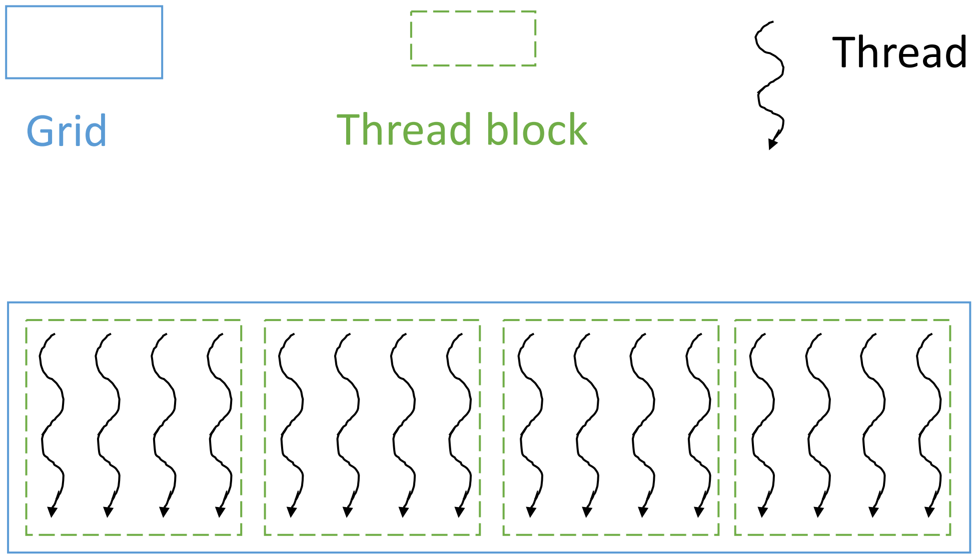
A Compiler Framework for Optimizing Dynamic Parallelism on GPUs

Mhd Ghaith Olabi[1], Juan Gómez Luna[2], Onur Mutlu[2], Wen-mei Hwu[3,4], Izzat El Hajj[1]

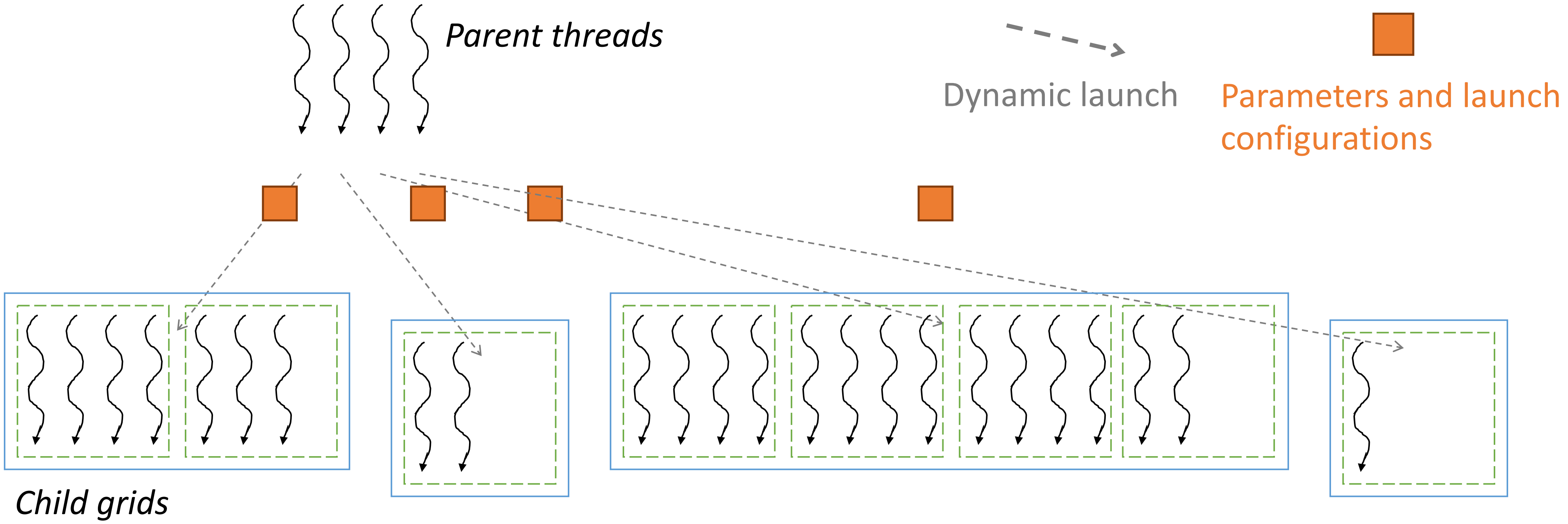
[1]American University of Beirut [2]ETH Zurich [3]NVIDIA [4]University of Illinois at Urbana-Champaign

Organization of GPU Kernels



Dynamic Parallelism on GPUs

- **Dynamic parallelism** enables executing GPU threads to launch other grids of threads



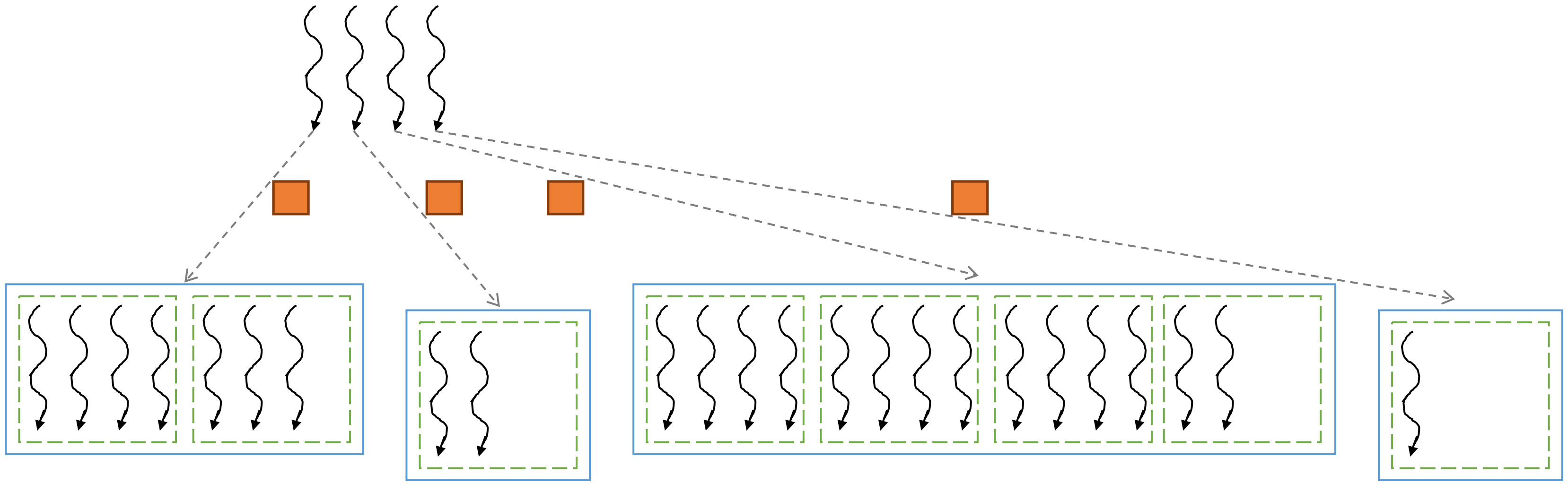
- Useful for implementing computations with **nested parallelism**

Dynamic Parallelism Overhead

- Using dynamic parallelism may cause many small grids to be launched
- Launching many small grids causes **performance degradation** due to:
  - **Congestion**
    - Limited number of grids can execute simultaneously (others need to wait)
  - **Hardware underutilization**
    - If grids are small, their may not be enough threads launched to fully utilize hardware resources
- Solution: launch **fewer grids** of **larger sizes**

Prior Work: Aggregation

- Aggregation is an optimization where:
  - Multiple child grids are consolidated into a single aggregated grid
  - One parent thread launches the aggregated grid on behalf of the rest



- I. El Hajj, J. Gomez-Luna, C. Li, L.-W. Chang, D. Milojicic, and W.-m. ´ Hwu, “KLAP: Kernel launch aggregation and promotion for optimizing dynamic parallelism,” in Microarchitecture (MICRO), 2016 49th Annual IEEE/ACM International Symposium on. IEEE, 2016, pp. 1–12
- D. Li, H. Wu, and M. Becchi, “Exploiting dynamic parallelism to efficiently support irregular nested loops on GPUs,” in Proceedings of the 2015 International Workshop on Code Optimisation for Multi and Many Cores. ACM, 2015, p. 5.
- Li, D., Wu, H., & Becchi, M., “Nested parallelism on GPU: Exploring parallelization templates for irregular loops and recursive computations,” in Parallel Processing (ICPP), 2015 44th International Conference on. IEEE, 2015, pp. 979– 988.
- H. Wu, D. Li, and M. Becchi, “Compiler-assisted workload consolidation for efficient dynamic parallelism on GPU,” arXiv preprint arXiv:1606.08150, 2016.

