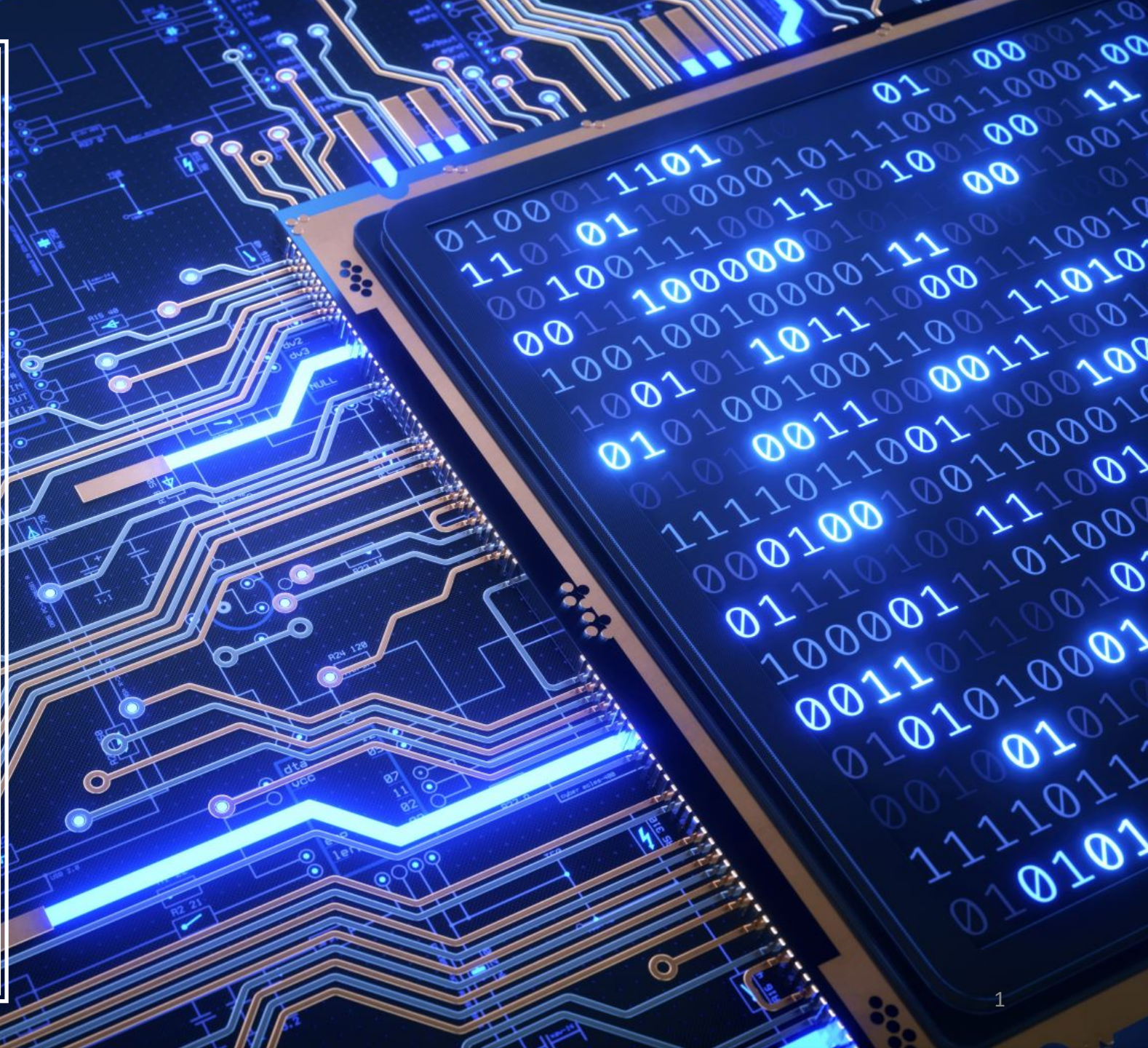


Hardware-Software Co-Design for Efficient Graph Application Computations on Emerging Architectures

