

# CSE 6220/CX 4220

## Introduction to HPC

# Lecture 18: Hierarchical Methods for the N-Body Problem

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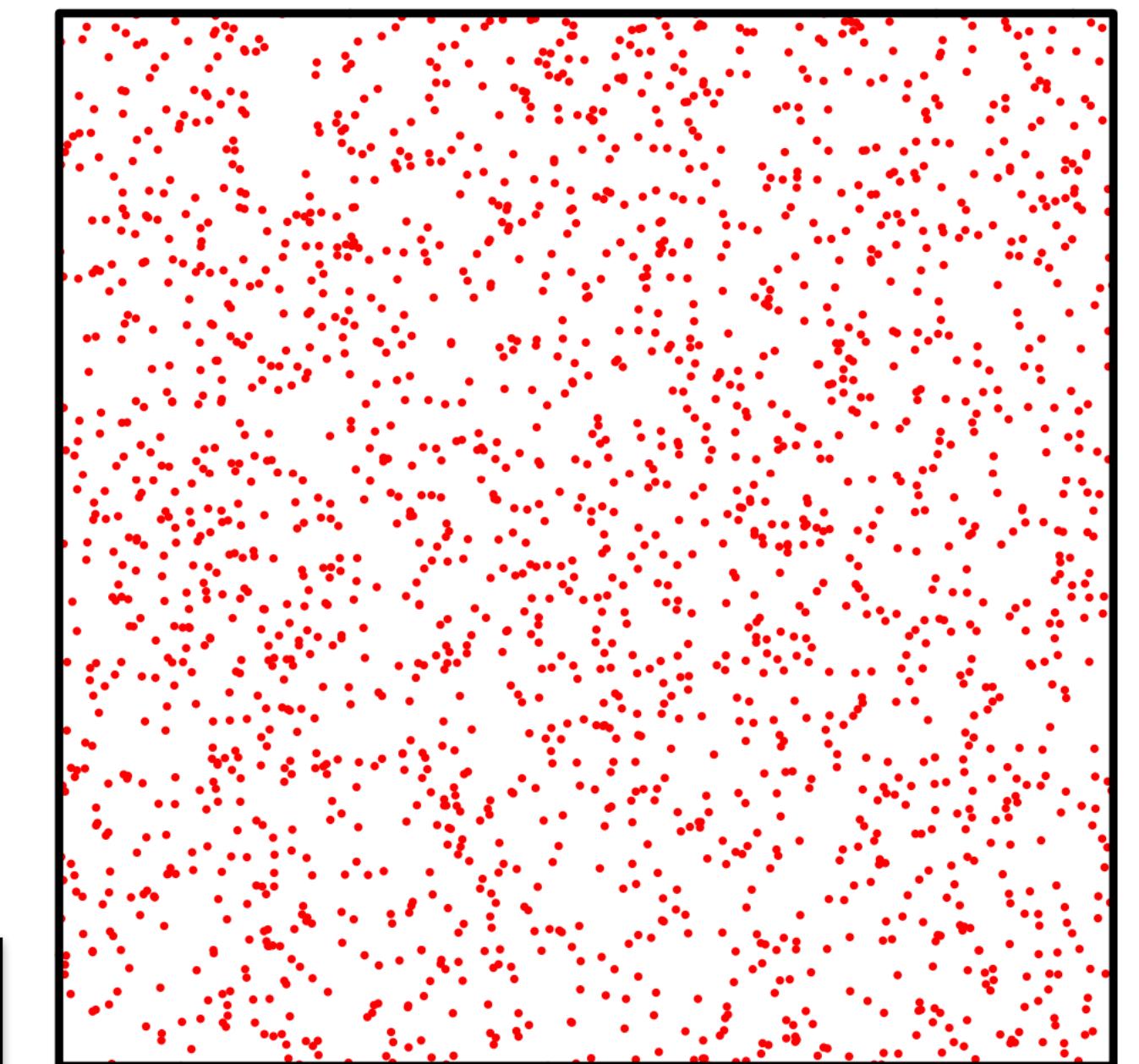
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# Motivation

- **Computational simulation** is becoming an accepted paradigm for scientific discovery - but can involve several million variables
- Most large problems boil down to solution of linear systems or matrix-vector product
- Regular product requires  $O(n^2)$  time and memory



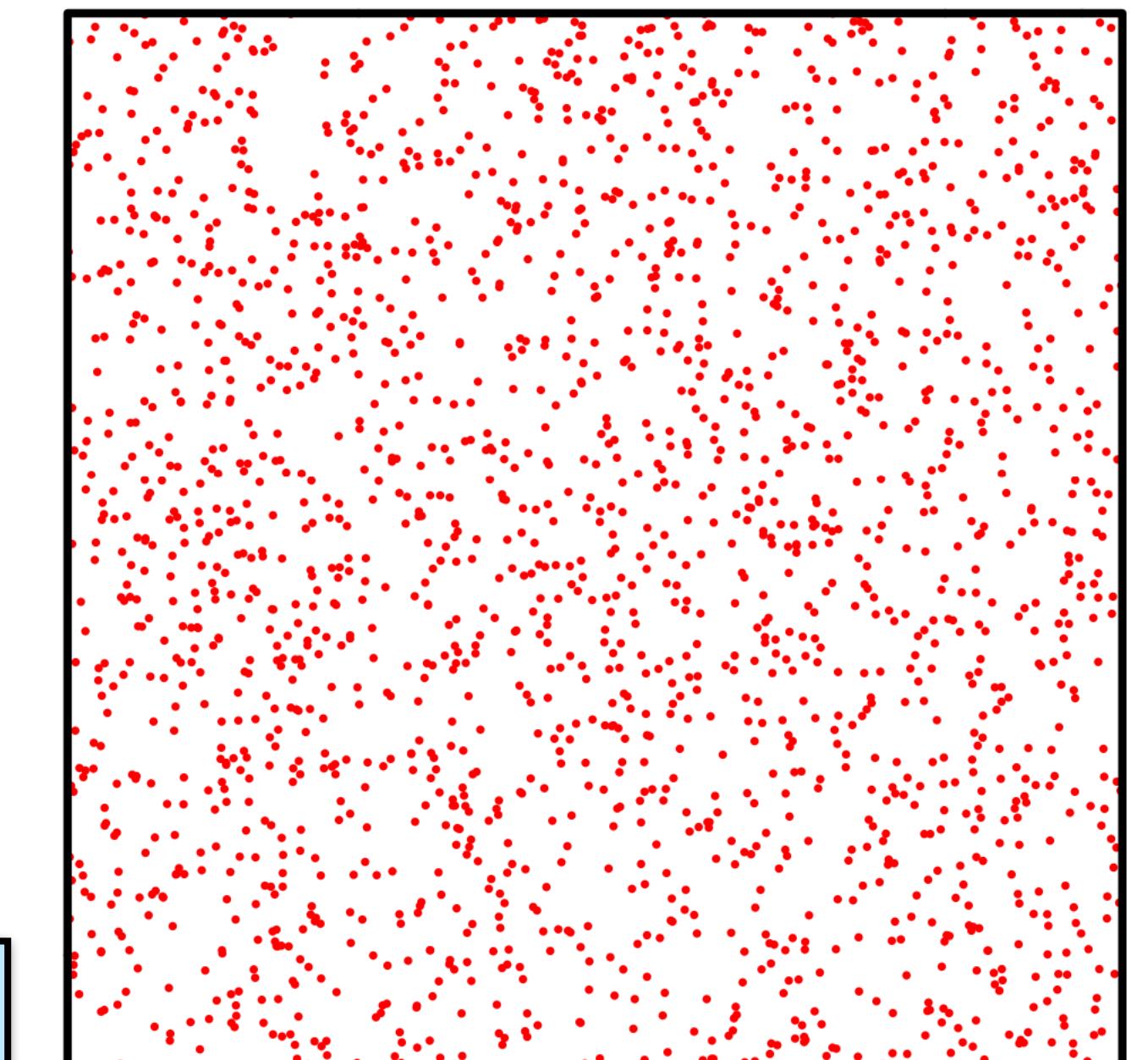
Applying the idea recursively: cost drops to  $O(n \log n)$  or even  $O(n)$

[https://www.cscamm.umd.edu/programs/fam04/dg\\_lecture1.pdf](https://www.cscamm.umd.edu/programs/fam04/dg_lecture1.pdf)

Diagram from [https://amath.colorado.edu/faculty/martinss/2014\\_CBMS/Lectures/lecture02.pdf](https://amath.colorado.edu/faculty/martinss/2014_CBMS/Lectures/lecture02.pdf)

# Motivation

- Intuition - **compress dependence on “distant” data**
- Compressing data of groups at nearby points can cut cost (work, communication) at distant points
- Examples:
  - multigrid for elliptic PDE
  - multilevel graph partitioning (METIS, Chaco, ...)
  - Barnes-Hut or Fast Multipole Method (FMM) for electrostatics/gravity/...



Applying the idea recursively: cost drops to  $O(n \log n)$  or even  $O(n)$

[https://www.cscamm.umd.edu/programs/fam04/dg\\_lecture1.pdf](https://www.cscamm.umd.edu/programs/fam04/dg_lecture1.pdf)

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# Particle Simulation

```
t=0
while t < t_final:
    for i = 1 to n
        compute f(i) = force on particle i
    for i = 1 to n
        move particle i under force f(i) for time dt
    compute interesting properties of particles (energy, etc.)
    t = t + dt
end while
```

Most complicated component in computing  $f(i)$  is **n-body force**, e.g., gravity or electrostatics

$$f(i) = \sum_{k \neq i} f(i, k)$$

$f(i, k) = \text{force on } i \text{ from } k$

Obvious algorithm requires computing all-to-all interactions for  $O(n^2)$ , but we can do better

# Motivation

- Listed as one of the top 10 algorithms of the 20th century (IEEE magazine)
- Frequently used in scientific computing

