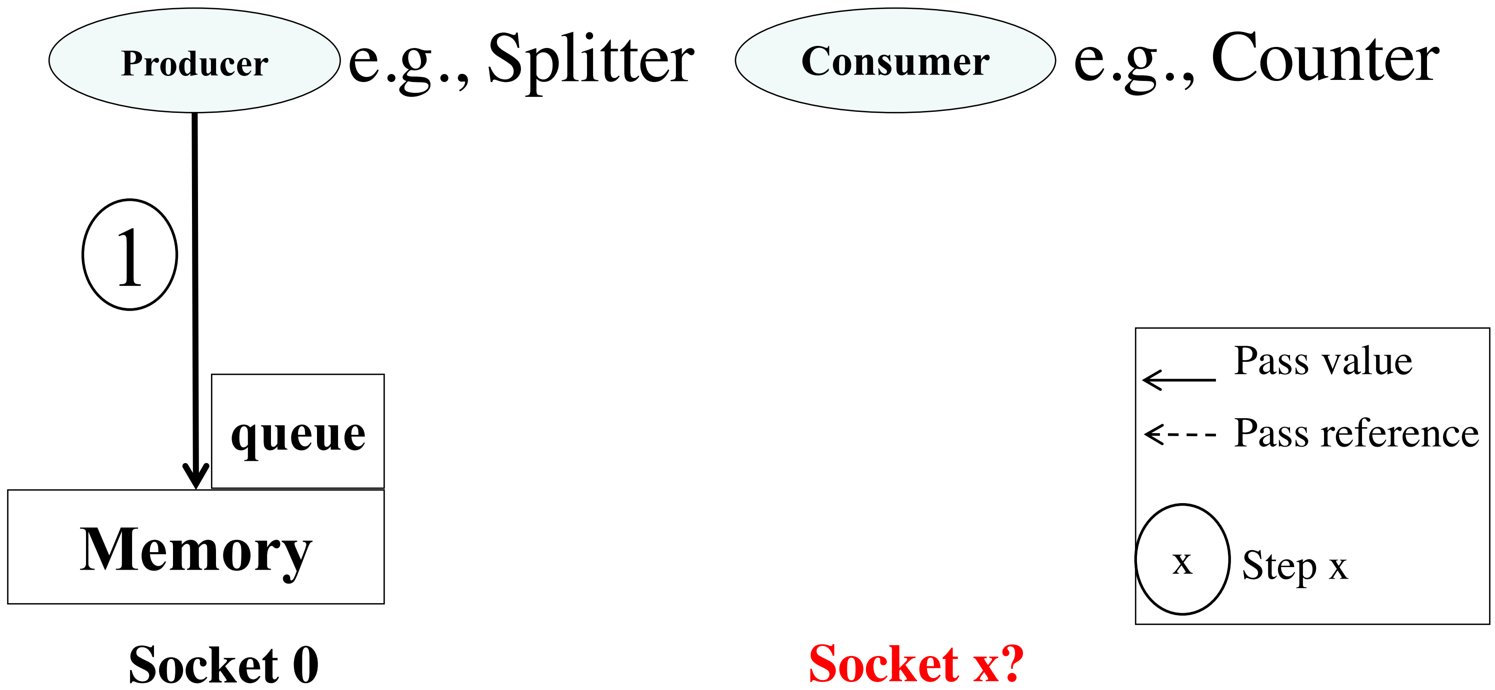

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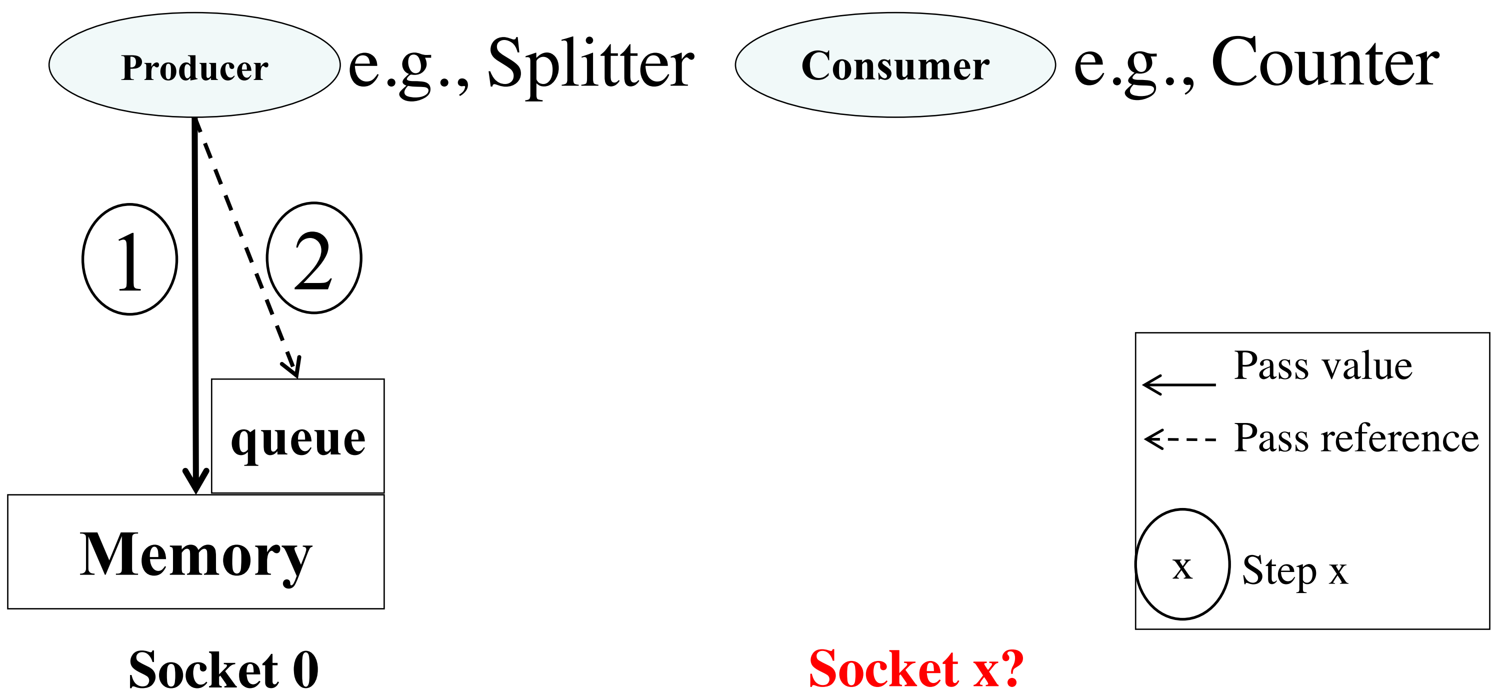

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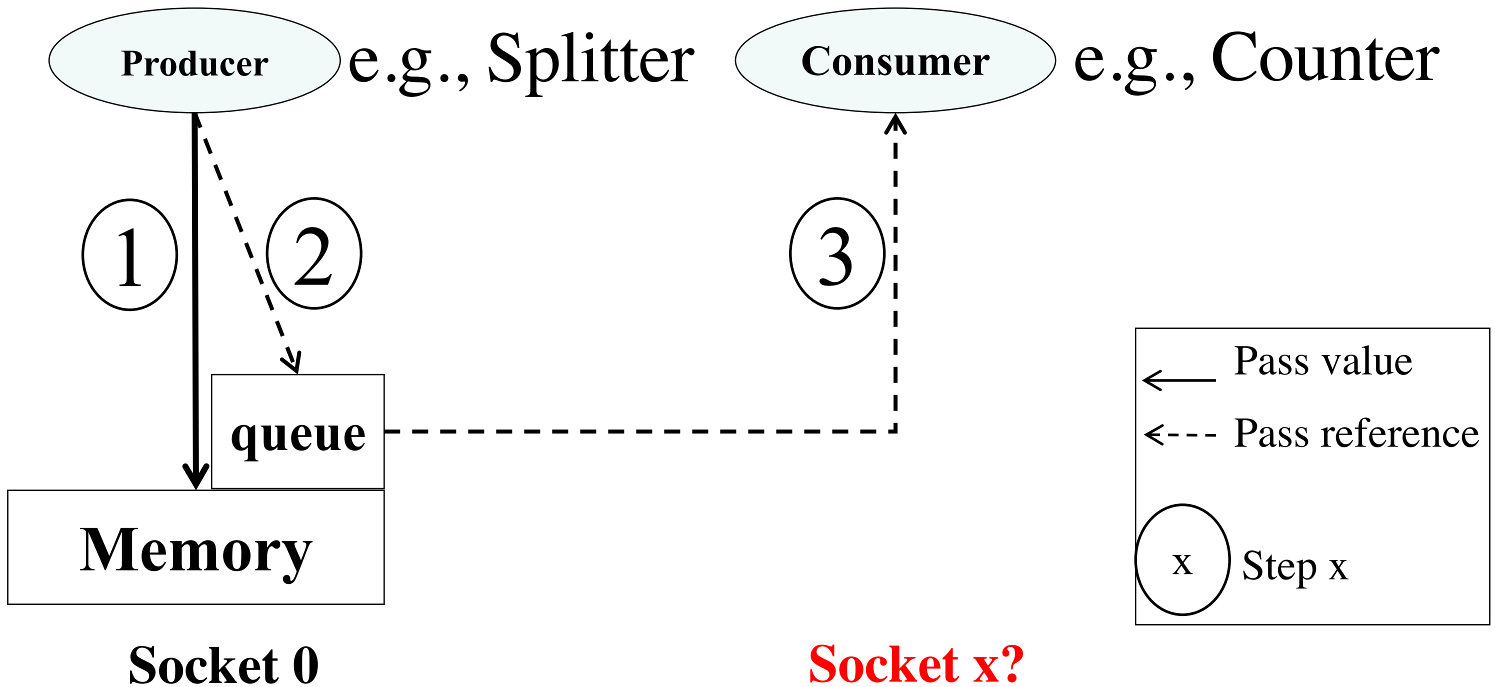

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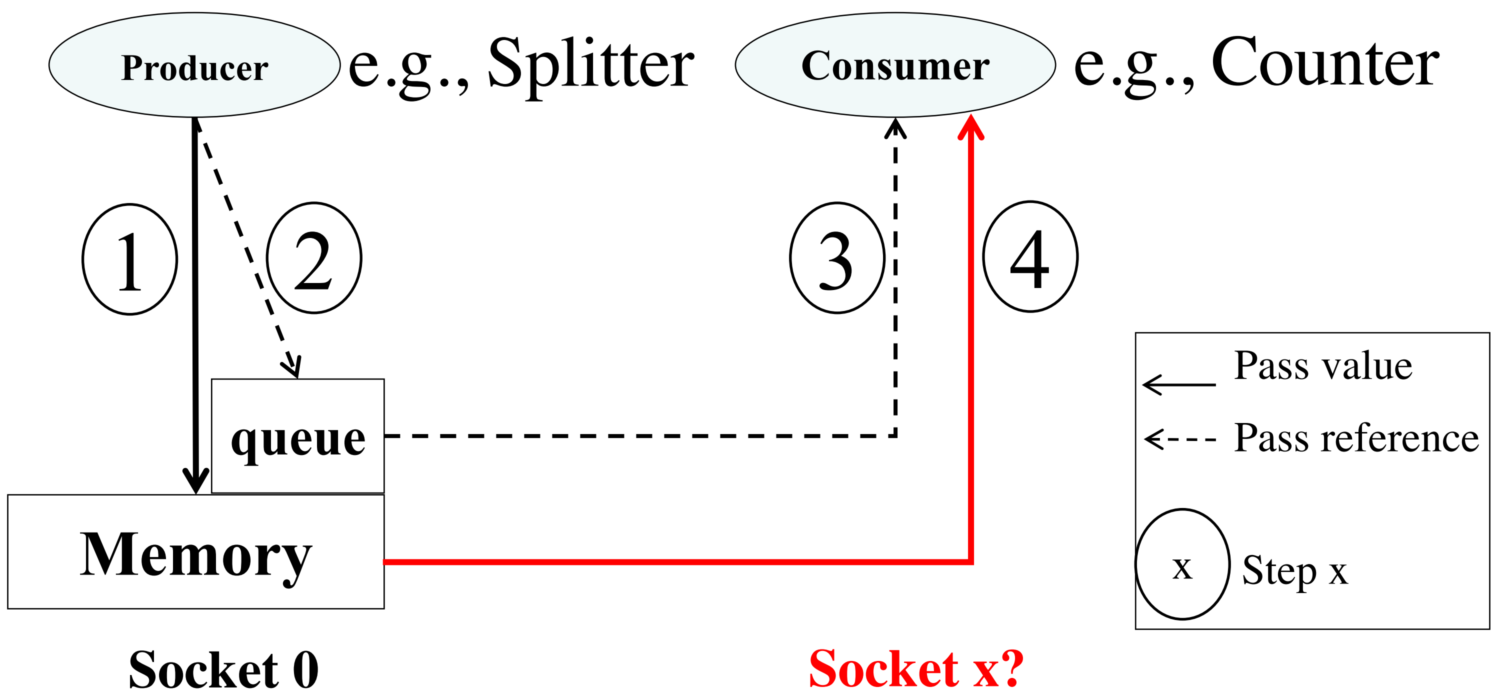