The DECADES Team

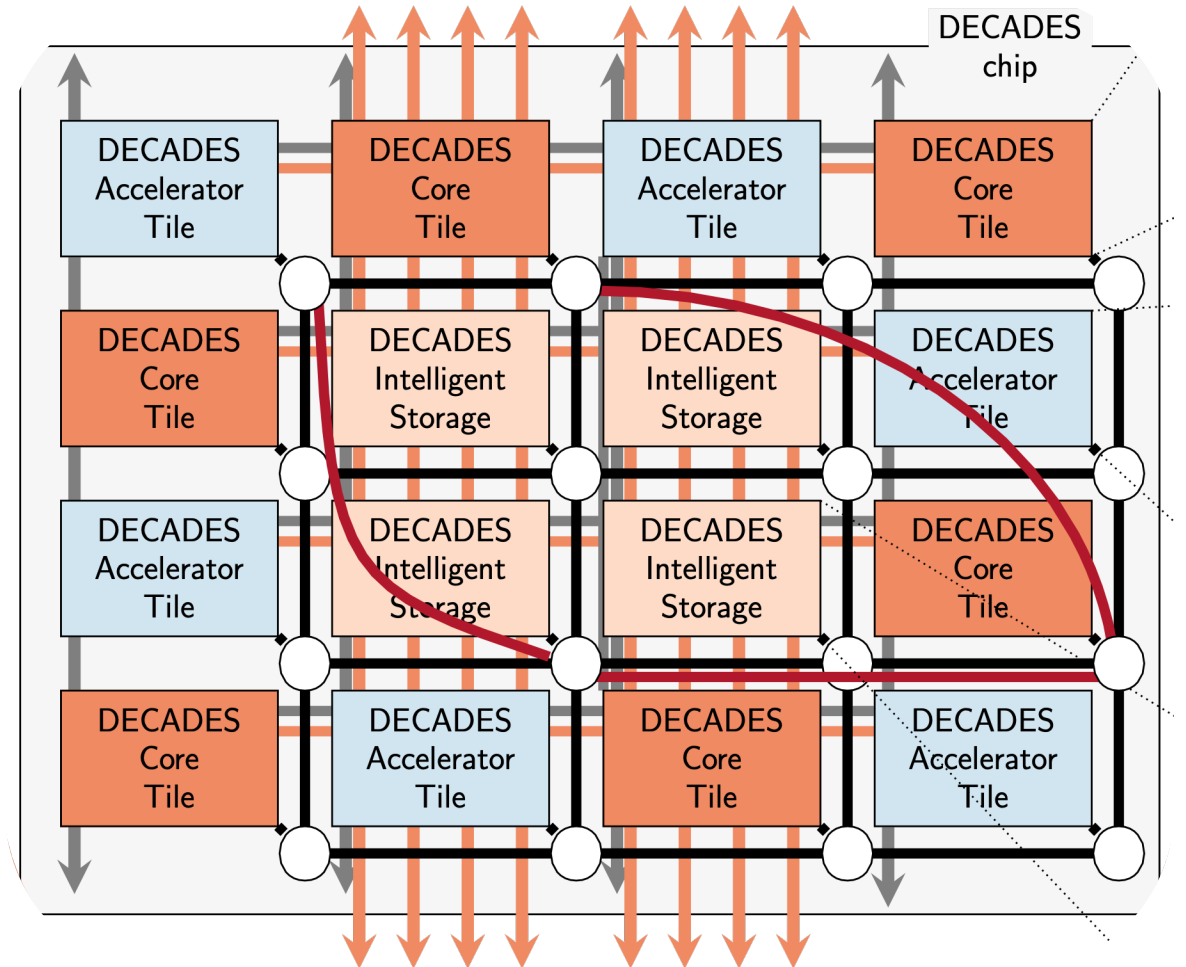
Princeton University

Columbia University



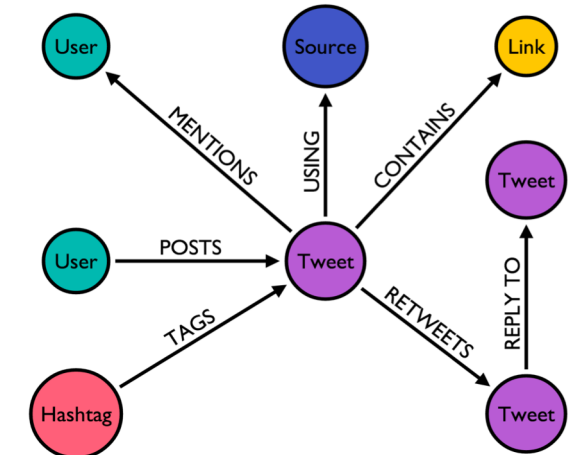
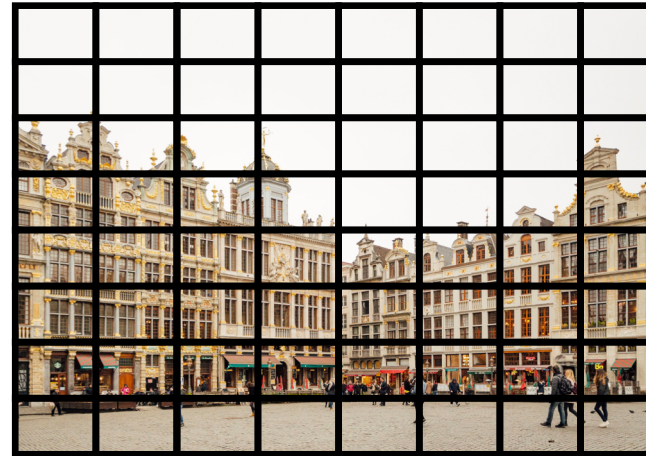
The DECADES Project

- Software Defined Hardware (SDH)
 - Design runtime-reconfigurable hardware to accelerate data-intensive software applications
 - Machine learning and data science
 - Graph analytics and sparse linear algebra
- DECADES: heterogeneous tile-based chip
 - Combination of core, accelerator, and intelligent storage tiles
 - Princeton/Columbia collaboration led by PIs Margaret Martonosi, David Wentzlaff, Luca Carloni
- Our tools are **open-source!**
 - <https://decades.cs.princeton.edu/>



Graphs and Big Data

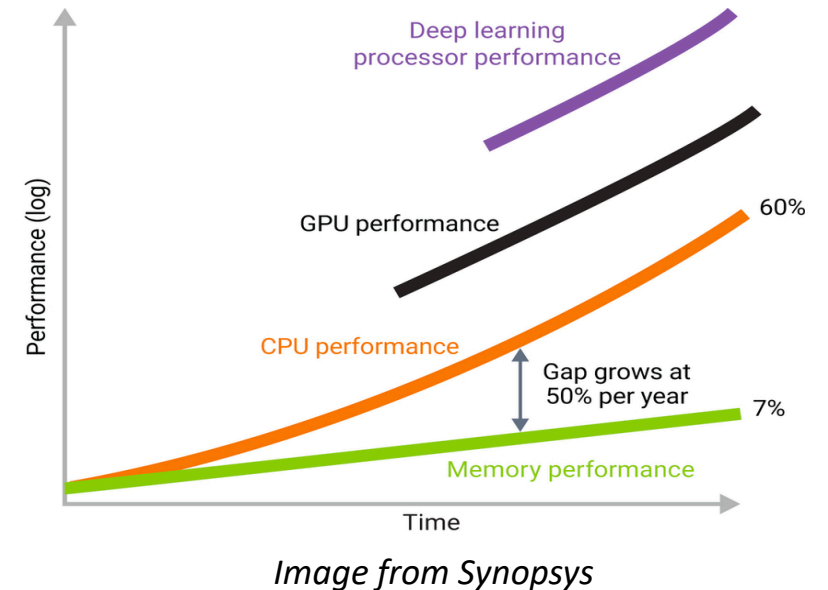
- Machine learning and data science process large amounts of data
 - Huge strides in dense data (e.g. images)
- Graph databases and structures can efficiently represent big data
 - What about sparse data (e.g. social networks)?
- Graph applications in big data analytics
 - E.g. recommendation systems