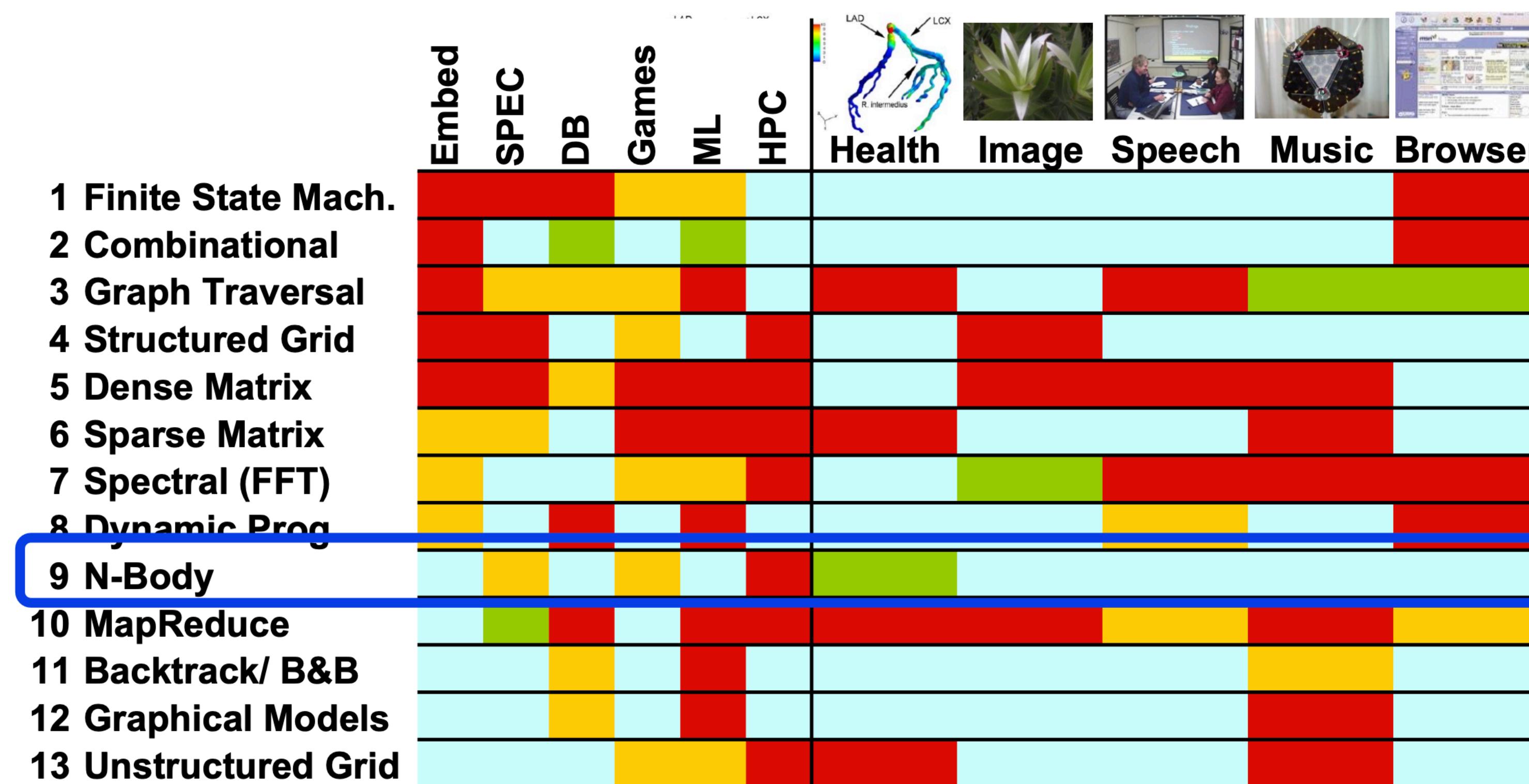


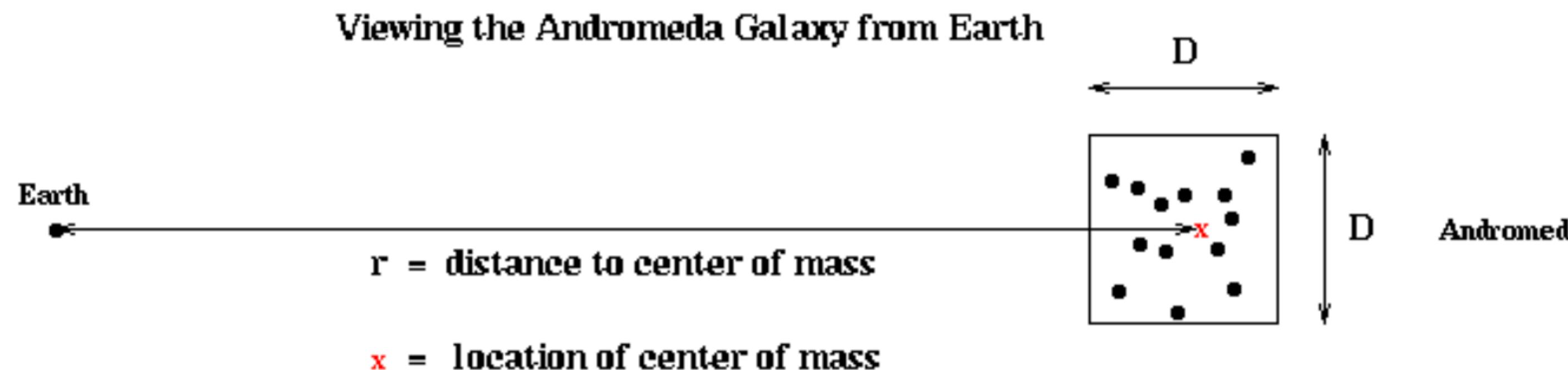
diagram from UC  
Berkeley  
CS267

# Applications

- **Astrophysics and Celestial Mechanics - 1992**
  - Intel Delta = 1992 supercomputer, 512 Intel i860s
  - **17 million particles, 600 time steps, 24 hours elapsed time**
    - M. Warren and J. Salmon
    - **Gordon Bell Prize at Supercomputing 1992**
  - **Sustained 5.2 Gigaflops = 44K Flops/particle/time step**
  - **1% accuracy**
  - Direct method (17 Flops/particle/time step) at 5.2 Gflops would have taken 18 years, 6570 times longer
- **Vortex particle simulation of turbulence – 2009**
  - Cluster of 256 NVIDIA GeForce 8800 GPUs
  - **16.8 million particles**
    - T. Hamada, R. Yokota, K. Nitadori. T. Narumi, K. Yasuki et al
    - **Gordon Bell Prize for Price/Performance at Supercomputing 2009**
  - **Sustained 20 Teraflops, or \$8/Gigaflop**

# Reducing the number of particles in the force sum

- All later divide and conquer algorithms use same intuition
- Consider computing force on earth due to all celestial bodies
  - Look at night sky, # terms in force sum  $\geq$  number of visible stars
  - Oops! One “star” is really the Andromeda galaxy, which contains billions of real stars
    - Seems like a lot more work than we thought ...
- Don’t worry, ok to approximate all stars in Andromeda by a single point at its center of mass (CM) with same total mass (TM)
  - D = size of box containing Andromeda , r = distance of CM to Earth
  - Require that  $D/r$  be “small enough”

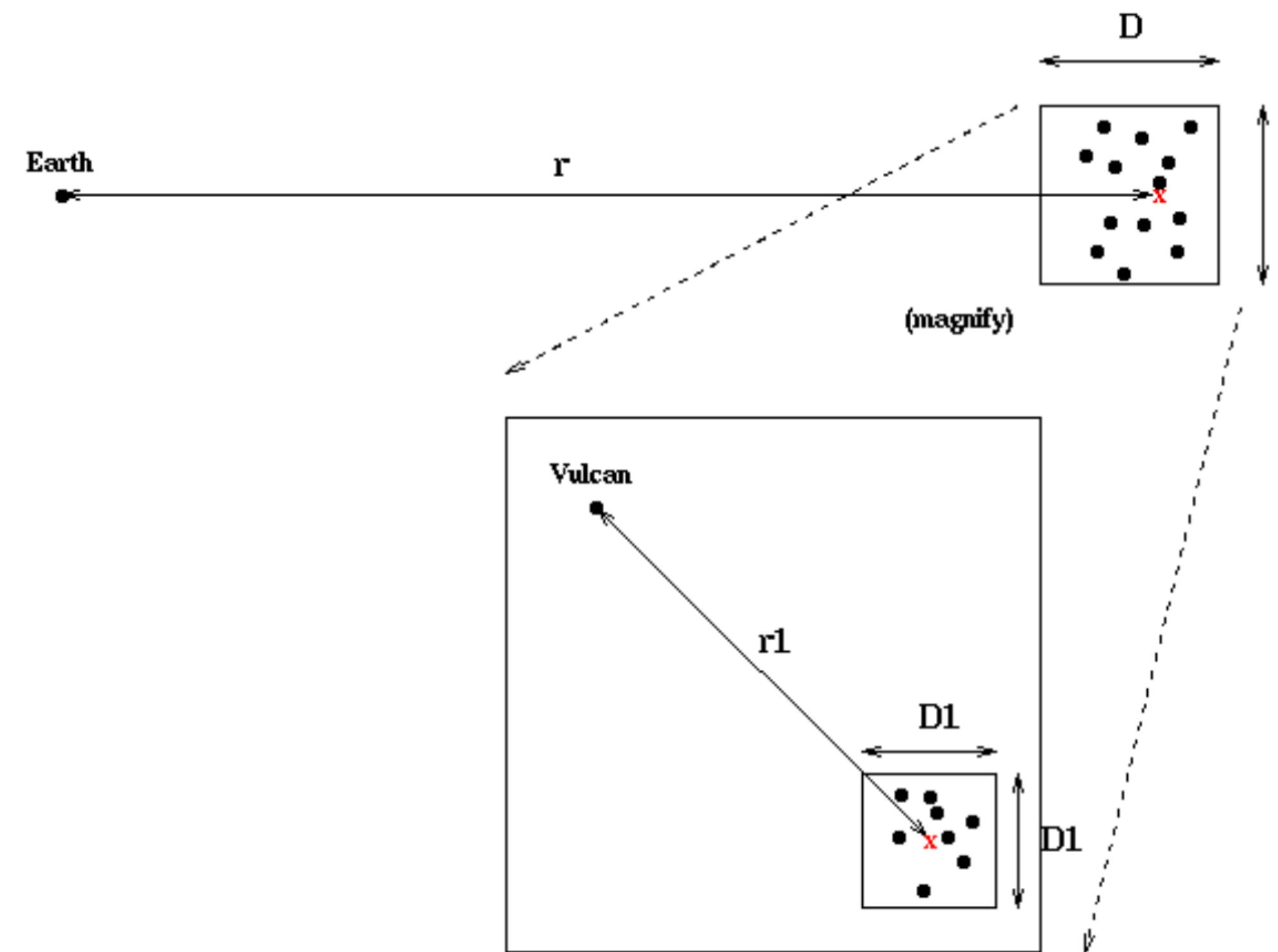


- Idea not new: Newton approximated earth and falling apple by CMs

# What is new: Using points at CM recursively

- ° From Andromeda's point of view, Milky Way is also a point mass
- ° Within Andromeda, picture repeats itself
  - As long as  $D_1/r_1$  is small enough, stars inside smaller box can be replaced by their CM to compute the force on Vulcan
  - Boxes nest in boxes recursively