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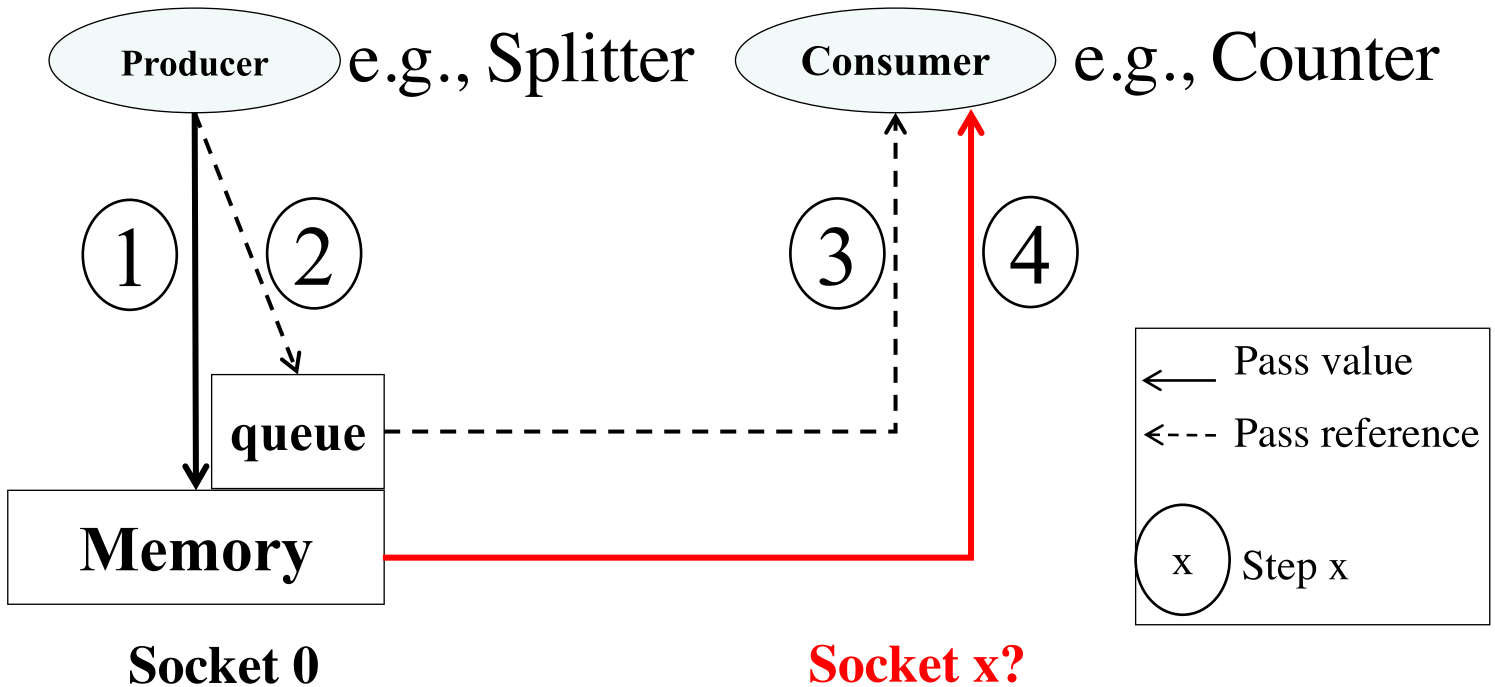


- **Relative location affects the processing behavior of consumer.**

# Key Idea

- **Construct a performance model that is able to estimate each operator's processing behavior under different execution plans.**
  - Based on Rate-based Optimization Framework (RBO model-SIGMOD'02).
  - Extend it to capture the NUMA effect.

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  - Based on Rate-based Optimization Framework (RBO model-SIGMOD'02).
  - Extend it to capture the NUMA effect.

Introduce remote-memory-access (RMA) overhead factor to the original RBO model.

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- **Our model estimates (varying) processing behavior of each operator accurately but the problem is not yet solved.**
- **Branch and Bound technique to rescue.**
  - Bounding function: operators remaining scheduled are free to collocate with all of its producers.
  - Heuristics: to further reduce searching space.

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| A' | S0 |
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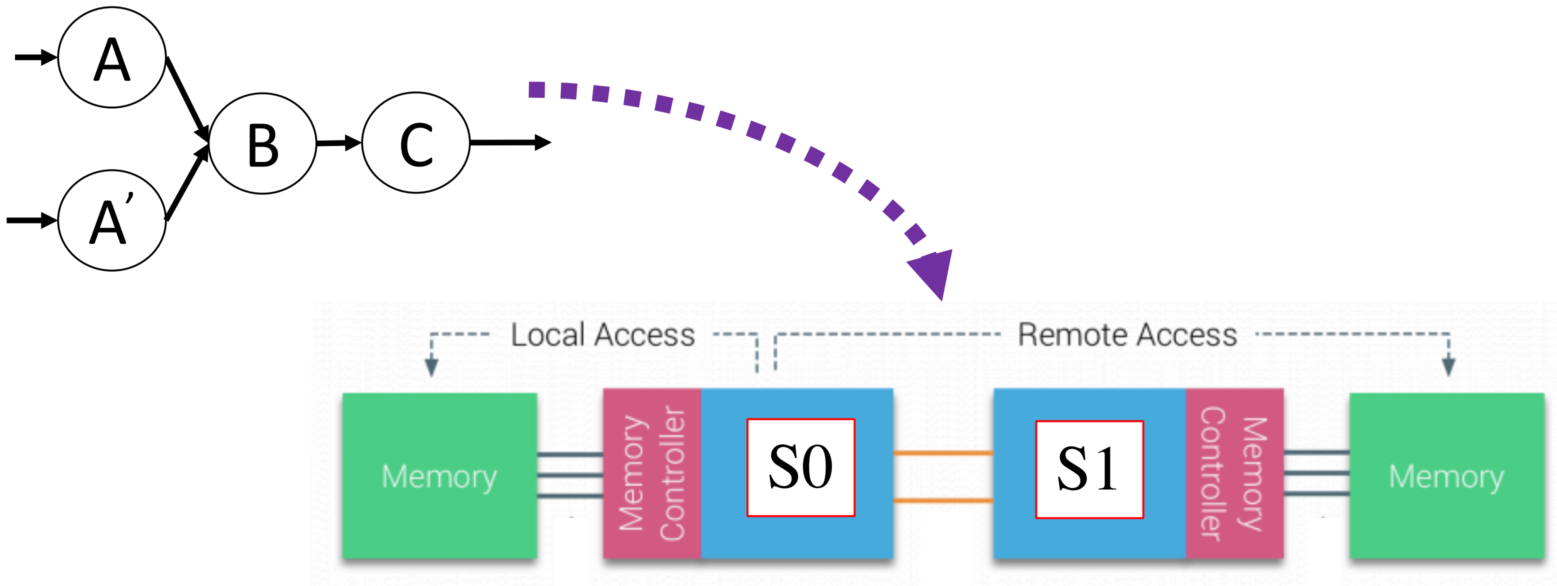
| C | S1 |



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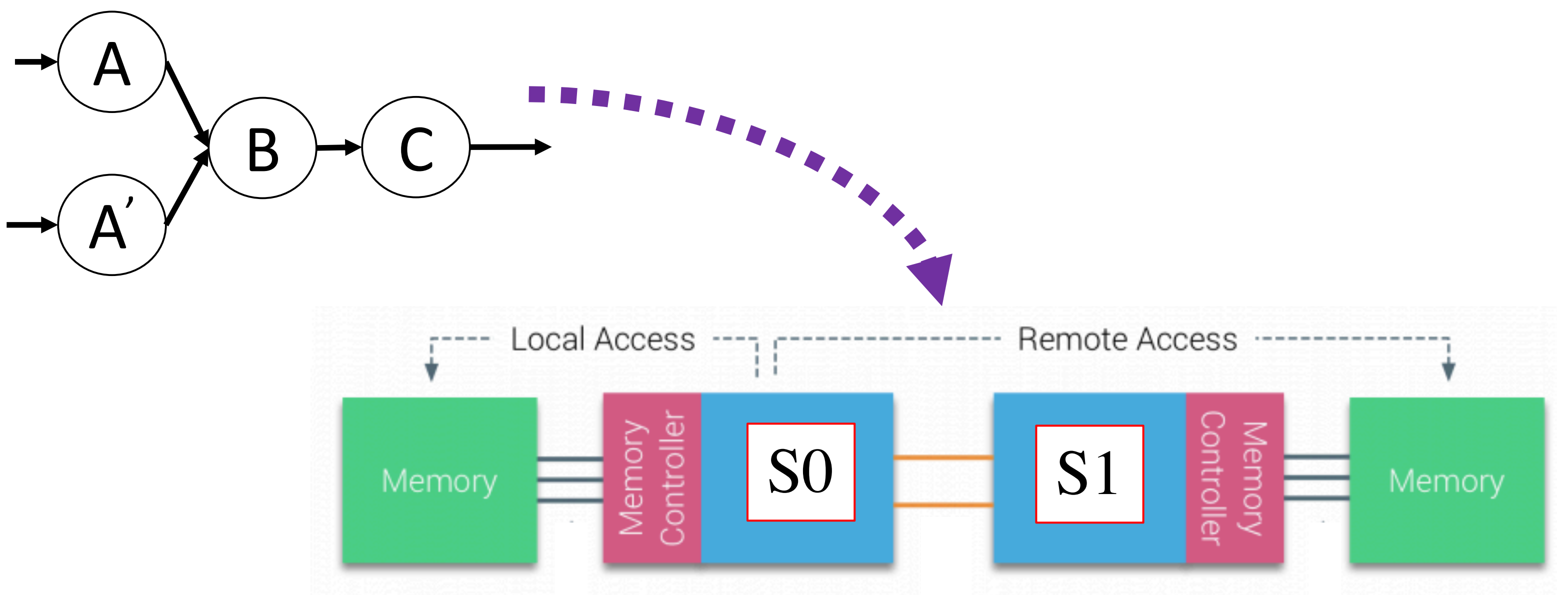


- **Allocate four operators into two sockets (2^4).**
- **Three operators cannot be allocated at the same socket due to resource constraint.**

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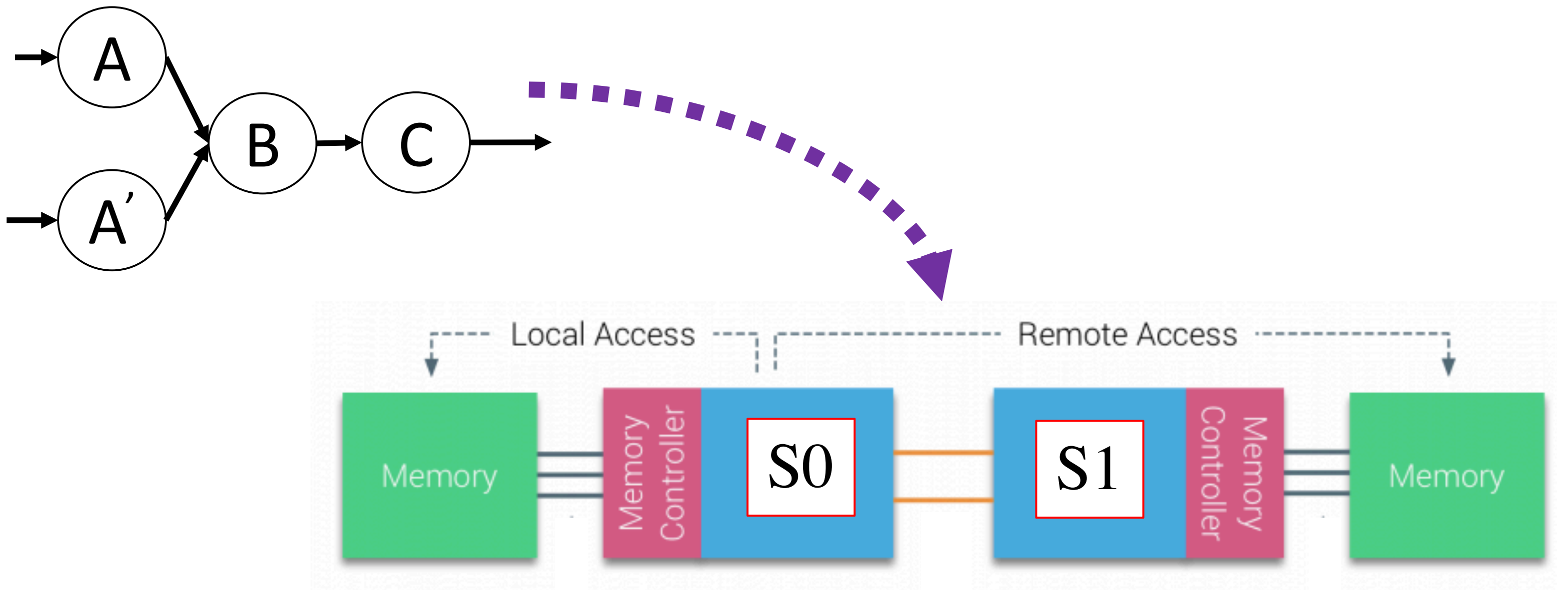


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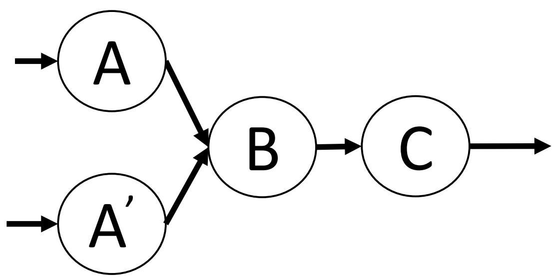