Images from TripSavvy, Neo4j, and Twitter

Modern Technology Trends and Big Data

- Modern system designs employ specialized hardware (e.g. GPUs and TPUs), accelerator-oriented heterogeneity, and parallelism
 - Significantly benefit **compute-bound** workloads
- Amdahl's Law perspective: faster compute causes relative memory access time to increase
 - Leads to memory latency bottlenecks
- Many graph applications are **memory-bound**
- Datasets are massive and growing exponentially
 - The ability to process modern networks has not kept up



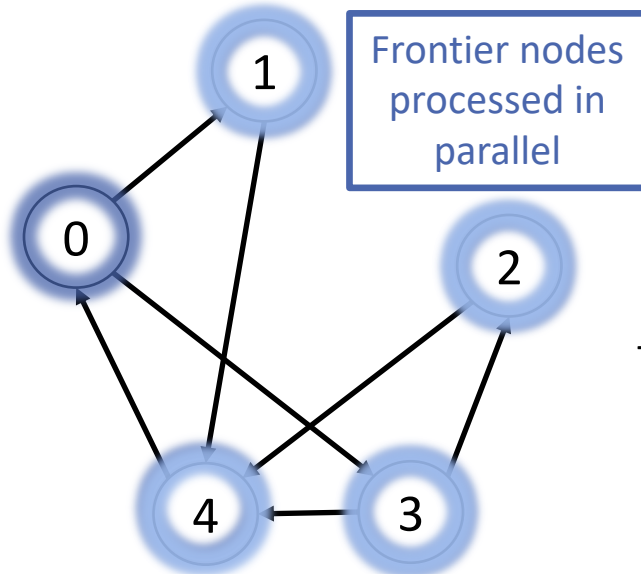
We need efficient graph processing techniques that can scale!

Graph Applications: Access Patterns are Irregular

- Iterative, frontier-based graph applications
 - Describes many graph processing workloads (e.g. BFS, SSSP, PR)
- *Indirect* accesses to neighbor data
 - Conditionally populate next frontier

```
for node in frontier:  
    val = process_node(node)  
    for neib in G.neighbors(node):  
        update = update_neib(node_vals, val, neib)  
        if (add_to_frontier(update)):  
            new_frontier.push(neib)
```

Indirect memory
access due to
neighbor locations



	neighbors				
	0	1	2	3	4
0	0	1	0	1	0
1	0	0	1	0	0
2	0	0	0	0	1
3	0	0	1	0	1
4	1	0	0	0	0

Stores IDs of
nodes to process

frontier

0	1	2	3	4
0	1			

Stores node
property data

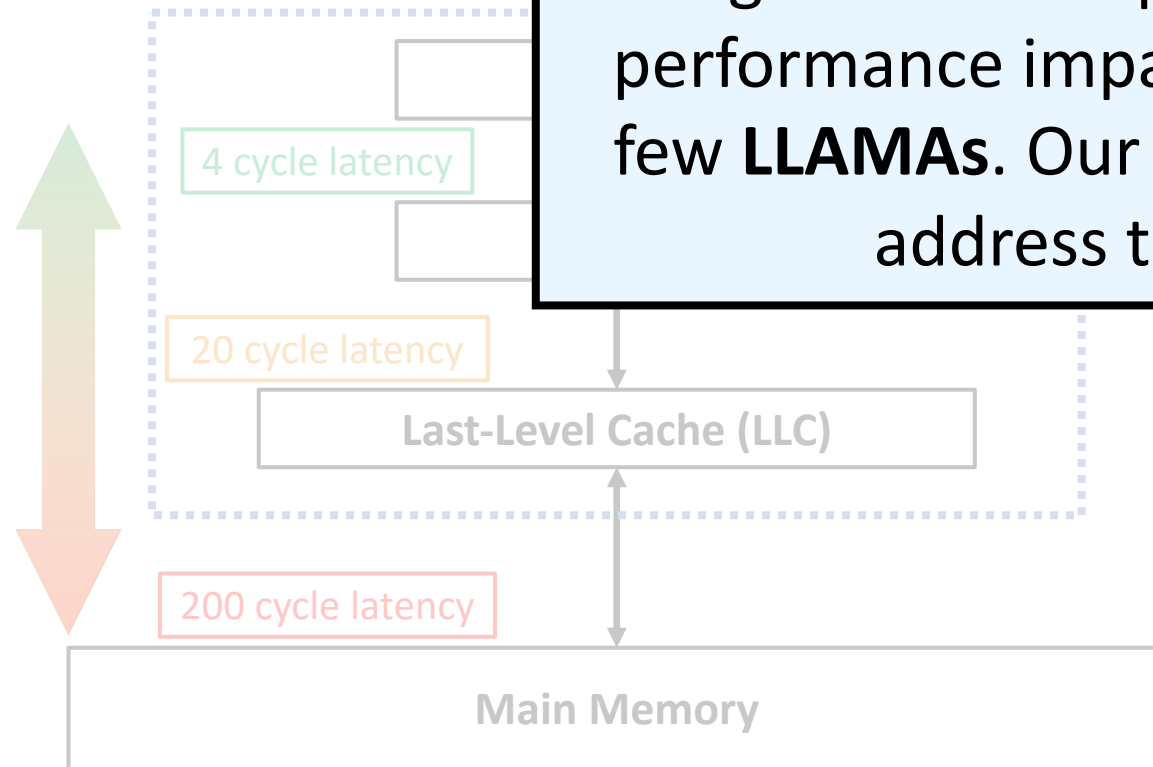
node_vals
(hops from 0)