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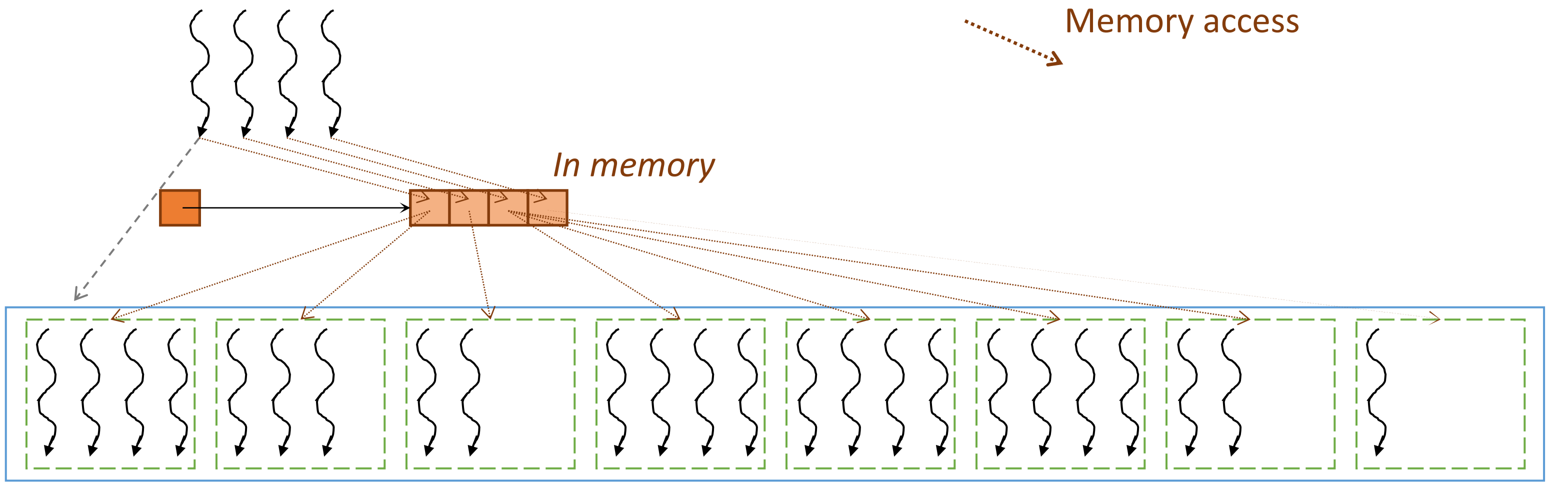


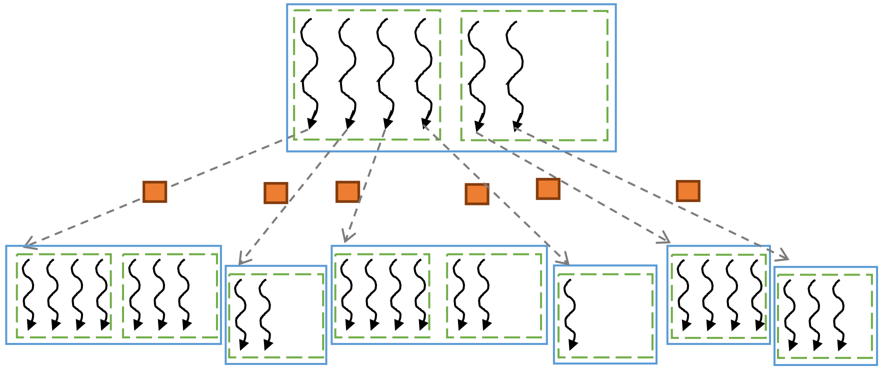
Aggregated child grid

+ Reduces congestion by reducing the number of launched grids

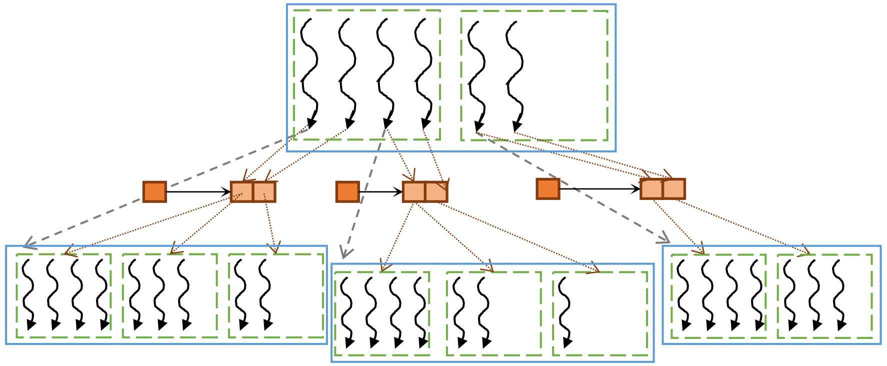
+ Improves utilization because aggregated child grids have more threads then original ones

Prior Work: Aggregation

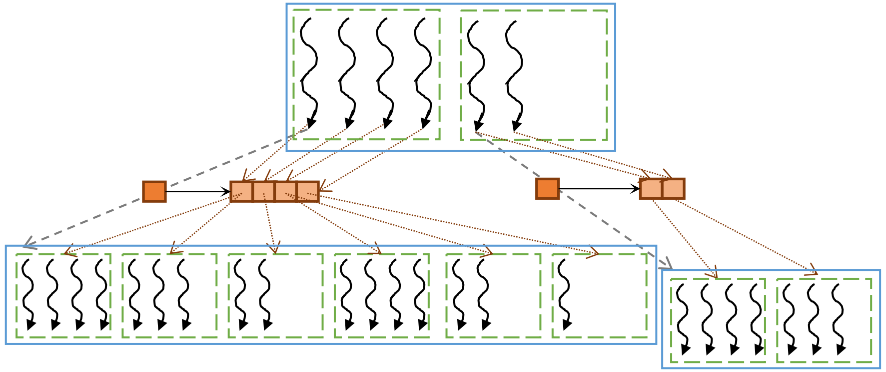
- Aggregates launches at different levels of granularity



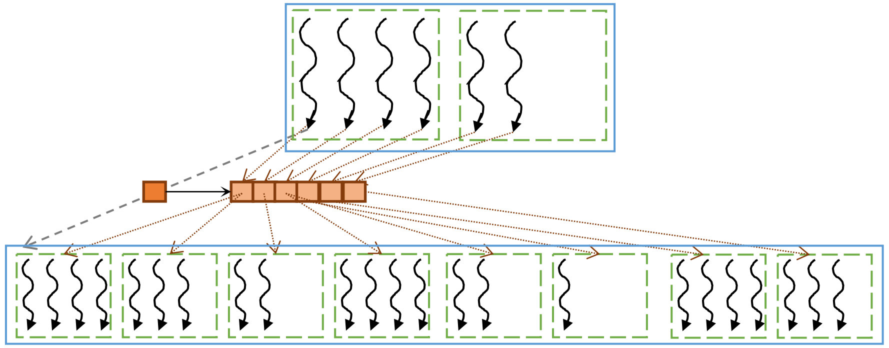
Original Kernel



Warp-Granularity



Block-Granularity



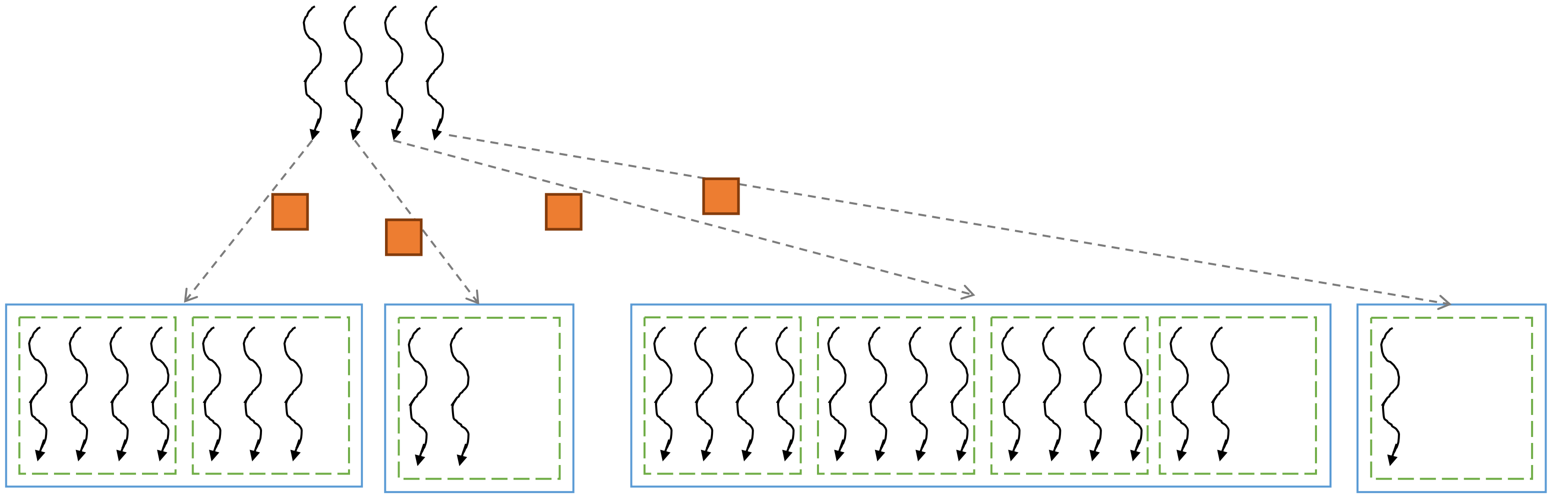
Grid-Granularity

Contributions

- **Thresholding** (as a compiler optimization)
  - Prior work relies on programmers to apply it manually
- **Coarsening** of child thread blocks
  - Prior work on compiler-based coarsening not specialized for dynamic parallelism
- **Aggregation** of child grids at multi-block granularity
  - Prior work only compiler-based aggregation only considers warp, block, and grid granularity
- One **compiler framework** that combined the three optimizations

