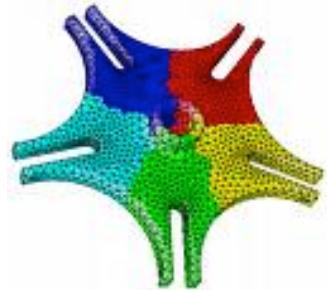




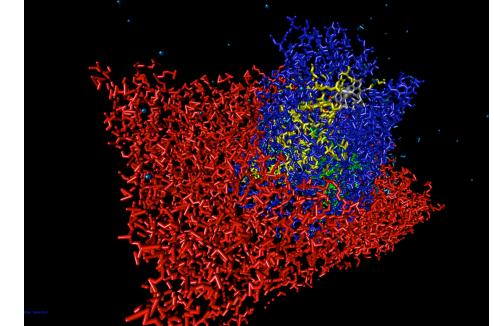
# Cache and Data Structures

Bruno Raffin  
DataMove  
INRIA - LIG  
GRENOBLE

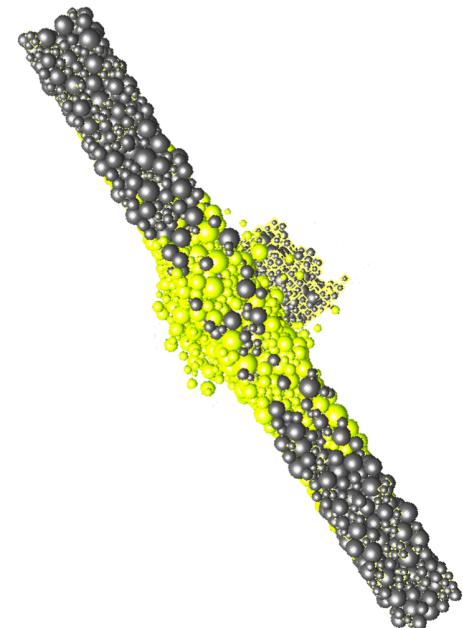
Part of the Slides are from  
Marc Tchiboukdjian  
and  
Marie Durand



# Motivation 1/2



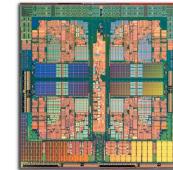
- Numerical simulations:
  - 3D objects: meshes, particles
  - Spatial and temporal coherency
- Computer memories: 1D



# Motivation 2/2

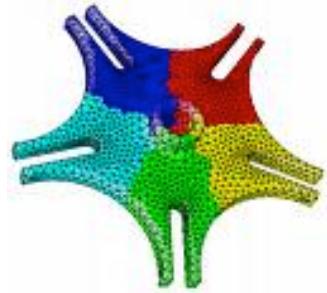
Today's machines:

-> complex memory hierarchies

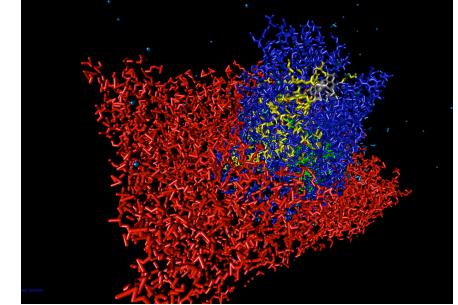


Access by blocks of continuous data (memory pages, cache lines, read/write coalescing)

Need to carefully consider data access schemes and memory layouts



# Spatial Coherency



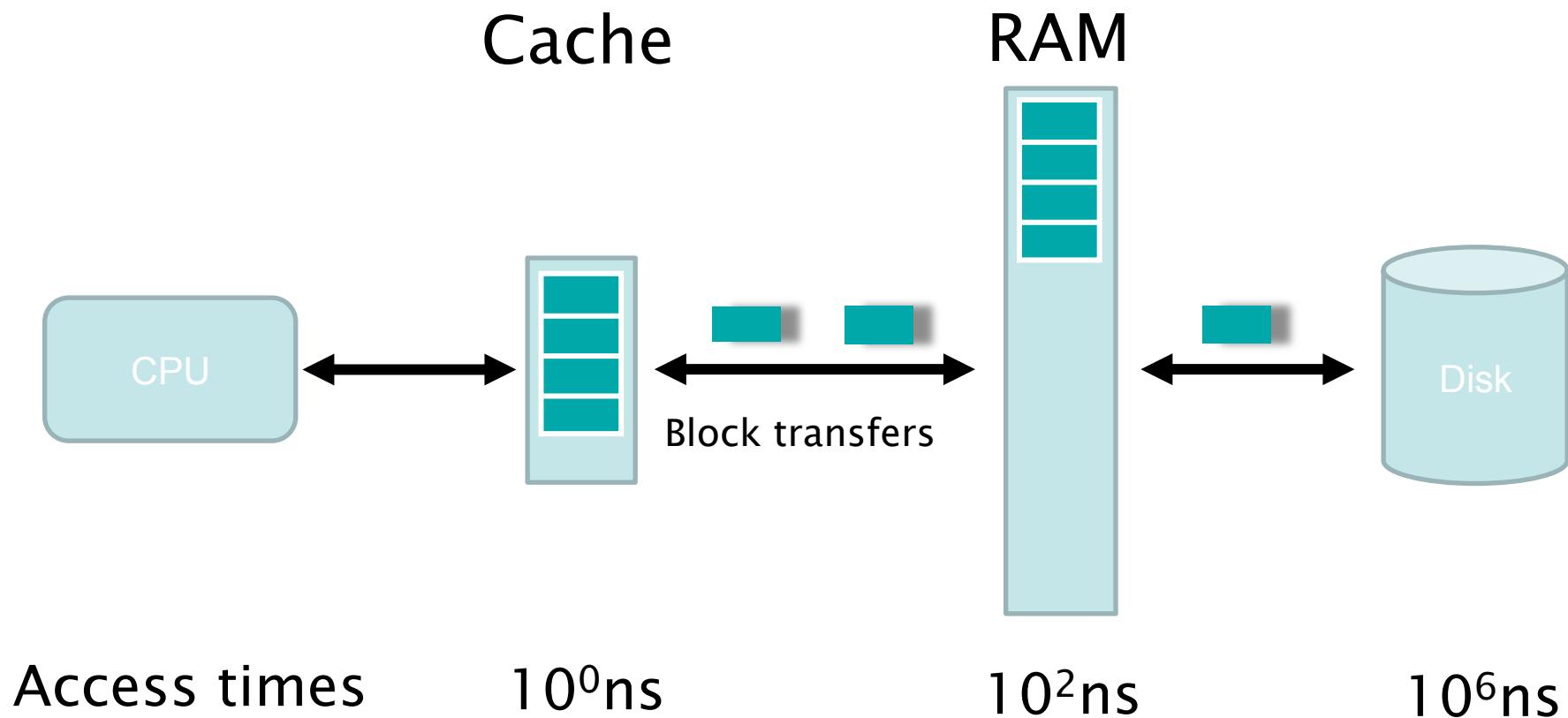
(3D) Neighbor data tend to be accessed together

-> Mesh topology, Atoms, etc.

Try to keep this 3D locality when projecting the data in the 1D memory:

Goal: Access  $n$  neighbor data by  
 $n/B$  memory block transfers (B-size)

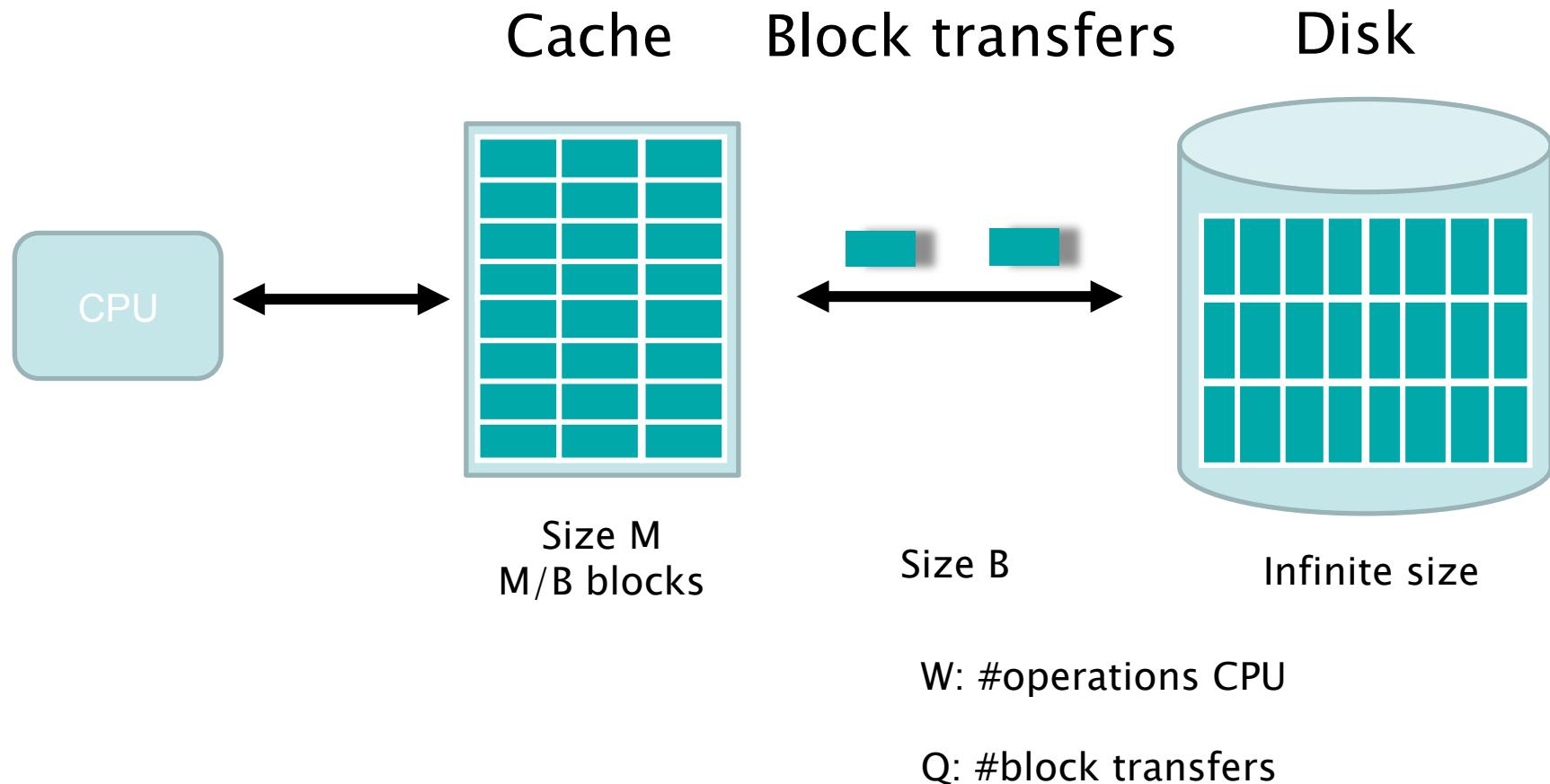
# Memory Hierarchy



# Disk Access Model (DAM)

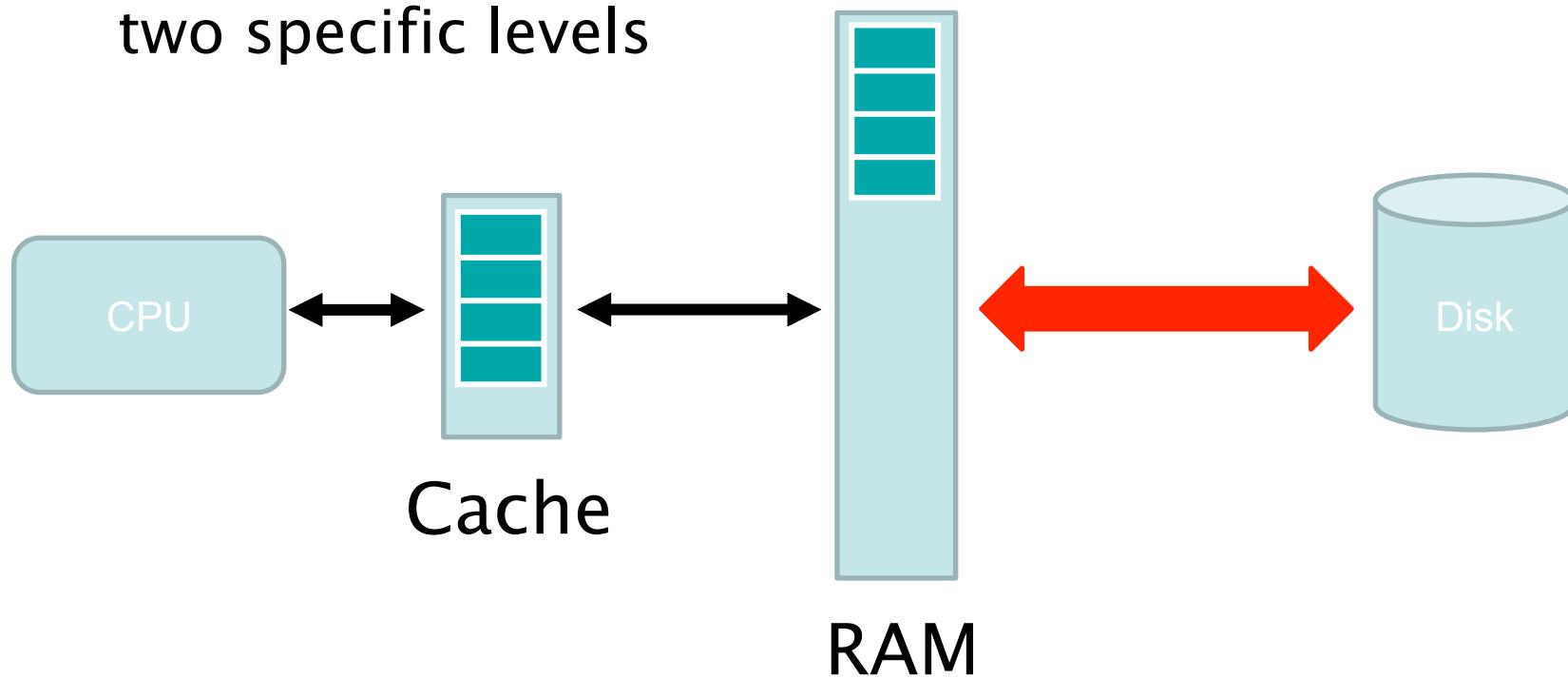
or external memory  
out-of-core  
cache-aware  
I/O model

[Aggarwal and Vitter 1988]



# Advantages of the DAM model

- Simple: only two levels
- Good when the bottleneck is between two specific levels