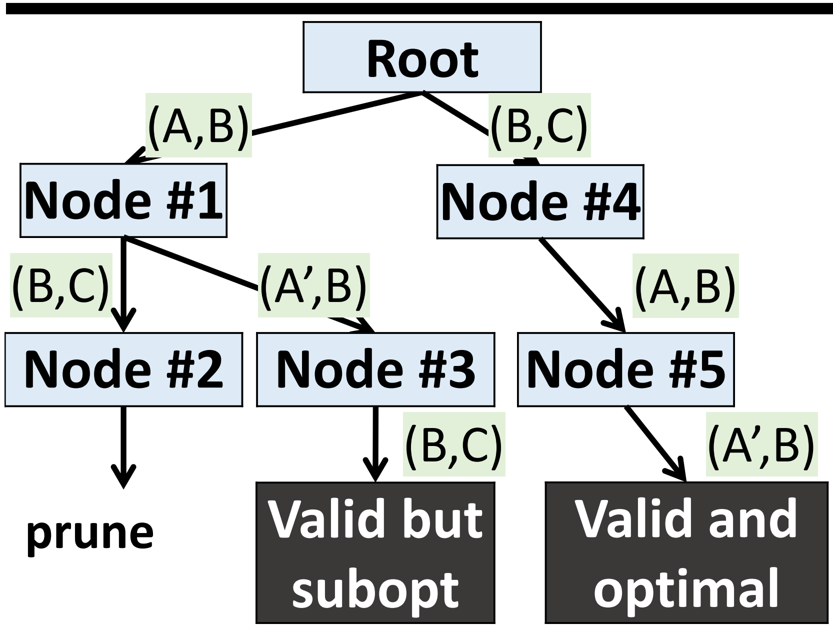


| Root | | | | |
|---|---|---|---|---|
| | allocation | Decisions | | |
| | | (A,B) | (A’,B) | (B,C) |
| A | - | - | - | - |
| A’ | - | - | - | - |
| B | - | ✓ | ✓ | - |
| C | - | - | - | ✓ |

| Node #1 | | | | |
|---|---|---|---|---|
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|---|---|---|---|---|
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| C | S1 | - | - | ✗ |

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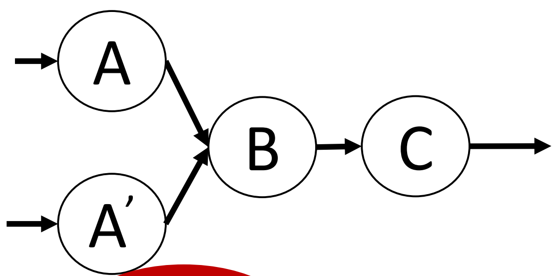


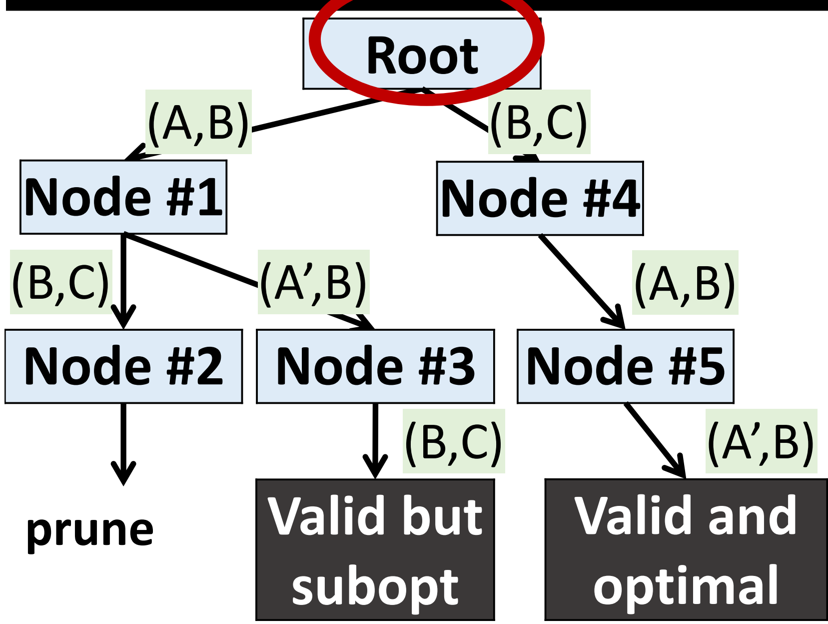


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**Node #2**

| | allocation | Decisions (A,B) | (A',B) | (B,C) |
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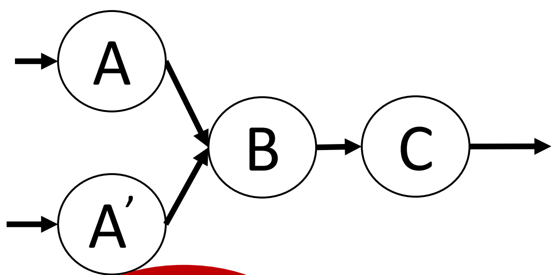


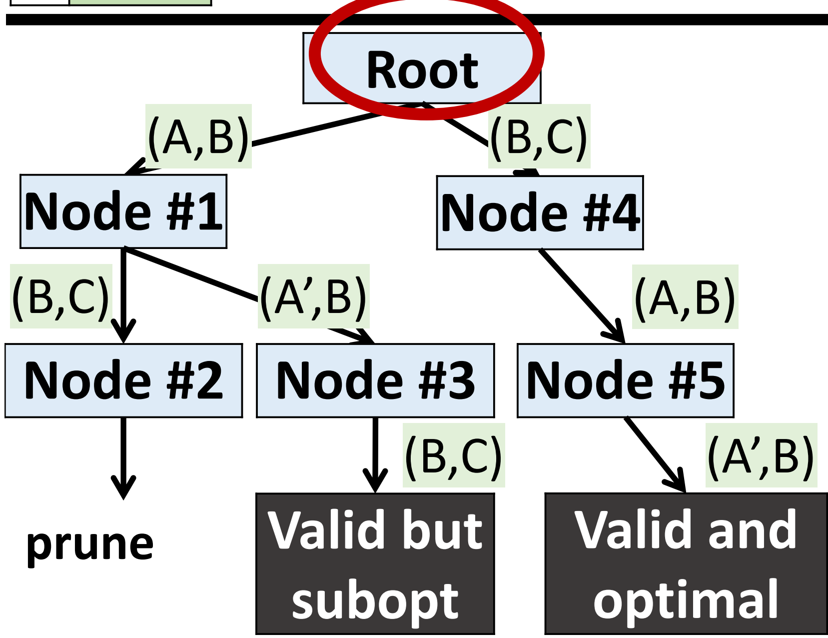


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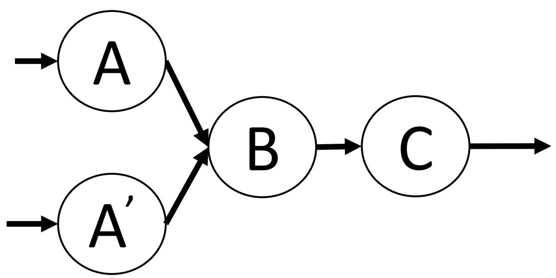


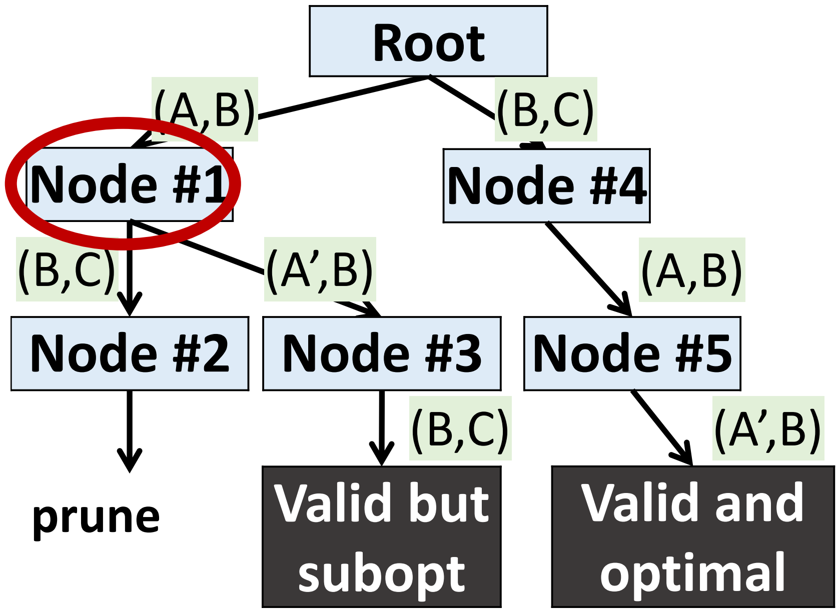


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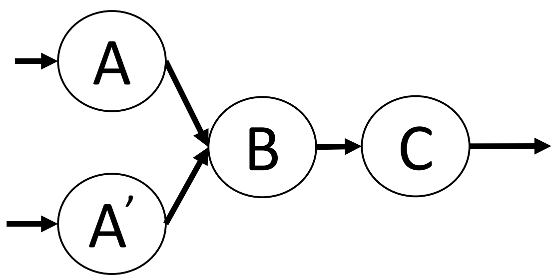


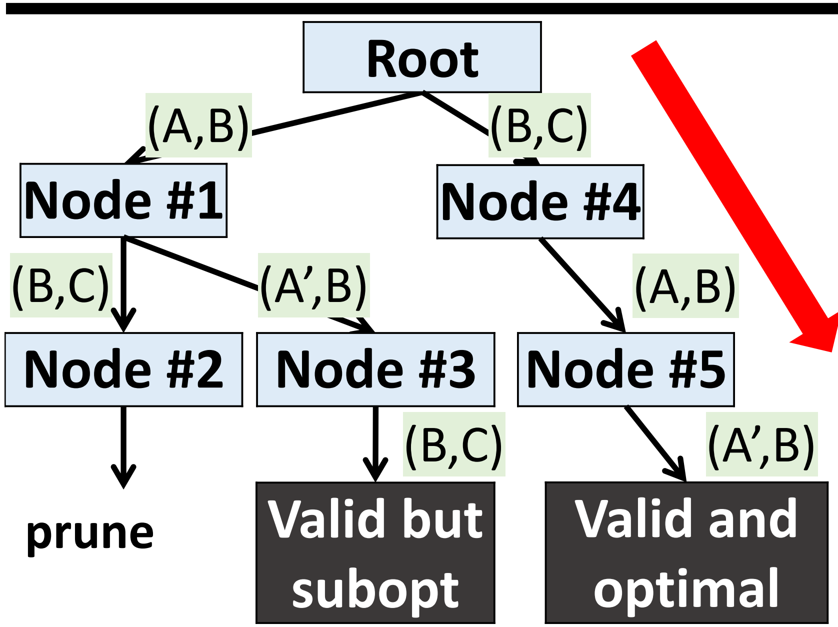


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# RLAS Overview

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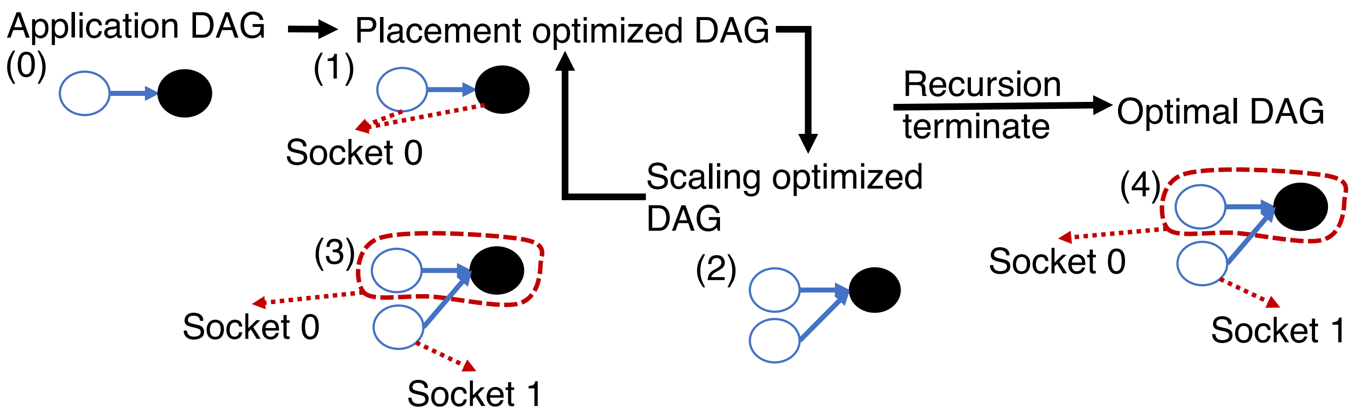
## RLAS optimization
## = Repeat {Scaling Optimization + Placement Optimization}.

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# BriskStream Implementation

- **Optimized for shared-memory multicore architecture.**
  - Reduced instruction footprint.
  - Improved communication efficiency.
- **Integrated RLAS optimization framework.**
  - Performance model.
    - **Profiling frameworks.**
  - Optimization Algorithms.