Thresholding

- Thresholding is an optimization where:
  - A grid is launched dynamically only if the number of child threads exceeds a certain threshold
  - Otherwise, work is executed sequentially by the parent thread



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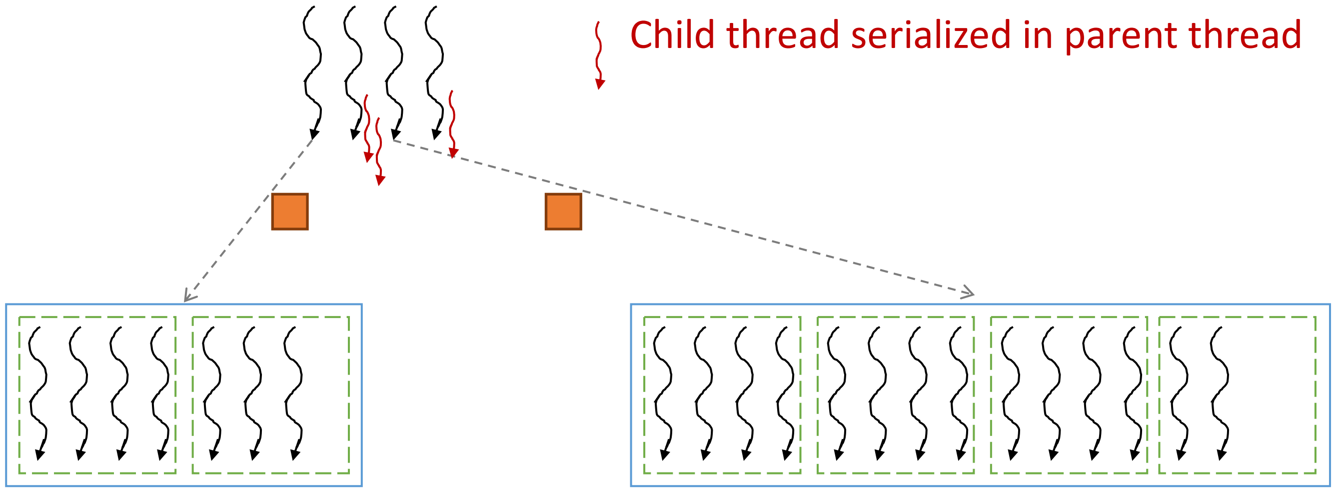


+ Reduces congestion by reducing the number of launched grids

+ Improves utilization by only allowing grids with many threads to be launched

Thresholding: Code Transformation

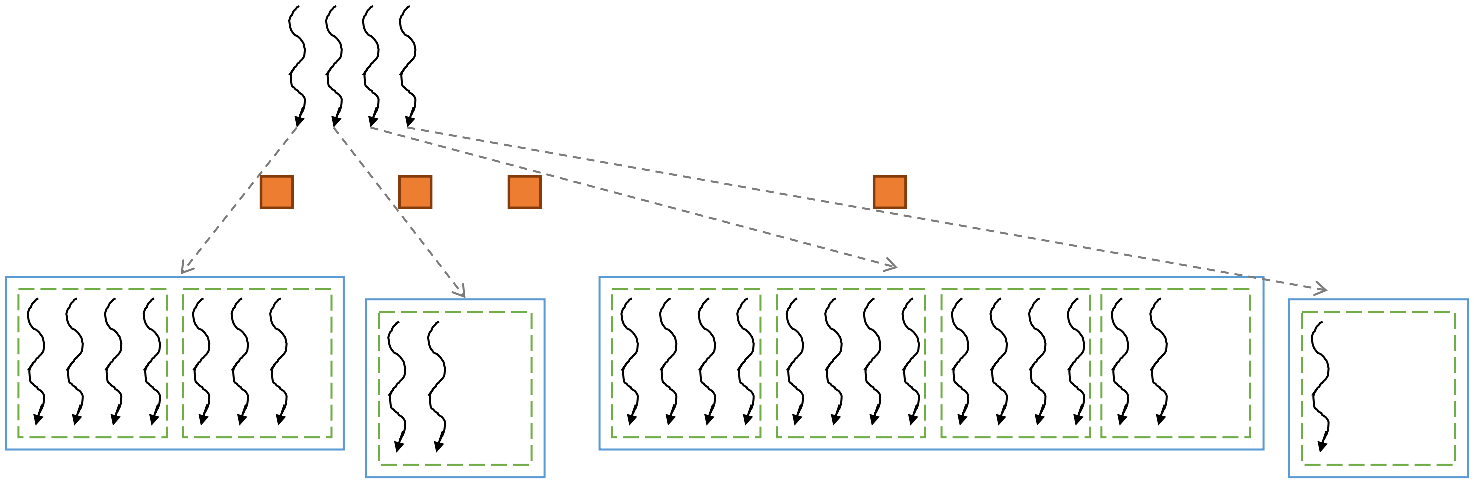
```
__global__ child(...) {
    child body
}

__global__ parent(...) {
    ...
    child <<< gDim, bDim >>> (...);
    ...
}
```

```
__device__ child_serial(..., dim3 _gDim, dim3 _bDim) {
    for(_bx = 0; _bx < _gDim.x; ++_bx) {
        for(_tx = 0; _tx < _bDim.x; ++_tx) {
            child body // Replace uses of blockIdx.x with _bx,
        }          // threadIdx.x with _tx, gridDim with
    }              // _gDim, and blockDim with _bDim
}
__global__ parent(...) {
    ...
    _threads = ...; // Extracted from gDim expression
    if(_threads >= _THRESHOLD) {
        child <<< gDim, bDim >>> (...);
    } else {
        child_serial (..., gDim, bDim);
    }
    ...
}
```

- Create a serial device function executable by the parent
- Heuristic to detect total number of threads to be compared with threshold
  - Detect number of threads to be launched by observing commonly used grid dimension calculation expressions, such as ceiling divisions
- Apply a conditional guard to either launch or serialize

Coarsening

- Coarsening is a transformation where:
  - The work of multiple child blocks is assigned to a single child block



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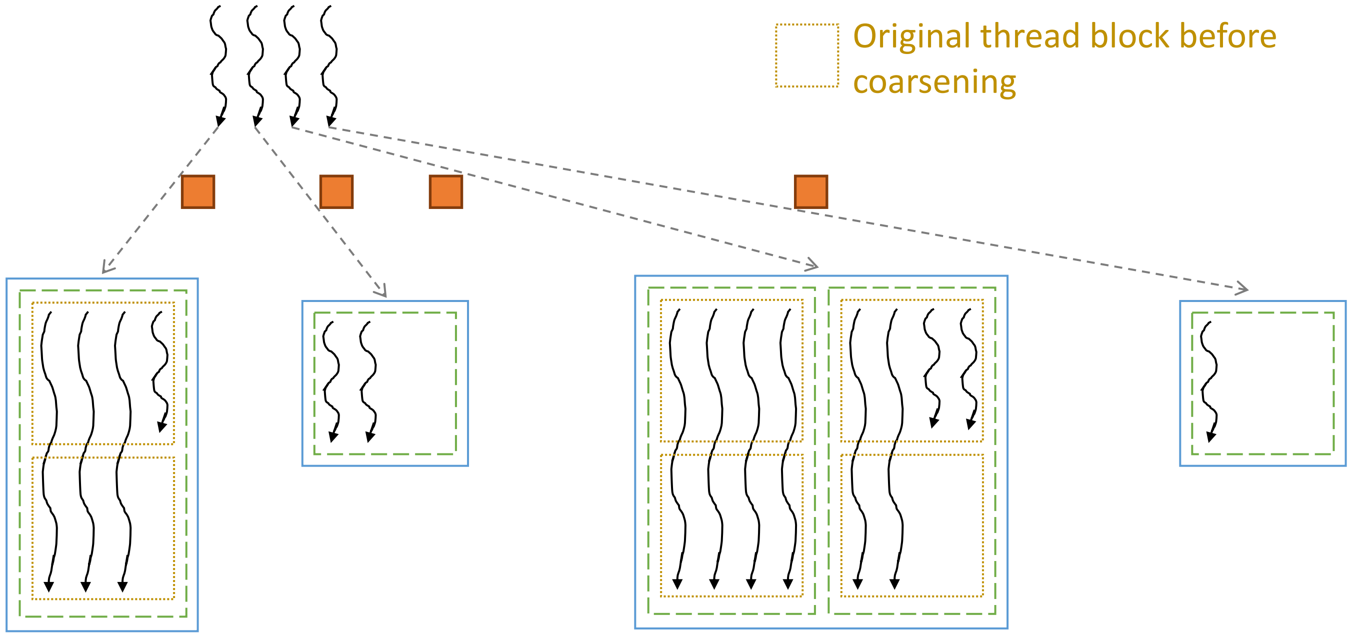