Replacing Clusters by their Centers of Mass Recursively

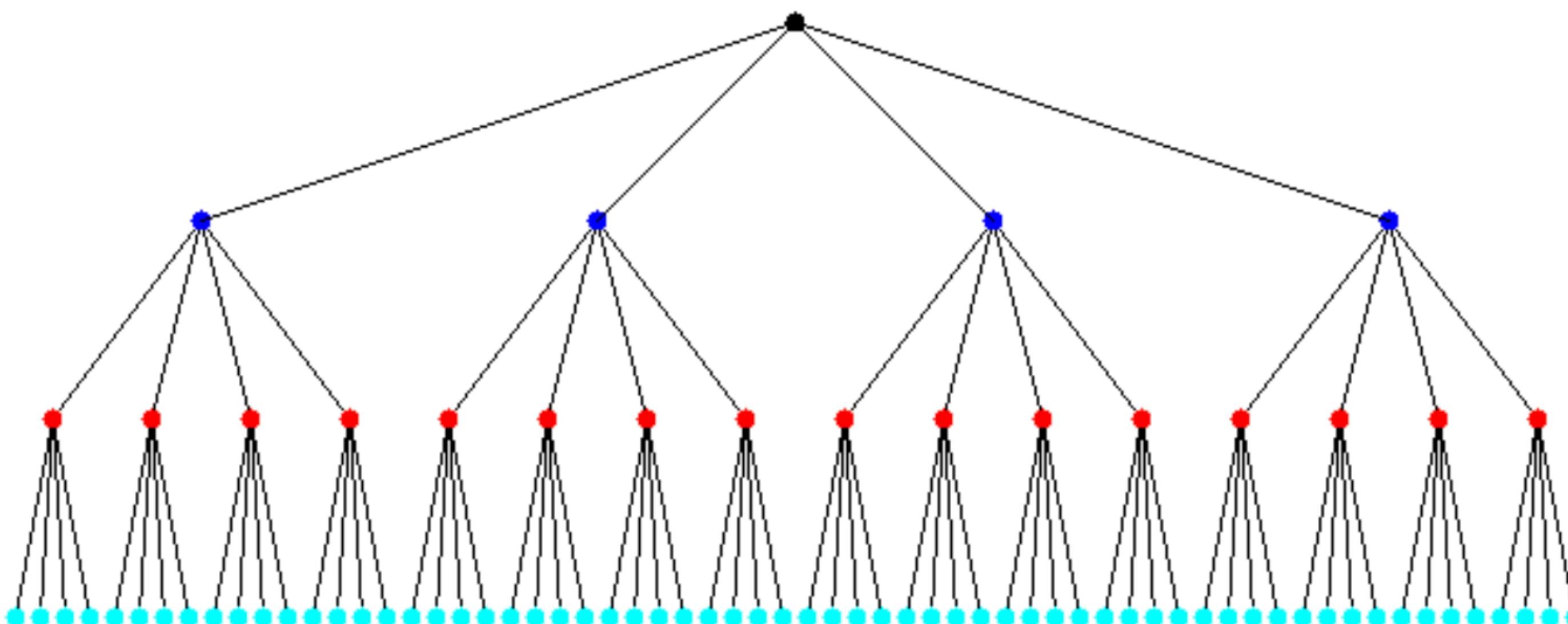
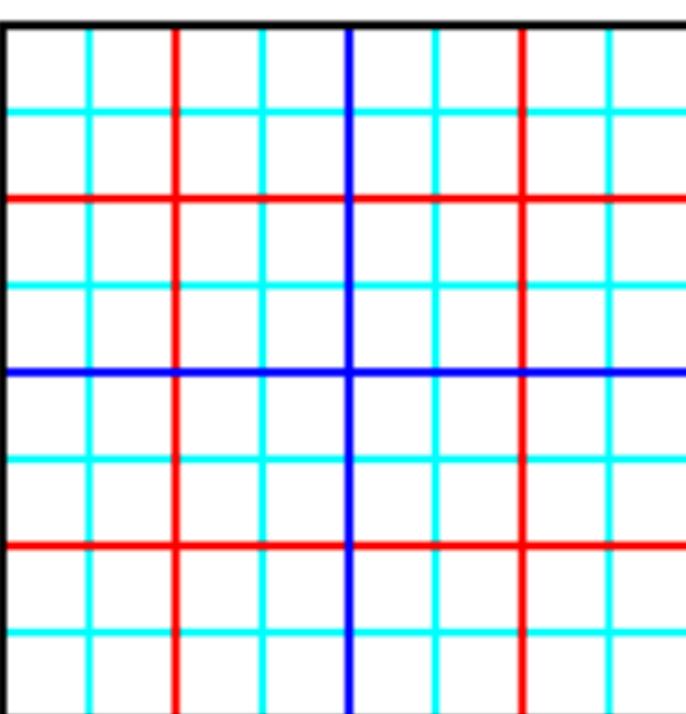


# **Basic Data Structures: Quad Trees and Oct Trees**

# Quad Trees

- ° **Data structure to subdivide the plane**
  - Nodes can contain coordinates of center of box, side length
  - Eventually also coordinates of CM, total mass, etc.
- ° **In a complete quad tree, each nonleaf node has 4 children**

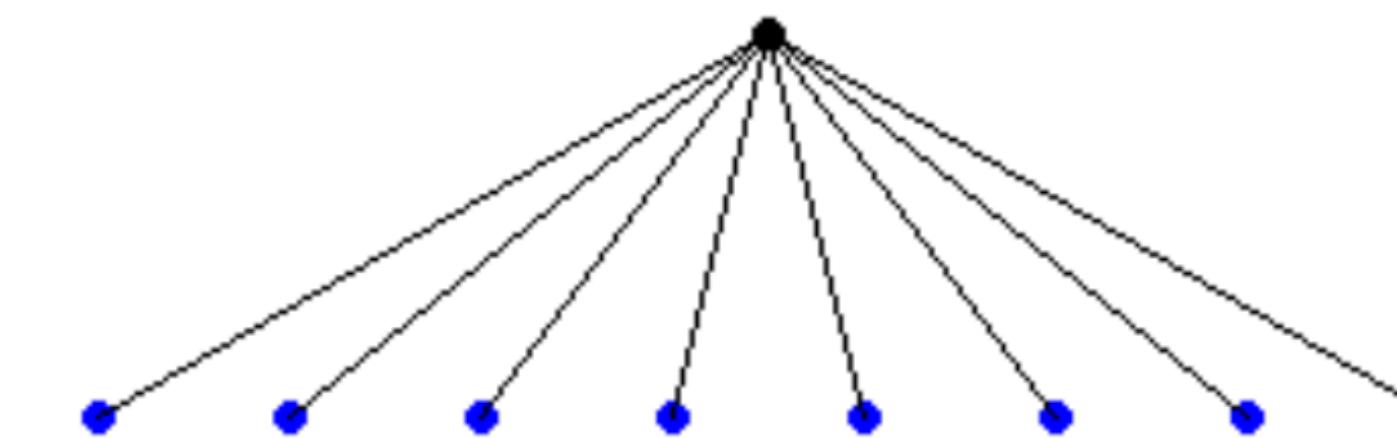
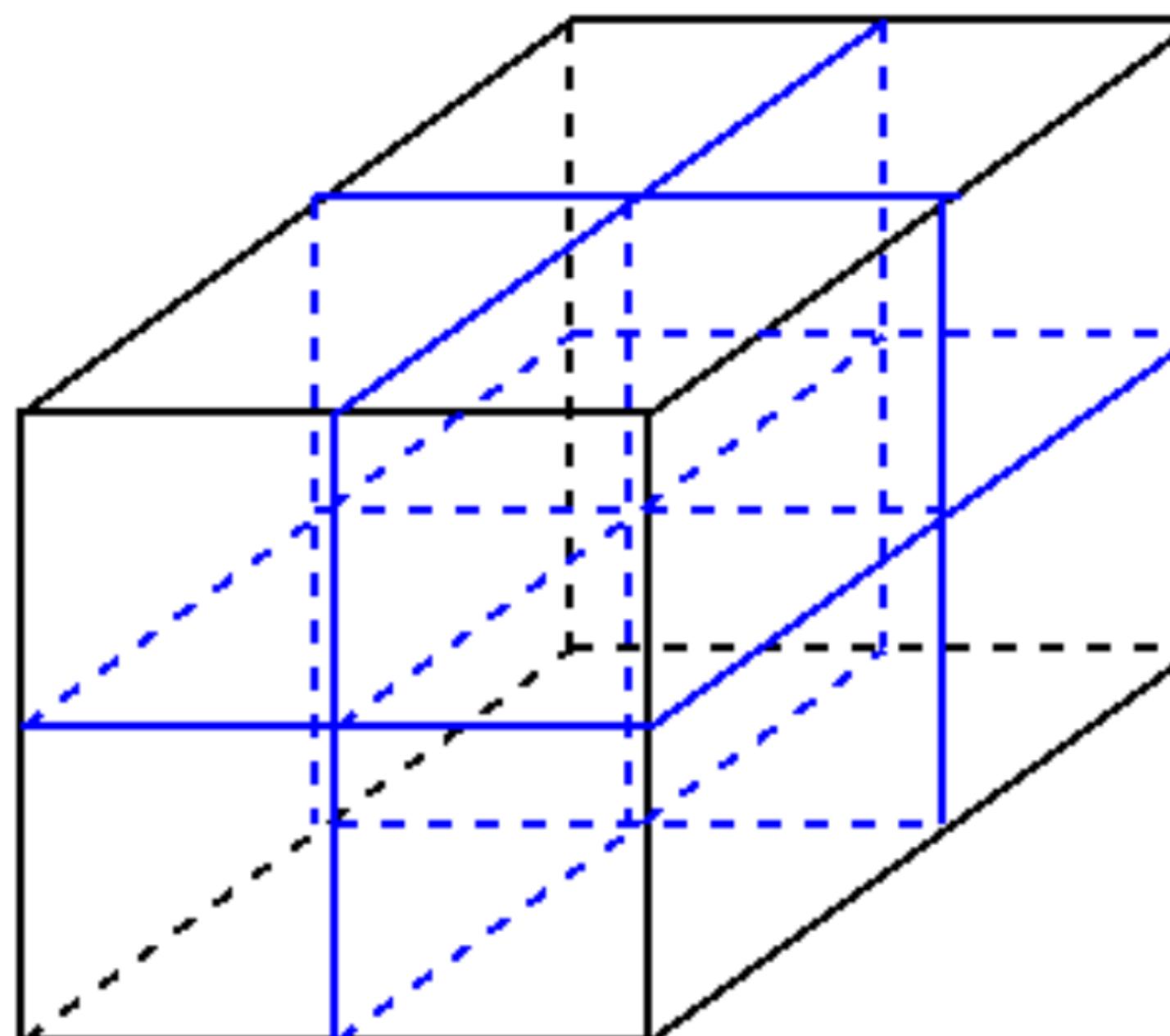
A Complete Quadtree with 4 Levels