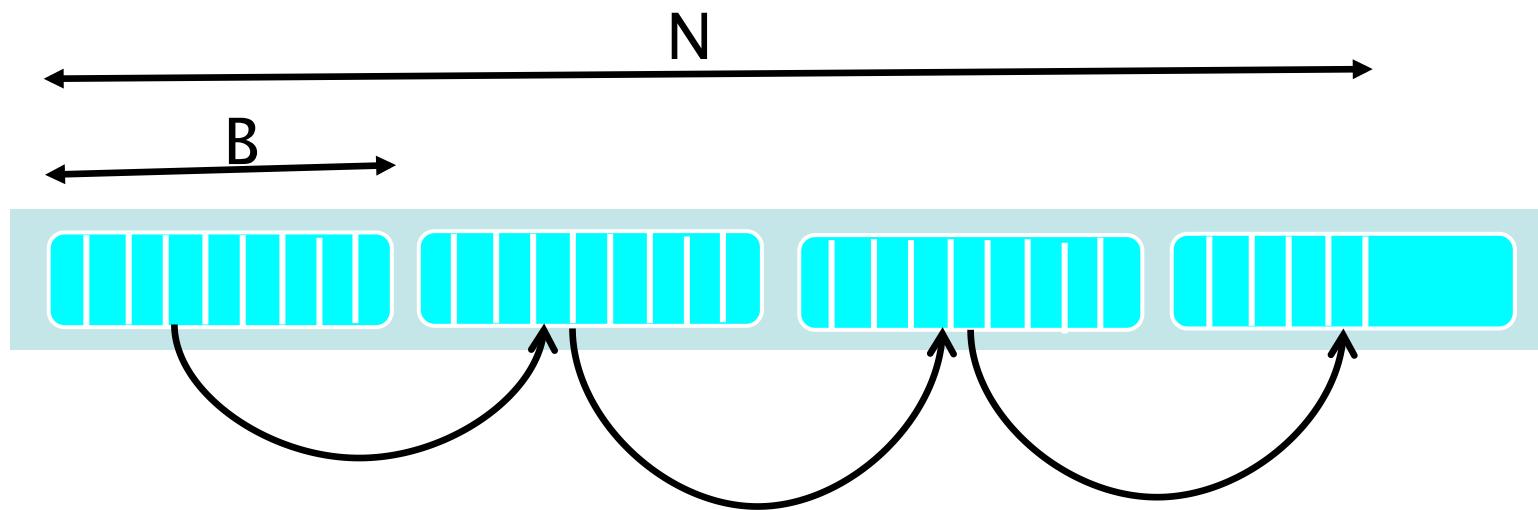


# Principles of external-memory algorithm design

- *Internal efficiency*: work is comparable to the best internal memory algorithms
- *Spatial locality*: a block should contain as much useful data as possible
- *Temporal locality*: as much useful work as possible before the block is ejected

# Scanning in the DAM model

Read an  $N$ -elements array: the naive algorithm is optimal



$$W(N) = N$$

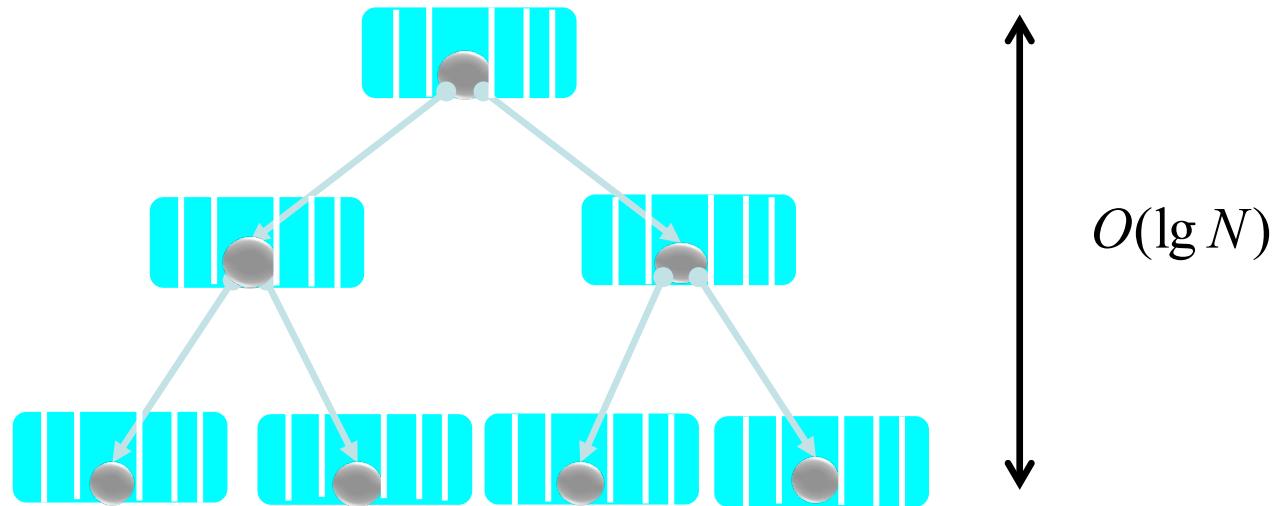
$$Q(N) = \lceil N / B \rceil$$

$$\text{scan}(N) = \lceil N / B \rceil$$

this bound is optimal

# Searching in the DAM model

Searching a key in an  $N$ -nodes balanced binary tree : naive doesn't work



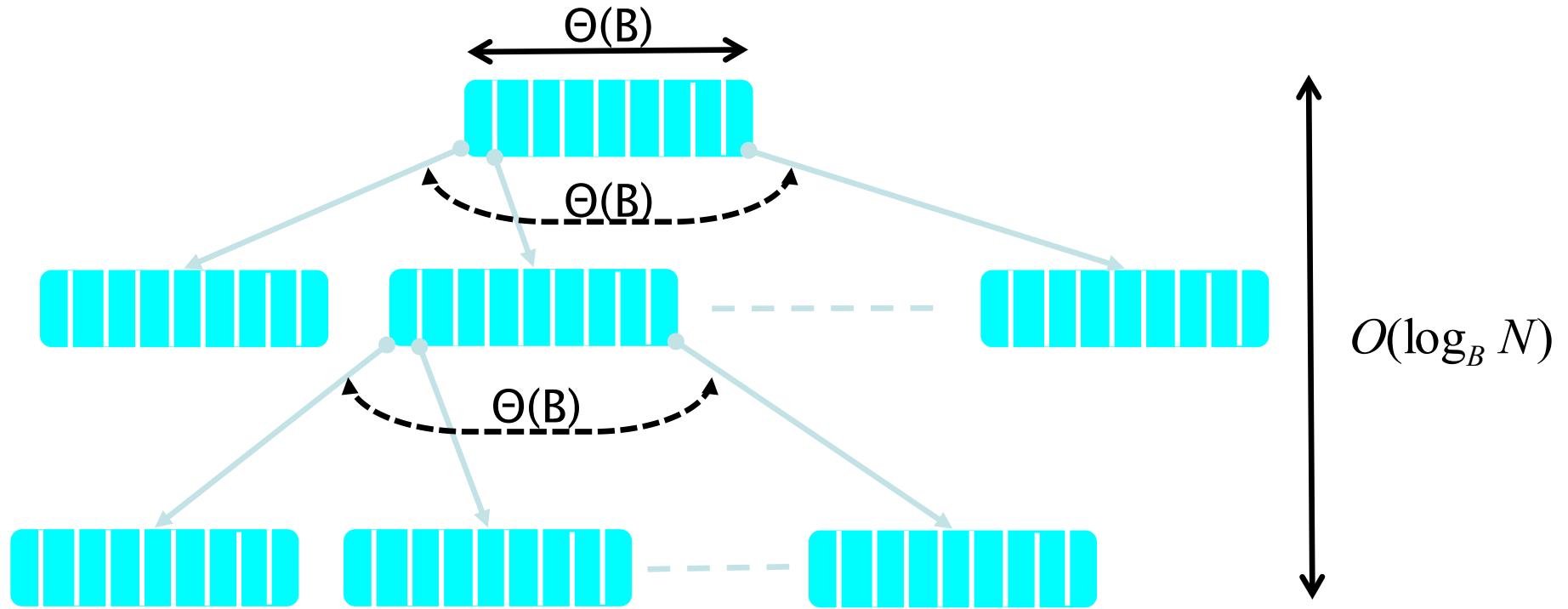
$$W(N) = 1 \cdot O(\lg N) = O(\lg N)$$

$$Q(N) = 1 \cdot O(\lg N) = O(\lg N)$$

# Searching in the DAM model

Searching a key in an N-elements B-tree

[Bayer and McCreight 1972]



$$W(N) = \lg B \cdot O(\log_B N) = O(\lg N)$$

$$Q(N) = 1 \cdot O(\log_B N) = O(\log_B N)$$

# Multiplying in the DAM model

NxN matrices in row-major order

: naive doesn't work

Using the naive  $N^3$  algorithm:

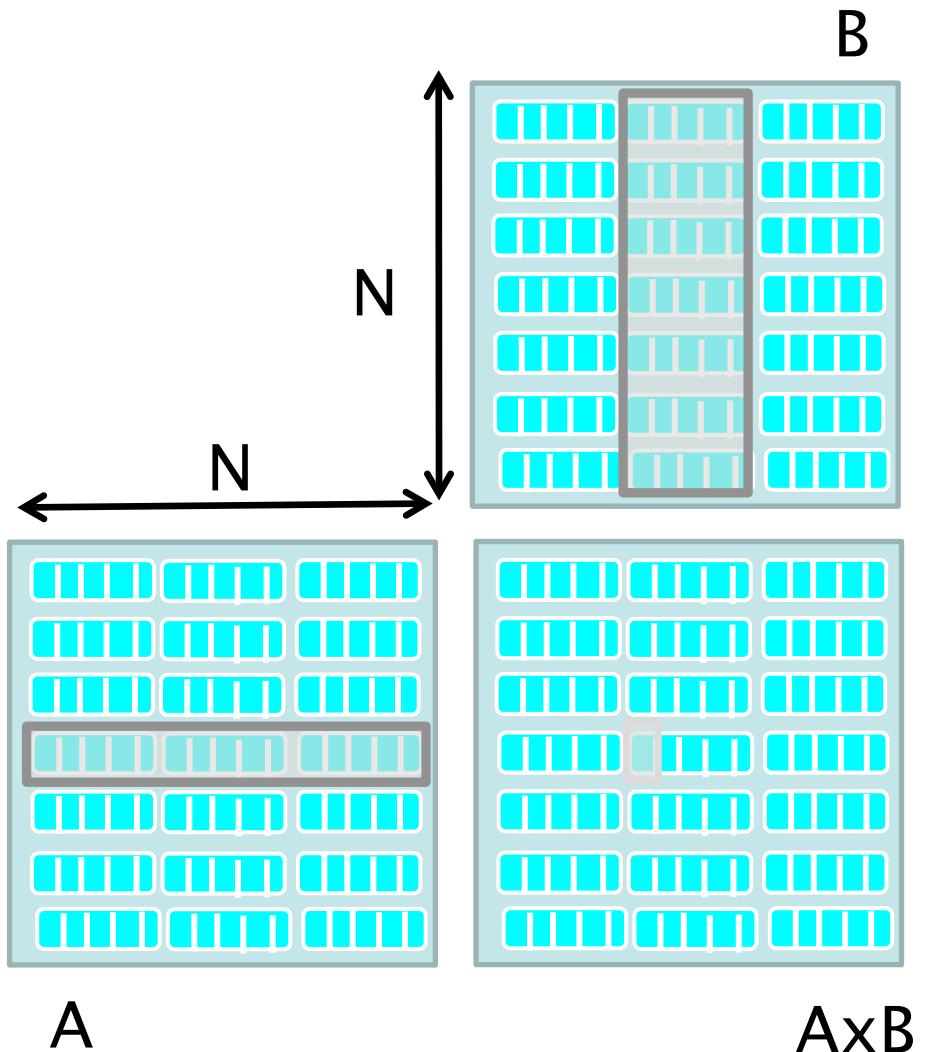
$$W(N) = O(N).N^2$$

$$W(N) = O(N^3)$$

Memory accesses in B are suboptimal:

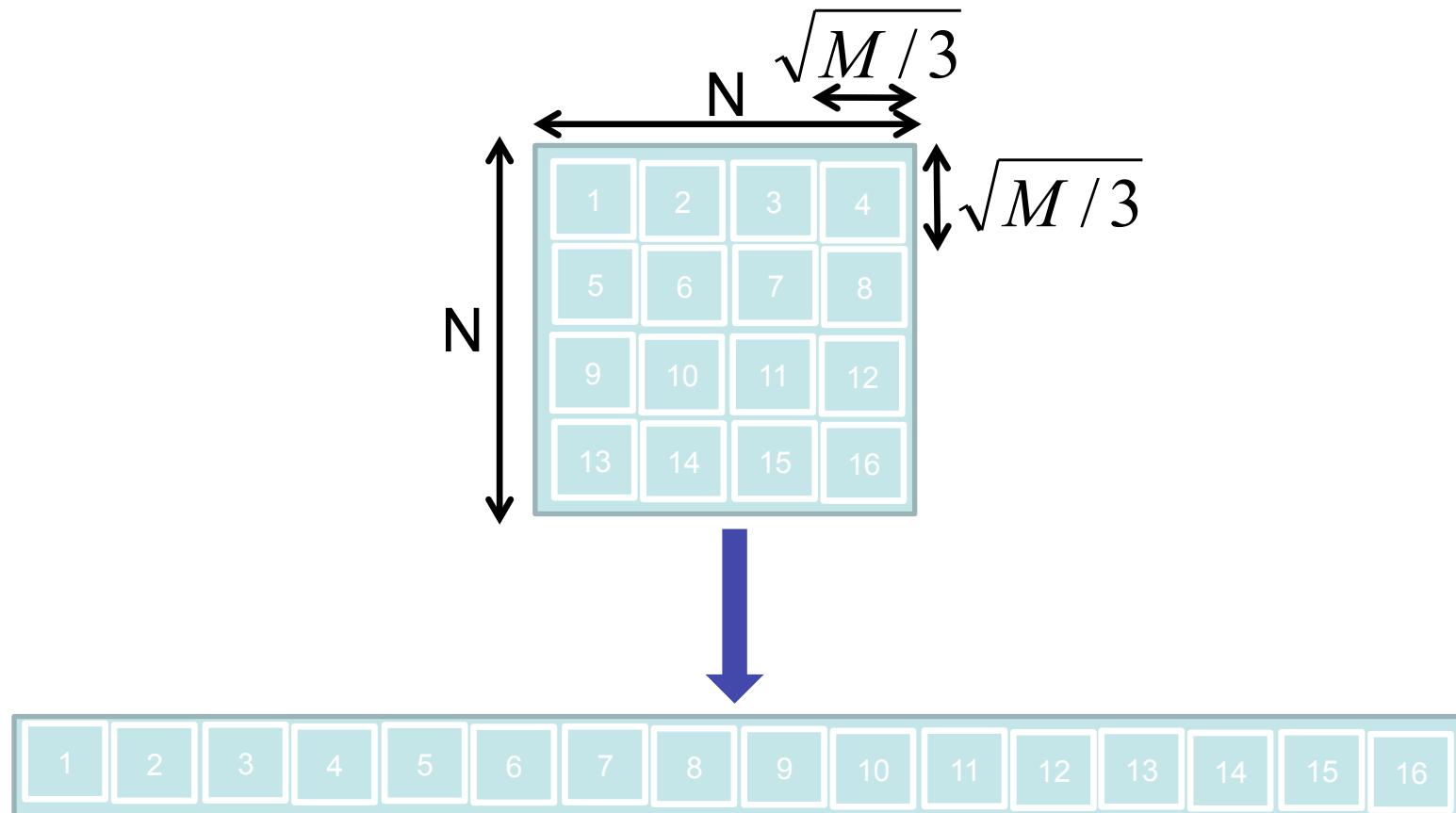
$$Q(N) = O\left(\frac{N}{B} + N\right).N^2$$