Coarsened child grids

+ When applied before aggregation, amortizes the cost of disaggregation (incurred once per child blocks)

Coarsening: Code Transformation

```
__global__ child(...) {
    child body
}

__global__ parent(...) {
    ...
    child <<< gDim, bDim >>> (...);
    ...
}
```

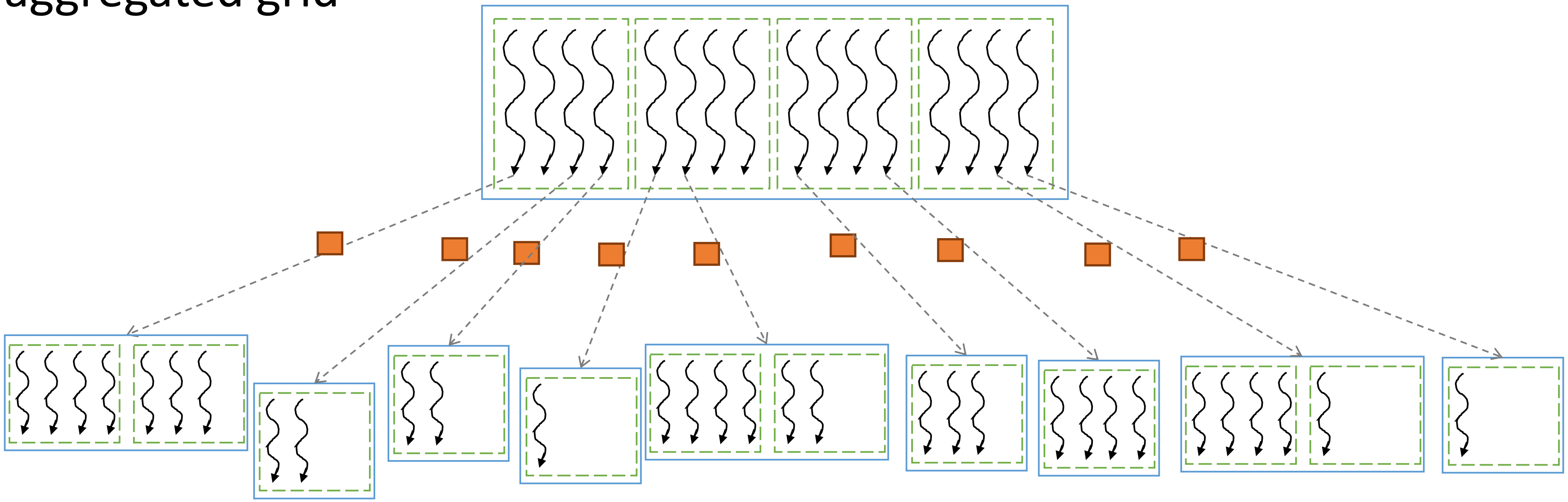
```
__global__ child(params, _gDim) {
   for(_bx = blockIdx.x; _bx < _gDim.x; _bx += gridDim.x) {
      child body  // Replace uses of blockIdx.x with _bx
   }              // and gridDim with _gDim
}

__global__ parent(...) {
    ...
    _cgDim = _gDim = gDim ;
    _cgDim.x = (_gDim.x + _CFACTOR – 1)/_CFACTOR;
    child <<< _cgDim, bDim >>>(args, _gDim);
    ...
}
```

- Coarsening child kernel
  - Insert the coarsening loop around the child kernel body
- Modify kernel parameters
  - Add an extra parameter _gDim (being the original grid dimension) to be passed to the coarsened child kernel
- Modify launch parameters
  - Update grid dimension considering _CFACTOR

Multi-block Granularity Aggregation

- Multi-block granularity aggregation is an optimization where:
  - The child grids of multiple parent blocks are consolidated into a single aggregated grid



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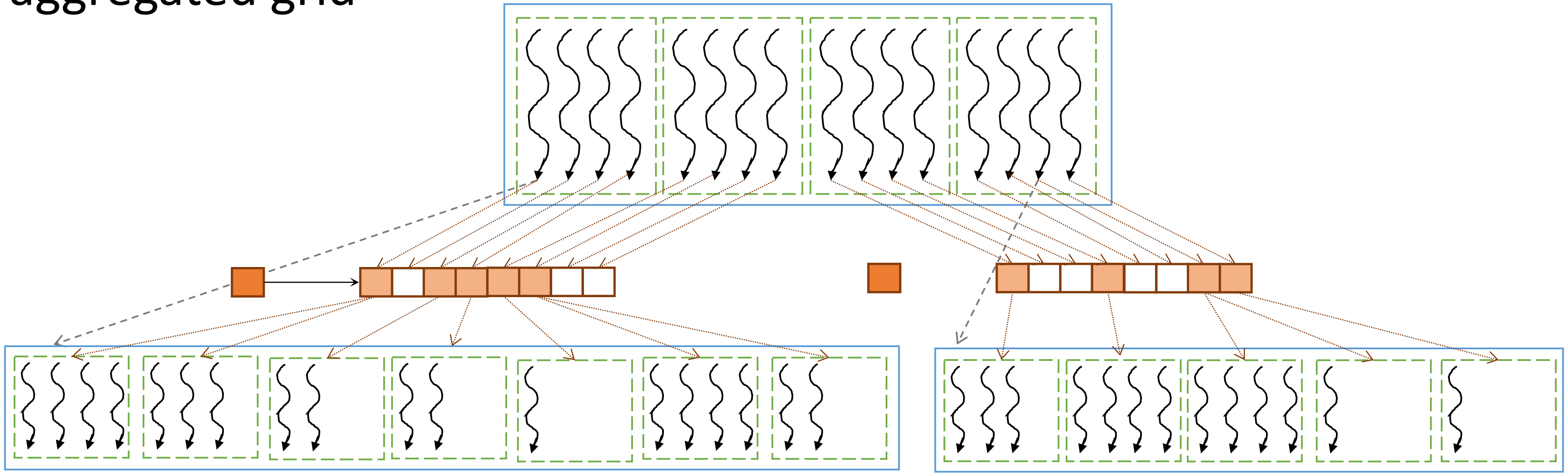


\+ Compared to block granularity, launches fewer and larger grids

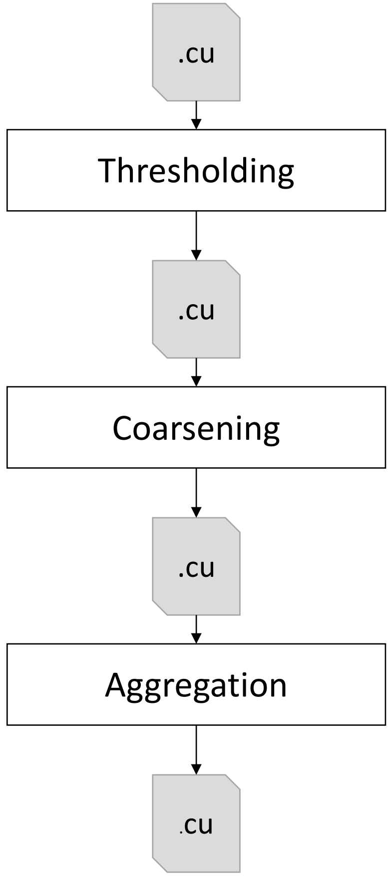
\+ Compared to grid granularity, launches child grids more eagerly

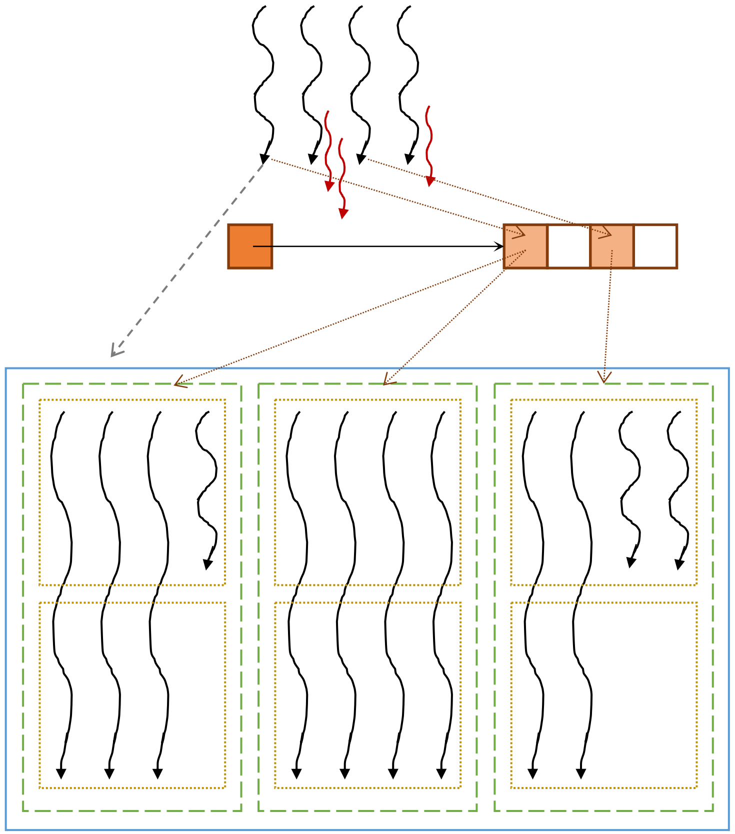
Multi-block Aggregation: Code Transformation