# Oct Trees

- ° Similar Data Structure to subdivide space

2 Levels of an Octree

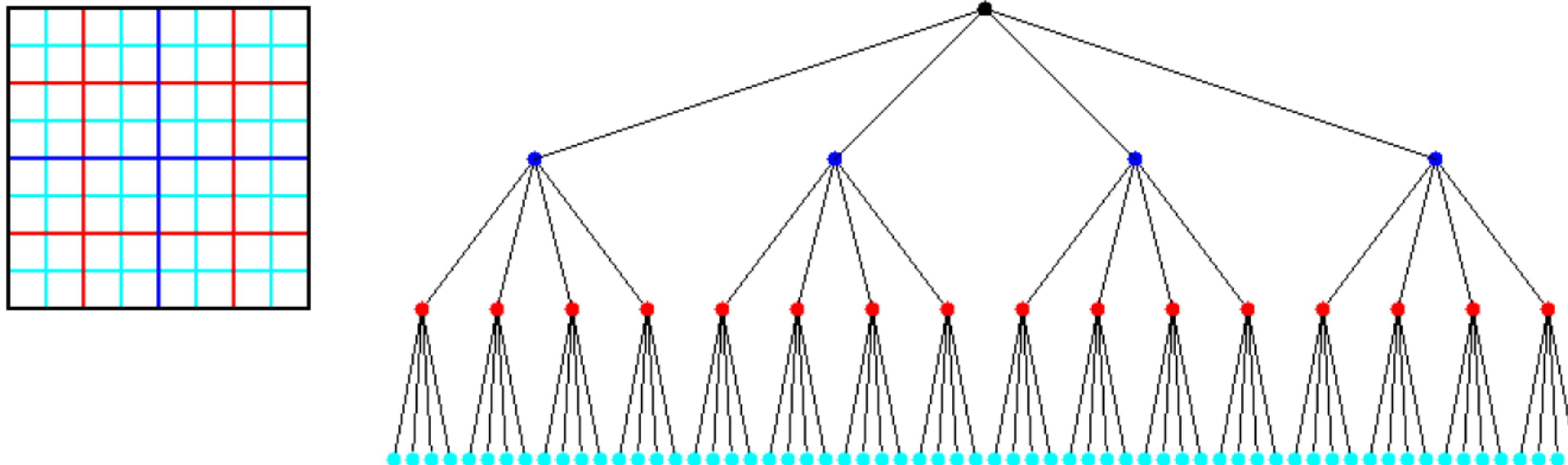


# Using Quad Trees and Oct Trees

- All our algorithms begin by constructing **a tree to hold all the particles**
- Interesting cases have nonuniformly distributed particles

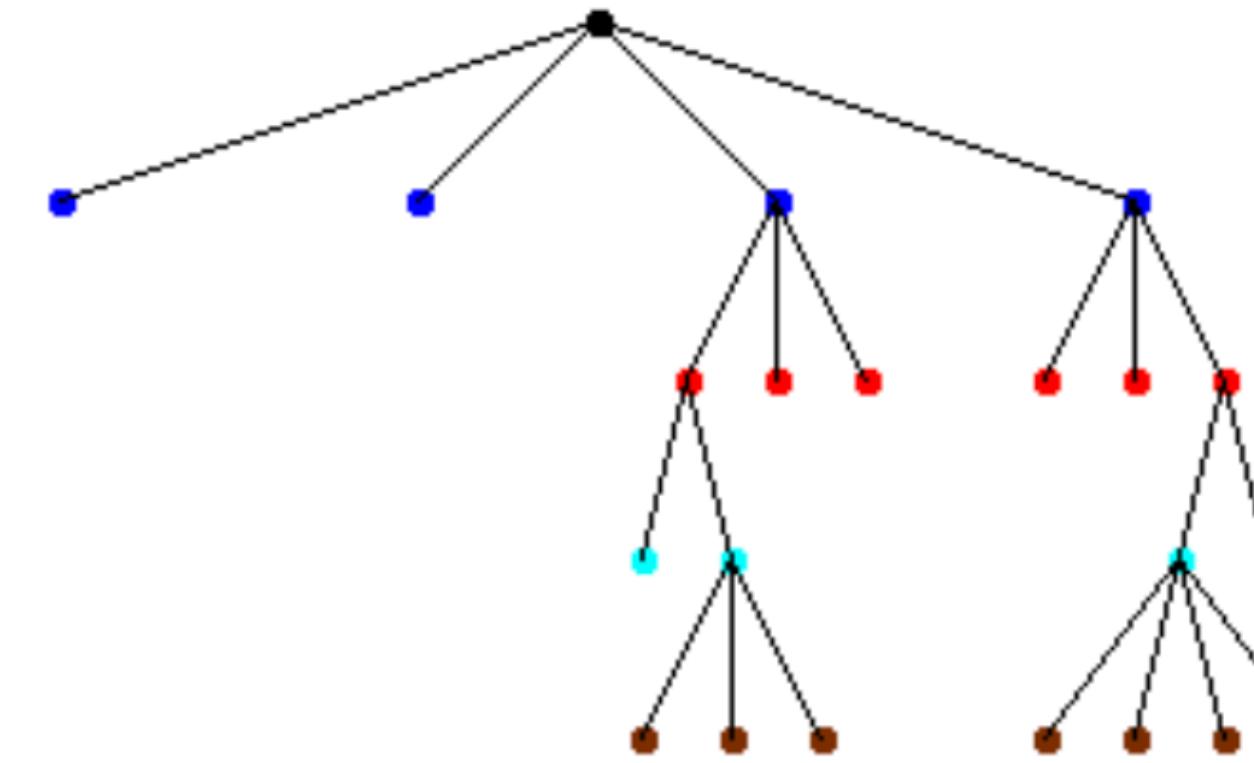
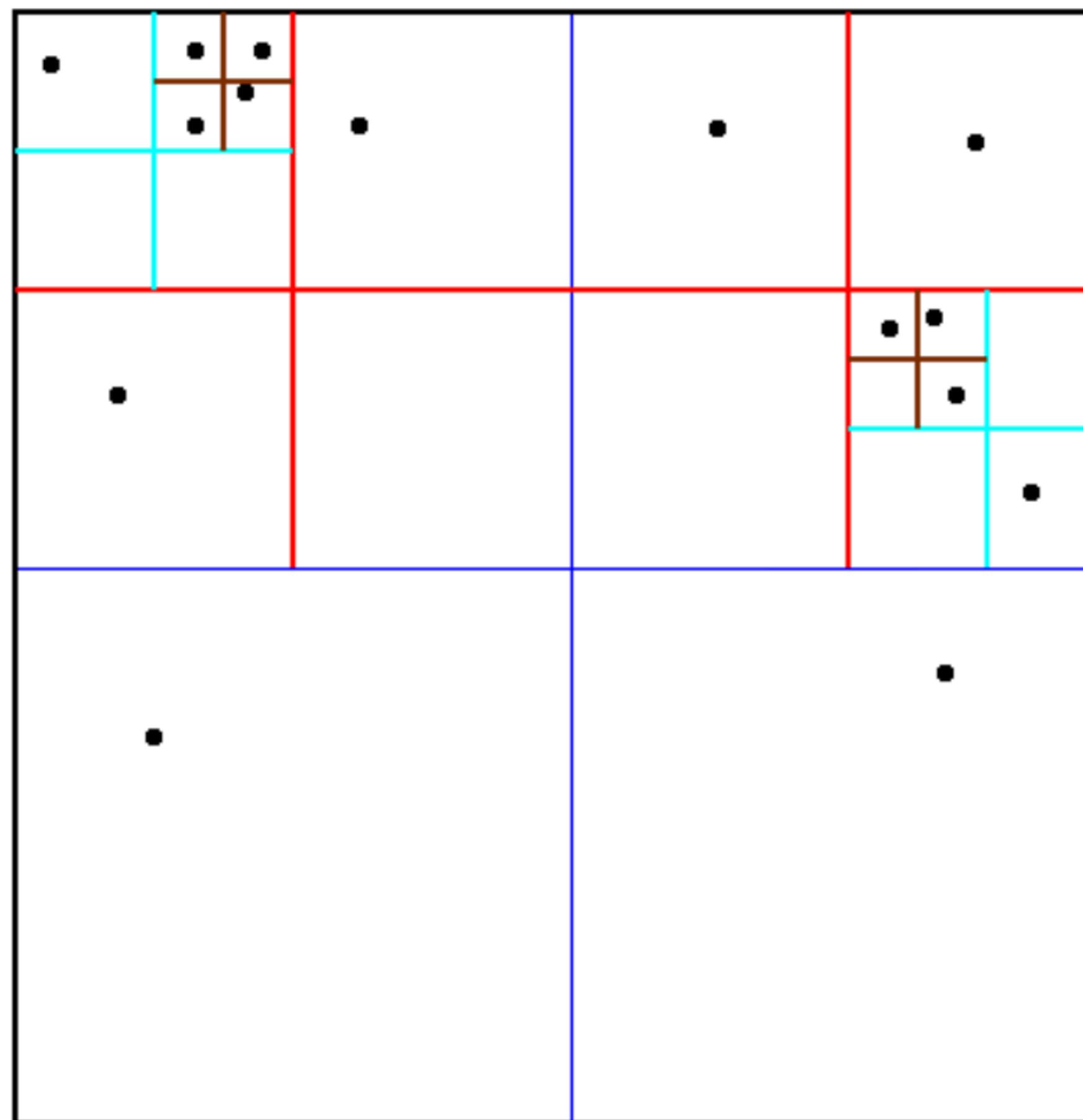
In a complete tree most nodes would be empty, wasting space and time