# Experimental Evaluation

**Applications:**

WC: word-count; FD: fault-detection; SD: spike-detection; LR: linear road benchmark

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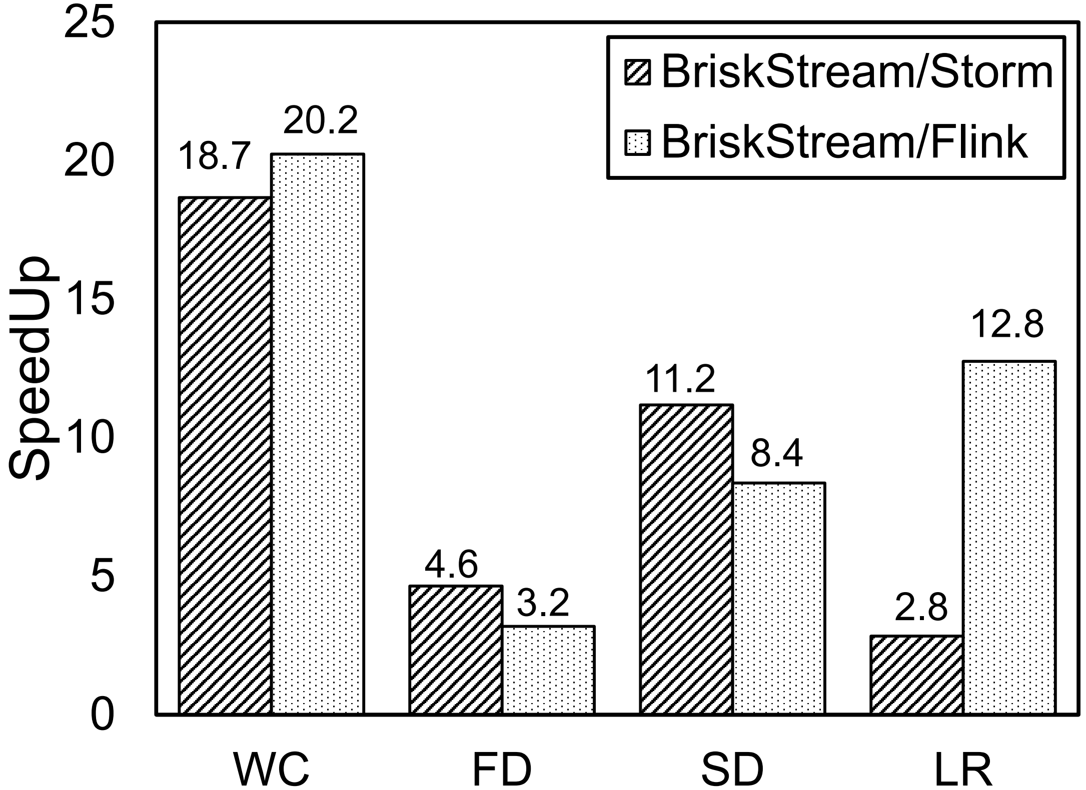
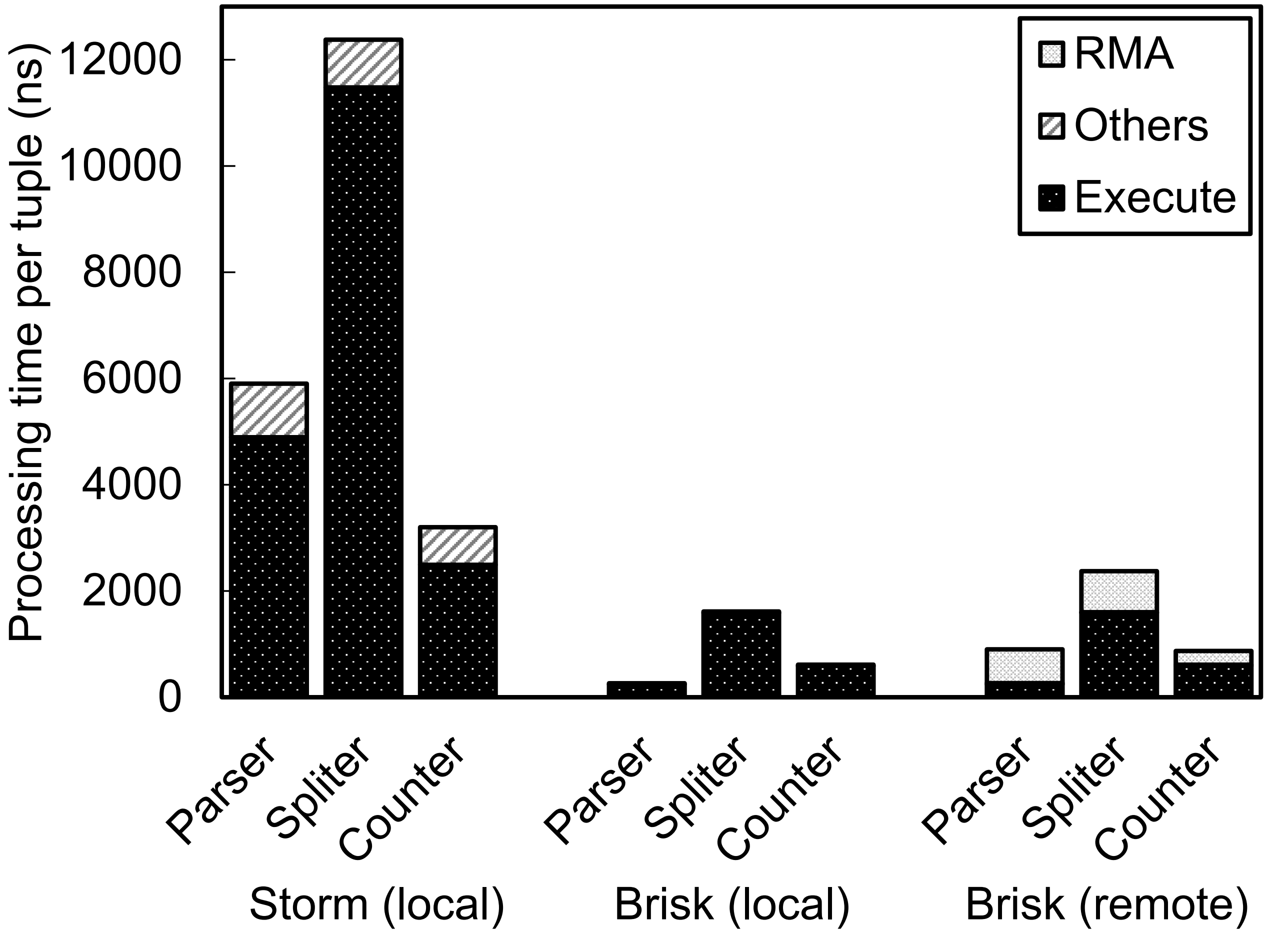



- Much higher throughput

# Execution Time Breakdown



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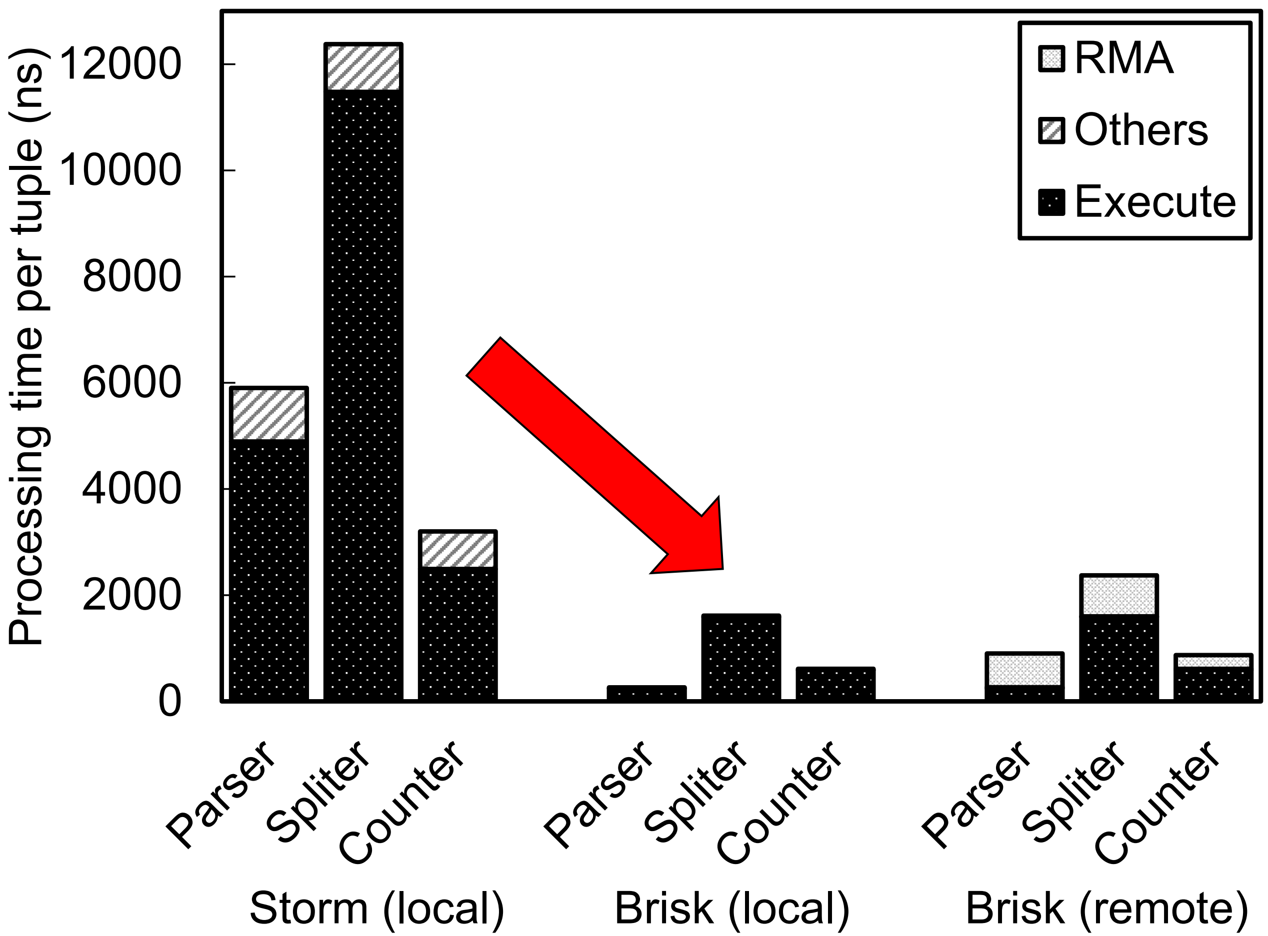


(1) "Execute" is significantly reduced to only 5 ~ 24% of that of Storm.

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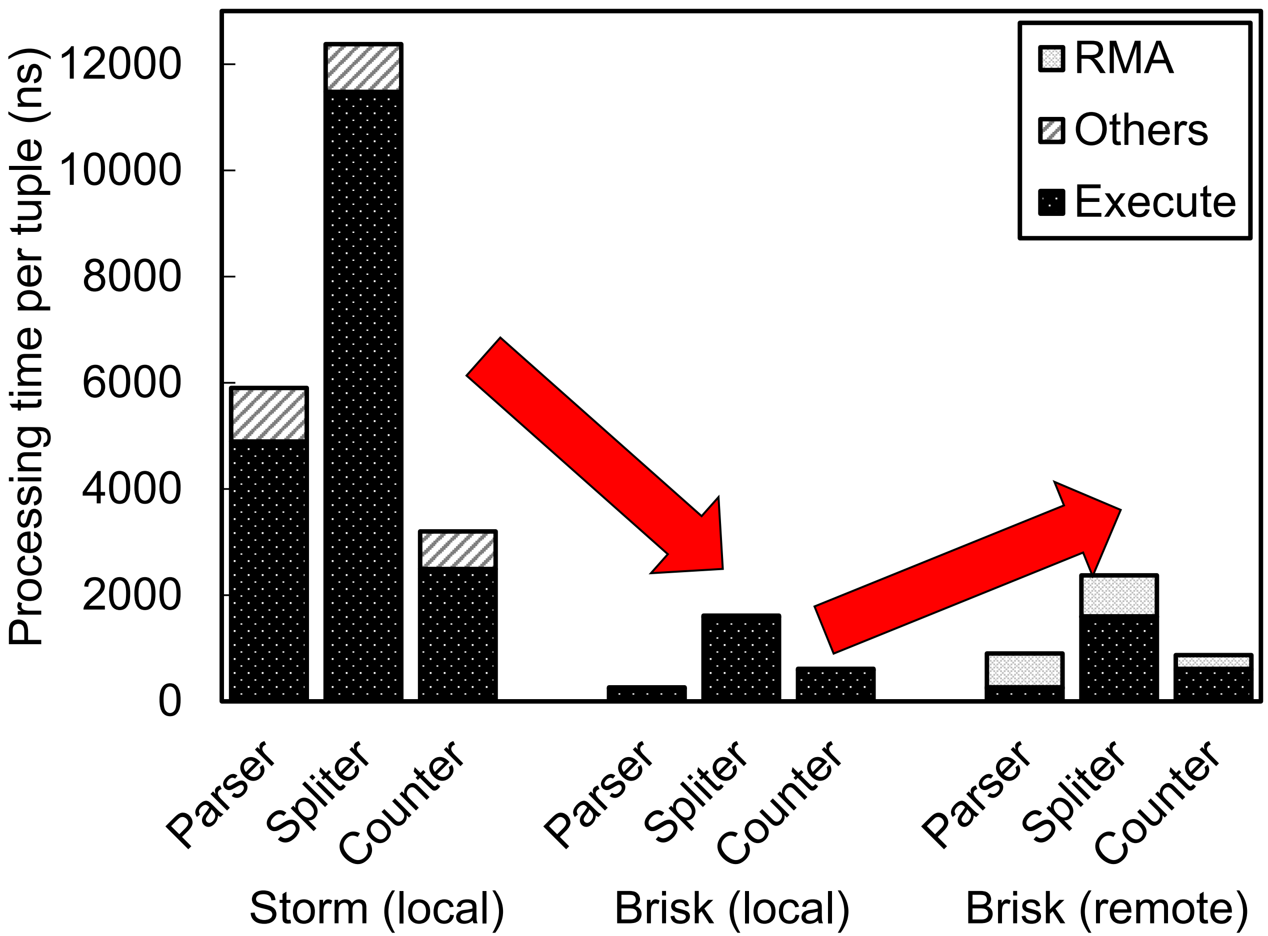
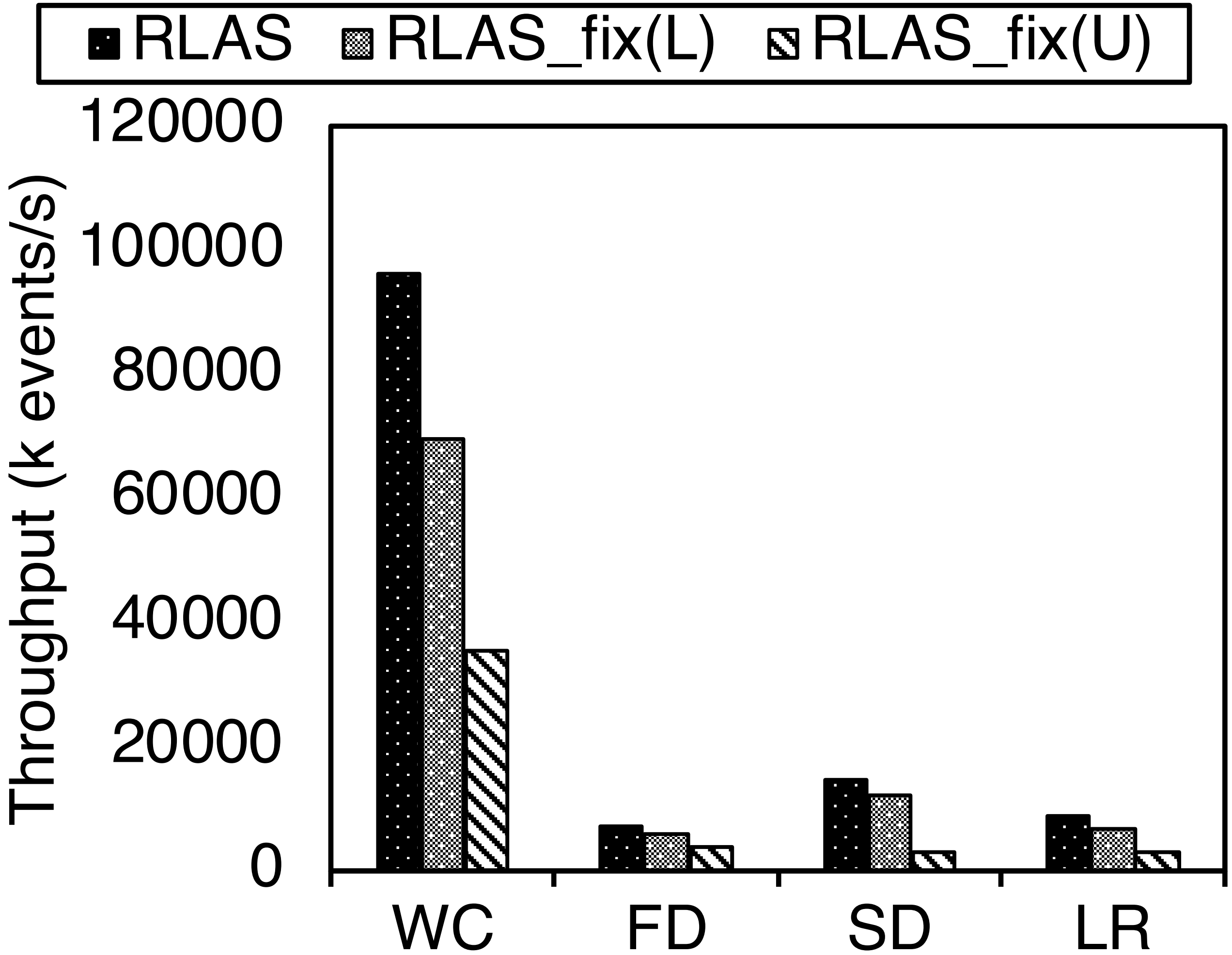