- See paper for detailed description of the code transformation
- Key difference from other techniques:
  - Every *k* blocks maintain a shared counter
  - Each block atomically increments shared counter when reaching launch
  - The k^{th} block to increment the counter performs the launch
  - Use thread fences to ensure that memory visibility semantics are preserved

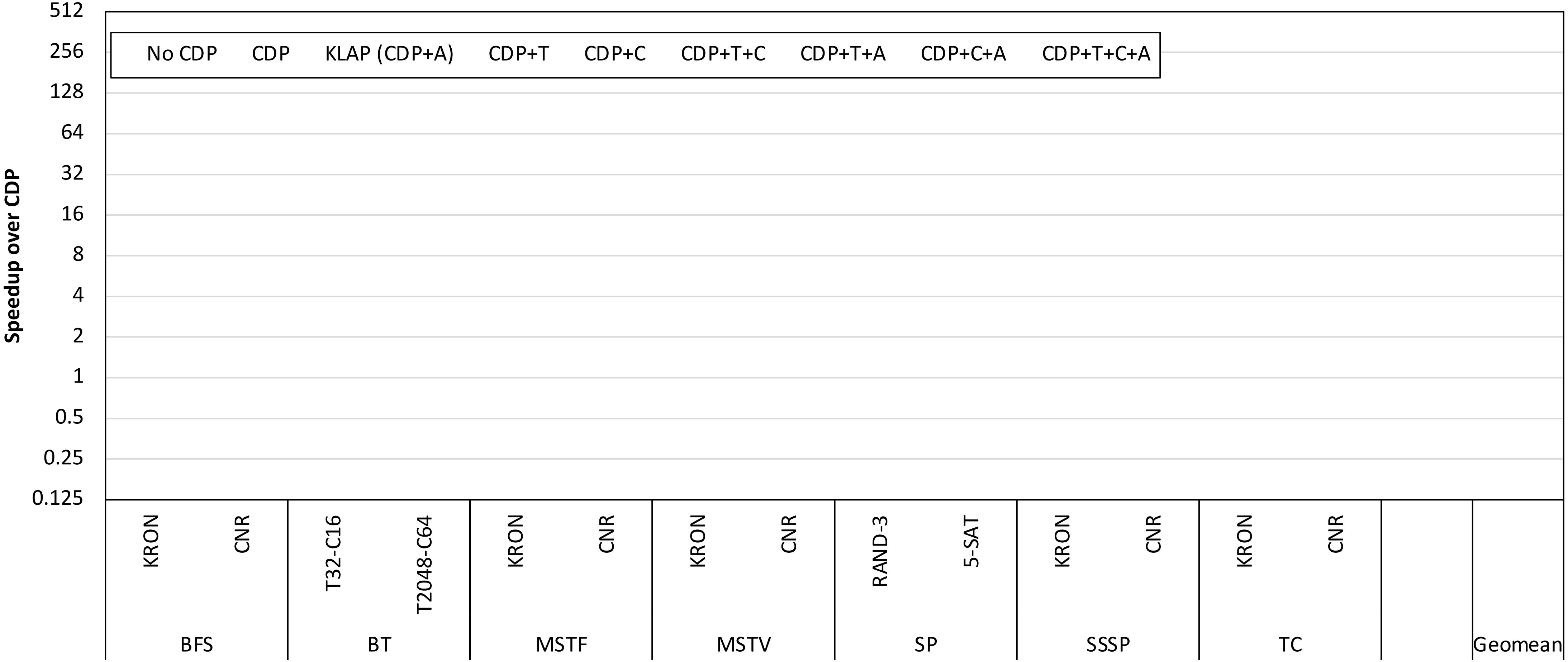
```
__global__ child(_paramsArray, _gDimScannedArray, _bDimArray) {
    _parentIdx = binary search in _gDimScannedArray
    params = _paramsArray[_parentIdx]
    _gDim = _gDimScannedArray[_parentIdx] - _gDimScannedArray[_parentIdx - 1]
    _bx = blockIdx.x - _gDimScannedArray[_parentIdx - 1]
    _bDim = _bDimArray[_parentIdx]
    if(threadIdx < _bDim) {
        child body    // Replace uses of blockIdx.x with _bx
                      // and gridDim with _gDim
    }
}
__global__ parent(...) {
    ...
    _gDim = gDim
    _bDim = bDim
    _groupIdx = blockIdx.x/_AGG_GRANULARITY
    find group's memory segments in a pre-allocated buffer based on _groupIdx
    if(_gDim > 0) {
        (_parentIdx, _sumPrevGDim) =
          atomicAdd(&(_numParents[_groupIdx], _sumGDim[_groupIdx]), (1, _gDim))
        _argsArray[_parentIdx] = args
        _gDimScannedArray[_parentIdx] = _sumPrevGDim + _gDim
        _bDimArray[_parentIdx] = _bDim
        atomicMax(&_maxBDim[_groupIdx], _bDim)
    }
    __threadfence()
    __syncthreads()
    if(threadIdx == launcher thread in block) {
        _nFinishedBlocks = atomicAdd(&_numFinishedBlocks[_groupIdx], 1) + 1
        _isLastBlockToFinish = (_nFinishedBlocks == _AGG_GRANULARITY)
        if(_isLastBlockToFinish) {
            child <<< _sumGDim[_groupIdx] , _maxBDim[_groupIdx] >>>
                  (_argsArray, _gDimScannedArray, _bDimArray);
        }
    }
    ...
}
```