- **Adaptive** Quad (Oct) Tree only subdivides space where particles are located



# Example of an Adaptive Quad Tree

Adaptive quadtree where no square contains more than 1 particle



Child nodes enumerated counterclockwise  
from SW corner, empty ones excluded

In practice, have  $q > 1$  particles/square; tuning parameter

# Cost of Adaptive Quad Tree Construction

- ° **Cost  $\leq N * \text{maximum cost of Quad\_Tree\_Insert}$**   
**=  $O( N * \text{maximum depth of Quad\_Tree})$**
- ° **Uniform Distribution of particles**
  - Depth of Quad\_Tree =  $O( \log N )$
  - Cost  $\leq O( N * \log N )$
- ° **Arbitrary distribution of particles**
  - Depth of Quad\_Tree =  $O( \# \text{ bits in particle coords} ) = O( b )$
  - Cost  $\leq O( b N )$

## Barnes-Hut Algorithm (BH)

An  $O(n \log n)$  approximation algorithm for the  
N-Body Problem

# Barnes-Hut Algorithm

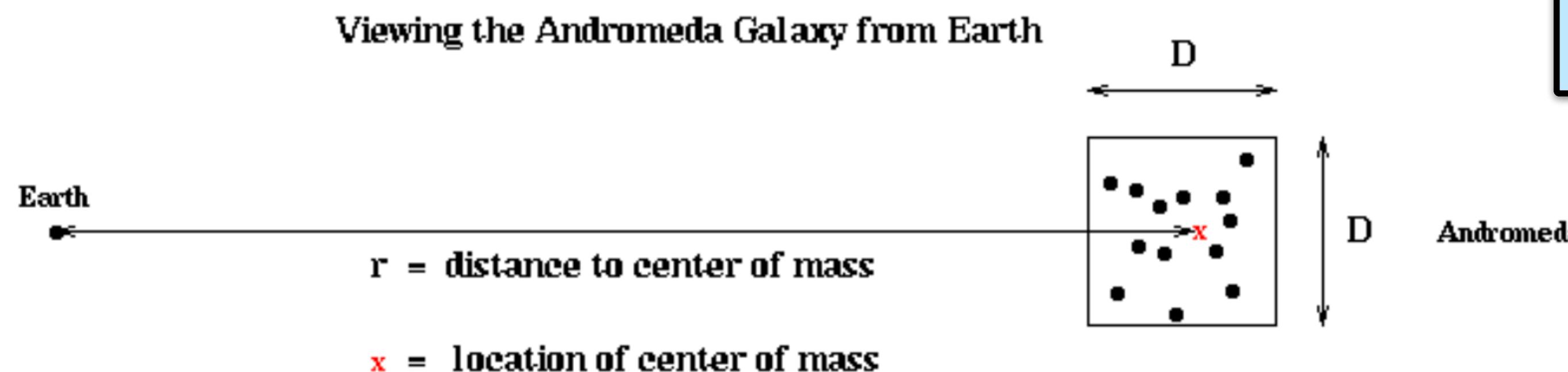
- ° **High Level Algorithm (in 2D, for simplicity)**

- 1) Build the QuadTree using QuadTreeBuild
  - ... already described, cost =  $O(N \log N)$  or  $O(bN)$
- 2) For each node = subsquare in the QuadTree, compute the CM and total mass (TM) of all the particles it contains
  - ... “post order traversal” of QuadTree, cost =  $O(N \log N)$  or  $O(bN)$
- 3) For each particle, traverse the QuadTree to compute the force on it, using the CM and TM of “distant” subsquares
  - ... core of algorithm
  - ... cost depends on accuracy desired but still  $O(N \log N)$  or  $O(bN)$

Center of mass of  
a cell is the  
weighted average  
of centers of its  
children

# Step 3 of BH: Compute force on each particle

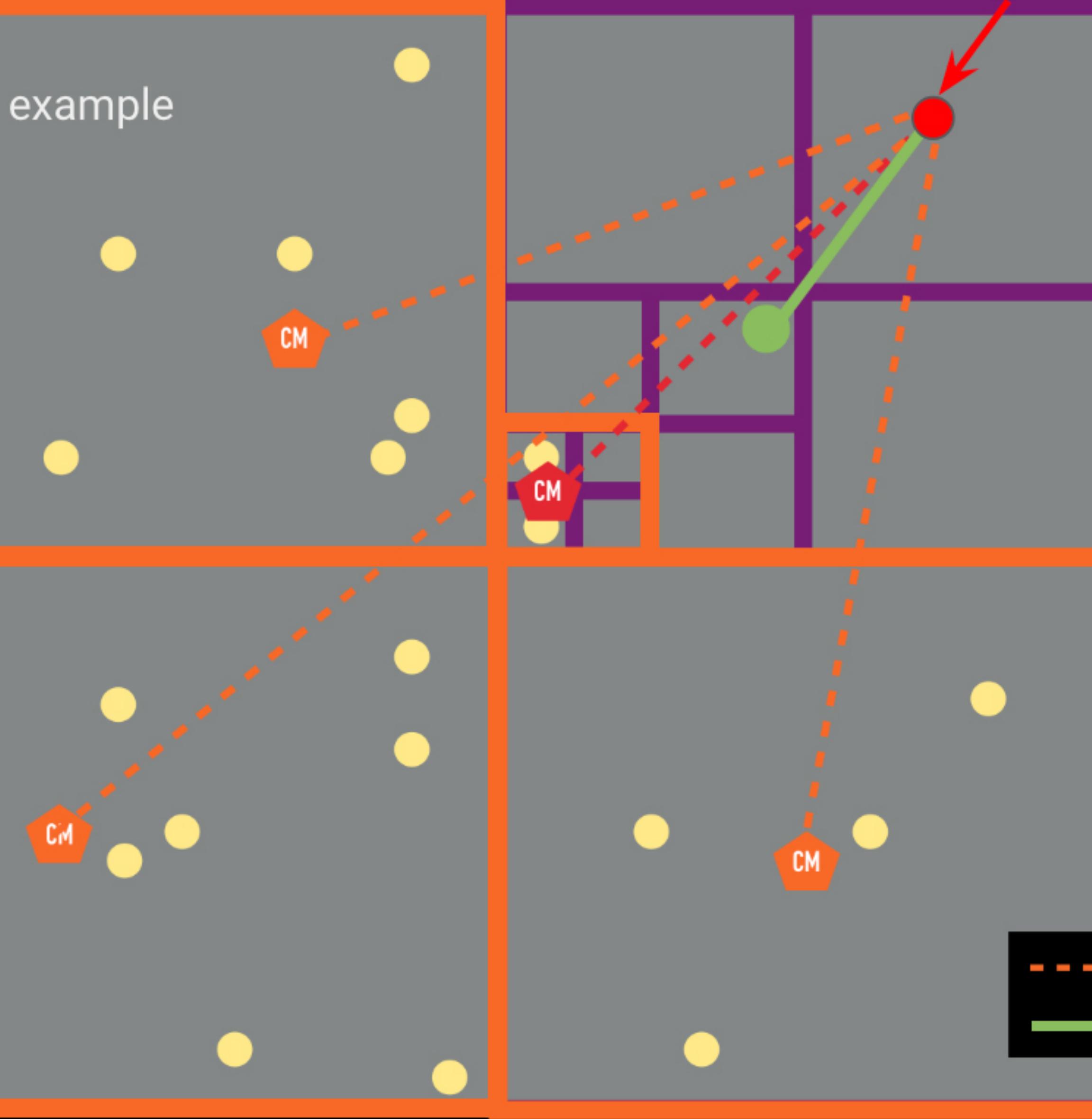
- For each node = square, can approximate force on particles outside the node due to particles inside node by using the node's CM and TM
- This will be accurate enough if the node is “far away enough” from the particle
- For each particle, use as few nodes as possible to compute force, subject to accuracy constraint
- Need criterion to decide if a node is far enough from a particle
  - $D$  = side length of node
  - $r$  = distance from particle to CM of node
  - $\theta$  = user supplied error tolerance  $< 1$
  - Use CM and TM to approximate force of node on box if  $D/r < \theta$



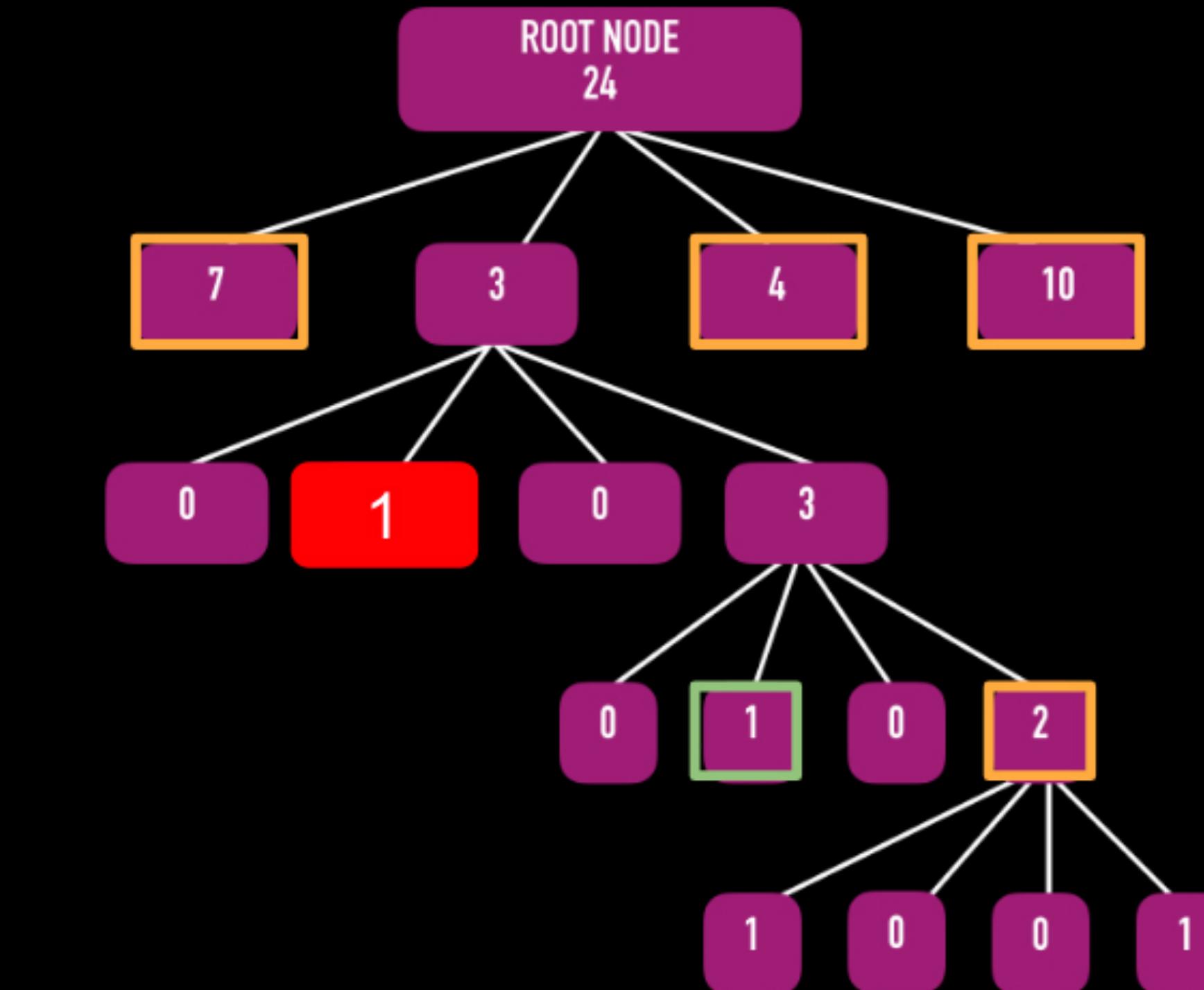
If ratio of (cell width / node's center of mass) is more than  $\Theta$