0	1	2	3	4

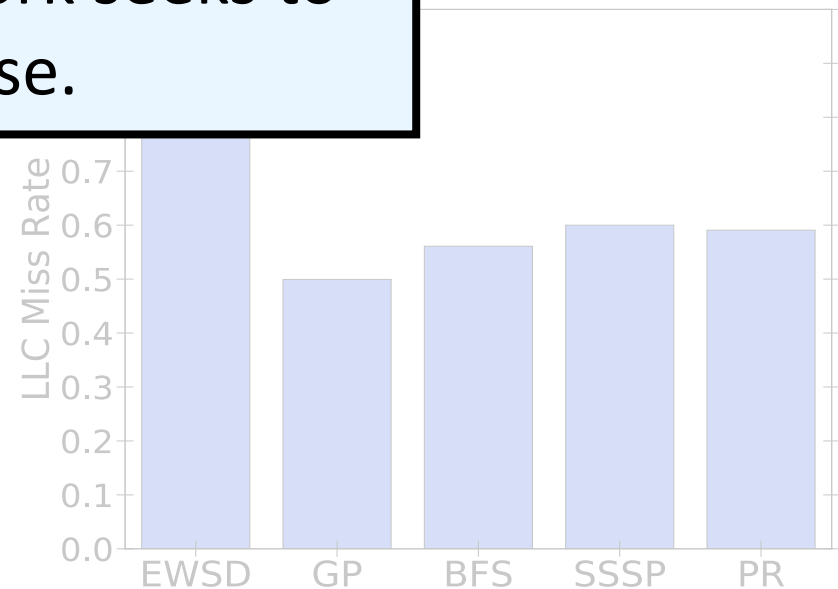
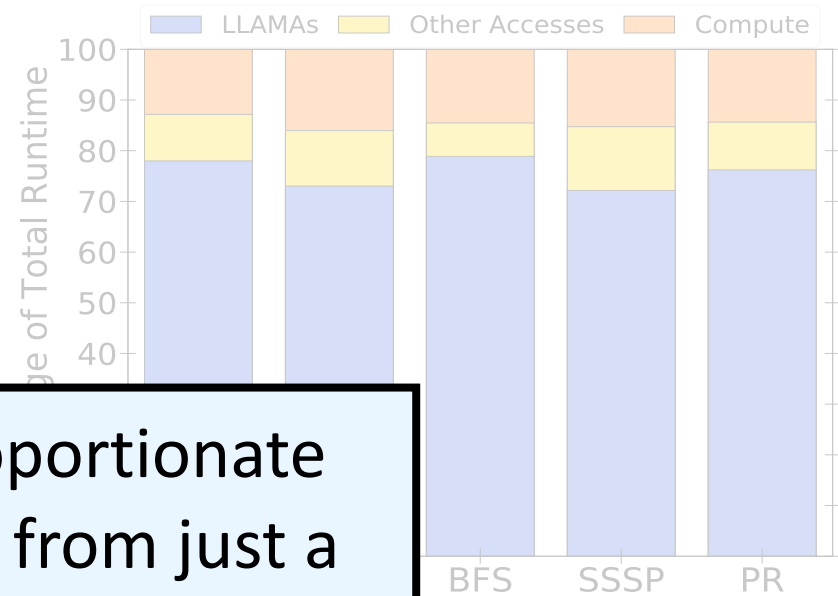
Updates are irregular!

LLAMAs: The Problem

- Irregular accesses experience cache misses
- **Long-Latency Memory Accesses (LLAMAs)**: irregular memory accesses



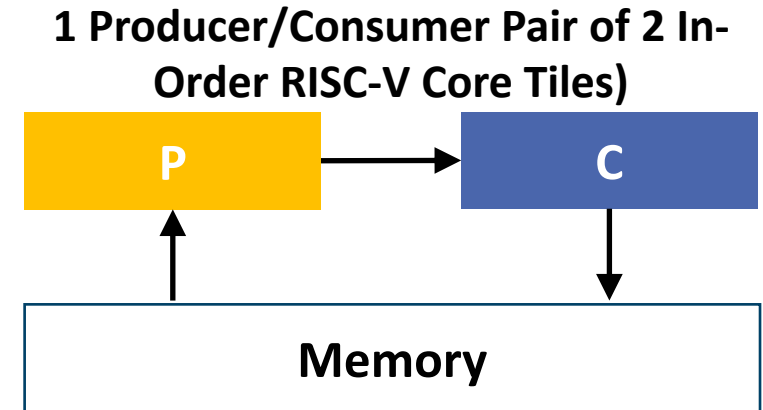
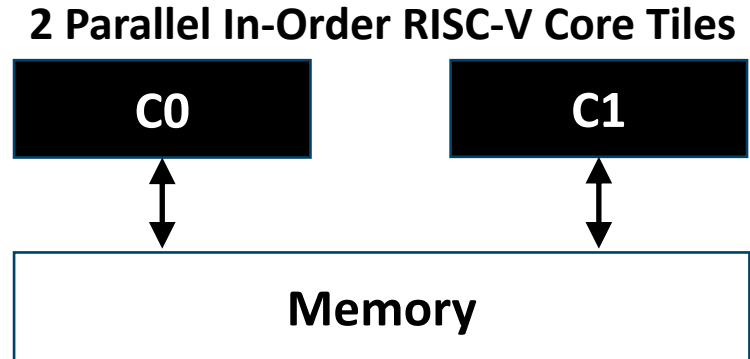
Programs see disproportionate performance impact from just a few **LLAMAs**. Our work seeks to address these.