$$Q(N) = O(N^3)$$



# Multiplying in the DAM model

NxN matrices in submatrices



# Multiplying in the DAM model

NxN matrices in submatrices

- Cost for two sub-matrices

$$W(N) = O\left(\sqrt{M}^3\right) \quad Q(N) = O\left(\frac{M}{B}\right)$$

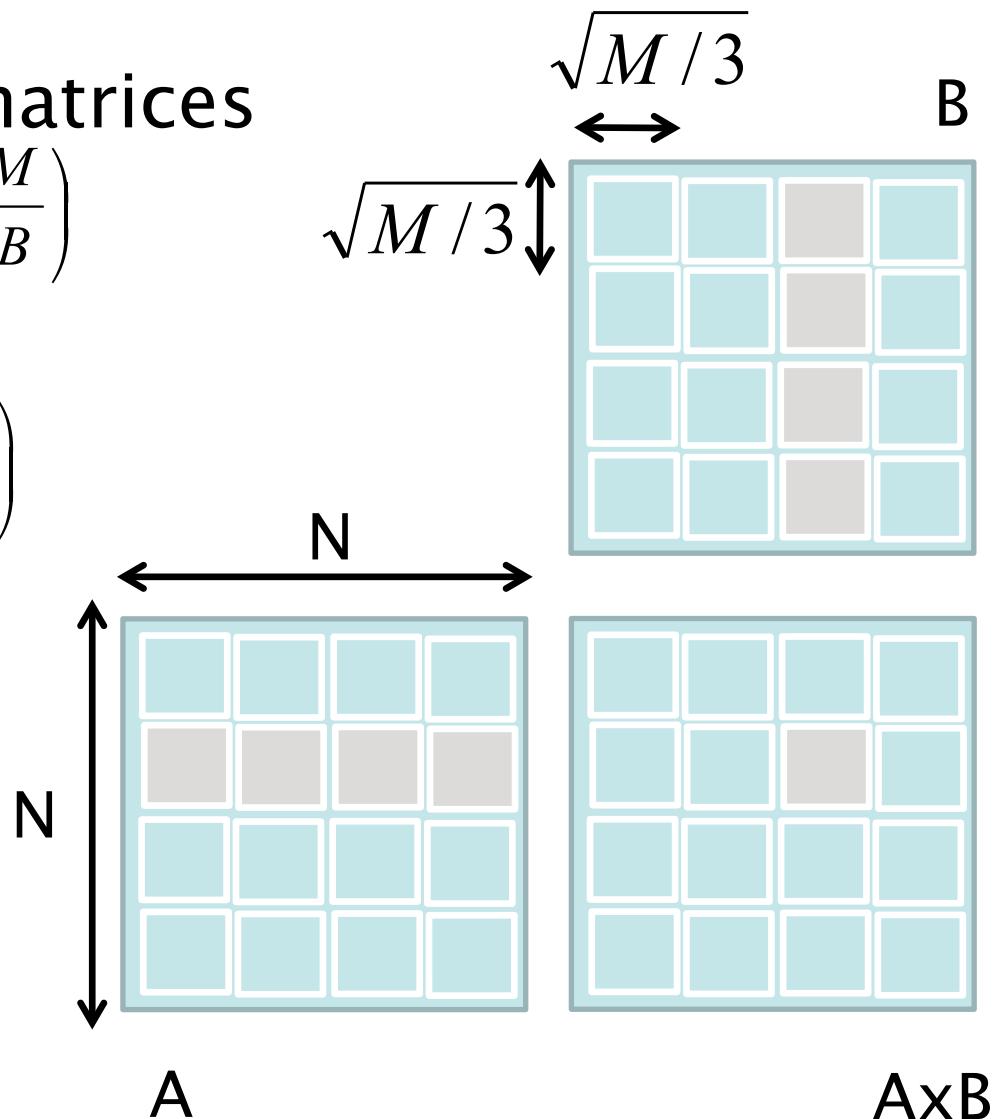
- Total cost

$$W(N) = O\left(\sqrt{M}^3\right).O\left(\frac{N}{\sqrt{M}}\right).O\left(\frac{N^2}{M}\right)$$

$$W(N) = O\left(N^3\right)$$

$$Q(N) = O\left(\frac{M}{B}\right).O\left(\frac{N}{\sqrt{M}}\right).O\left(\frac{N^2}{M}\right)$$

$$Q(N) = O\left(\frac{N^3}{B\sqrt{M}}\right)$$



# Sorting in the DAM model

M/B-way merge sort of an N-elements array

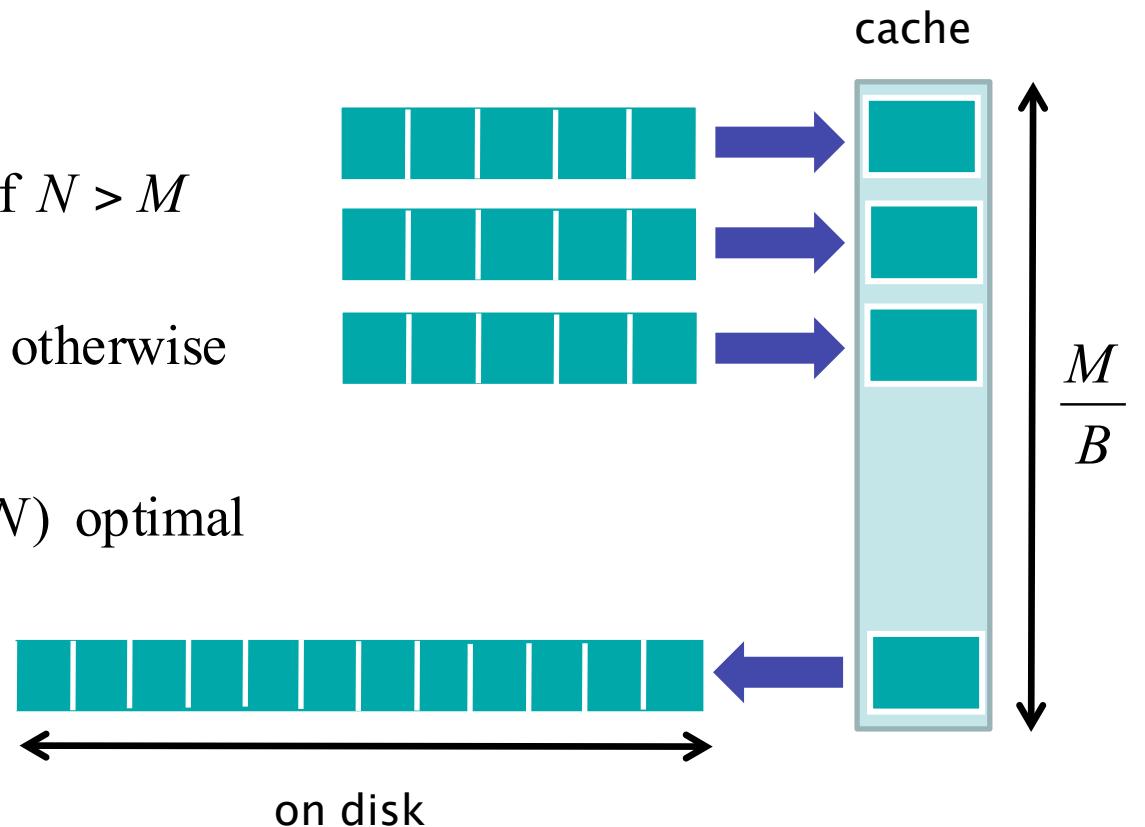
$$W(N) = \begin{cases} \frac{M}{B} W\left(\frac{N}{M/B}\right) + N \cdot O\left(\log \frac{M}{B}\right) & \text{if } N > 1 \\ O(1) & \text{otherwise} \end{cases}$$

$$W(N) = O(N \log N)$$

$$Q(N) = \begin{cases} \frac{M}{B} Q\left(\frac{N}{M/B}\right) + O\left(\frac{N}{B}\right) & \text{if } N > M \\ O\left(\frac{N}{B}\right) & \text{otherwise} \end{cases}$$

$$Q(N) = O\left(\frac{N}{B} \log_{M/B} \frac{N}{B}\right) = \text{sort}(N) \text{ optimal}$$

- Cut into M/B sublists
- Recursively sort them
- Merge using a heap of size M/B



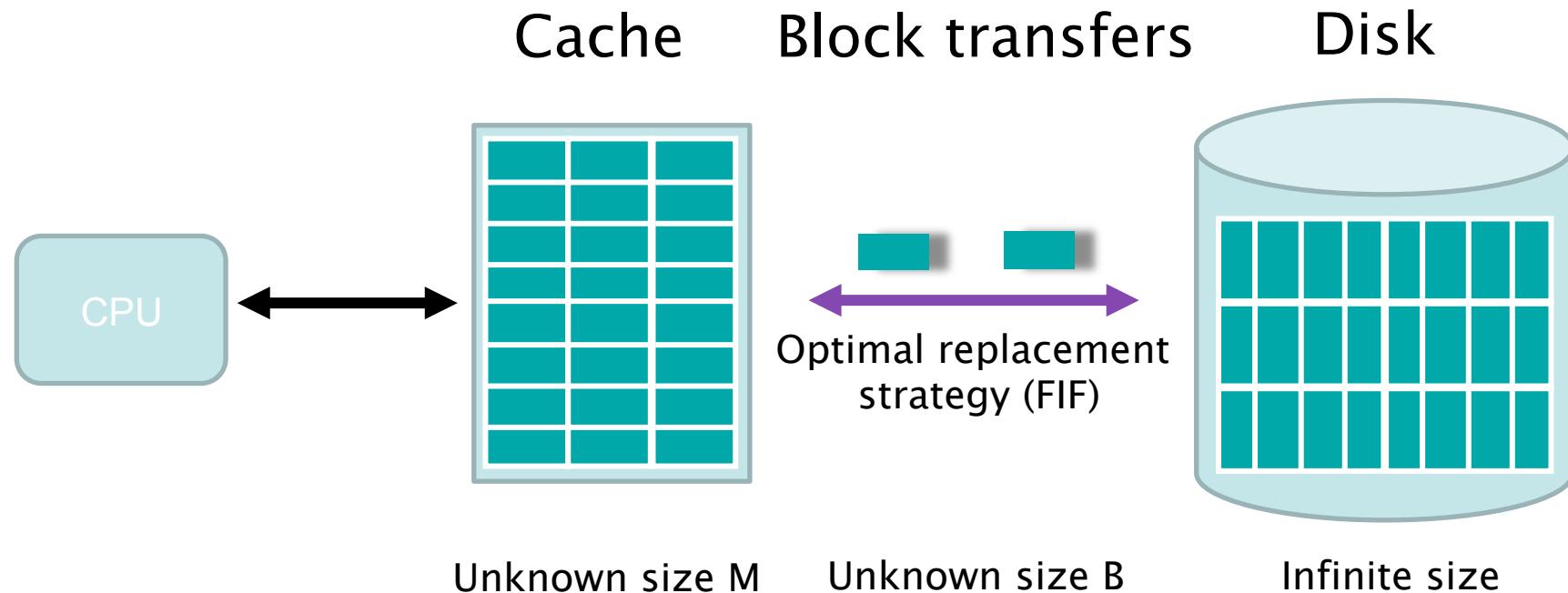
# Limitations of the DAM model

- B and M are needed to design the algorithm
- Only two levels of the hierarchy
- B and M can vary
  - e.g. multi-process scheduling
- Block transfer cost is not uniform
  - disk seek time

DAM Based Algorithms are said to be “cache-aware”

# Cache-Oblivious Model (CO)

[Frigo et al 1999]



# Advantages of the CO Model

Parameters are unknown when writing the algorithm (block and cache size):

- Machine-independent
- Efficient with all levels of the memory hierarchy

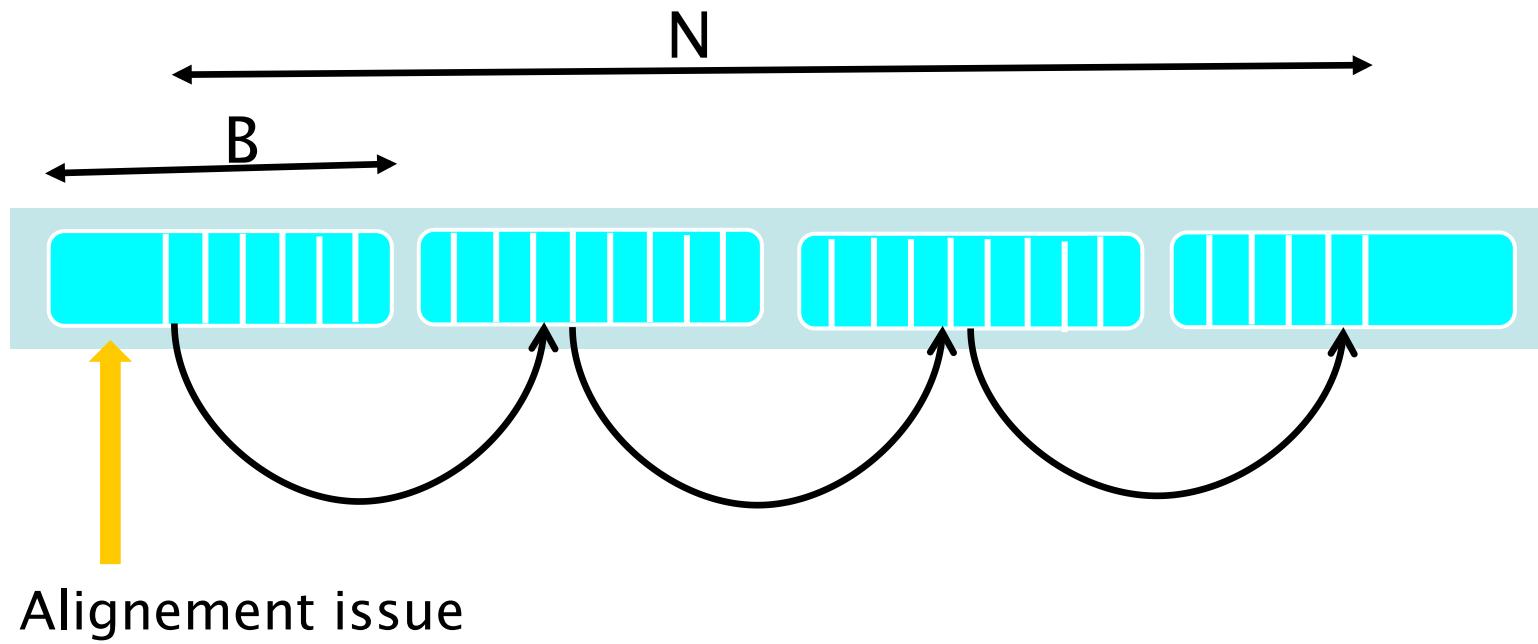
# Assumptions

- Optimal replacement
- Only two levels of memory
- Full associativity
- Tall-cache assumption

$$M = \Omega(B^2)$$

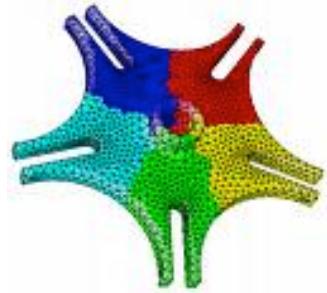
$$M = \Omega(B^{1+\varepsilon})$$

# Scanning in the CO model

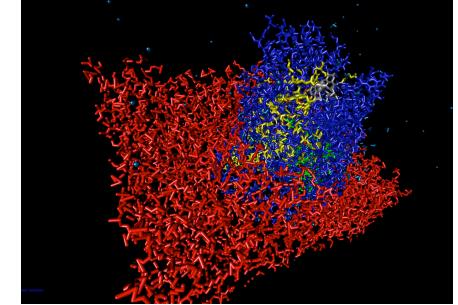


$$W(N) = N$$

$$Q(N) = \lceil N / B \rceil + 1$$



# Spatial Coherency



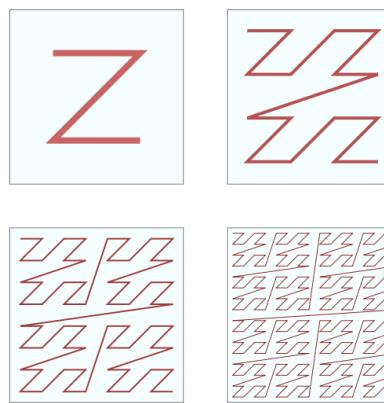
(3D) Neighbor data tend to be accessed together

-> Mesh topology, Atoms, etc.