Compute force on this particle

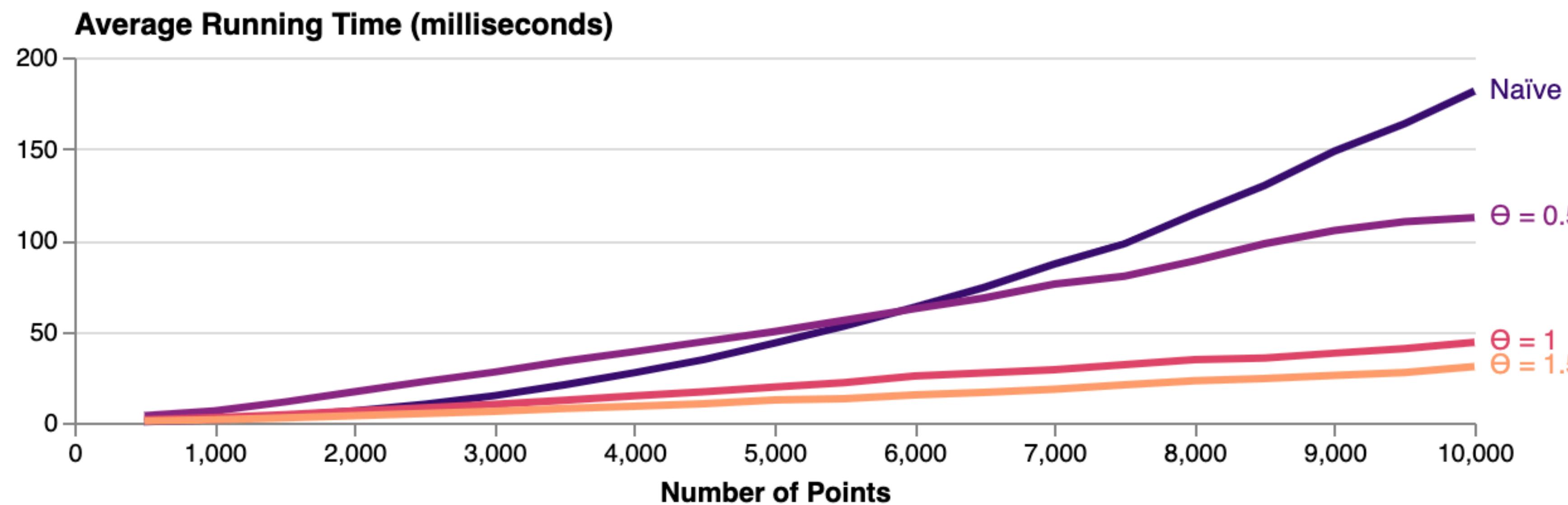
2D example



In total, Barnes-Hut required only 5 force calculations instead of 23!

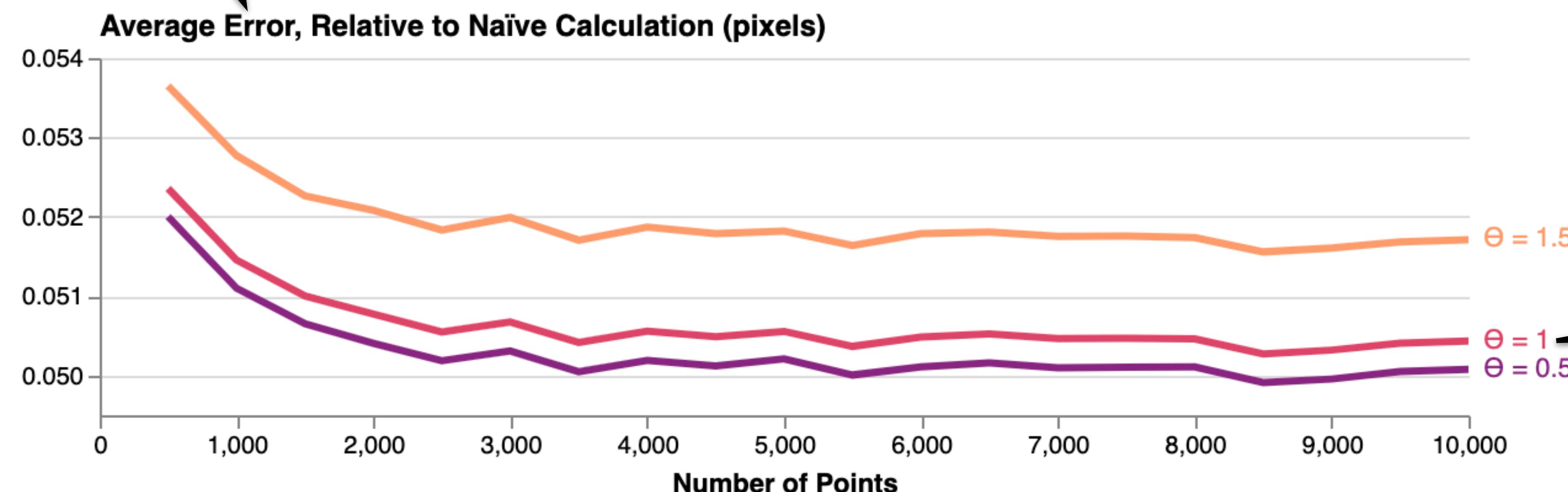


# Example Performance Analysis



# Example Error Analysis

Average vector distance between naive method and Barnes-Hut



In practice,  
1.0 is a  
good  
default  
value

# **Fast Multipole Method (FMM): An $O(N)$ approximate algorithm for the N-Body Problem**

Most slides by Prof. Lexing Ying (talk here: [https://www.youtube.com/watch?v=qMLlyZi8Sz0&ab\\_channel=IBMRResearch](https://www.youtube.com/watch?v=qMLlyZi8Sz0&ab_channel=IBMRResearch))

Some diagrams from <https://web.stanford.edu/~lexing/pfmm.pdf>

# Fast Multipole Method (FMM)

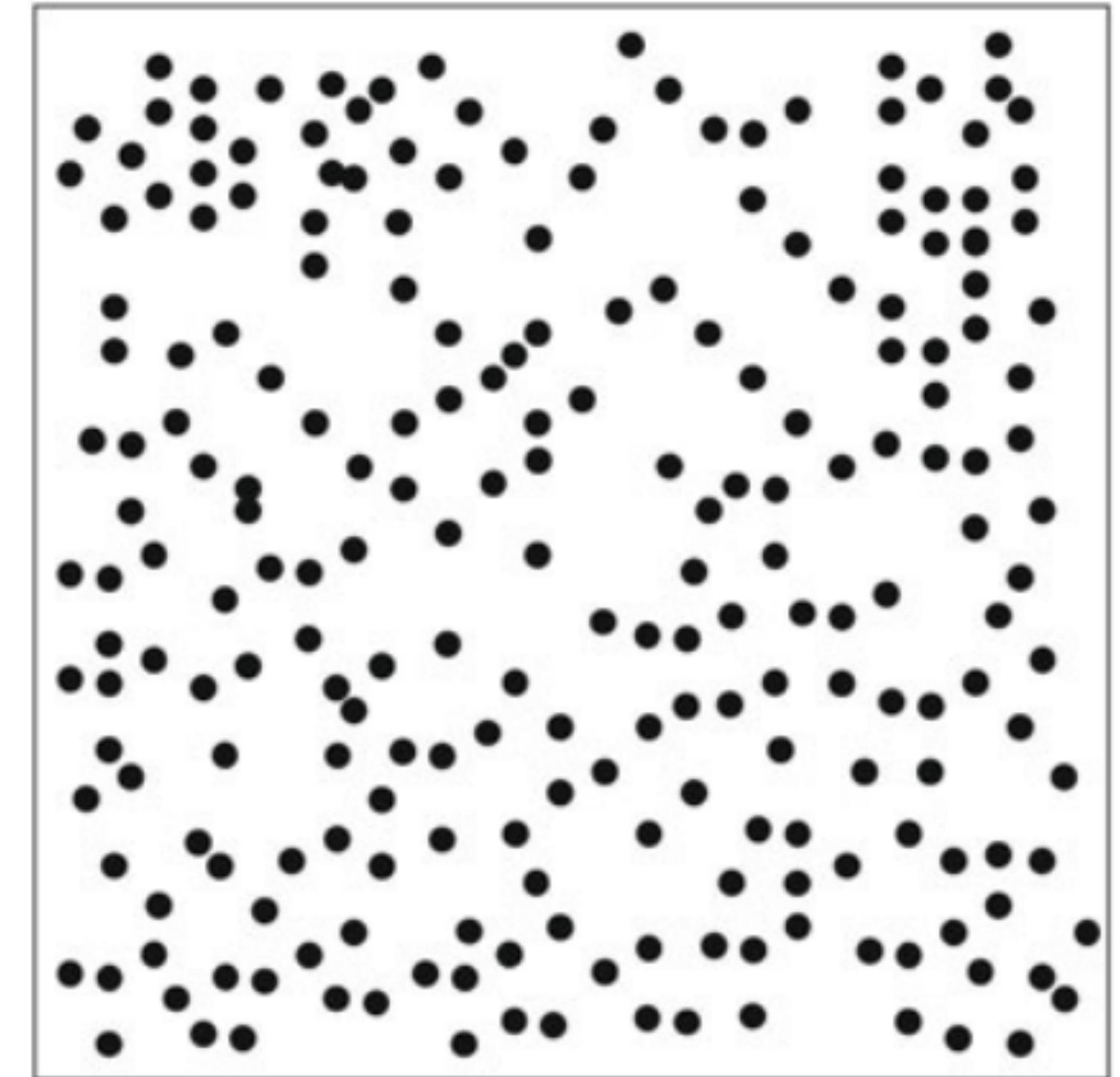
- “A fast algorithm for particle simulation”, L. Greengard and V. Rokhlin, J. Comp. Phys. V. 73, 1987, many later papers
  - Many awards
- Differences from Barnes-Hut
  - FMM computes the *potential* at every point, not just the force
  - FMM uses more information in each box than the CM and TM, so it is both more accurate and more expensive
  - In compensation, FMM accesses a fixed set of boxes at every level, independent of D/r
  - BH uses fixed information (CM and TM) in every box, but # boxes increases with accuracy. FMM uses a fixed # boxes, but the amount of information per box increases with accuracy.
- FMM uses two kinds of expansions
  - Outer expansions represent potential outside node due to particles inside, analogous to (CM,TM)
  - Inner expansions represent potential inside node due to particles outside; *Computing this for every leaf node is the computational goal of FMM*
- First review potential, then return to FMM