Putting it all together



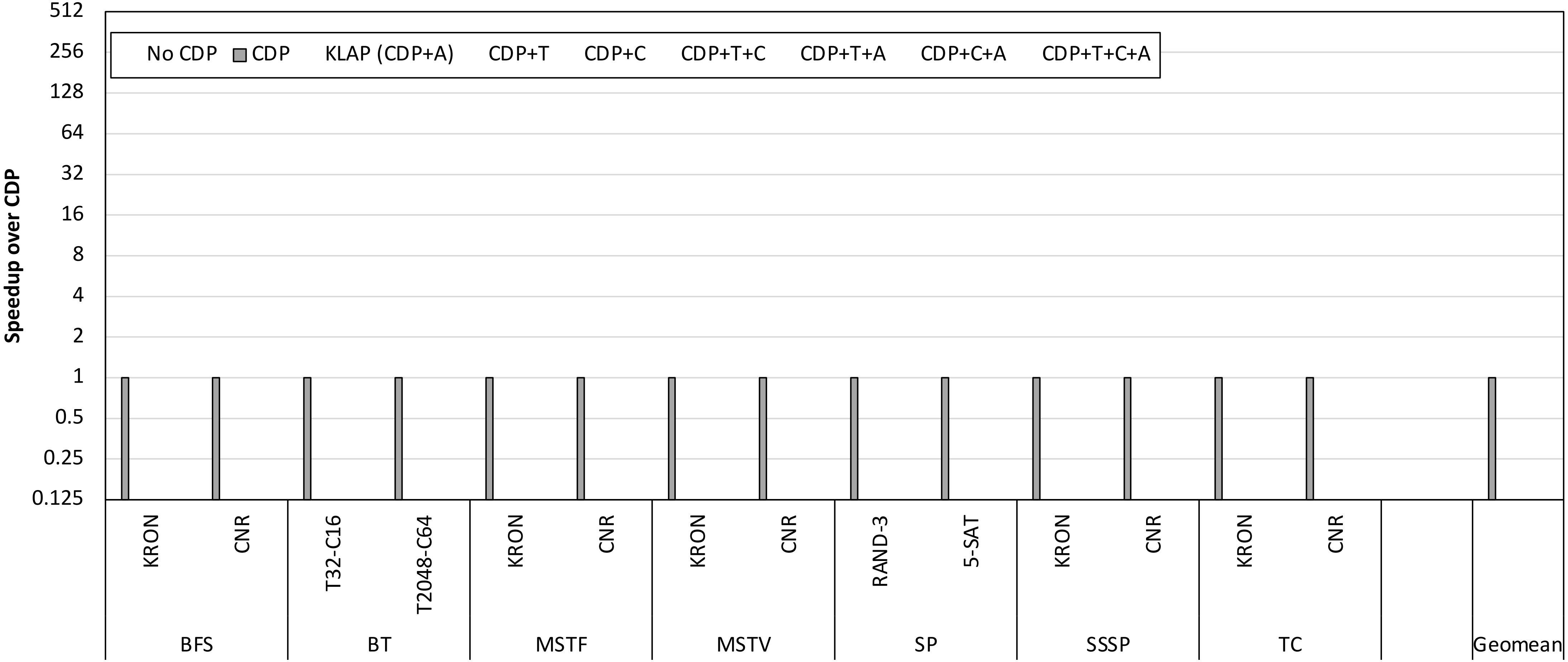


Overall Speedup



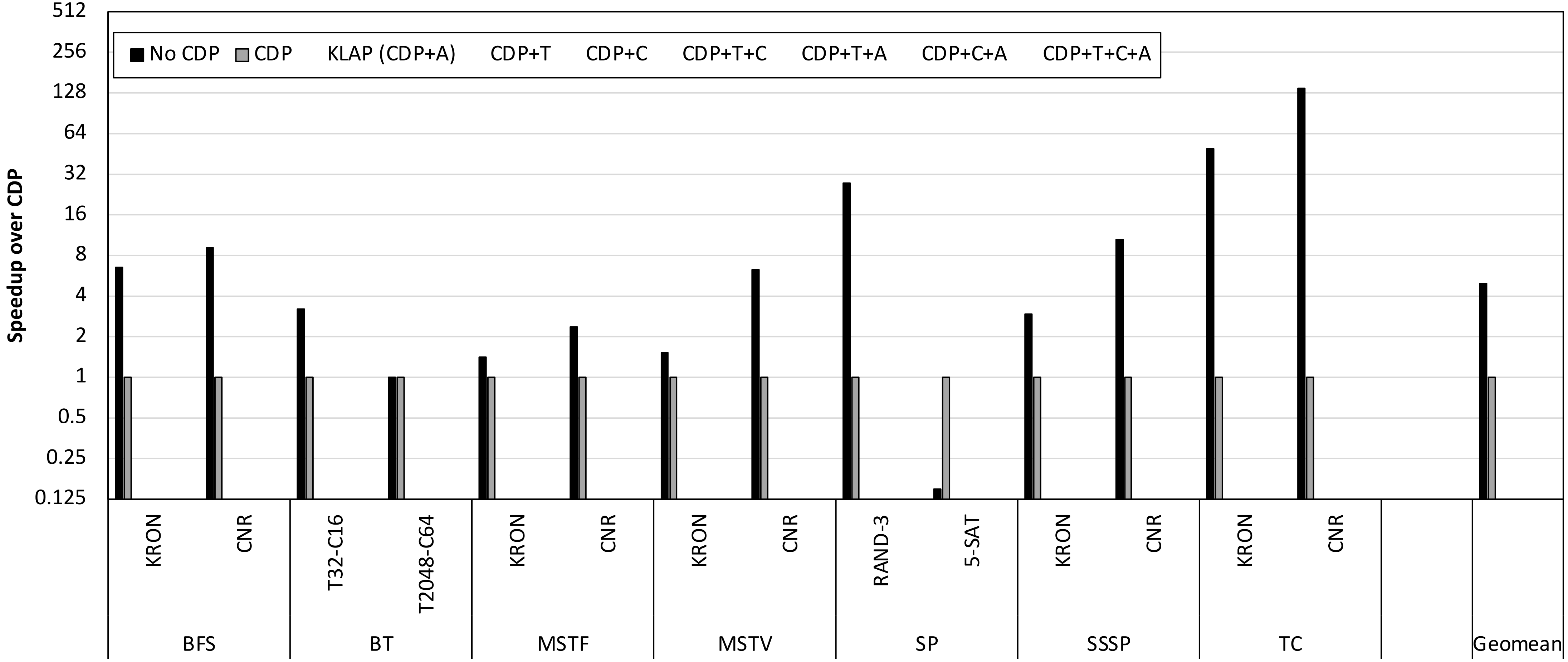
We evaluate all combinations of optimizations for 7 benchmarks with 2 datasets each

Overall Speedup



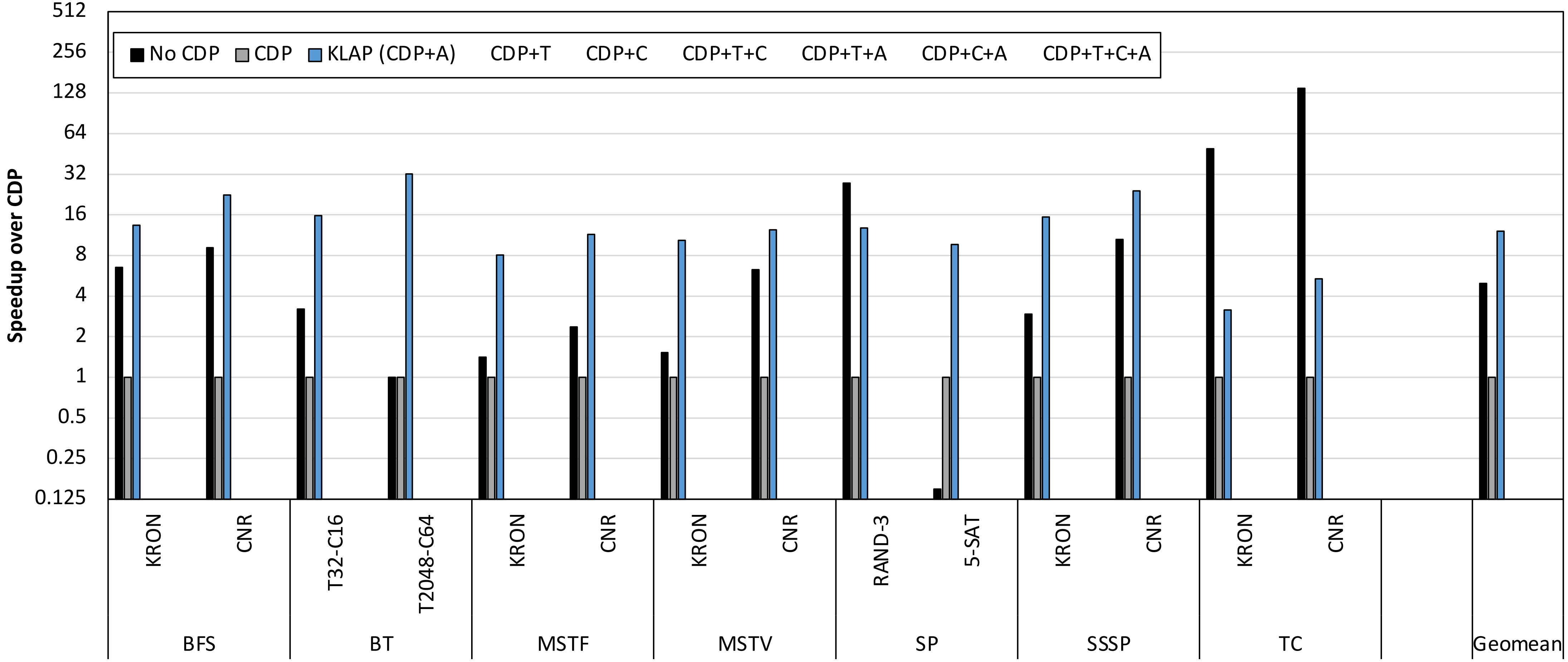
We report speedup (higher is better) over the baseline that uses **CUDA dynamic parallelism (CDP)**

Overall Speedup



<u>Observation #1:</u> Not using CDP performs better than **naïve CDP** (same observation as prior work).

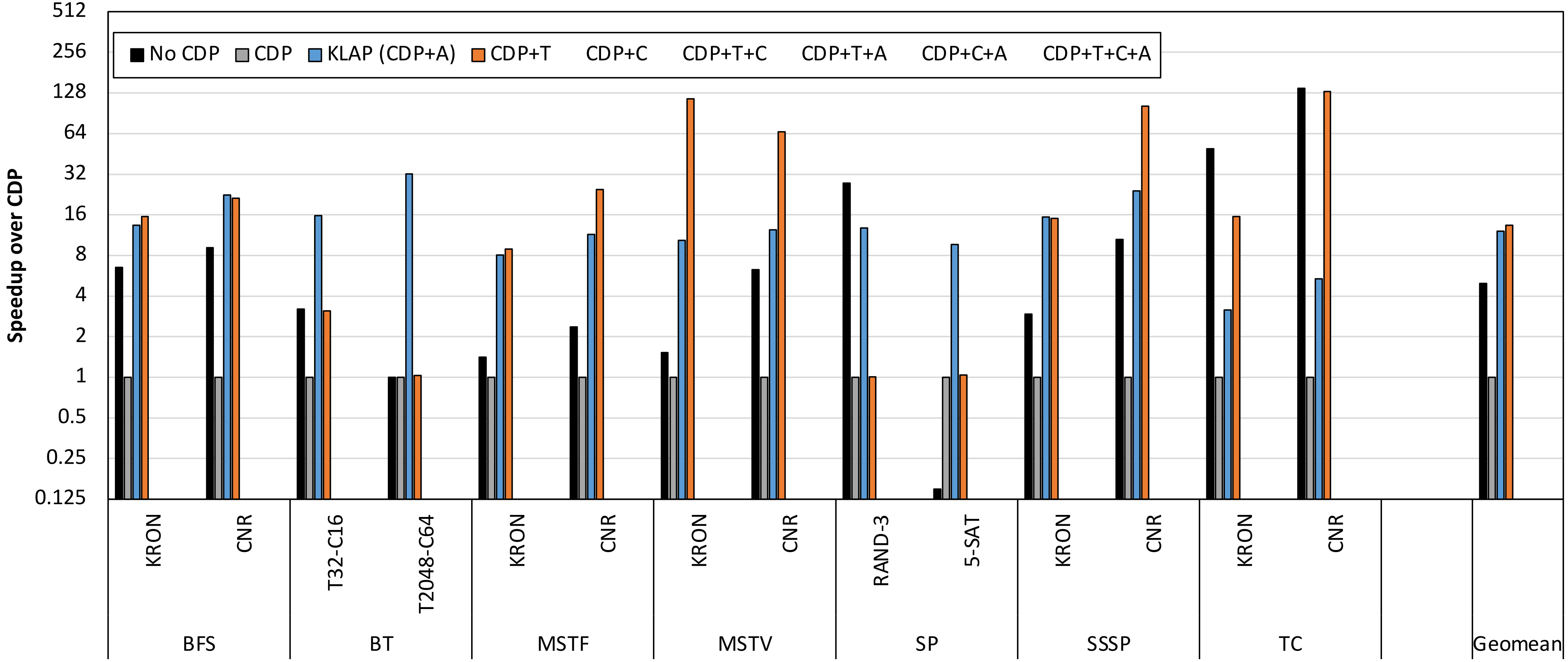
Overall Speedup



<u>Observation #2:</u> **Aggregation** improves performance of **naïve CDP** (same observation as prior work).