Try to keep this 3D locality when projecting the data in the 1D memory:

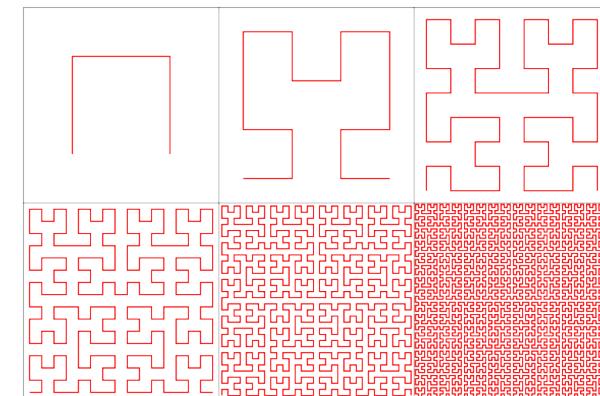
Goal: Access  $n$  neighbor data by  
 $n/B$  memory block transfers (B-size)

# Space-filling Curves



Morton Curve

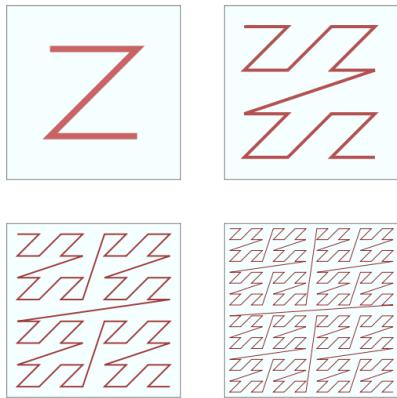
$(x,y,z) \rightarrow Z\text{-index by bit switches}$



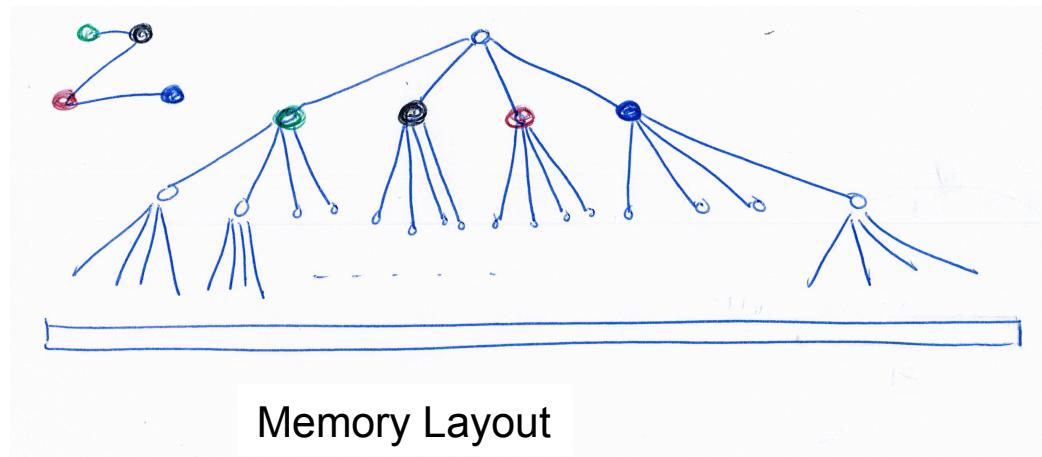
Hilbert Curve

Examples in 2D, but extends to higher dimensions

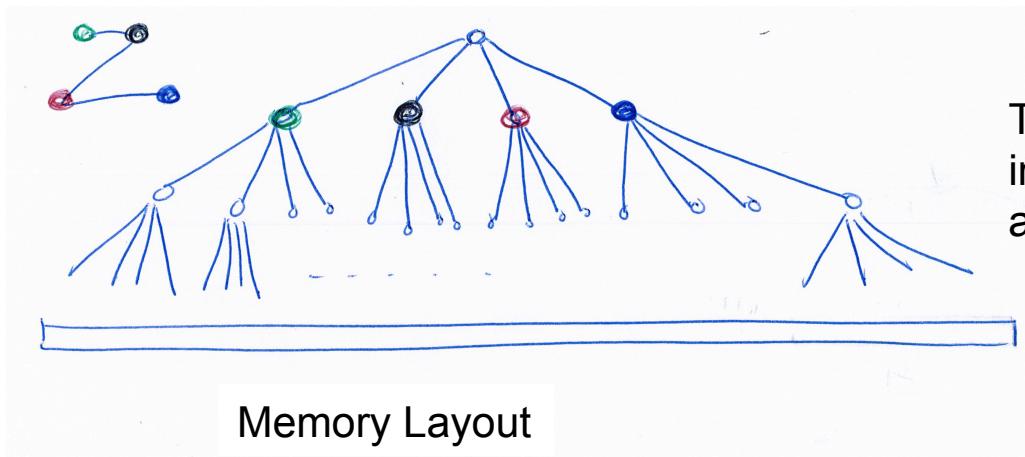
# Morton Curve



Morton Curve



# Morton Curve: Cache Oblivious Data Layouts

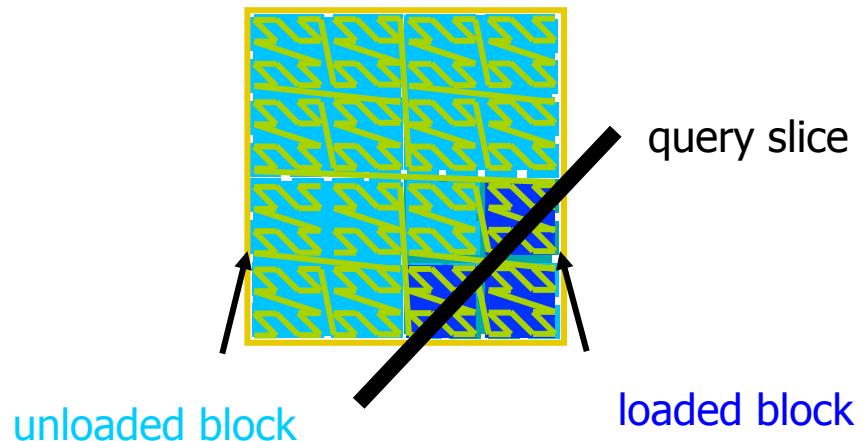


The layout is computed independently from a given M and B

Memory Layout

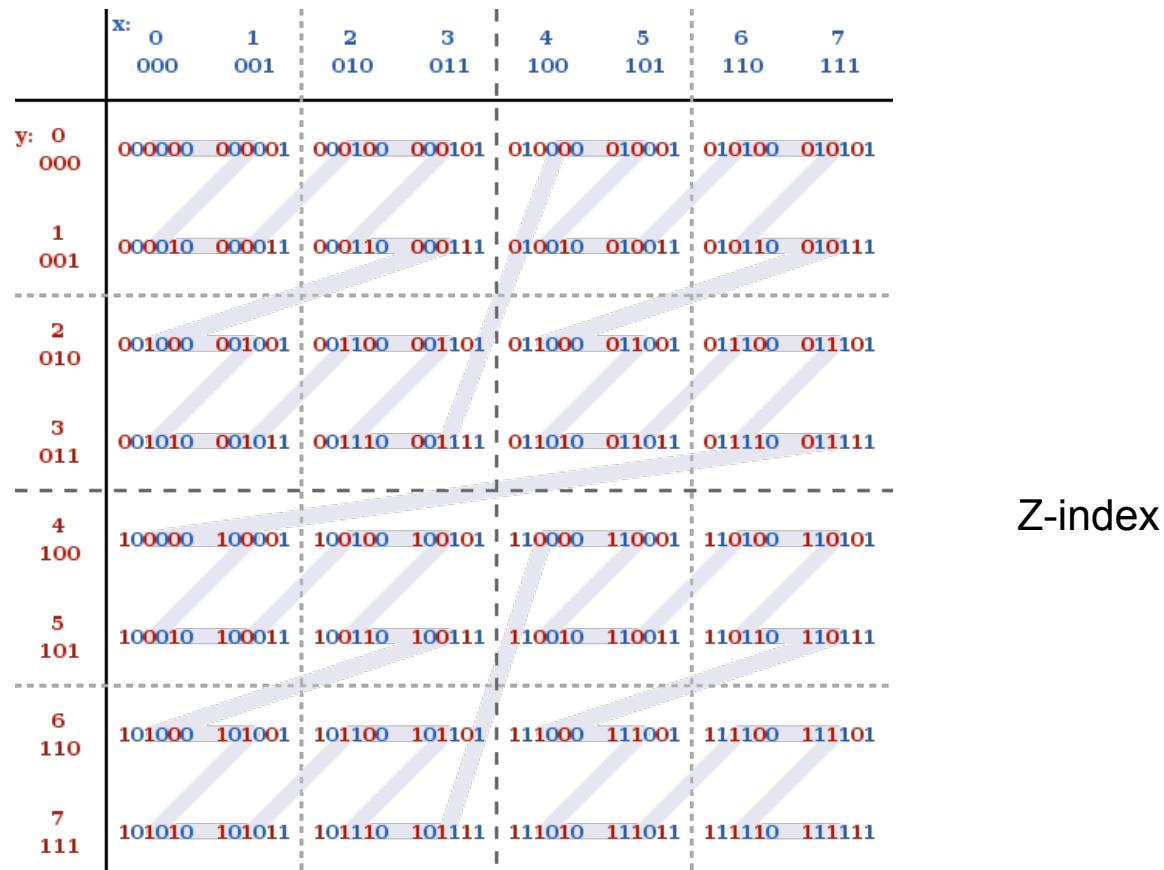
Spatially coherent accesses will show a good cache behavior

See [Pascucci, Siggraph-2005] or [Tchiboukdjian, TVCG 2010] for mesh specific CO layouts



# Morton Curve Indexing

Z-index obtained by Interleaving the binary coordinates of x and y



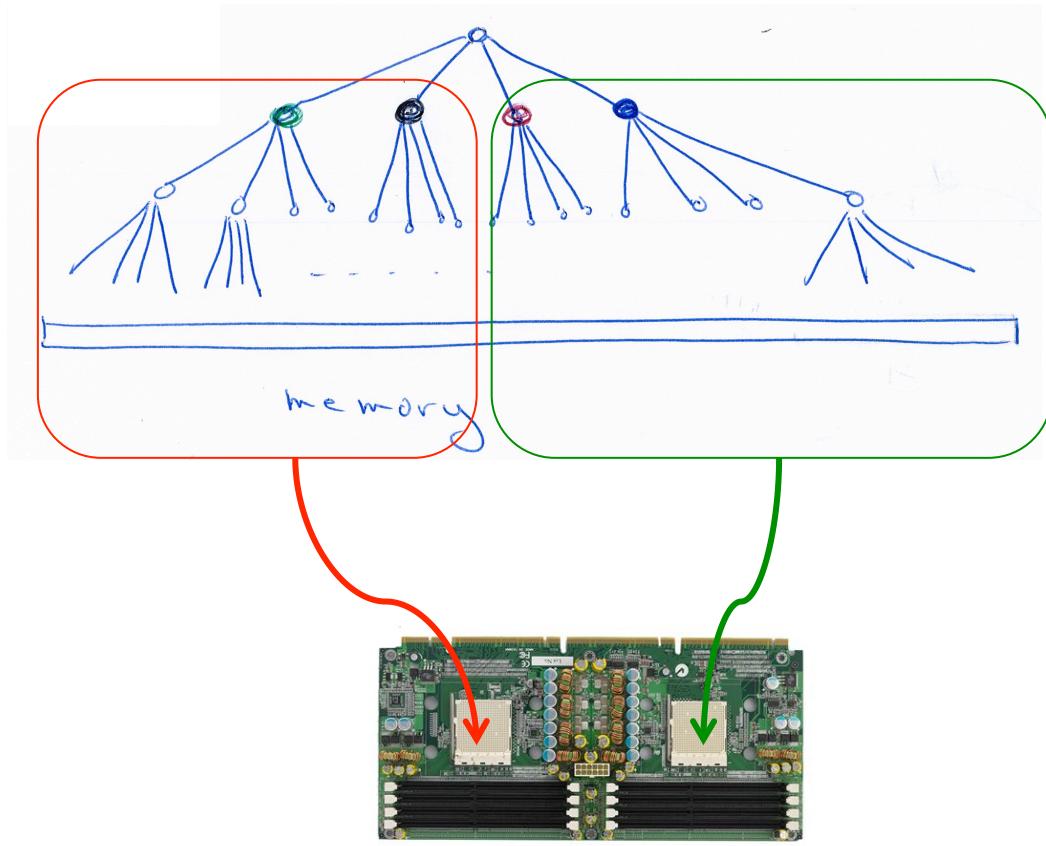
Z-curves are used by some databases data structures (trees, hash tables), or for data partitioning in numerical simulations.

# Morton Curve Based CO layout and Parallelism

- How would you manage such CO layout on a NUMA node ?
- How would you implement parallel element searches ?
- What are the benefits of this CO layout (on a NUMA node) ?

# Morton Curve Based CO layout and Parallelism

- Map data blocks to memory banks according to CO layout
- Make sure threads access local banks first



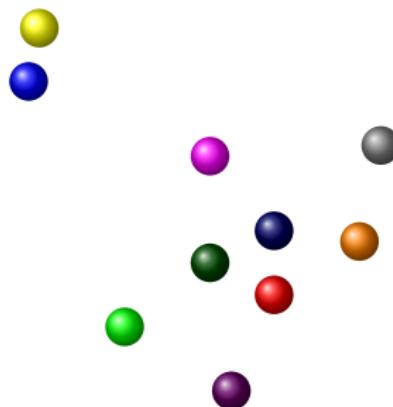
What about GPUs ?

# Packed Memory Array

A Cache Oblivious data structure for dynamics data.