# N-body Problem Formulation

- Points  $\{x_i, i = 1, \dots, N\}$
- Charges  $\{f_i, i = 1, \dots, N\}$
- Kernel  $G(x, y)$ , for example
  - $G(x, y) = \ln(|x - y|)$  in 2D
  - $G(x, y) = 1/|x - y|$  in 3D
- Compute potentials for  $x_i$  for  $i = 1, \dots, N$

$$u_i = \sum_{j=1}^N G(x_i, x_j) f_j$$

Can be expressed  
with matrix-vector  
multiplication



# Computational Cost

$$u_i = \sum_{j=1}^N G(x_i, x_j) f_j$$

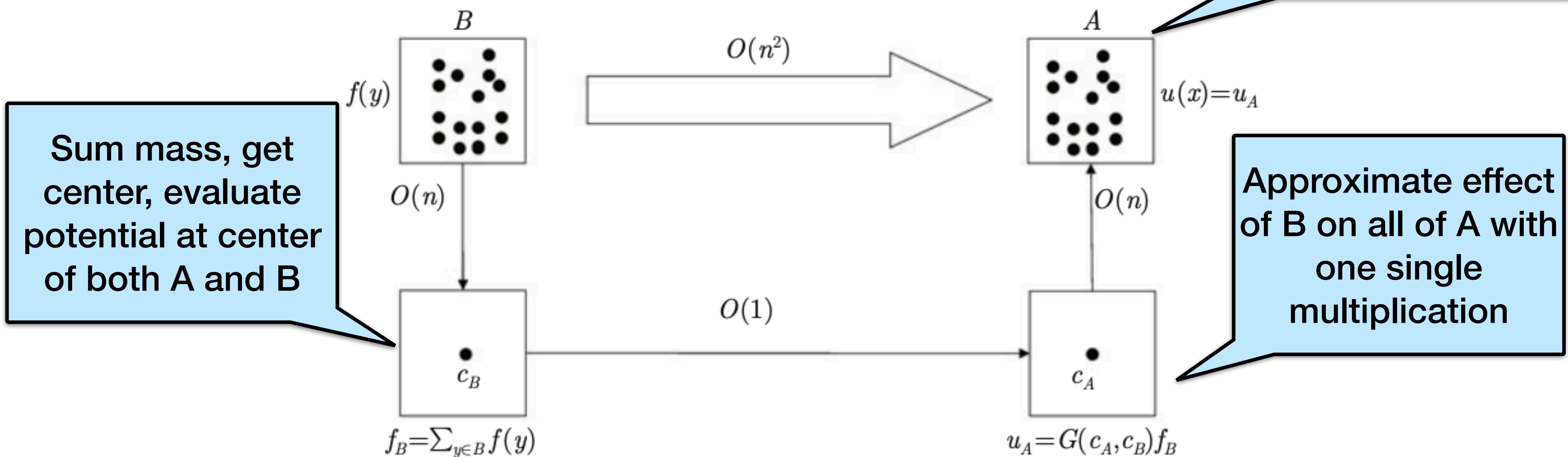
- Direct computation is  $O(N^2)$  steps : too costly
- Goal: lower the complexity
- Fast multipole method - Greengard and Rokhlin in 1987
  - For  $G(x, y) = \ln |x - y|$  or  $1/|x - y|$
  - Bring the complexity to  $O(N)$  for some fixed accuracy  $\epsilon$
- Based on four key ideas

# Idea 1: Well-separated Regions

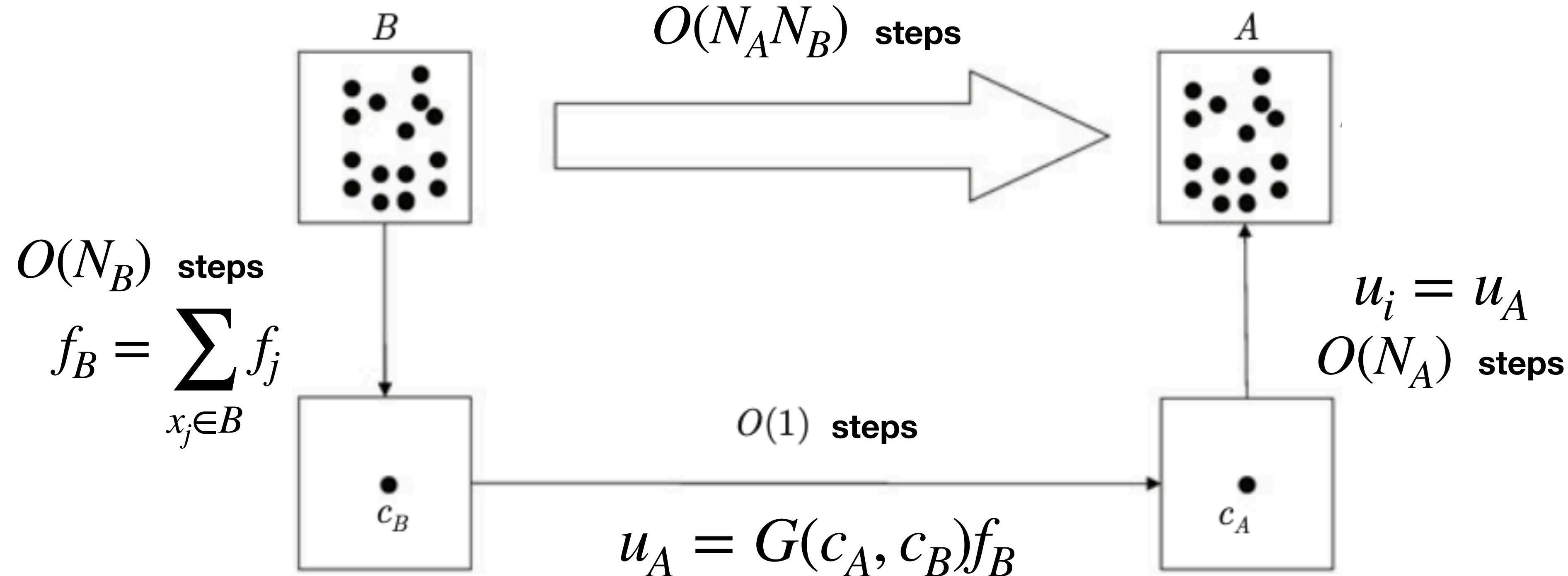
- Suppose boxes B and A are well-separated
- Consider the influence from B to A: at each  $x_i$  in A, evaluate

$$u_i = \sum_{x_j \in B} G(x_i, x_j) f_j$$

Consider boxes rather than individual points



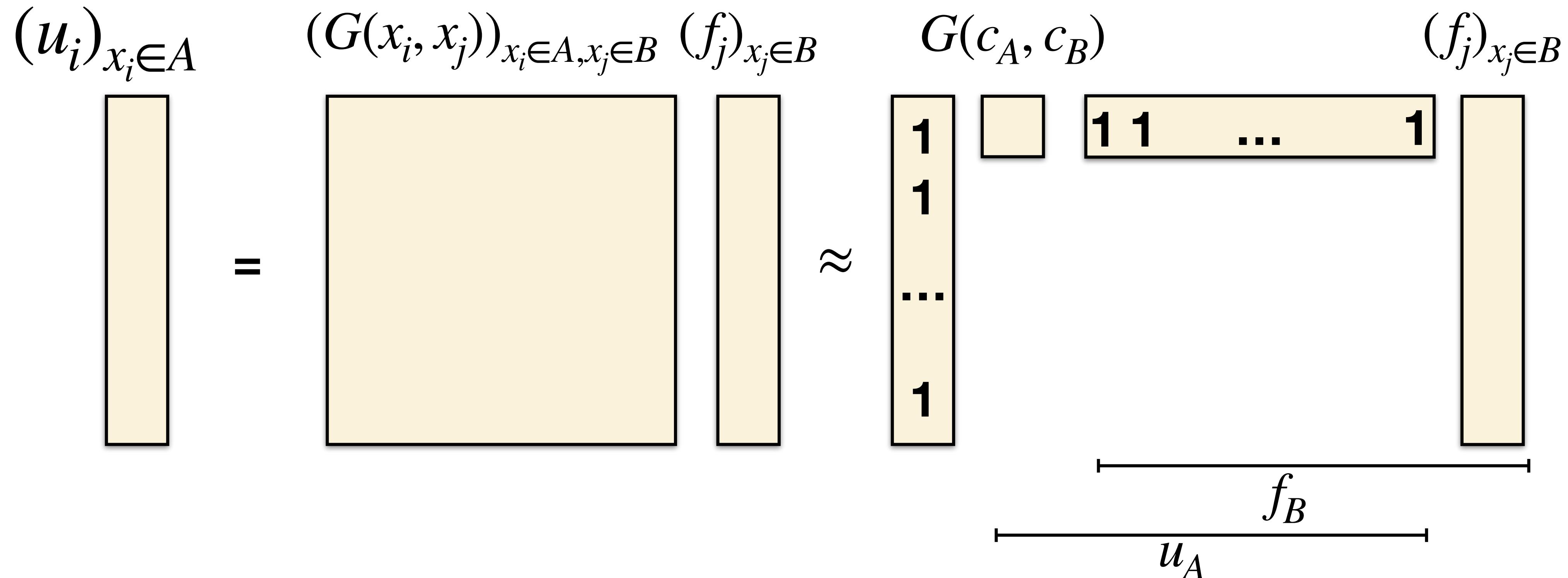
# Cost of 3 step approximation



- Reduce  $O(N_A N_B)$  steps to  $O(N_A + N_B)$  steps
- Good accuracy when **A, B are far away**
- We will use it whenever A and B are well separated