(1) "Execute" is significantly reduced to only 5 ~ 24% of that of Storm.

(2) RMA overhead becomes a critical issue to optimize.

# Importance of relative location awareness



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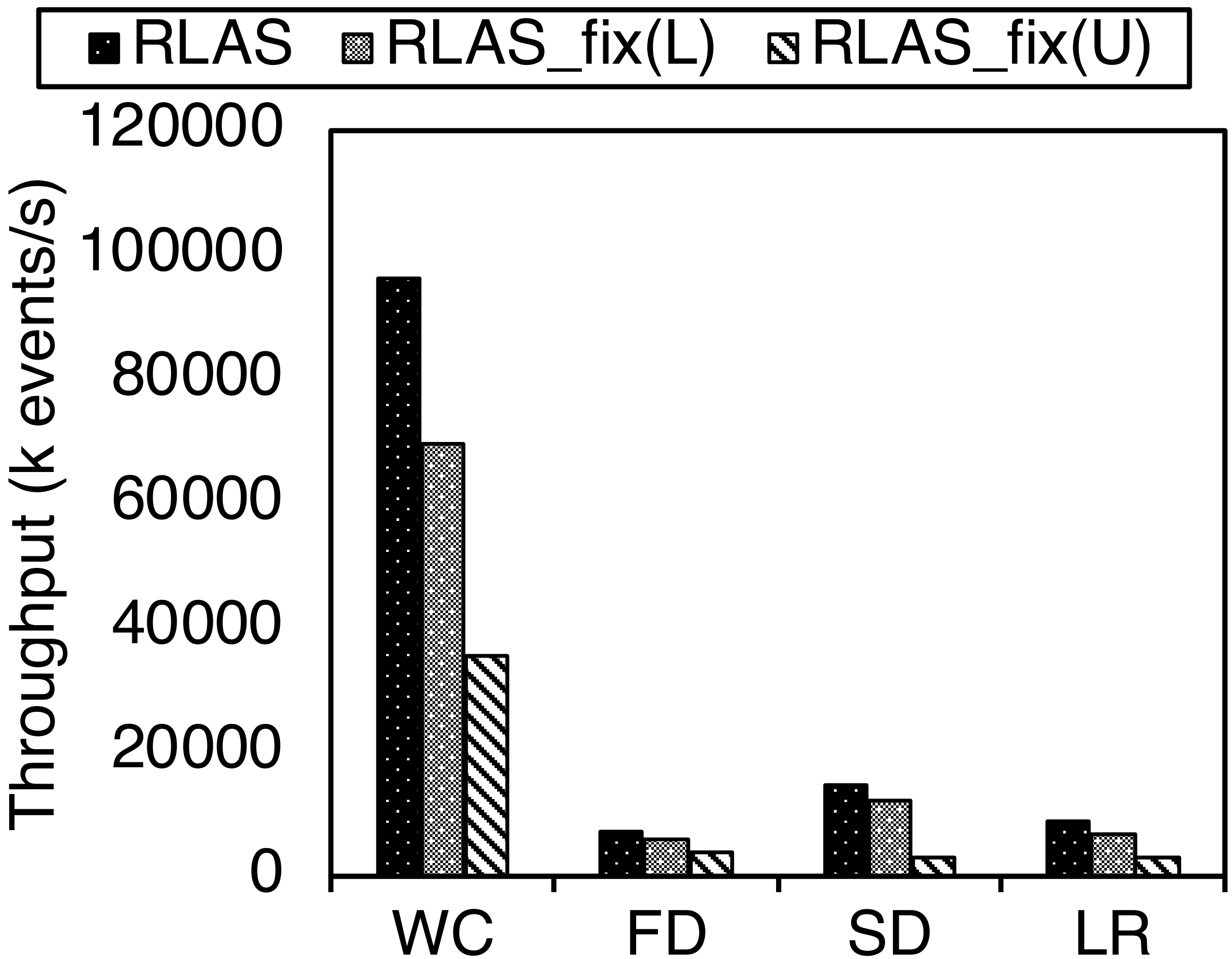


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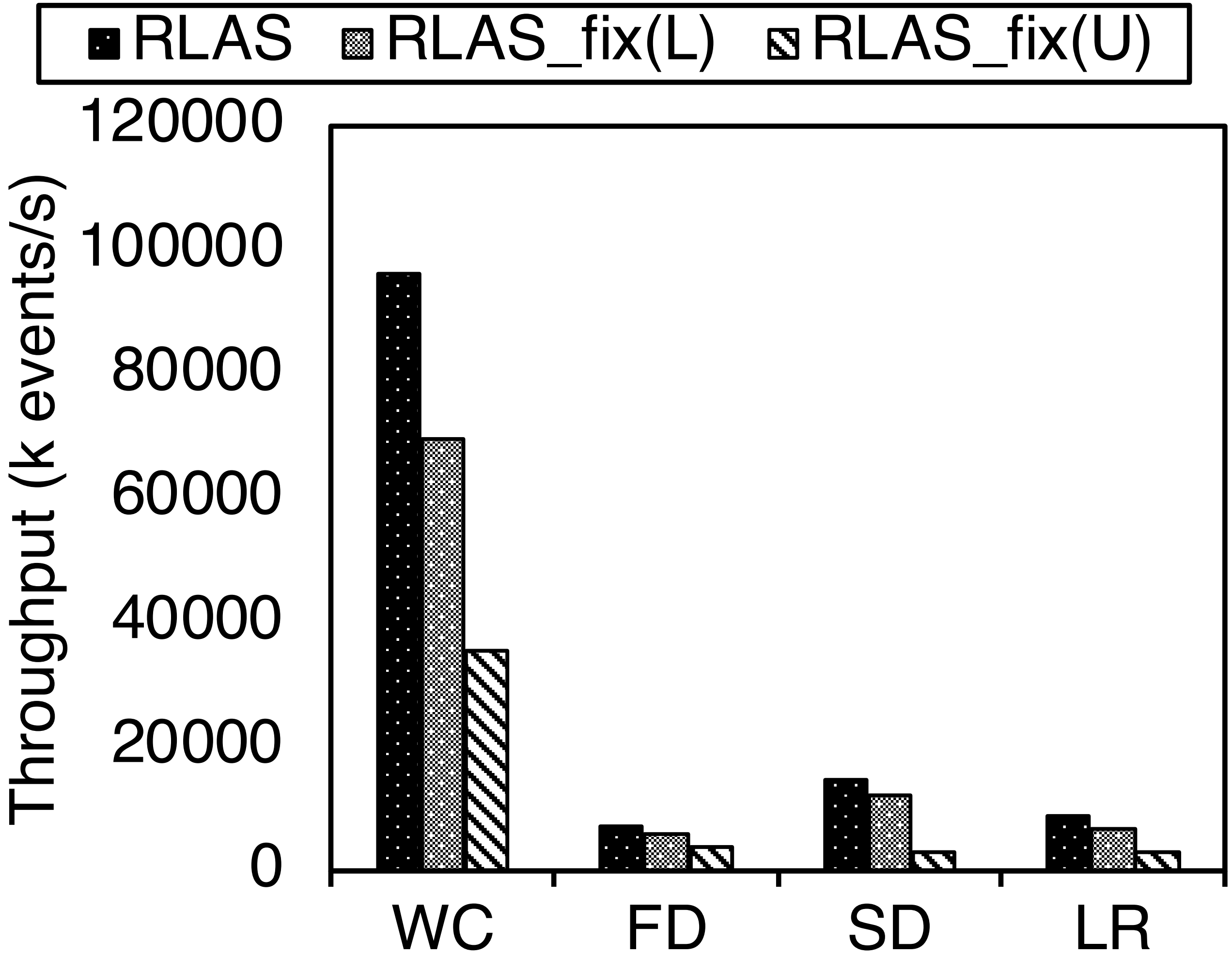


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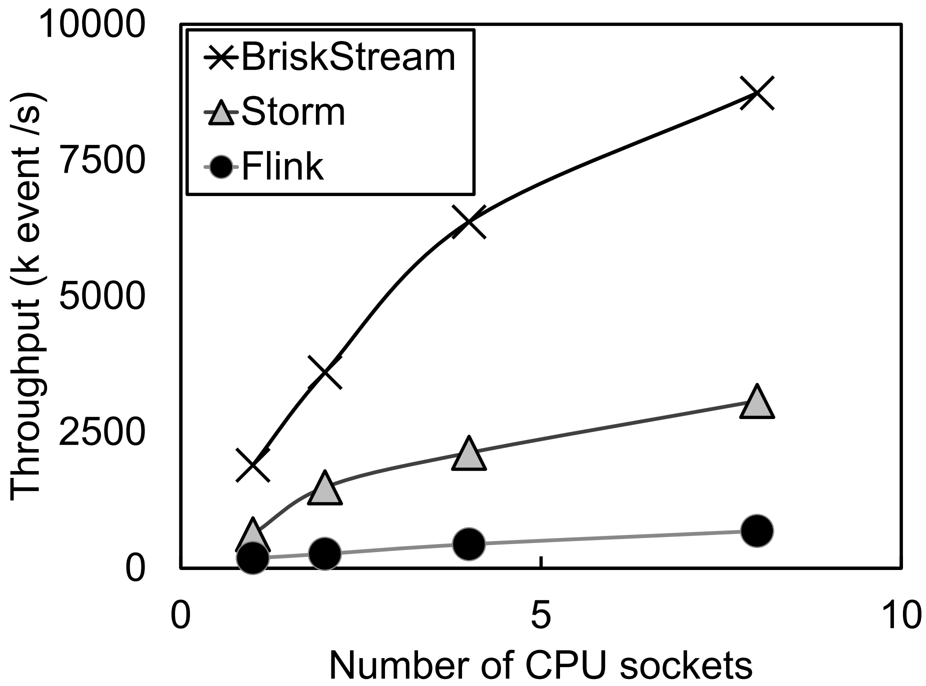
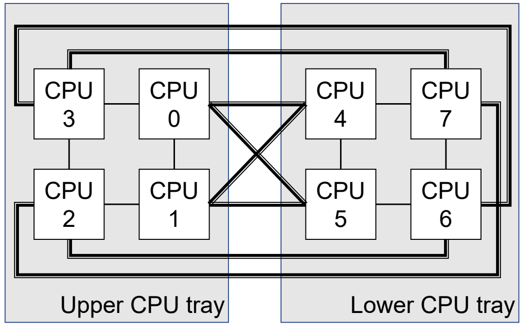



(144 cores)