Our Approach: FAST-LLAMAs

FAST-LLAMAs: Full-stack Approach and Specialization Techniques for *Hiding* Long-Latency Memory Accesses

- A **data supply** approach to provide performance improvements in graph/sparse applications through latency tolerance
 - **Programming model** to enable efficient producer/consumer mappings by explicitly directing LLAMA dependencies
 - **Specialized hardware support** for asynchronous memory operations
- Achieves up to an **8.66x** speedup on the DECADES architecture



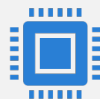
Outline



Introduction



Decoupling Overview



FAST-LLAMAs



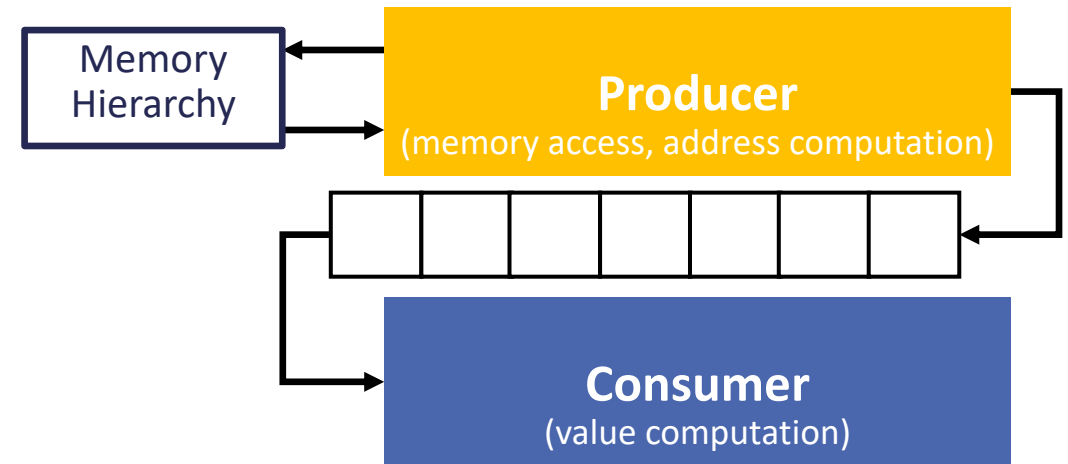
Results



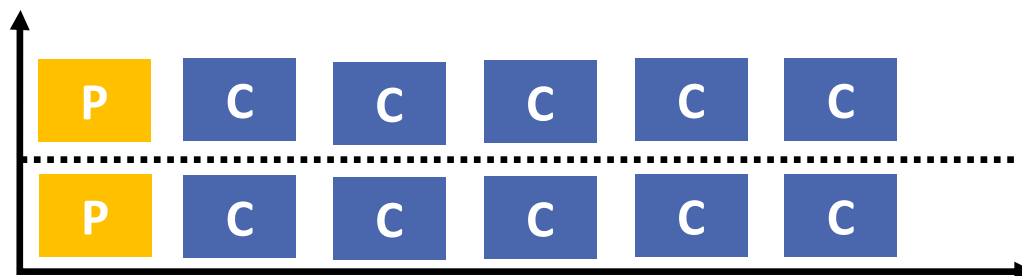
Conclusions

Decoupling for Latency Tolerance

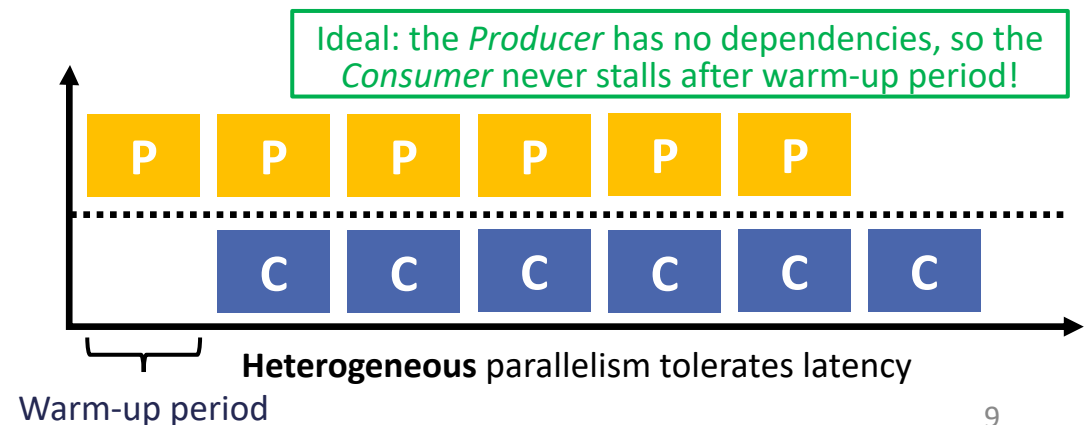
- **Decoupling:** static division of a program into [data] *Producer/Consumer* pair
 - Cores run independently; heterogeneous parallelism
- Ideally, the *Producer* runs ahead of the *Consumer*
 - Issues memory requests early and enqueues data
- The *Consumer* consumes enqueued data and handles complex value computation
 - Data has already been retrieved by the *Producer*



The *Producer* runs ahead and retrieves data for the *Consumer*



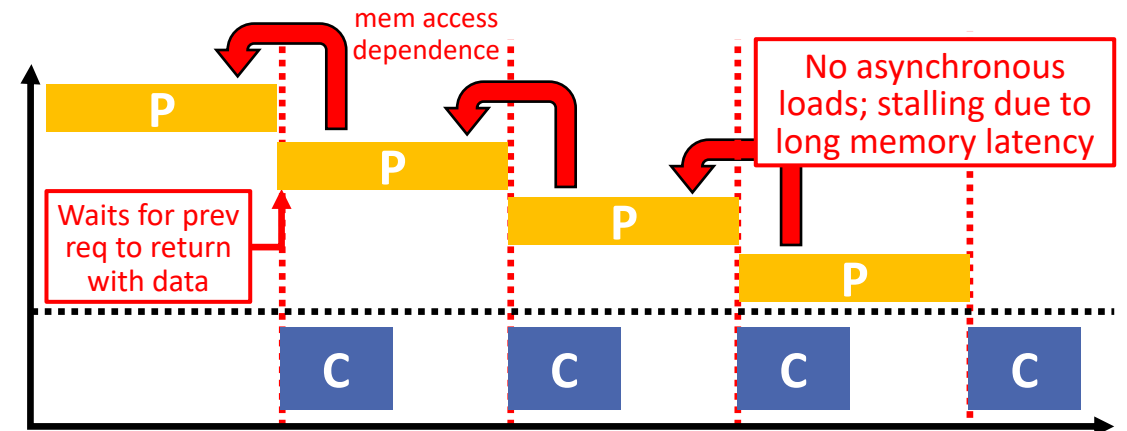
Homogeneous parallelism accelerates computation