KLAP(CDP+A) is 12.1× faster than **CDP** on average (geomean).

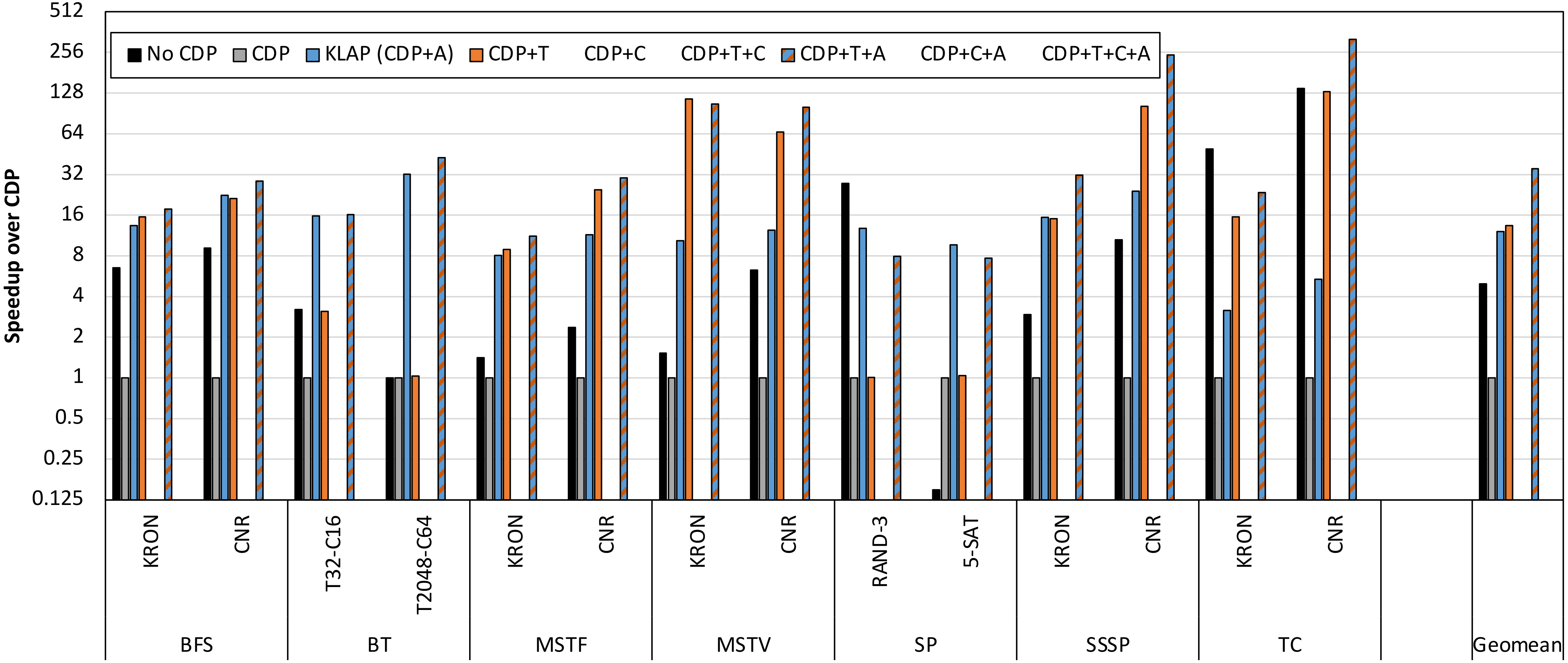
Overall Speedup



<u>Observation #3:</u> **Thresholding** alone improves the performance over **CDP**.

CDP+T is 13.4× faster than **CDP** on average (geomean).

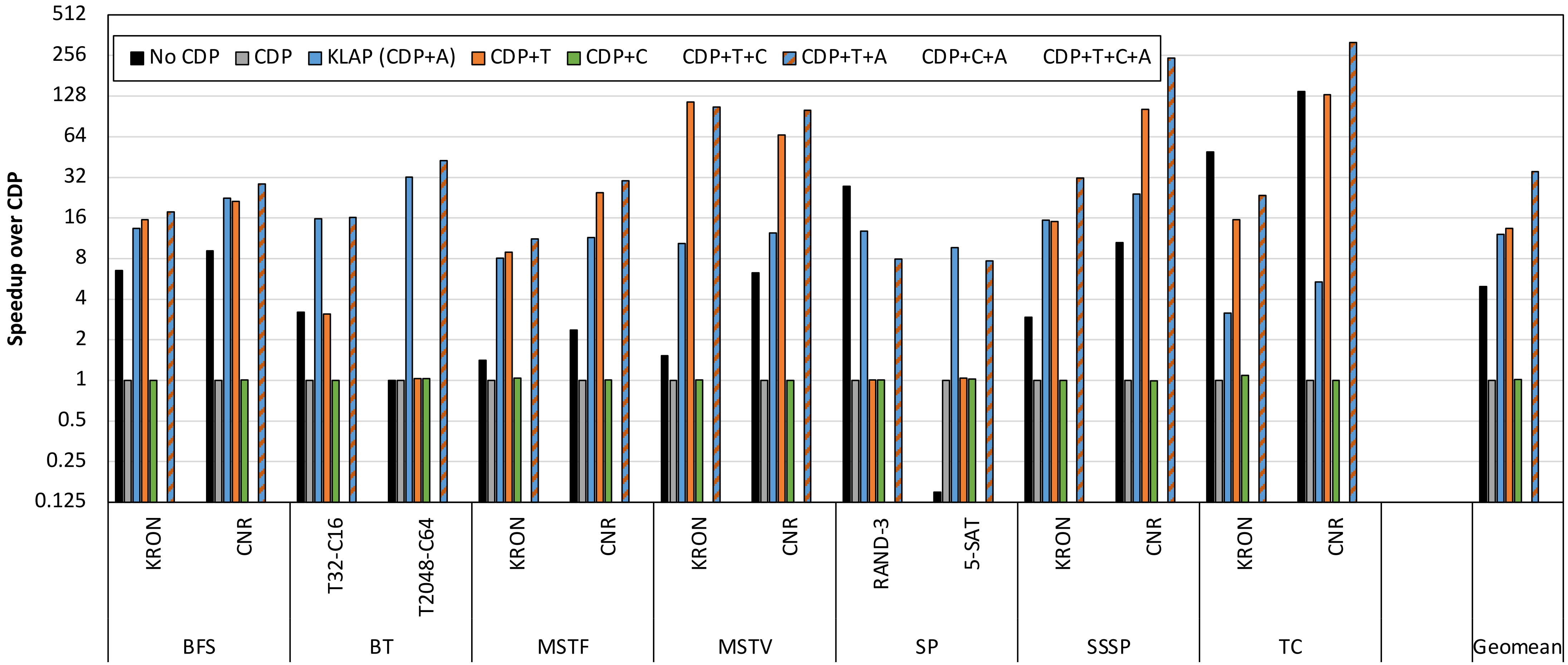
Overall Speedup



<u>**Observation #4:**</u> **Thresholding** and **Aggregation** together improve the performance over **CDP** even more.

Despite both targeting the same source of inefficiency, one optimization does not obviate the other.