# Cache Oblivious Data Structure for Moving Particles

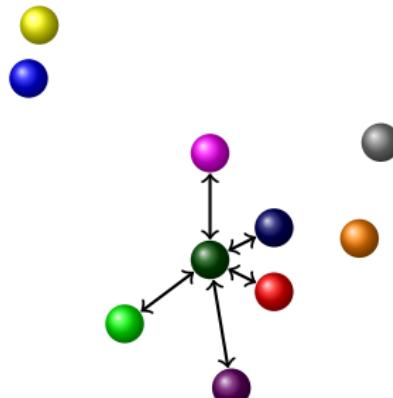
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# Cache Oblivious Data Structure for Moving Particles

---

particles



short-range  
interaction

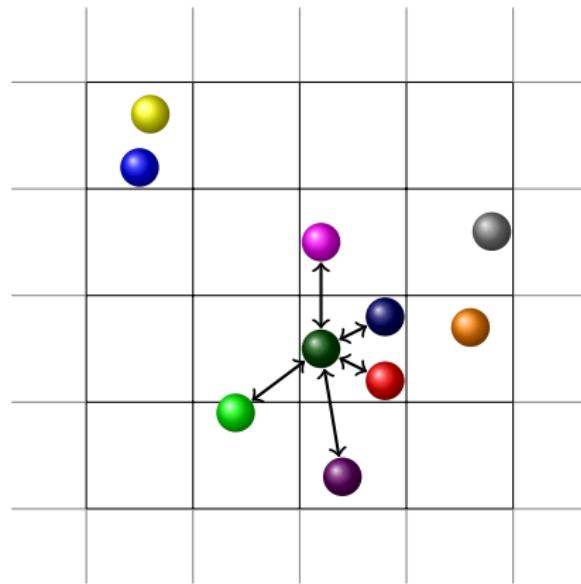
simulation

movement  
 $\vec{a} = \frac{1}{m} \sum \vec{F}$

# Cache Oblivious Data Structure for Moving Particles

particles

simulation

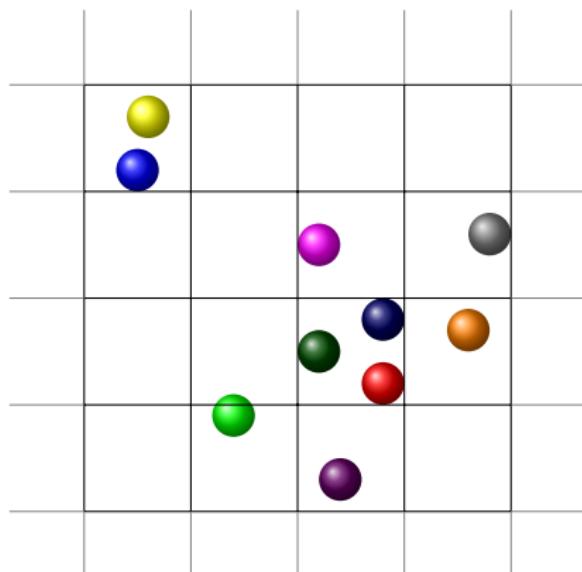


short-range  
interaction

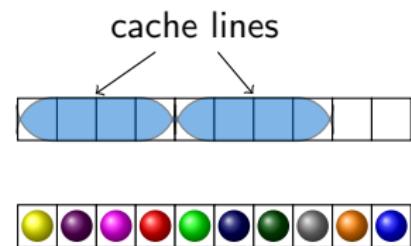
movement  
 $\vec{a} = \frac{1}{m} \sum \vec{F}$

# Spatial Locality Preserving Memory Layout

---



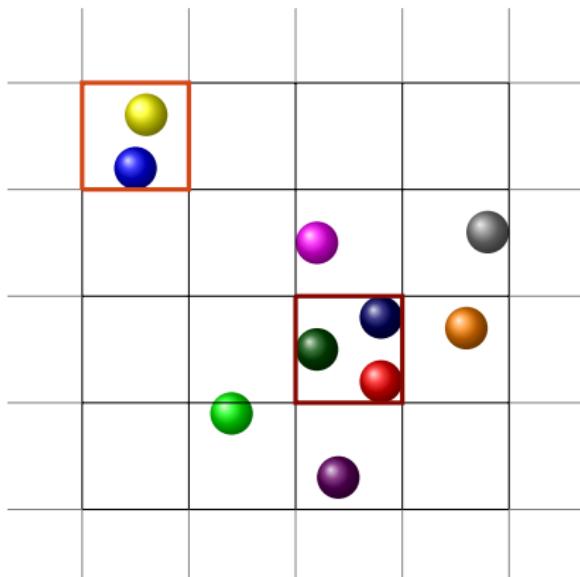
3D Space



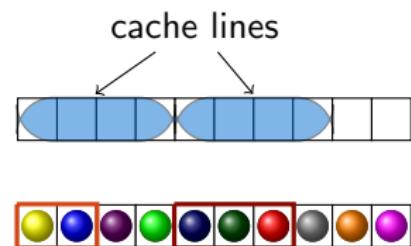
1D memory

# Spatial Locality Preserving Memory Layout

---



3D Space

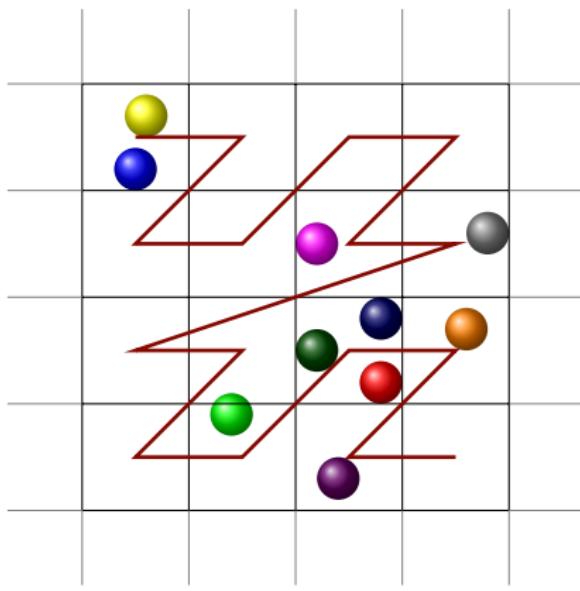


Group particles by cell.

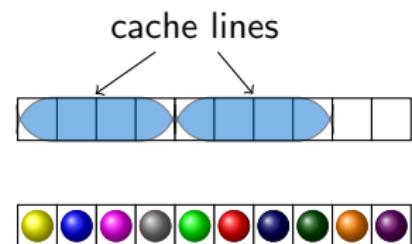
1D memory

# Spatial Locality Preserving Memory Layout

---



3D Space



Cell index sorting: Z-order

1D memory

# Related Data Structures

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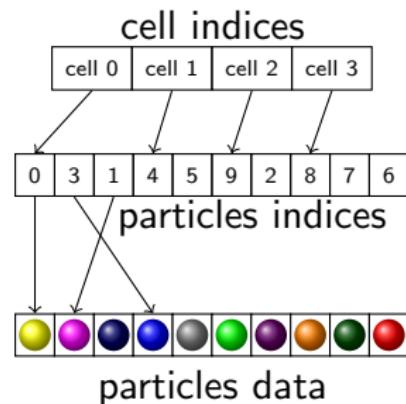
Classical approaches:

- **Z-index** sorting
- **Compact** (spatial) hashing

Periodically (1/100):

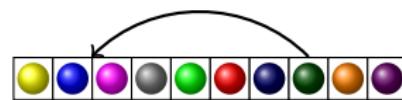
- sort particles data array

[Ihmsen et al., 2011]



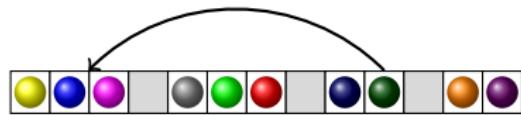
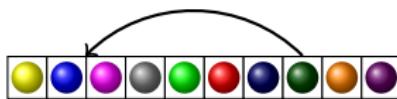
# Idea

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# Idea

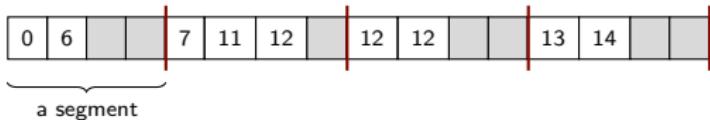
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# Packed Memory Array (PMA)

---

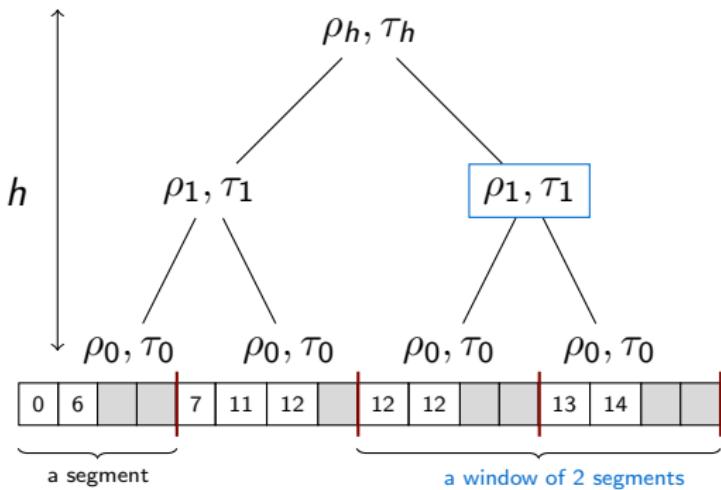
- $K$  elements in an array of size  $N$  ( $N - K$  gaps)
- Segments of size  $\log N$
- #segments: power of 2



[Bender et al. (2000, 2005)]

# Packed Memory Array (PMA)

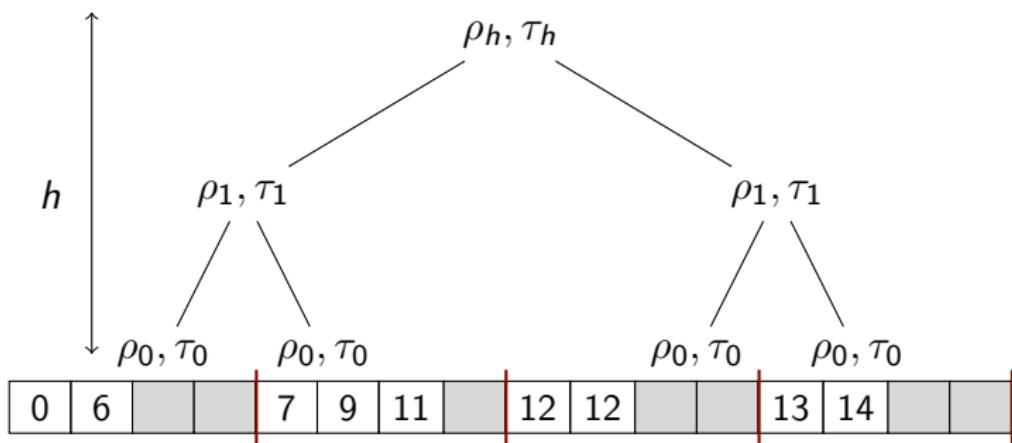
- Densities min  $\rho$ , max  $\tau$
- $\rho_0 < \dots < \rho_h < \tau_h < \dots < \tau_0$



[Bender et al. (2000, 2005)]

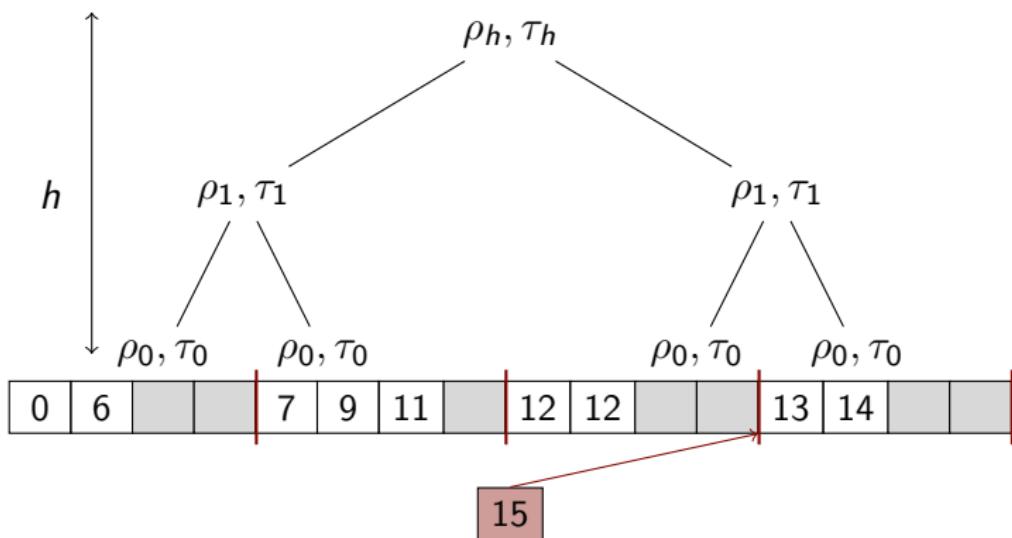
# How Does the Original PMA Work ?

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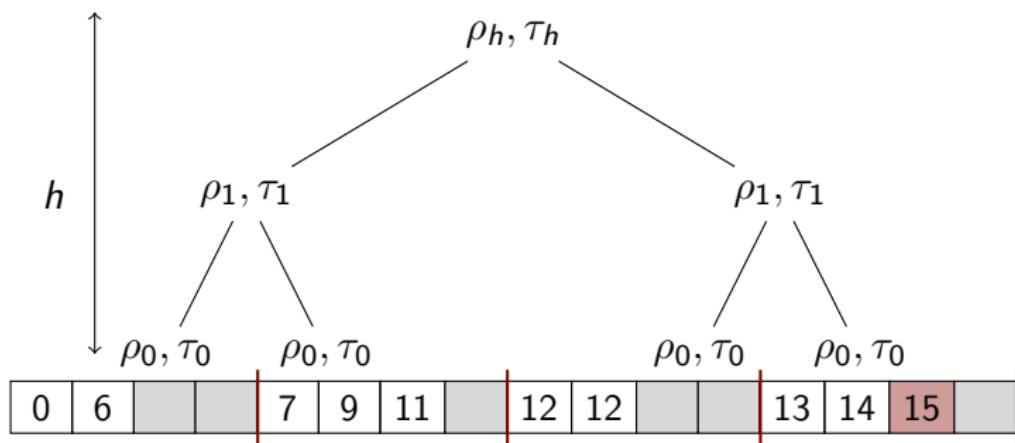
# How Does the Original PMA Work ?

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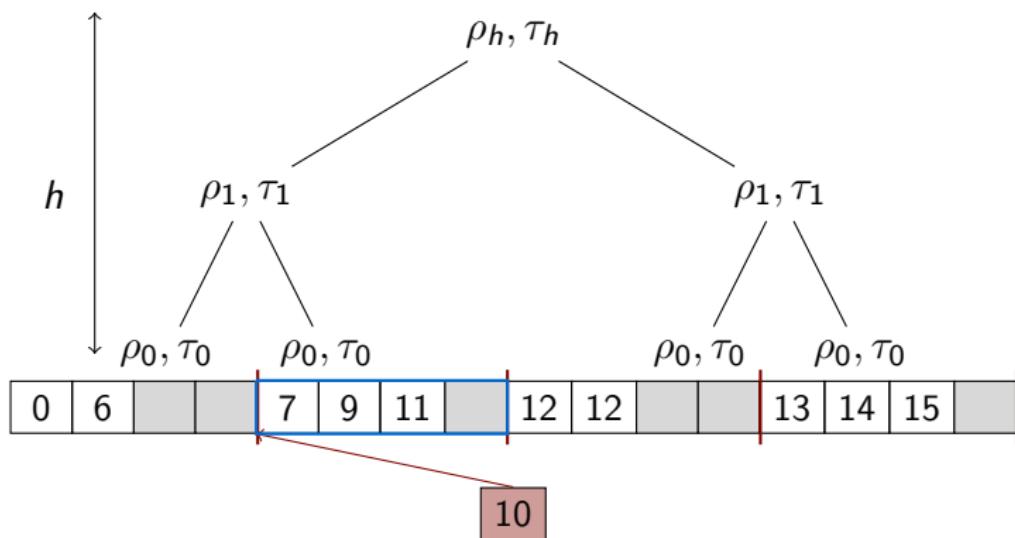
# How Does the Original PMA Work ?