Linear Road Benchmark



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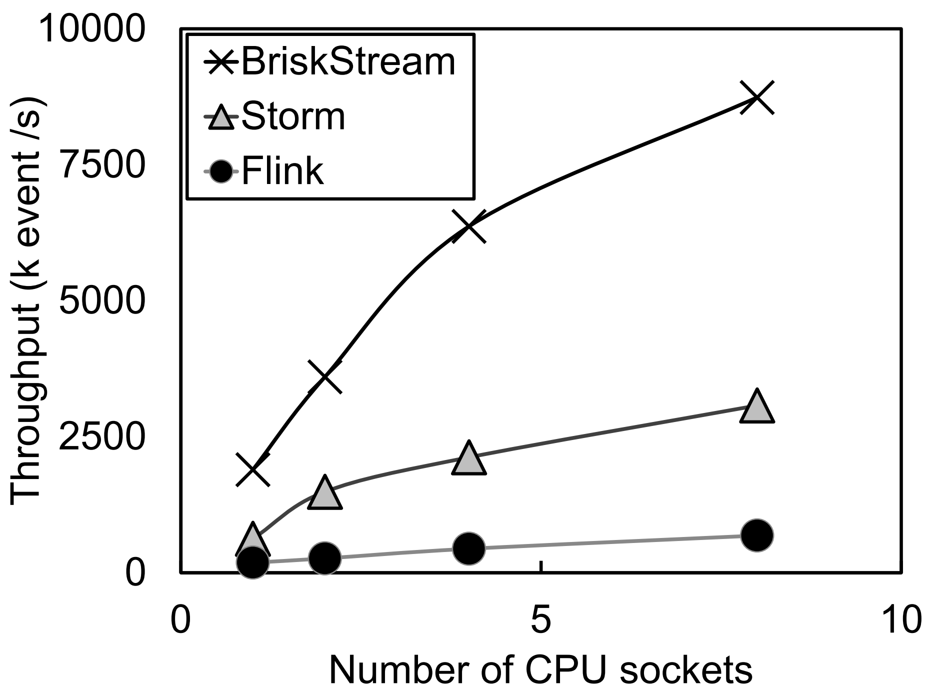


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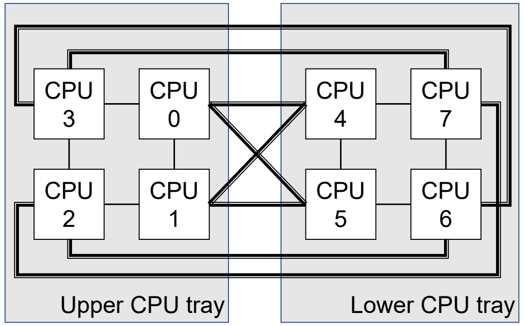
Linear Road Benchmark

(1) Scales much better



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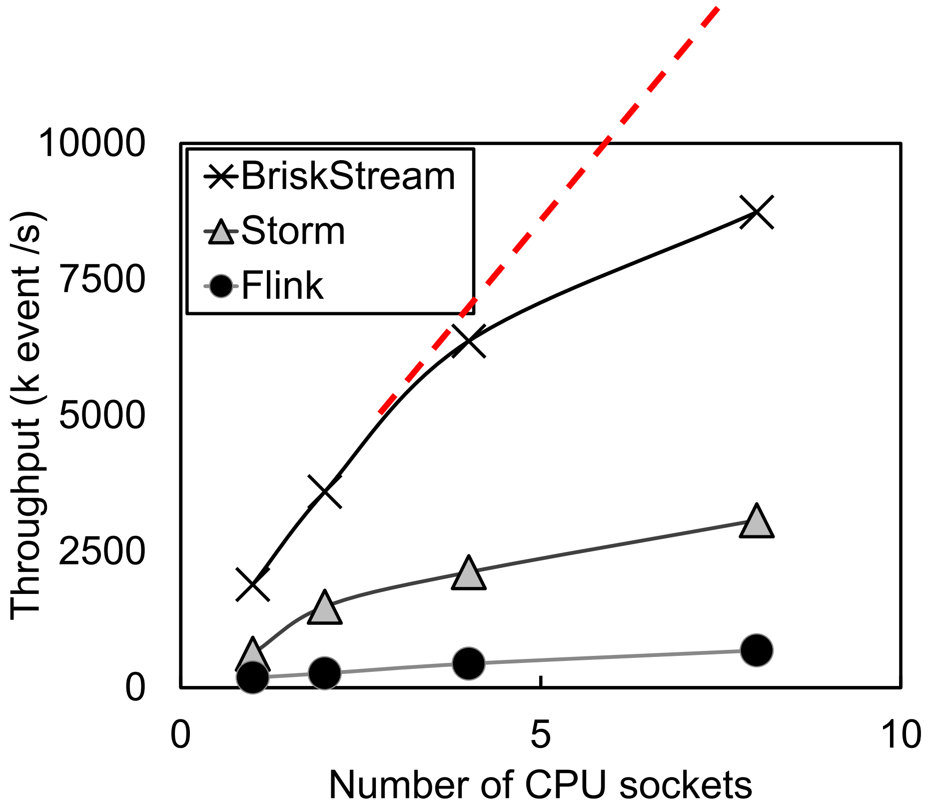


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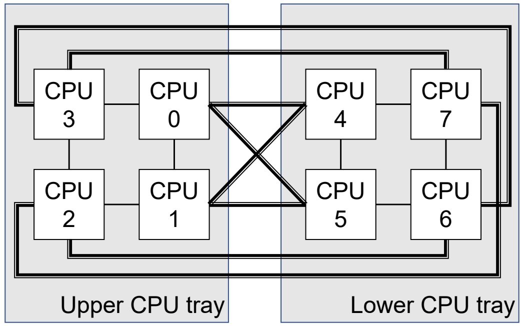

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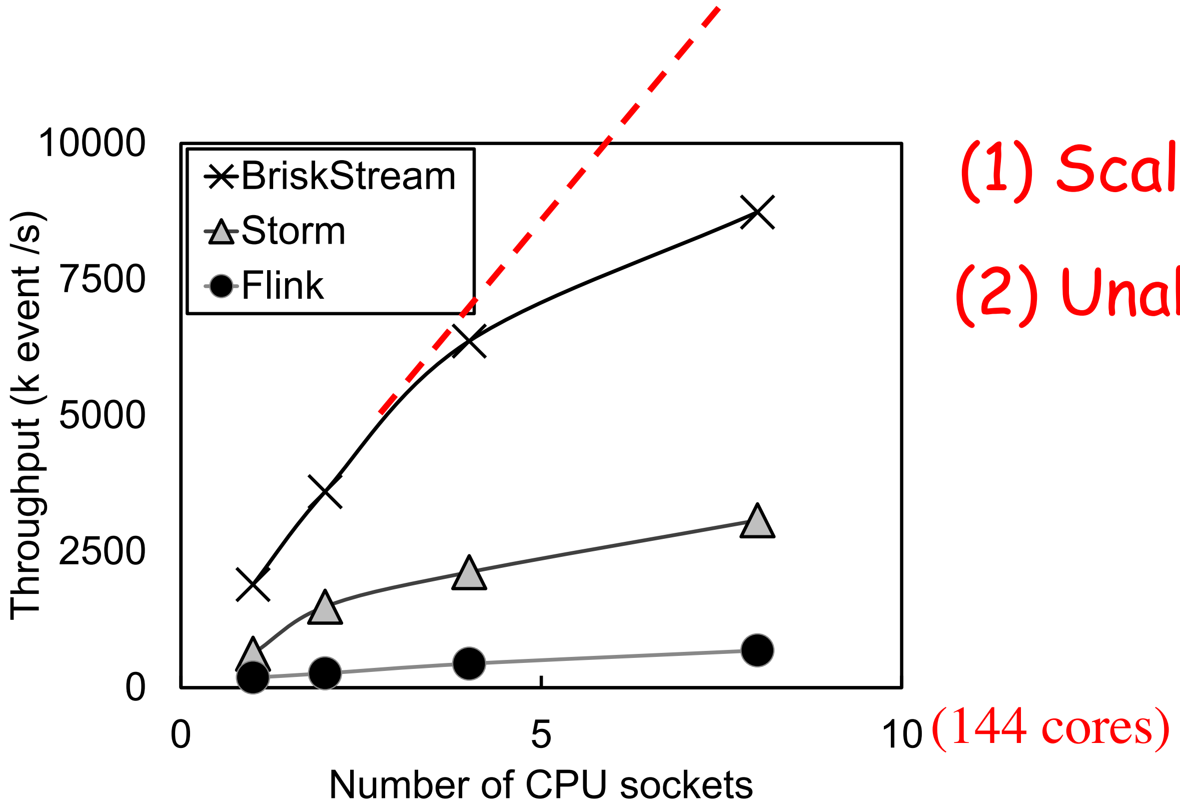


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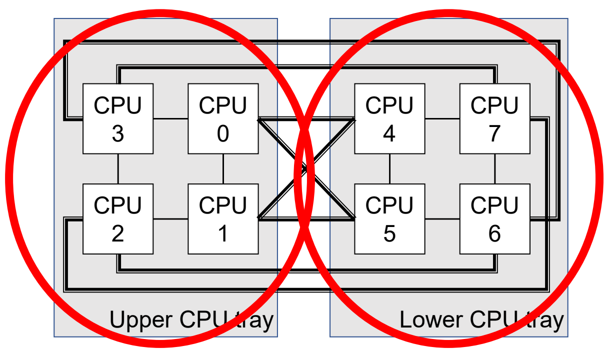


Tray 1 Tray 2

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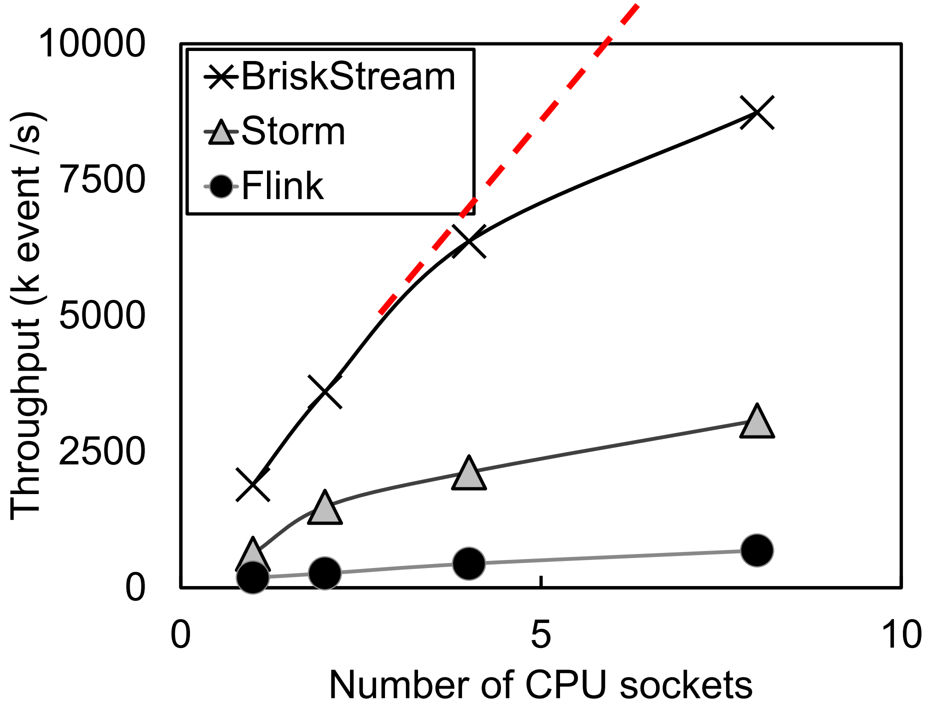


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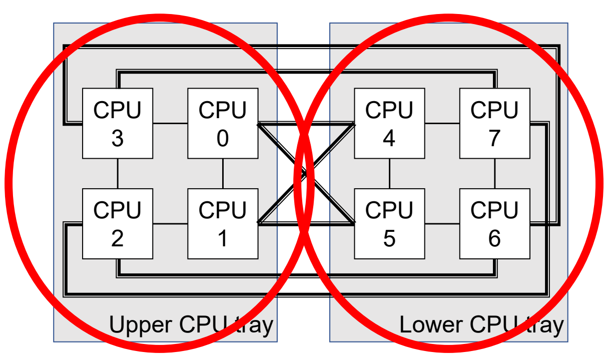
- Stream compression? [TerseCades, ATC'18]

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# Recap

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  - Strict state consistency guarantee.
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# Acknowledgement


- This work is supported by a MoE AcRF Tier 2 grant (MOE2017-T2-1-122) and an NUS startup grant in Singapore.
- Jiong He is supported by the National Research Foundation, Prime Ministers Office, Singapore under its Campus for Research Excellence and Technological Enterprise (CREATE) programme.
- Chi Zhou’s work is partially supported by the National Natural Science Foundation of China under Grant 61802260 and the Guangdong Natural Science Foundation under Grant 2018A030310440.

# Q&A

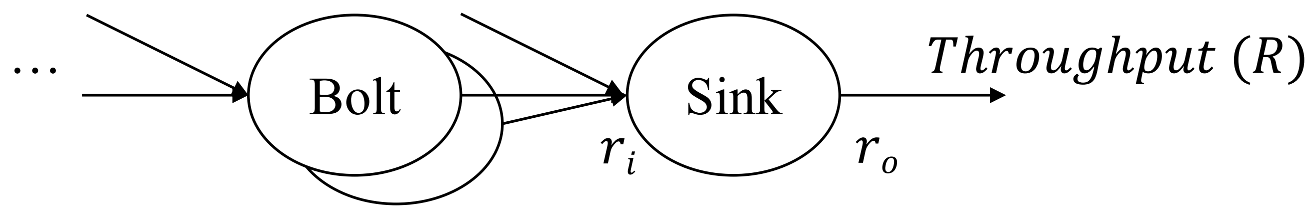
Thank you

shuhao.zhang@comp.nus.edu.sg

❖END

https://github.com/ShuhaoZhangTony/briskstream

# The Performance Model




- $r_i$ : input rate – depends on ($r_o$ of upstream operators).
- $r_o$: output rate – depends on (processing speed) and ($r_i$ of upstream operators).
- The model tries to estimate throughput ($R$), which is Sink's $r_o$.

# Estimating $r_o$ of an Operator (1)

- Output rate ($r_o$) can be estimate as #tuples processed ($N$) / time needed to process them ($t_p$).
- Consider an arbitrary observation time t,
  $N$= total aggregated input tuples arrived during t;
  $t_p = \sum_{n=1}^{N} T(p)$.
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Prior works assume $T(p)$ is predefined and independent to different execution plans (p).