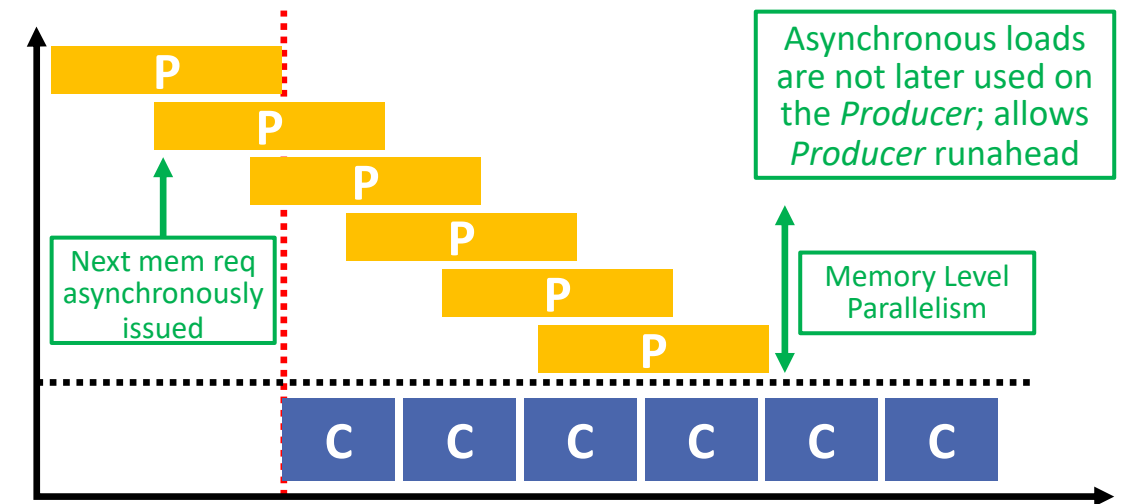
Heterogeneous parallelism tolerates latency

Decoupling for Asynchronous Accesses

- Decoupling into two instruction streams removes dependencies on each slice
 - The *Producer* might have to stall waiting for long-latency loads, but doesn't use data
 - Usually, only the *Consumer* needs the data
- Asynchronous accesses:** accesses whose data is not later used on the *Producer*
 - The *Producer* does not occupy pipeline resources waiting for their requests
 - These loads **asynchronously** complete early and are maintained in a **specialized buffer**
 - Asynchronous loads help maintain longer *Producer* runahead and exploit MLP



The *Producer* issues several **non-asynchronous** loads



The *Producer* issues several **asynchronous** loads

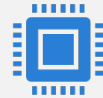
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FAST-LLAMAs

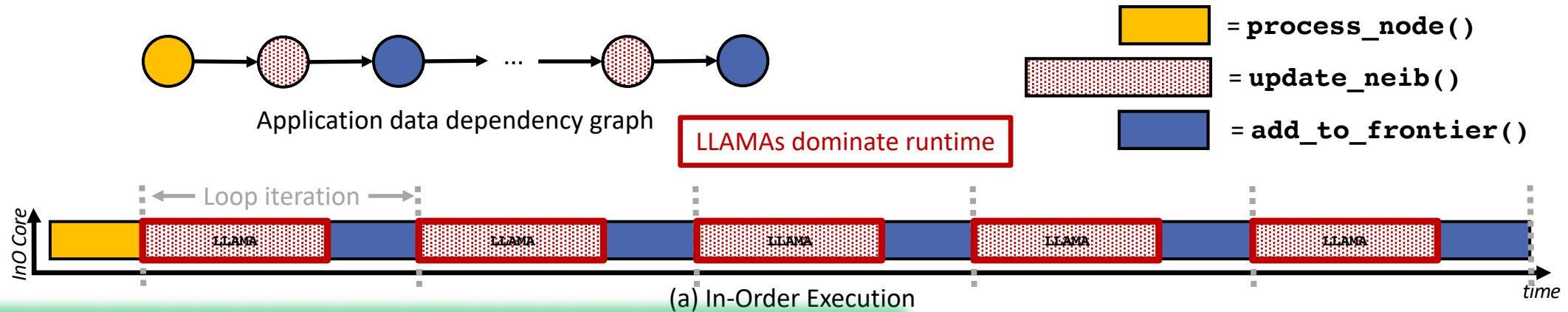


Results



Conclusions

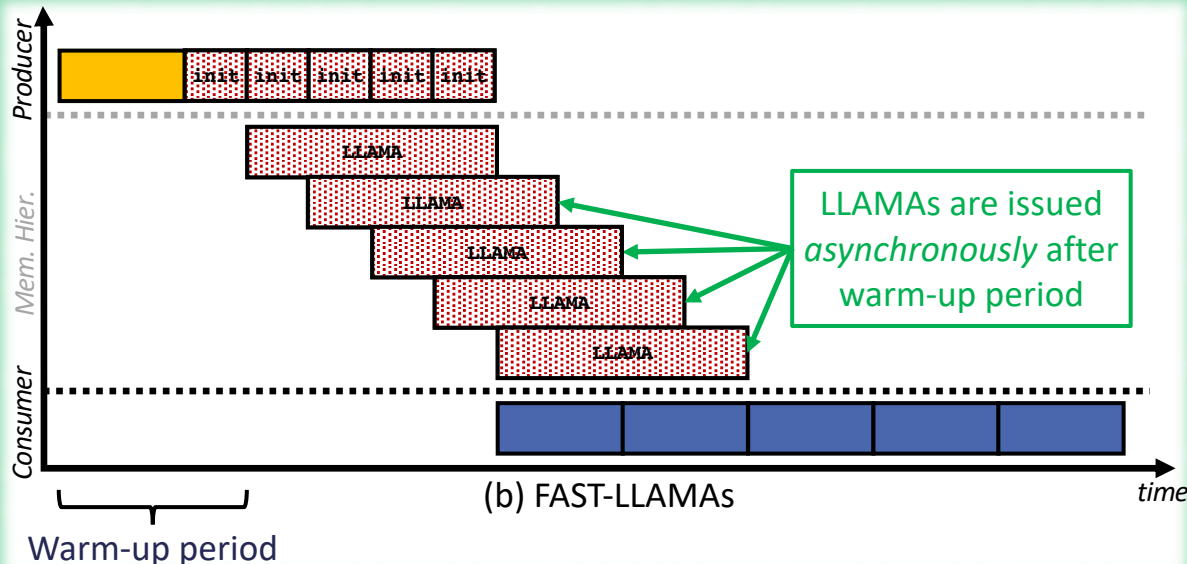
FAST-LLAMAs Tolerates Latency in Graph Applications by Making LLAMAs Asynchronous