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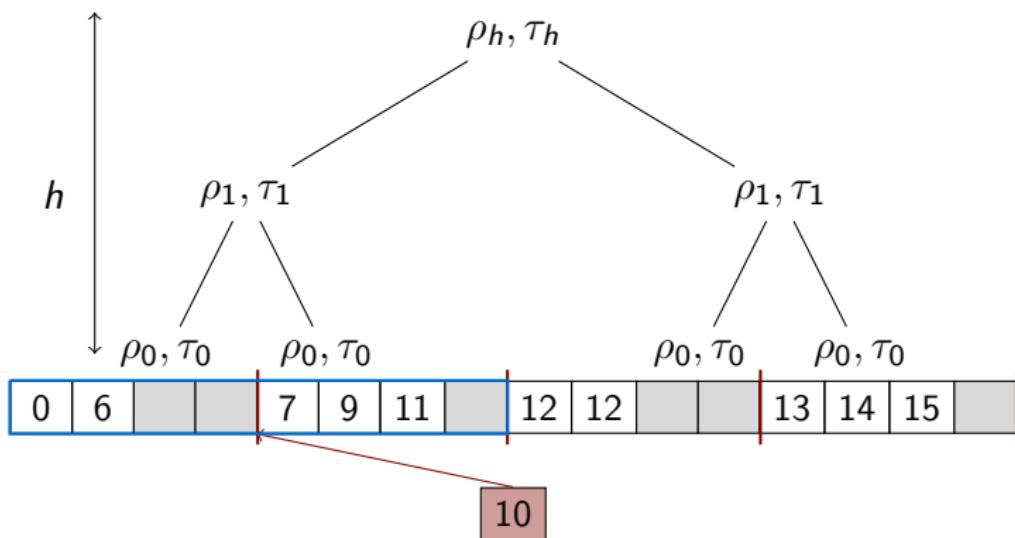
# How Does the Original PMA Work ?

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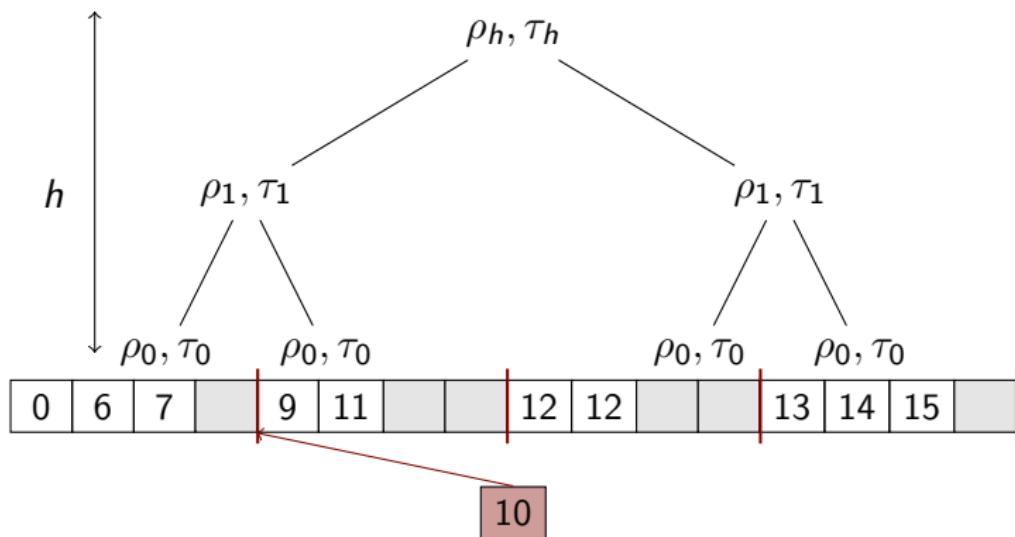
# How Does the Original PMA Work ?

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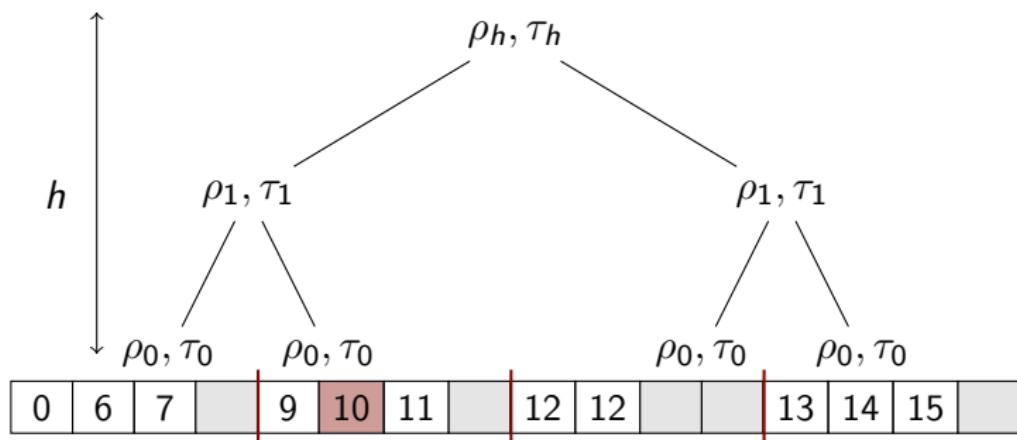
# How Does the Original PMA Work ?

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# How Does the Original PMA Work ?

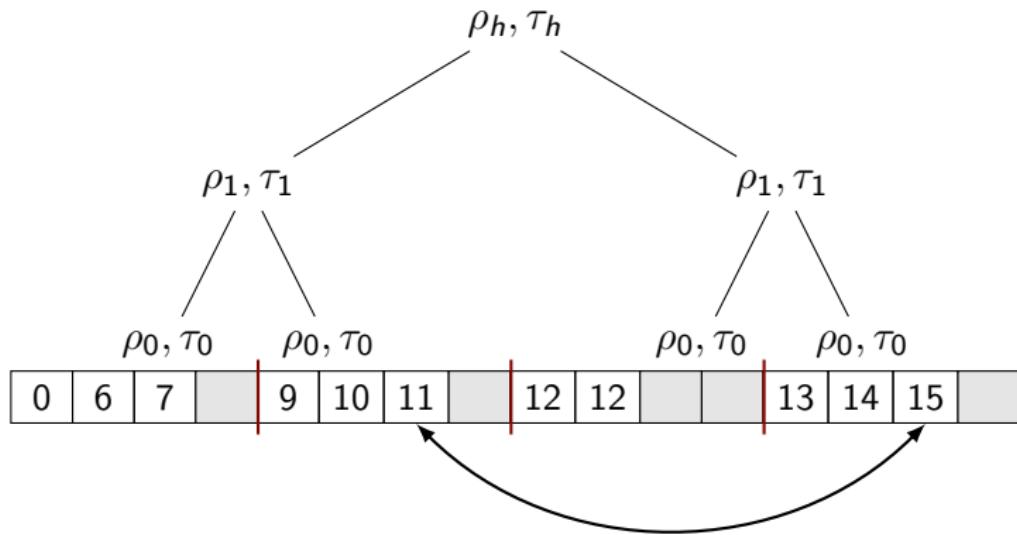
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Amortized number of moves:  $O(\log^2 N)$ .

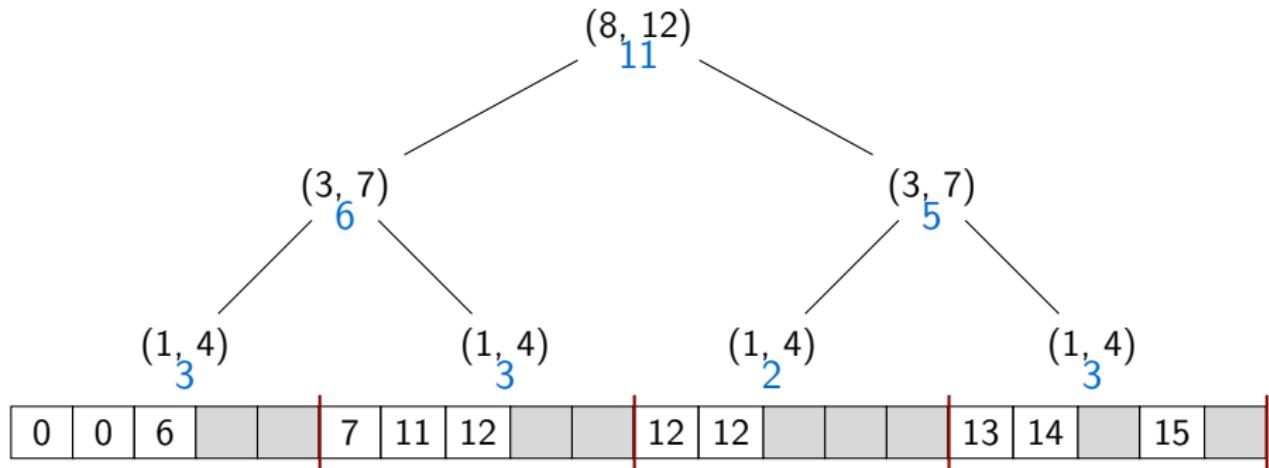
# Element Moves

---



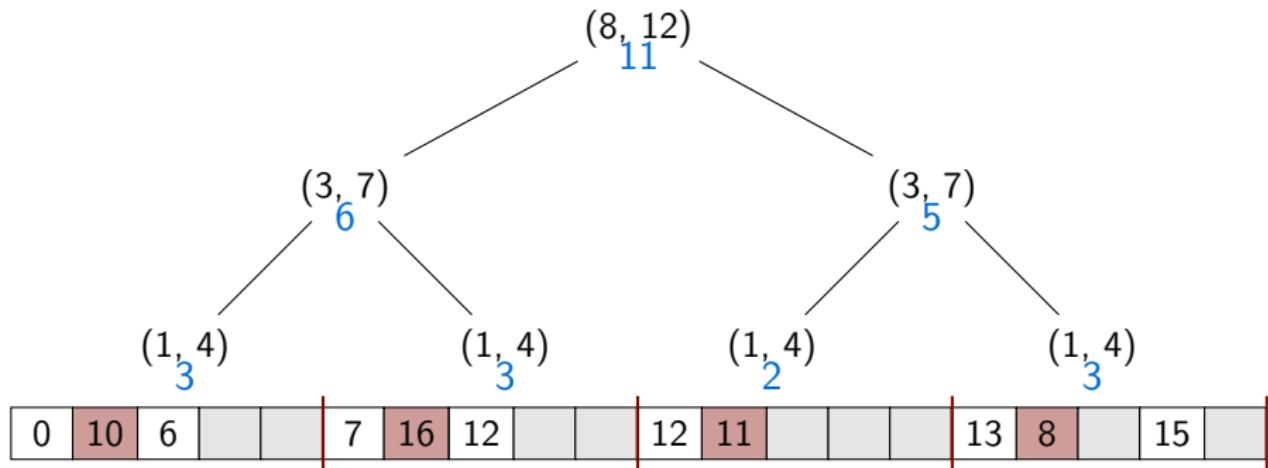
# Applying Moves by Batches

---



# Applying Moves by Batches

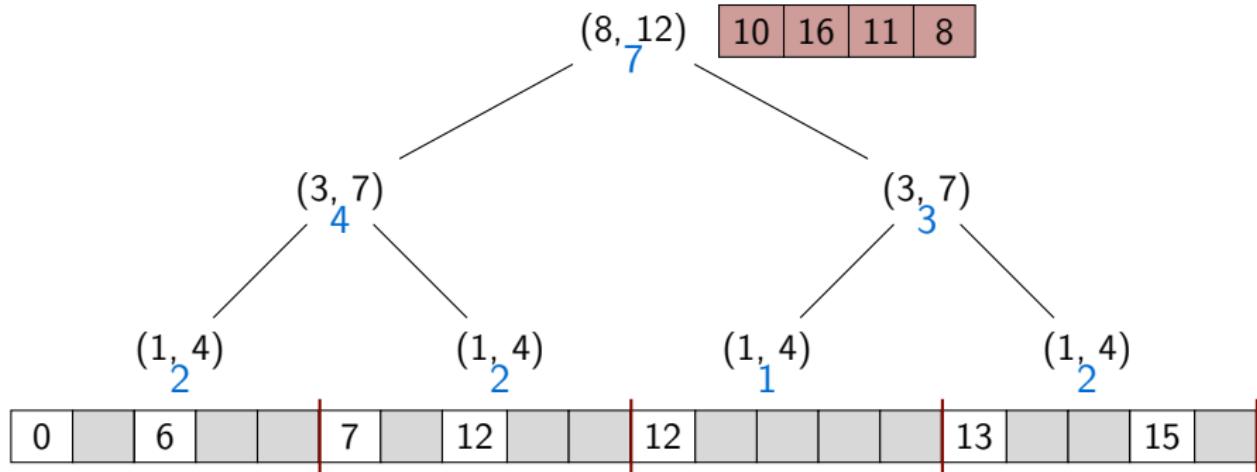
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- ① Some values change

# Applying Moves by Batches

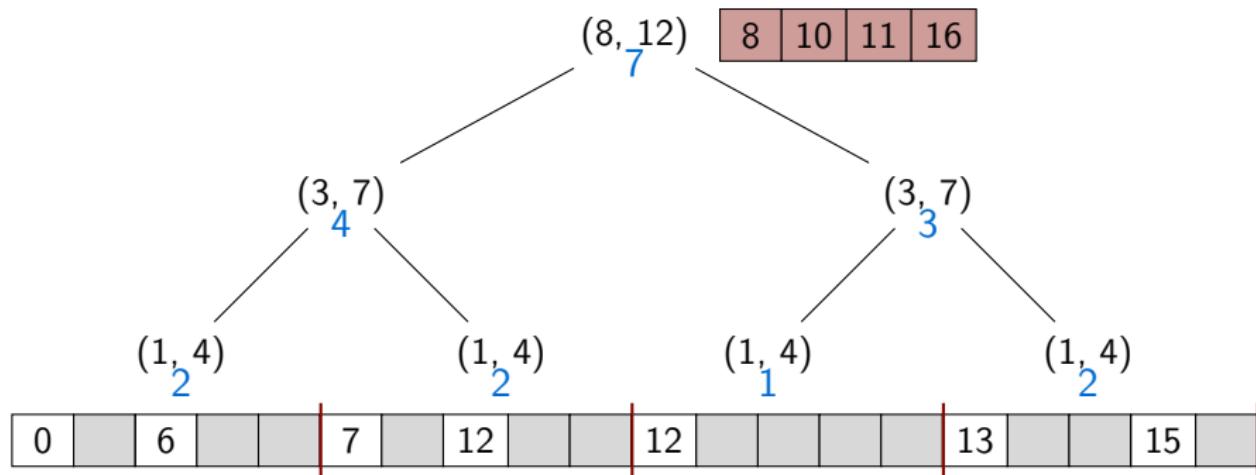
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- ① Some values change: gather in an array

# Applying Moves by Batches

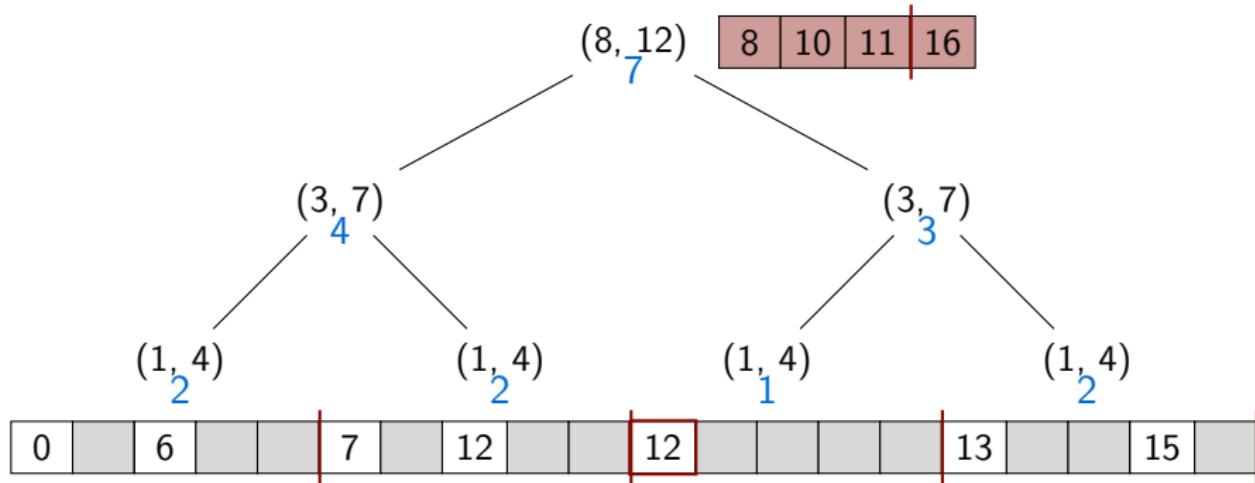
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- ① Some values change
- ② Sort of moving elements