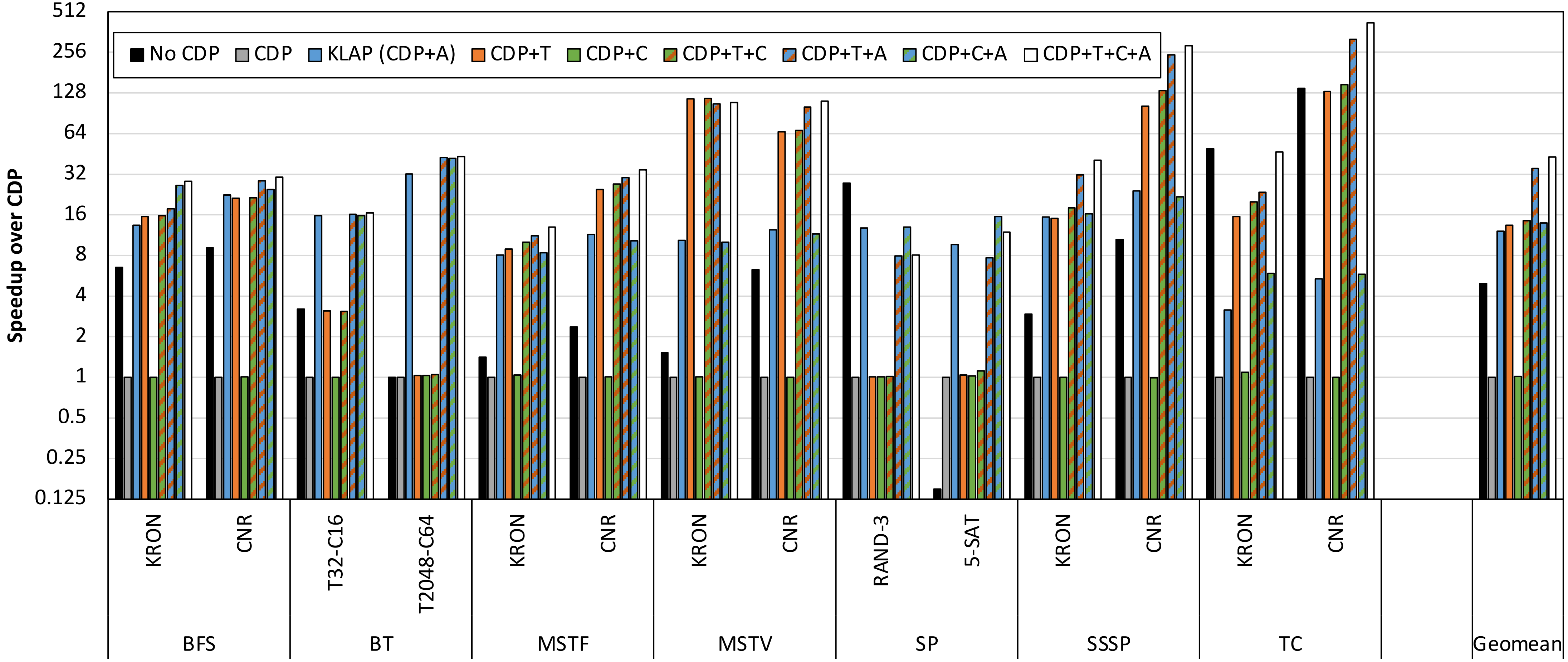
Overall Speedup



Observation #5: Coarsening alone does not improve performance substantially over CDP.

CDP+C is 1.01× faster than CDP.

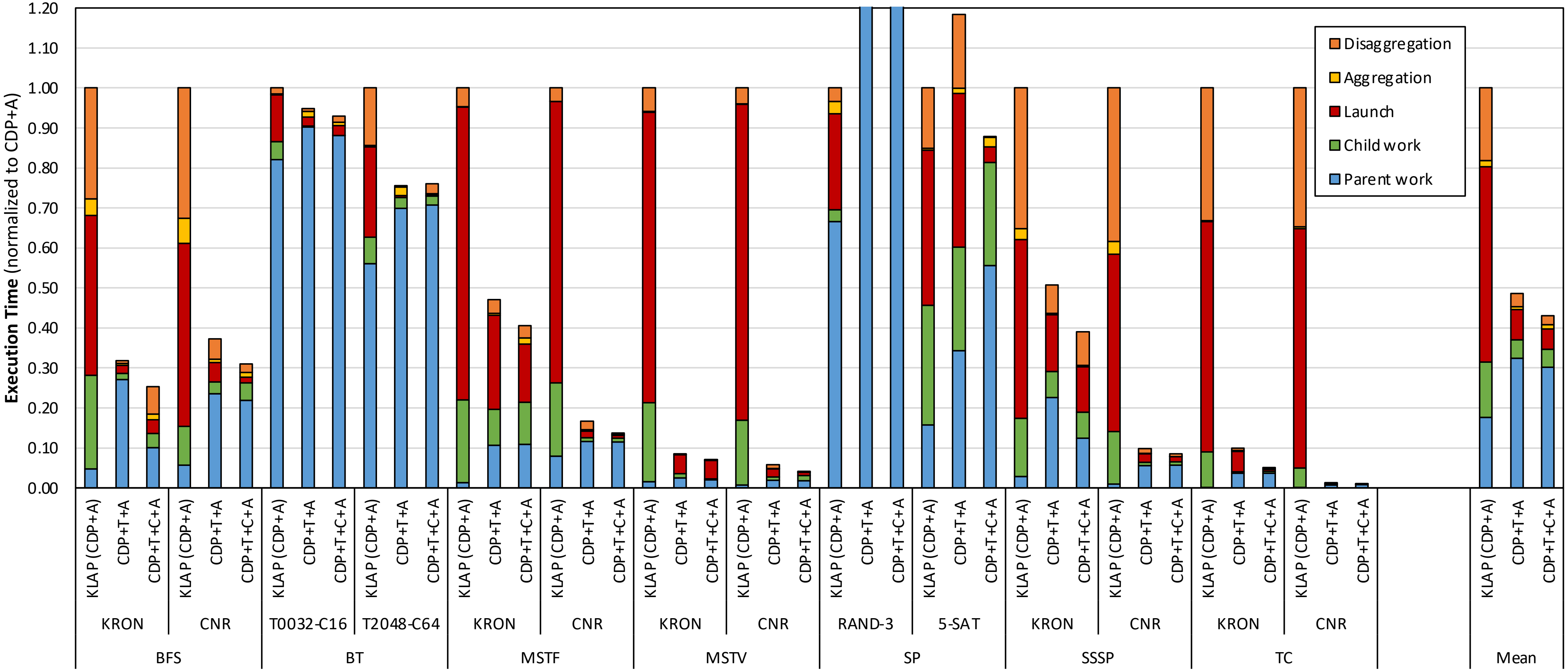
Overall Speedup



<u>Observation #6:</u> Coarsening does improve performance when combined with the other optimizations.

Recall: main benefit was amortizing overhead of aggregation. **CDP+T+C+A** is 1.22× faster than **CDP+T+A**.

Execution Time Breakdown

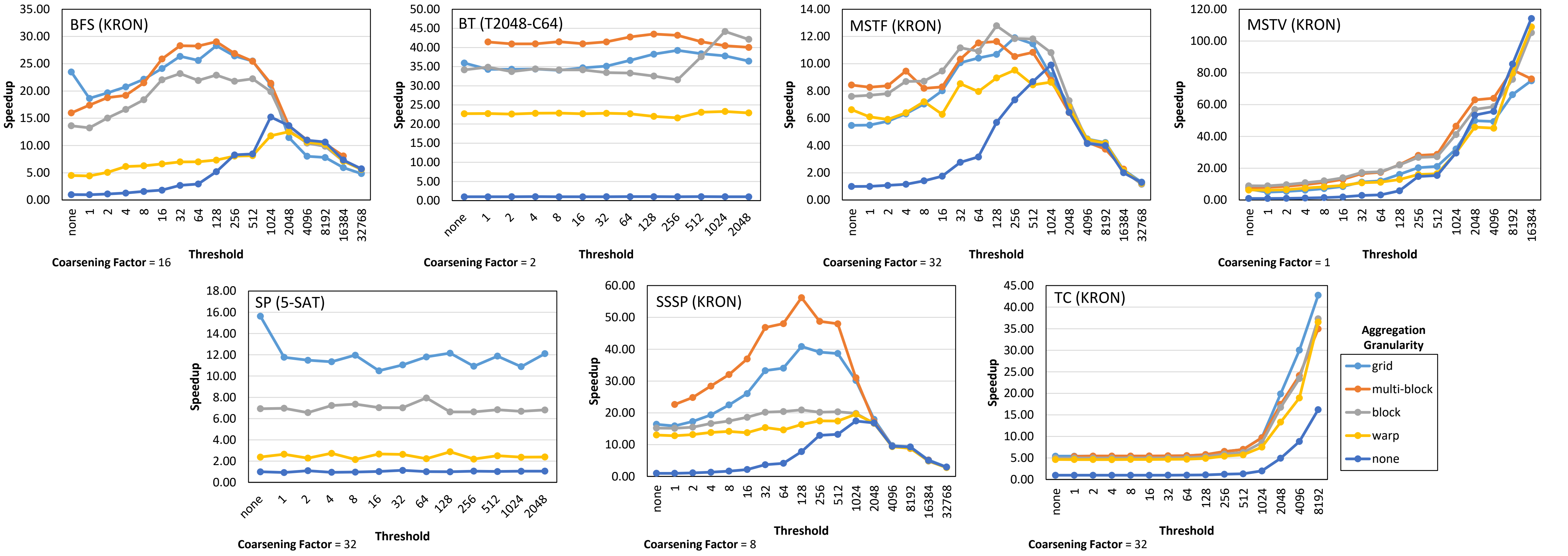


Observation #1: Thresholding increases parent work and decreases child work

Observation #2: Thresholding decreases the overhead from launching, aggregation, and disaggregation

Observation #3: Coarsening decreases the overhead from launching and disaggregation

Impact of Threshold and Aggregation Granularity



Observation #1: As the threshold increases initially, performance improves due to reduction in launches

Observation #2: For some benchmarks, increasing threshold too much degrades performance due to too much serialization

Observation #3: Different benchmarks perform best with different levels of aggregation granularity (including multi-block)

Summary

- We present a **compiler framework** for optimizing the use of dynamic parallelism on GPUs in applications with nested parallelism
- The framework includes **three key optimizations**:
  - Thresholding
  - Coarsening
  - Aggregation
- Our evaluation shows that our compiler framework **substantially improves performance of applications with nested parallelism** that use dynamic parallelism
  - 43.0× faster than CDP.
  - 8.7× faster than No CDP
  - 3.6× faster than prior aggregation work (KLAP)

Thank you!

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