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$$T(p) = T^e + T^f$$

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This is why $T(p)$ varies under different execution plans.

# Estimating $\overline{r_o}$ of an Operator

- Implict assumption: $tp \geq \mathrm{t}$
- What happen when the assumption does not hold?
  - What is the $\overline{r_o}$ in general?

# Bottleneck Operators

An operator can have only two possible conditions under a given execution plan.

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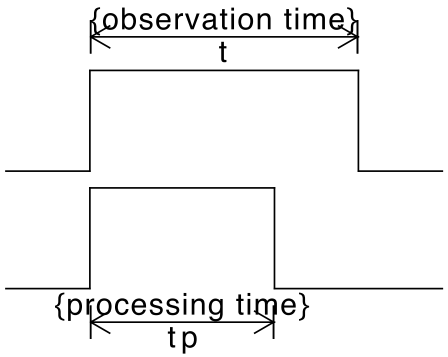


Under-supplied

Output rate is only
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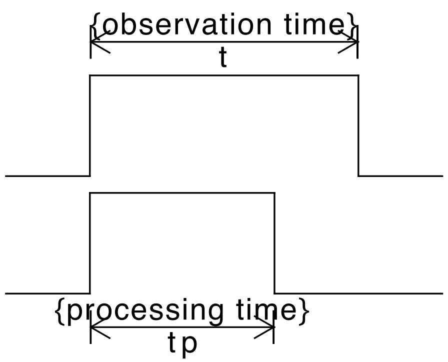


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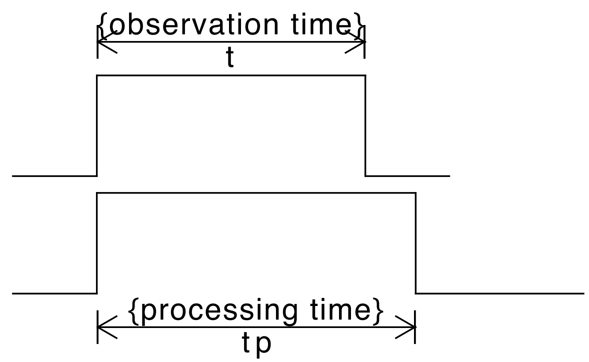


Over-supplied (or just fulfilled)

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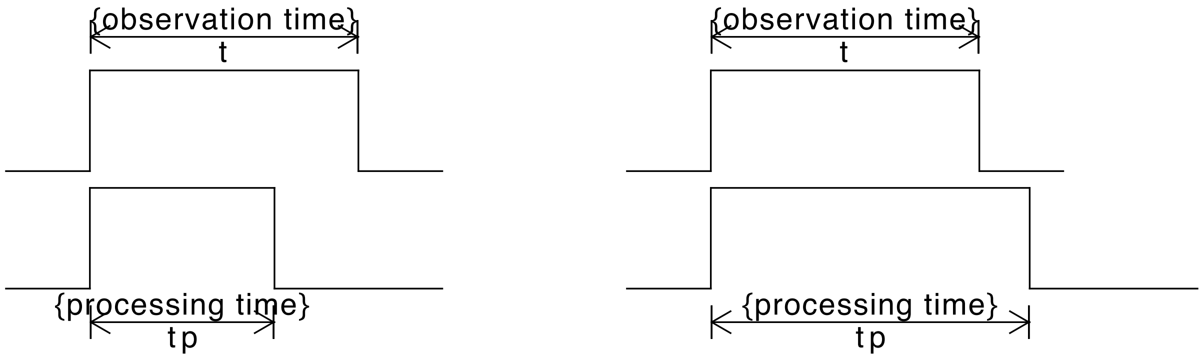


Under-supplied

Over-supplied (or just fulfilled)

Operator being over-supplied is essentially the bottleneck.

Output rate is only determined by its input rate

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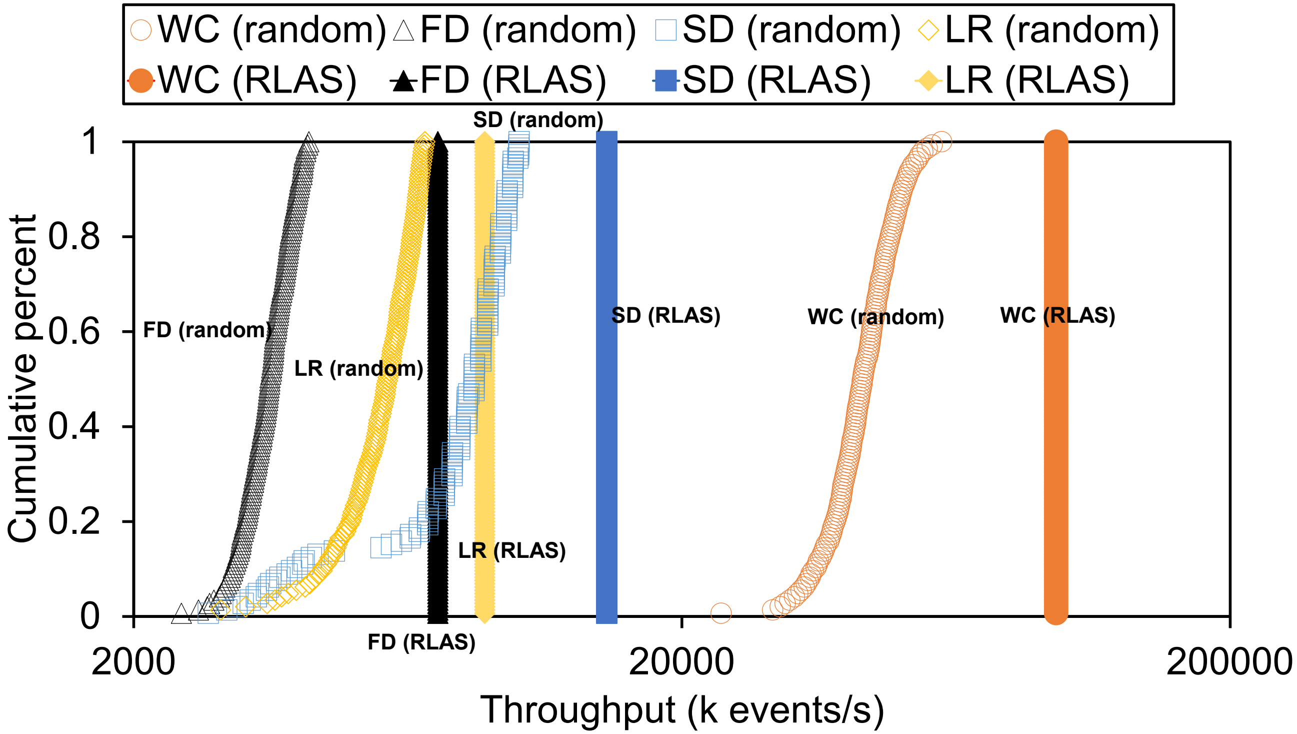
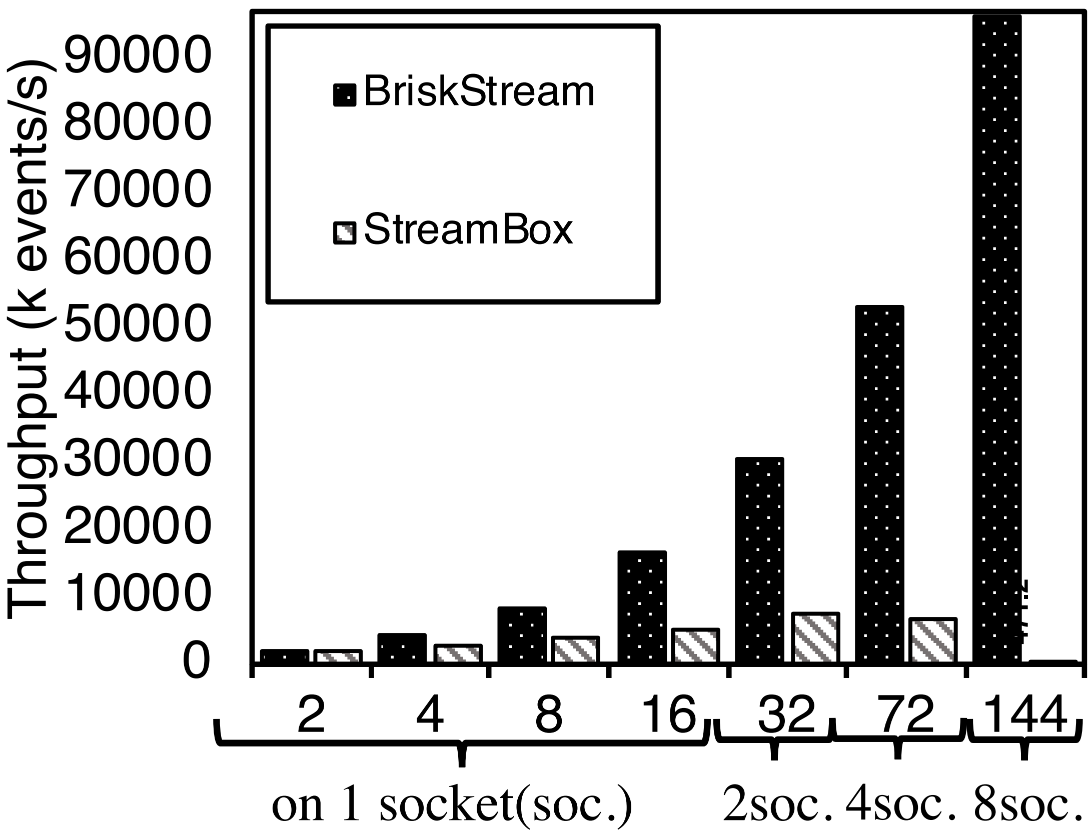
# Why do we need a model?




Random plans hurt the performance in a high probability due to the huge optimization space.

# How about other Single-node Optimized DSPS?



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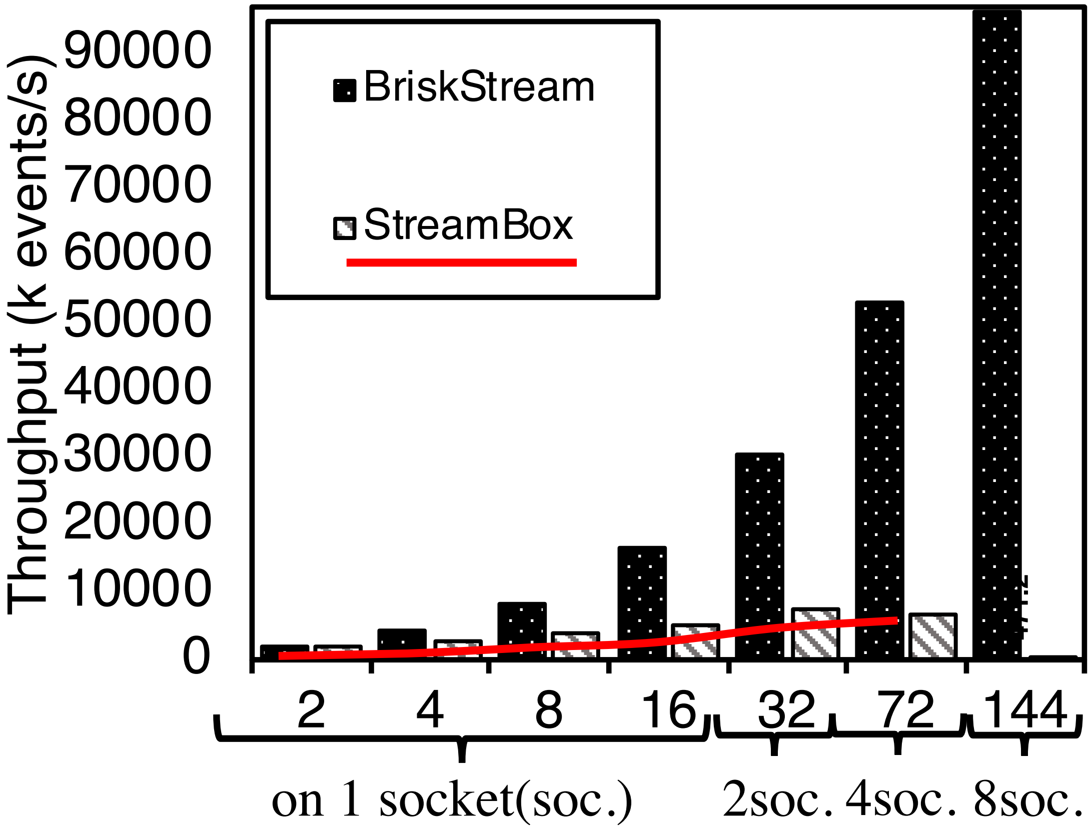


It shows a much poorer performance than BriskStream for its different design focus:

- providing ordering guarantee (bears heavy locking overhead).