# Applying Moves by Batches

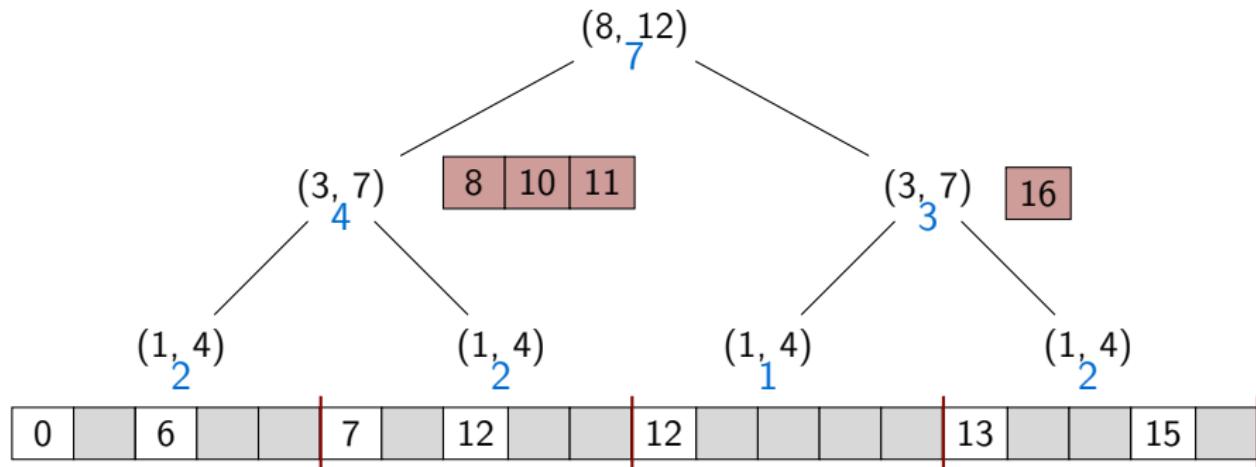
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- ① Some values change
- ② Sort of moving elements

# Applying Moves by Batches

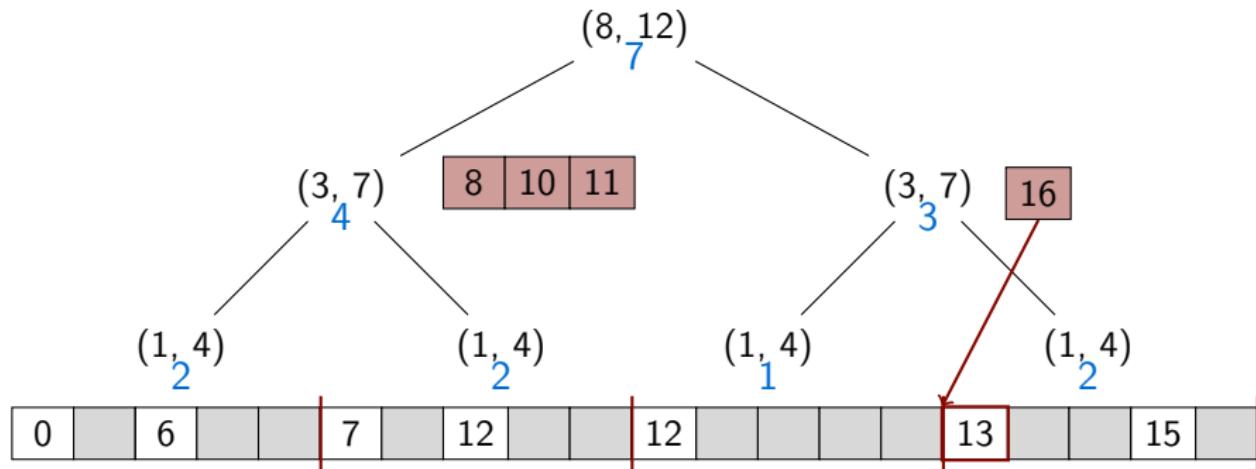
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- ① Some values change
- ② Sort of moving elements
- ③ Recursively split array according to window middle value

# Applying Moves by Batches

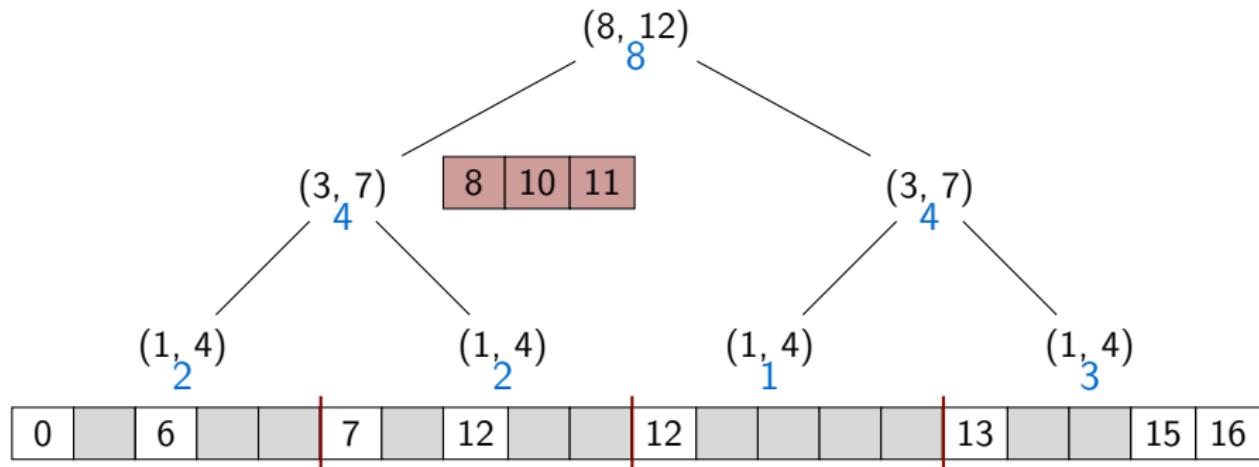
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- ① Some values change
- ② Sort of moving elements
- ③ Recursively split array according to window middle value

# Applying Moves by Batches

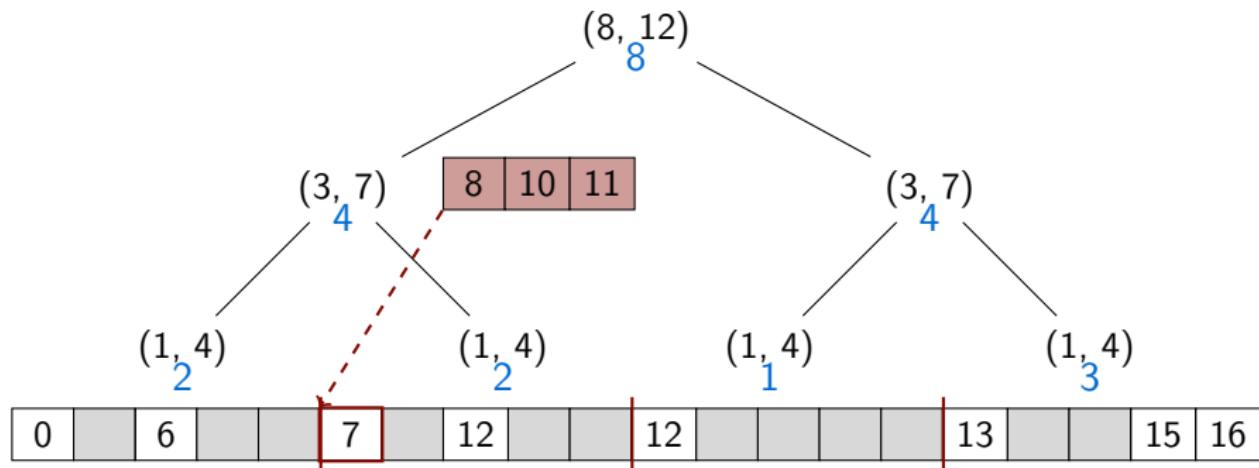
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- ① Some values change
- ② Sort of moving elements
- ③ Recursively split array according to window middle value
- ④ Direct insertion

# Applying Moves by Batches

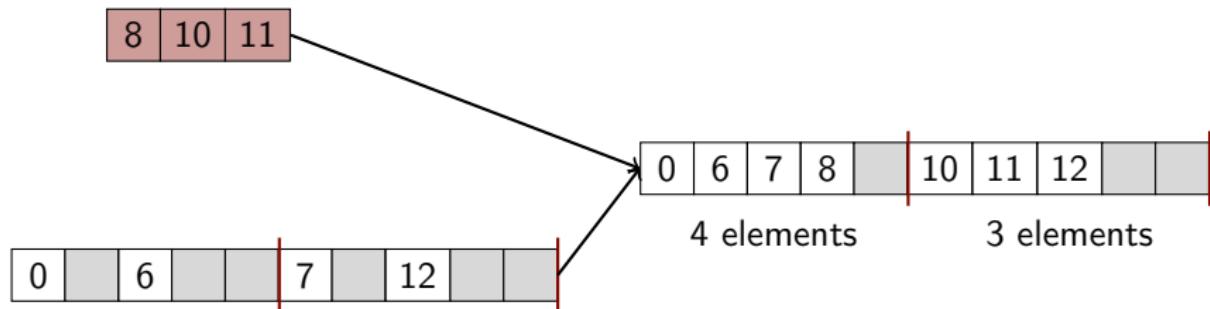
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- ① Some values change
- ② Sort of moving elements
- ③ Recursively split array according to window middle value
- ④ Direct insertion or rebalance

# Rebalance with a Single Scan

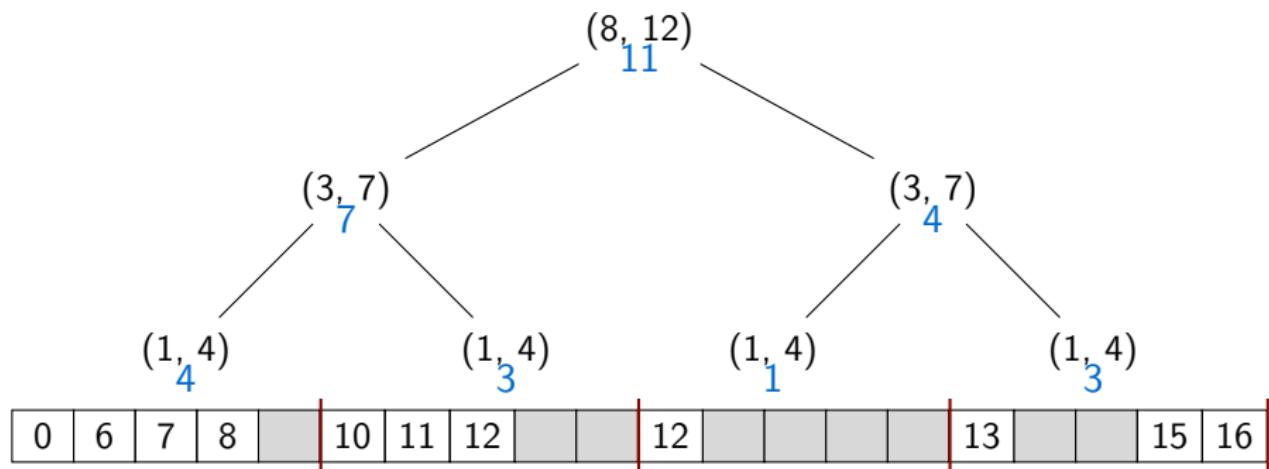
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Merging two sorted lists: one scan, in place.

## Applying Moves by Batches

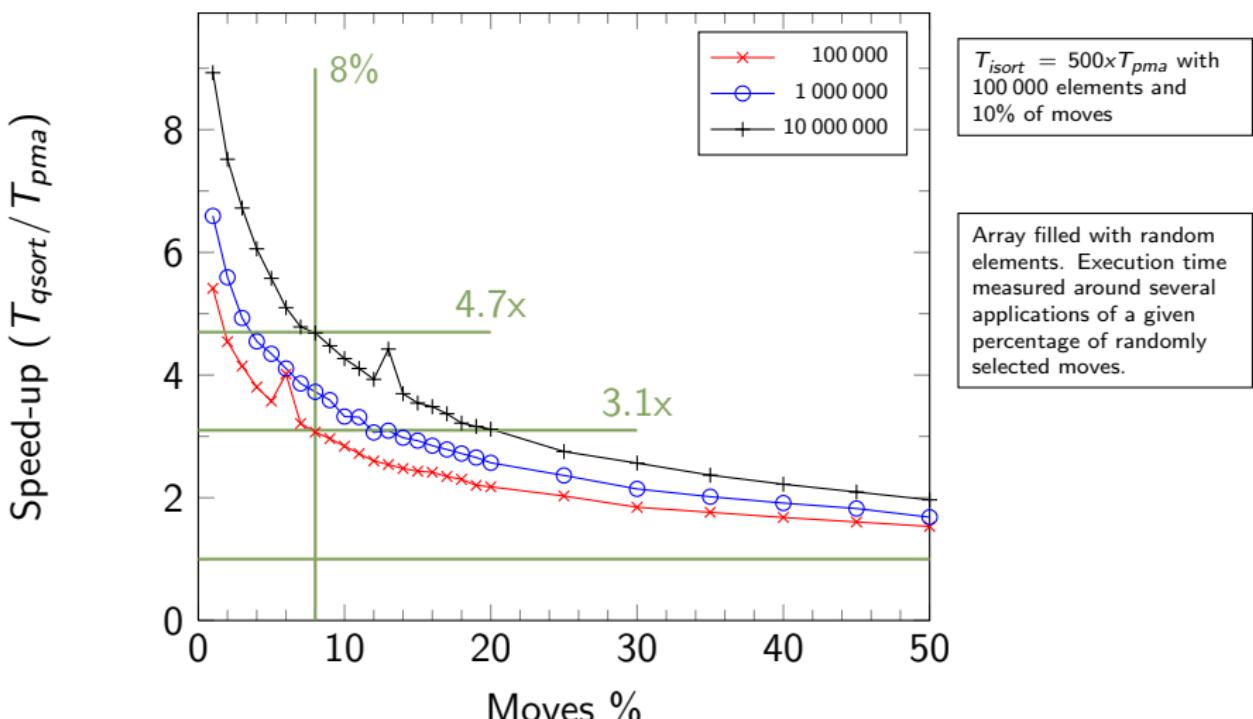
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Supports moves, insertions and deletions.