FAST-LLAMAs eliminates LLAMA dependencies, so decoupling achieves latency tolerance on graph applications!

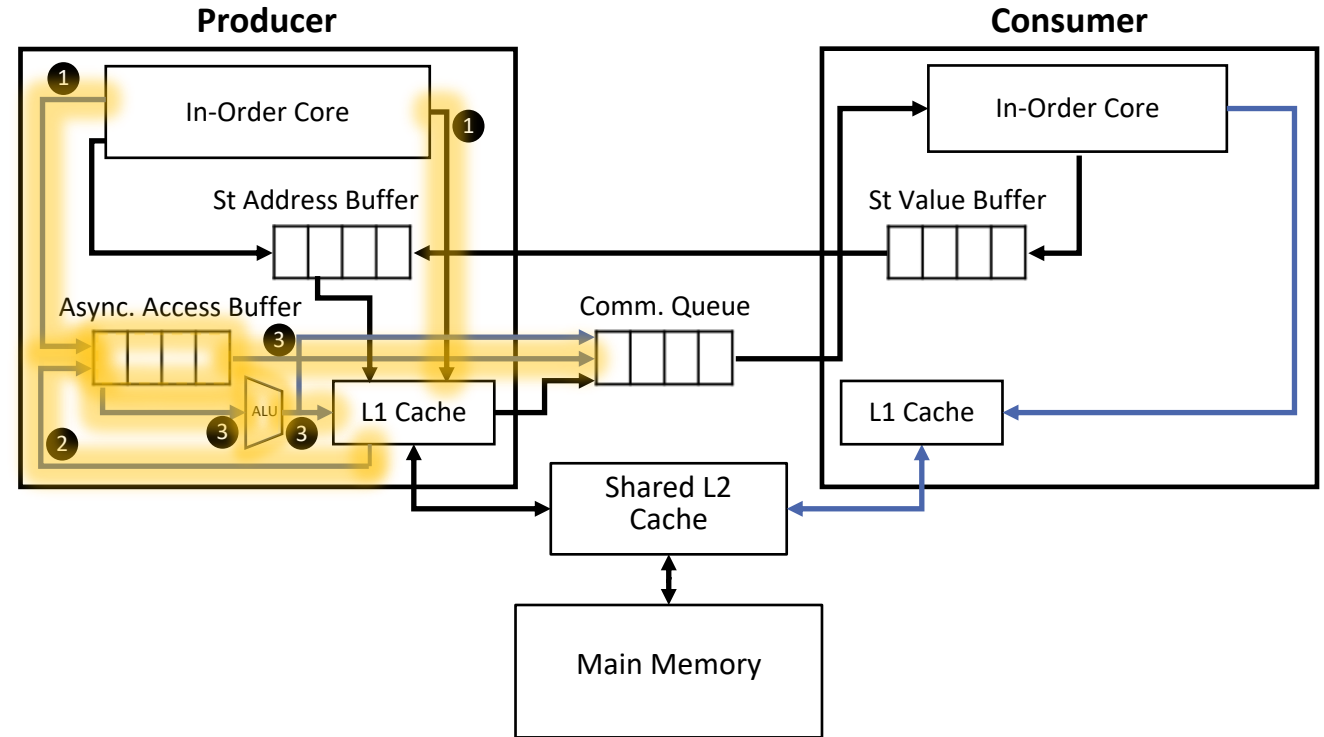
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    for neib in G.neighbors(node):
        update = update_neib(node_vals,
                               val, neib)
        if (add_to_frontier(update)):
            new_frontier.push(neib)
```

Iterative, frontier-based graph application template



FAST-LLAMAs Hardware Support

- Asynchronous access buffer holds data for **asynchronous accesses**
 - FIFO queue as simple hardware addition compatible with modern processors
 - E.g. in-order RISC-V core tiles
- **Asynchronous memory access** specialized hardware support
 - Memory request tracked in buffer
 - Returned data enqueued for *Consumer*
 - Modified (via ALU) data written to memory



Blue arrows indicate datapath additions for asynchronous accesses.
The numbers illustrate the order in which data proceeds through the system.

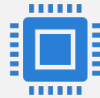
Outline



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FAST-LLAMAs



Results

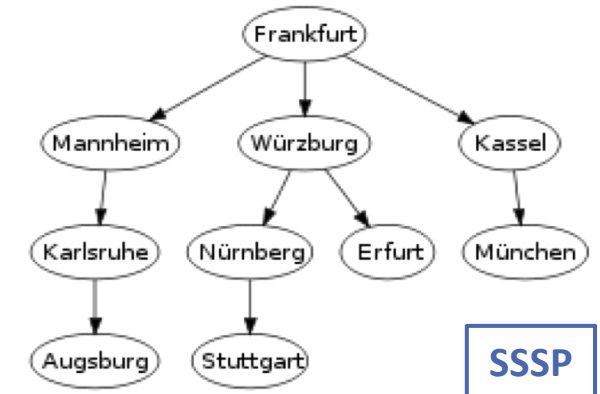


Conclusions

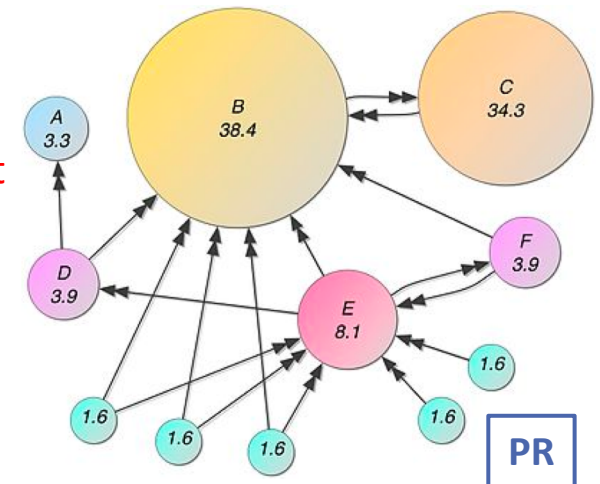
Graph/Sparse Applications

- **Elementwise Sparse-Dense (EWSD)**: Multiplication between a sparse and a dense matrix.
- **Bipartite Graph Projections (GP)**: Relate nodes in one partition based on common neighbors in the other.
- **Vertex-programmable (VP) graph processing primitives**:
 - **Breadth-First Search (BFS)**: Determine the distance (number of node hops) to all nodes.
 - **Single-Source Shortest Paths (SSSP)**: Determine the shortest distance (sum of path edge weights) to all nodes.
 - **PageRank (PR)**: Determine node ranks based on the distributed ranks of neighbors.

Can be efficiently sliced automatically



Currently require explicit annotations for efficient slicing



Images from Wikipedia

FAST-LLAMAs Tolerates Latency for Graph Applications

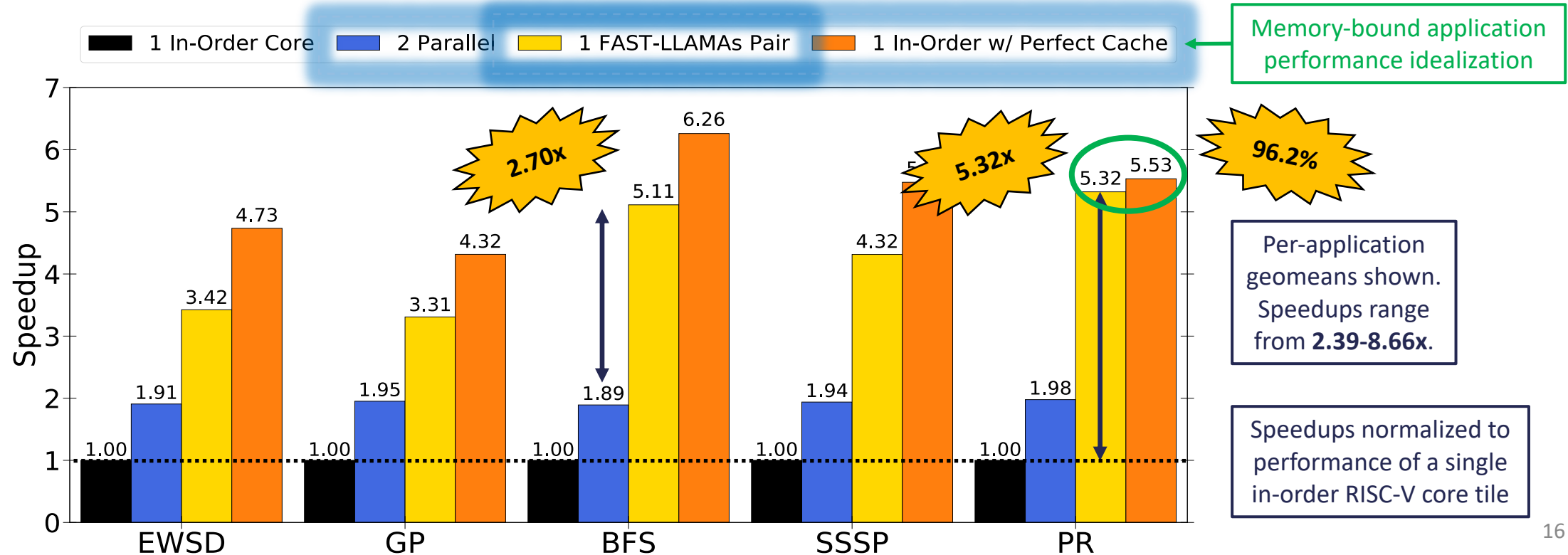


2 Parallel In-Order RISC-V Core Tiles

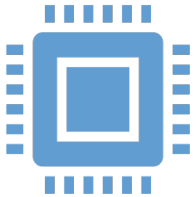
vs.



1 FAST-LLAMAs Pair of In-Order RISC-V Core Tiles



Conclusions



Overview

FAST-LLAMAs: hardware-software co-design for efficient graph application computations

- Applications are sliced and mapped onto producer/consumer pairs
- Achieves up to **8.66x** speedup over single in-order core



The DECADES Team

People: Margaret Martonosi, David Wentzlaff, Luca Carloni, Juan L. Aragón, Jonathan Balkind, Ting-Jung Chang, Fei Gao, Davide Giri, Paul J. Jackson, Aninda Manocha, Opeoluwa Matthews, Tyler Sorensen, Esin Türeci, Georgios Tziantzioulis, and Marcelo Orenes Vera

Website: <https://decades.cs.princeton.edu/>

Presenter: Aninda Manocha

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- <https://cs.princeton.edu/~amanocha>



Open-Source Tools

Applications:

<https://github.com/amanocha/FAST-LLAMAs>

Compiler:

<https://github.com/PrincetonUniversity/DecadesCompiler>

Simulator:

<https://github.com/PrincetonUniversity/MosaicSim>

DECADES RTL: *Coming soon!*