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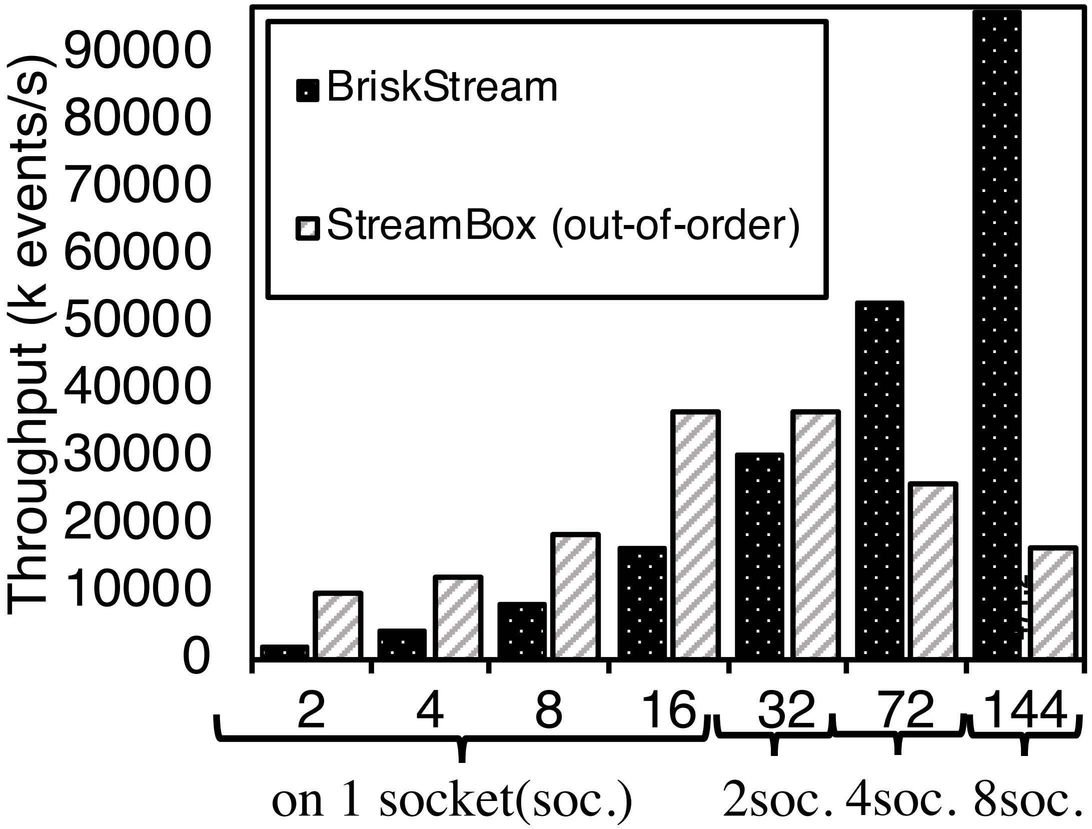

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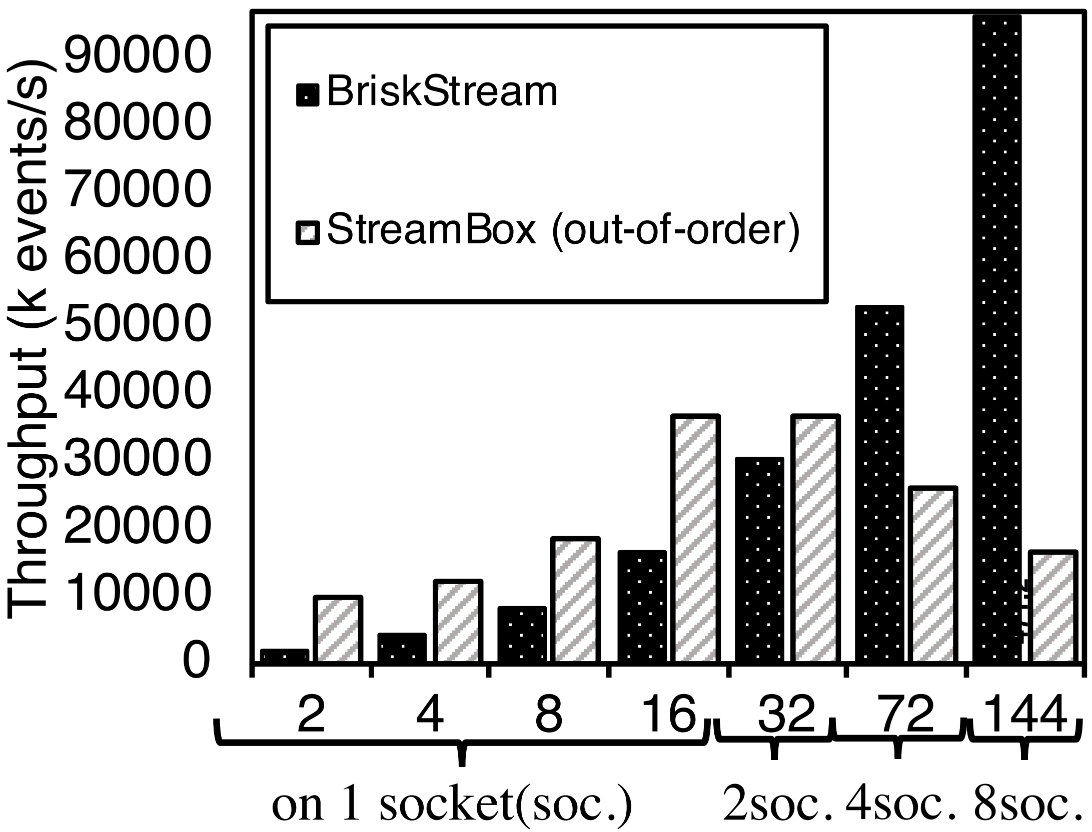
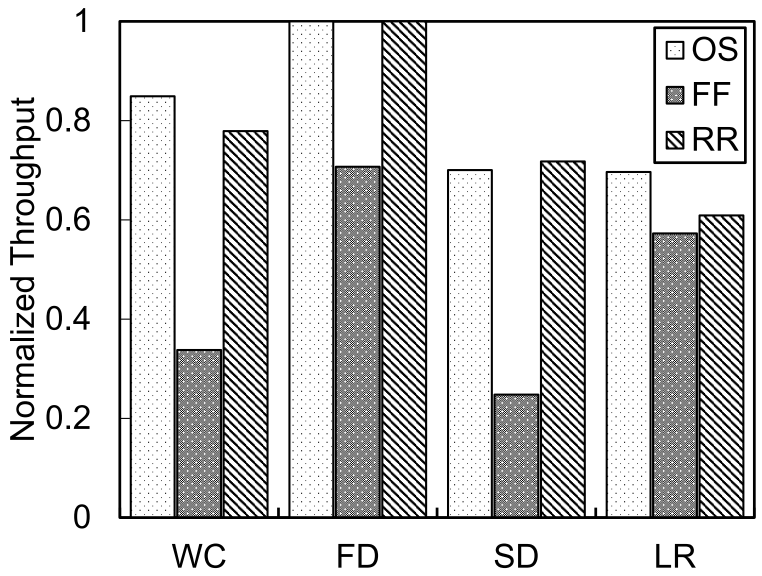



- StreamBox (w/o ordering guarantee) still leads to sub-optimality under large core count due to its greedy nature for addressing NUMA effect.
- Nevertheless, we foresee an interesting future work to employ morsel-driven execution into BriskStream.

# Why not simple heuristics? (1)




- OS: No explicit placement optimization
- FF: Greedily minimize cross-operator traffic.
- RR: Greedily balance workloads among CPU sockets.

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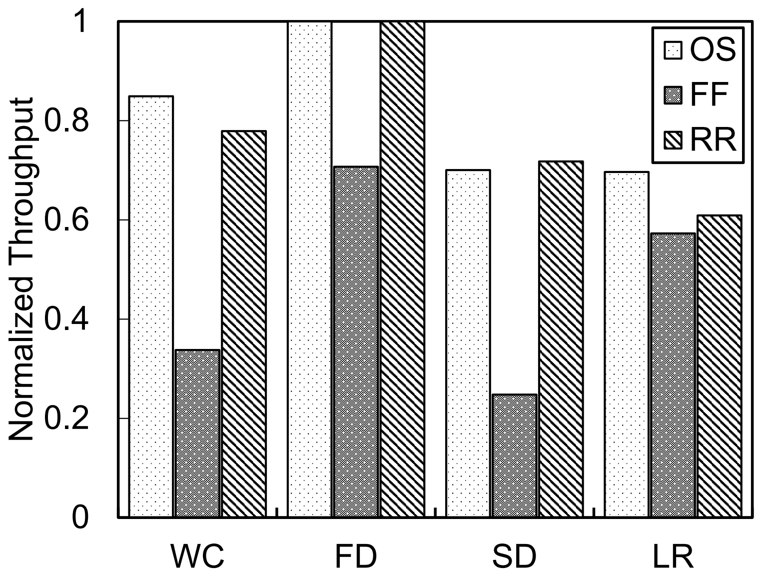


- OS: No explicit placement optimization
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- RR: Greedily balance workloads among CPU sockets.

Heuristic approaches commonly used in distributed environment

- either oversubscribe a few CPU sockets (FF)
- or unnecessarily involve RMA overhead (RR).

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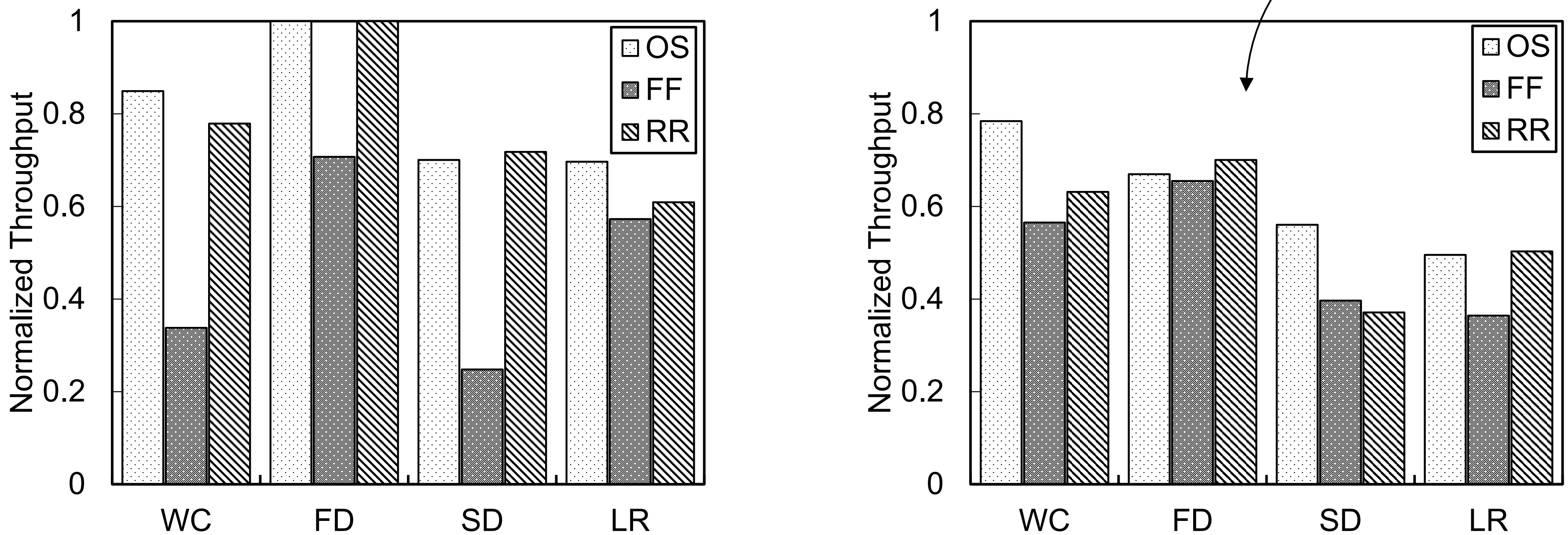
# Why not simple heuristics? (2)

Generally worse




Server A

Server B

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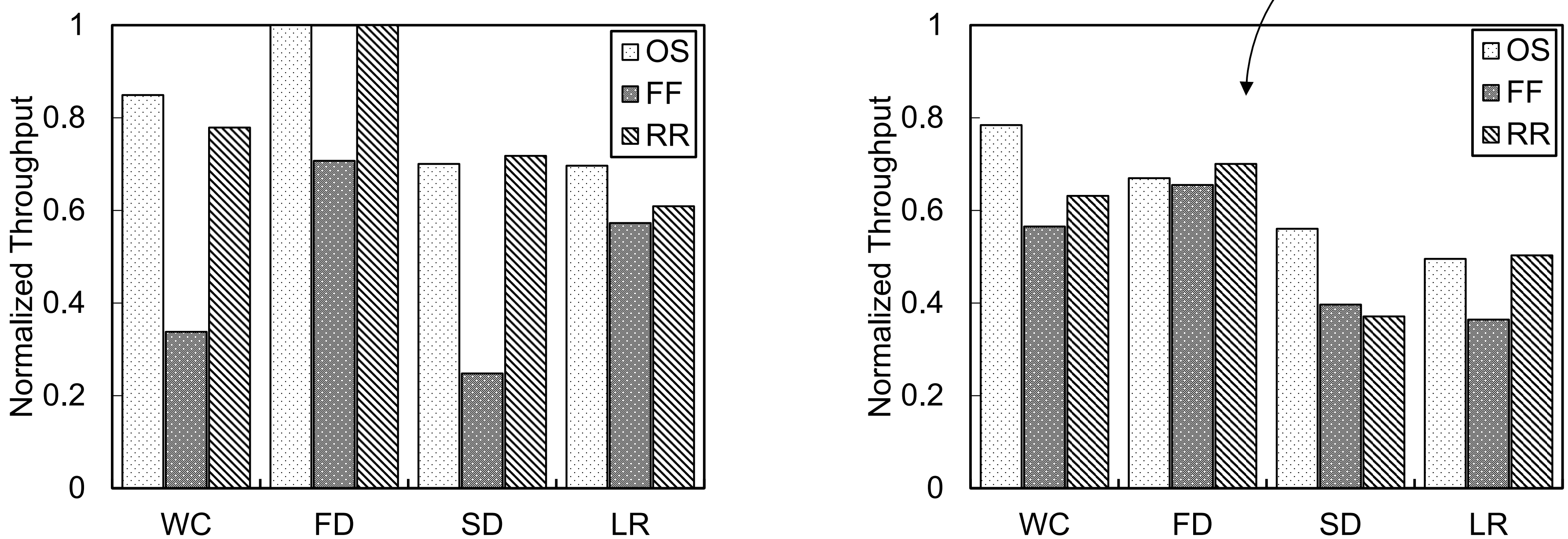


Server A

Server B

Heuristic approach requires tedious tuning process to determine the suitable usage of HW resource.