# Experimental Results: Moving Integers

## Sorting Moving Elements: Speed-up of PMA vs Qsort (Libc)



## Scan Performance

---

Dense array:

```
for i in 1 to K do  
    sum += a[i]
```

PMA:

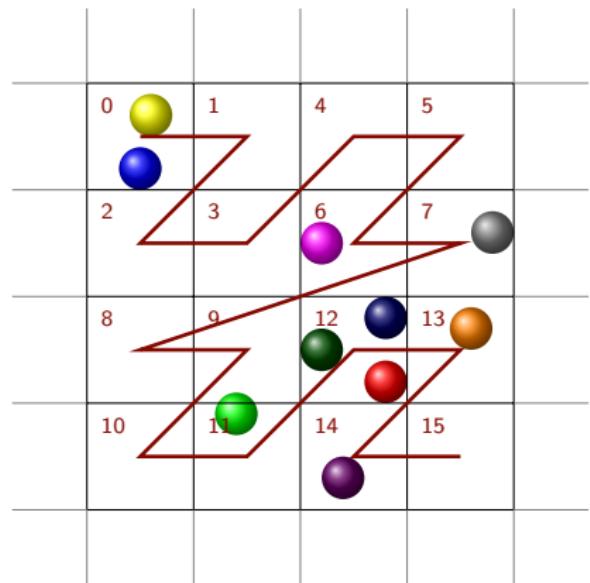
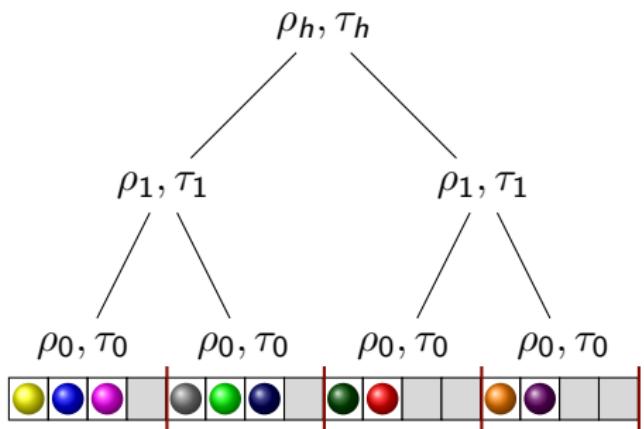
```
for i in 1 to N do  
    if isValid(a[i])  
        sum += a[i]
```

$K$	$N$	$N/K$	$T_{PMA}/T_{array}$
100 000	163 840	1.64	1.69
1 000 000	1 572 864	1.57	1.86
2 900 000	4 456 448	1.54	1.74
10 000 000	15 728 640	1.57	1.78

- Test case built to exacerbate the overhead. On realistic computation schemes it fades away.

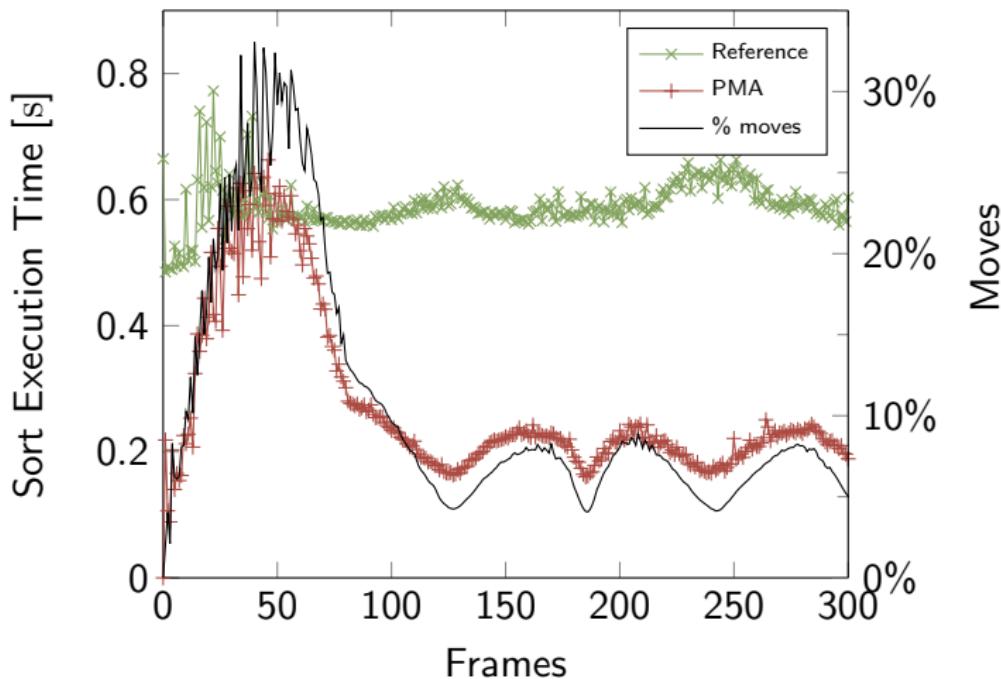
# Application to Particles

---



## Application to Particles: Results

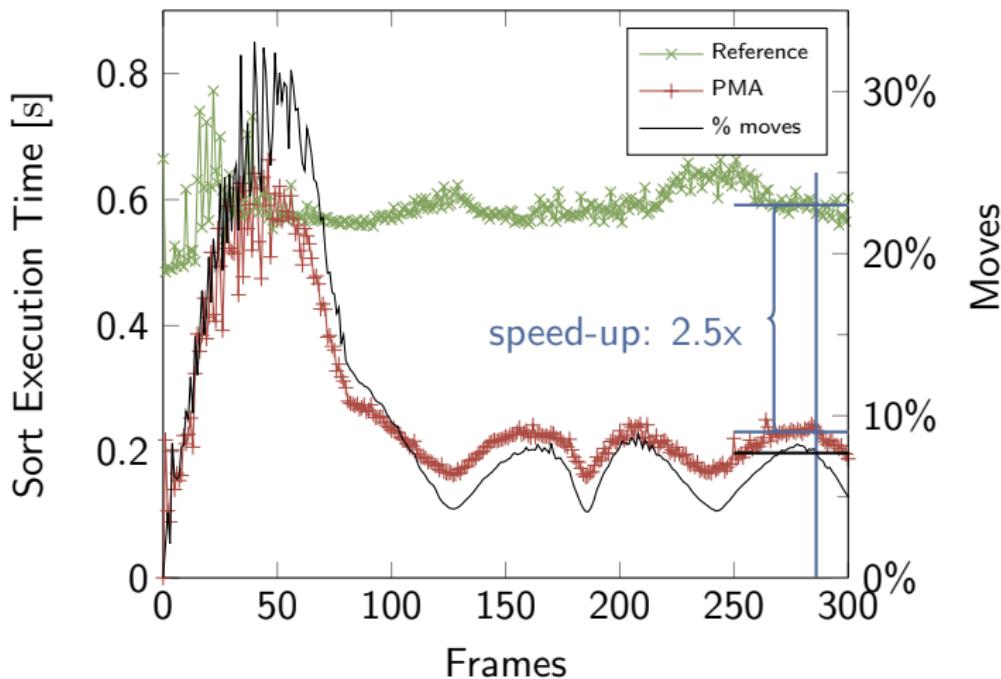
Implementation in Fluids [Hoetzlein, 2008]:  $2.9 \cdot 10^6$  particles



Global performance: 2.8% (sort is 4.5% of total simulation time).

# Application to Particles: Results

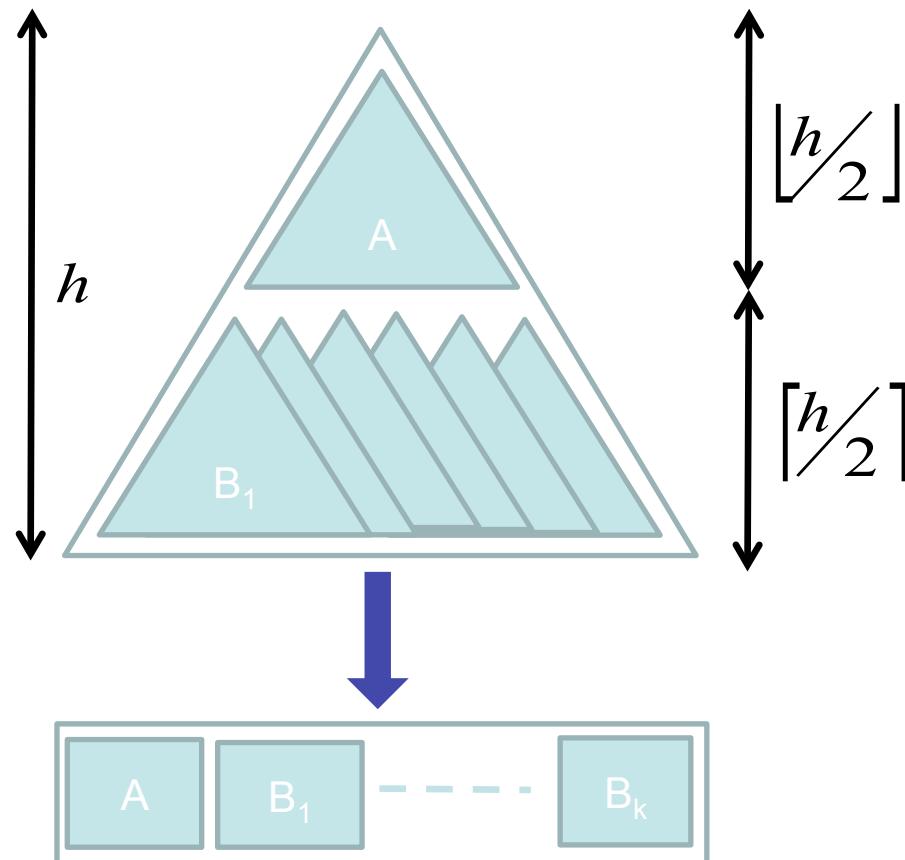
Implementation in Fluids [Hoetzlein, 2008]:  $2.9 \cdot 10^6$  particles



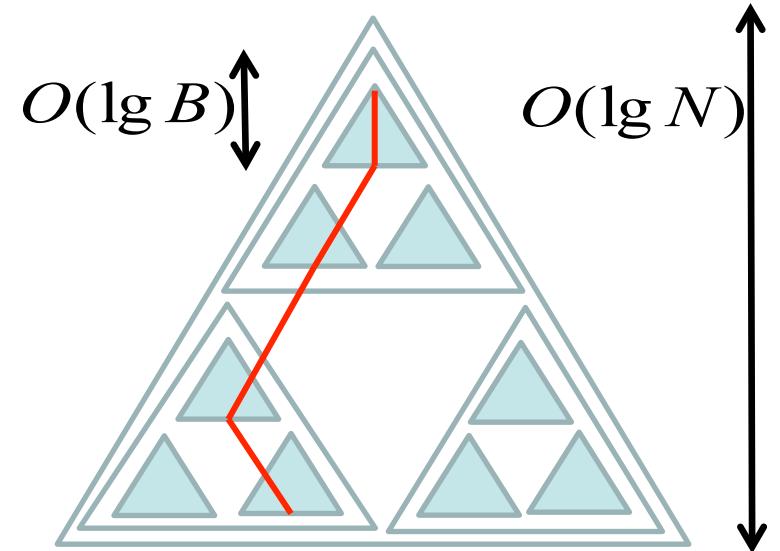
Global performance: 2.8% (sort is 4.5% of total simulation time).

# Searching in the CO model

Binary tree mapped in memory using a recursive layout



[Bender et al 2000]

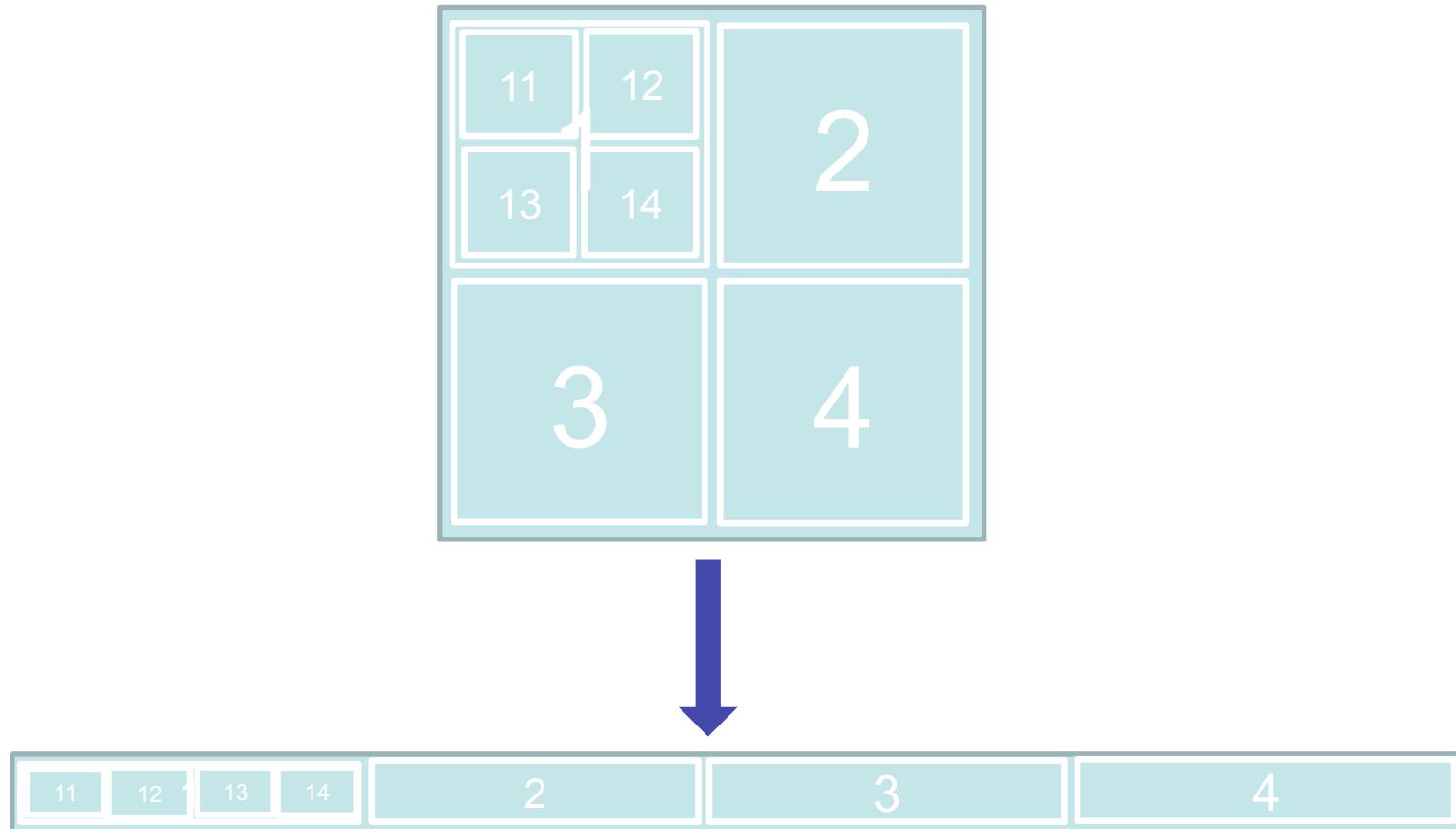


$$W(N) = O(\lg N)$$

$$Q(N) = O(1) \cdot \frac{O(\lg N)}{O(\lg B)} = O(\log_B N)$$

# Multiplying in the CO model

D&C matrix multiplication using a recursive layout



# Multiplying in the CO model

D&C matrix multiplication using a recursive layout

$$W(N) = \begin{cases} 8W\left(\frac{N}{2}\right) + O(N^2) & \text{if } N > 1 \\ O(1) & \text{otherwise} \end{cases}$$
$$W(N) = O(N^3)$$

$$Q(N) = \begin{cases} 8Q\left(\frac{N}{2}\right) + O\left(\frac{N^2}{B}\right) & \text{if } N^2 > M/3 \\ O\left(\frac{N^2}{B}\right) & \text{otherwise} \end{cases}$$

$$Q(N) = O\left(\frac{N^3}{B\sqrt{M}}\right)$$