Low-rank matrix  
approximation

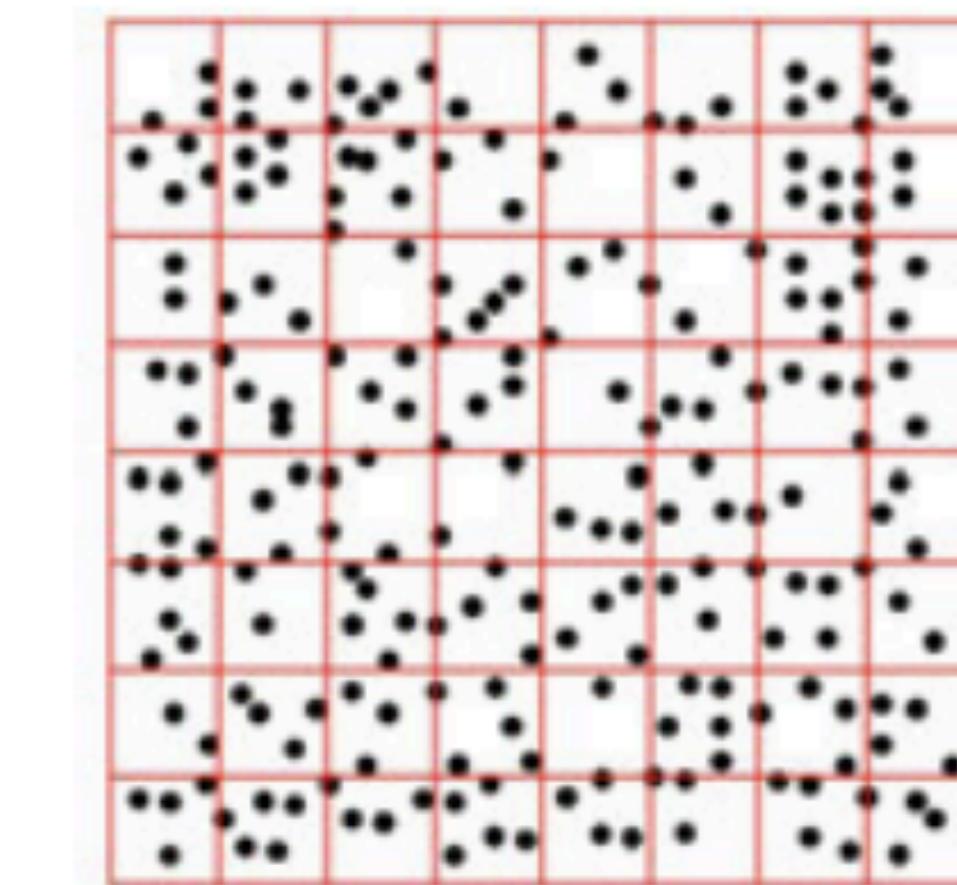
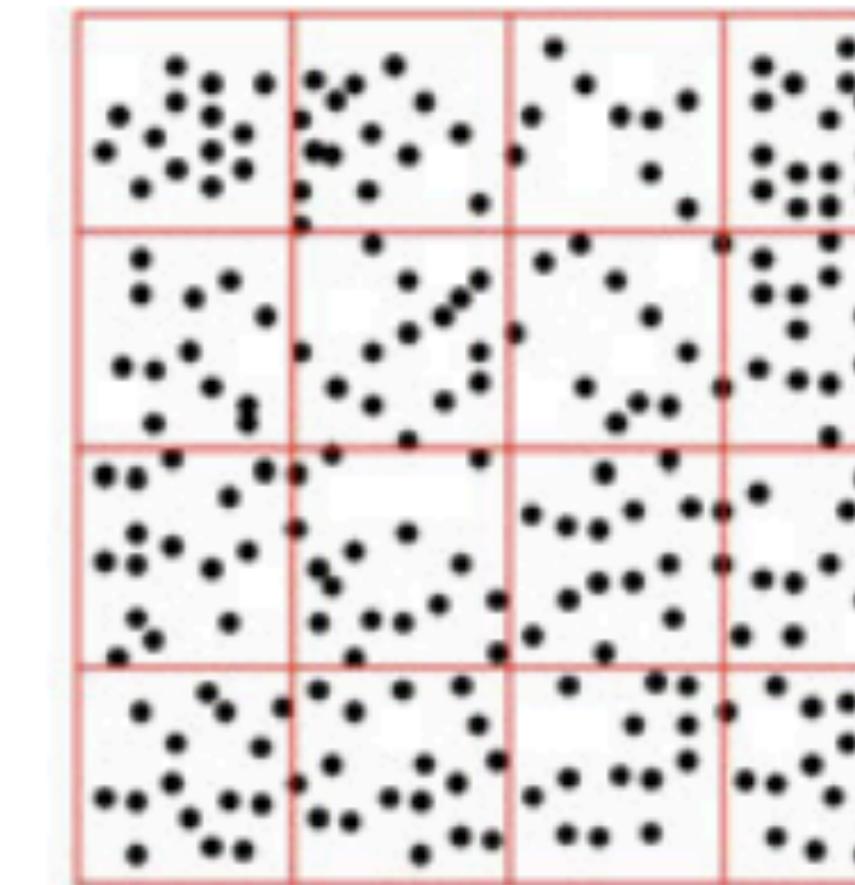
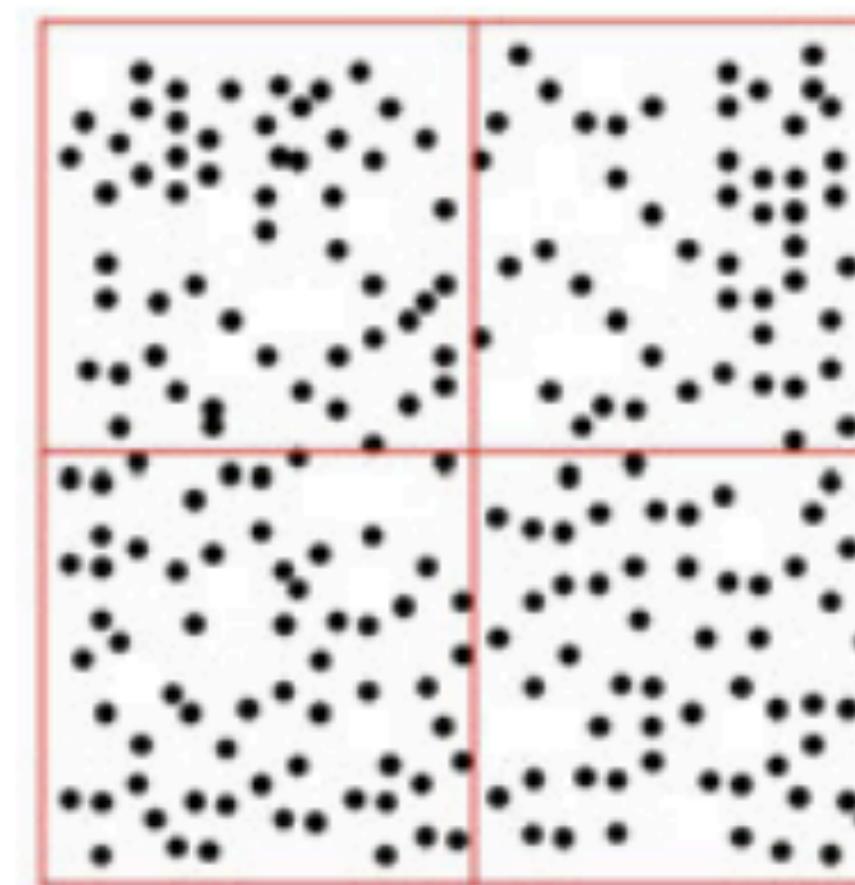
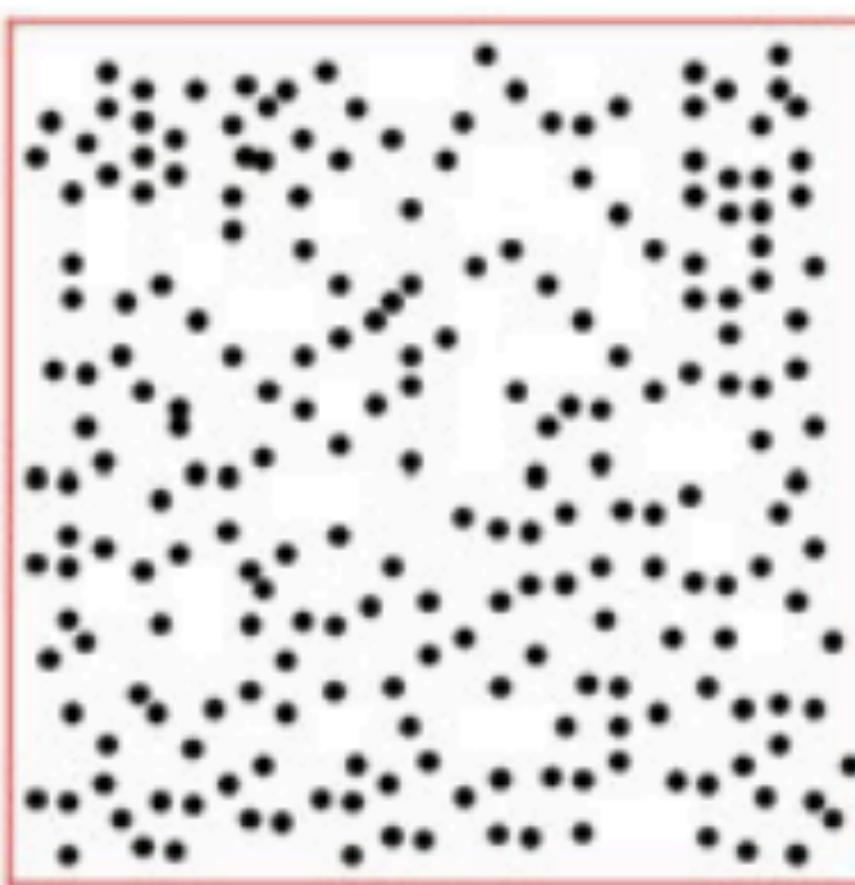
# Algebraic Interpretation



- $f_B$  = source representation
- $u_A$  = target representation
- Problem: but each point  $x_i$  serves as **both a source and target**

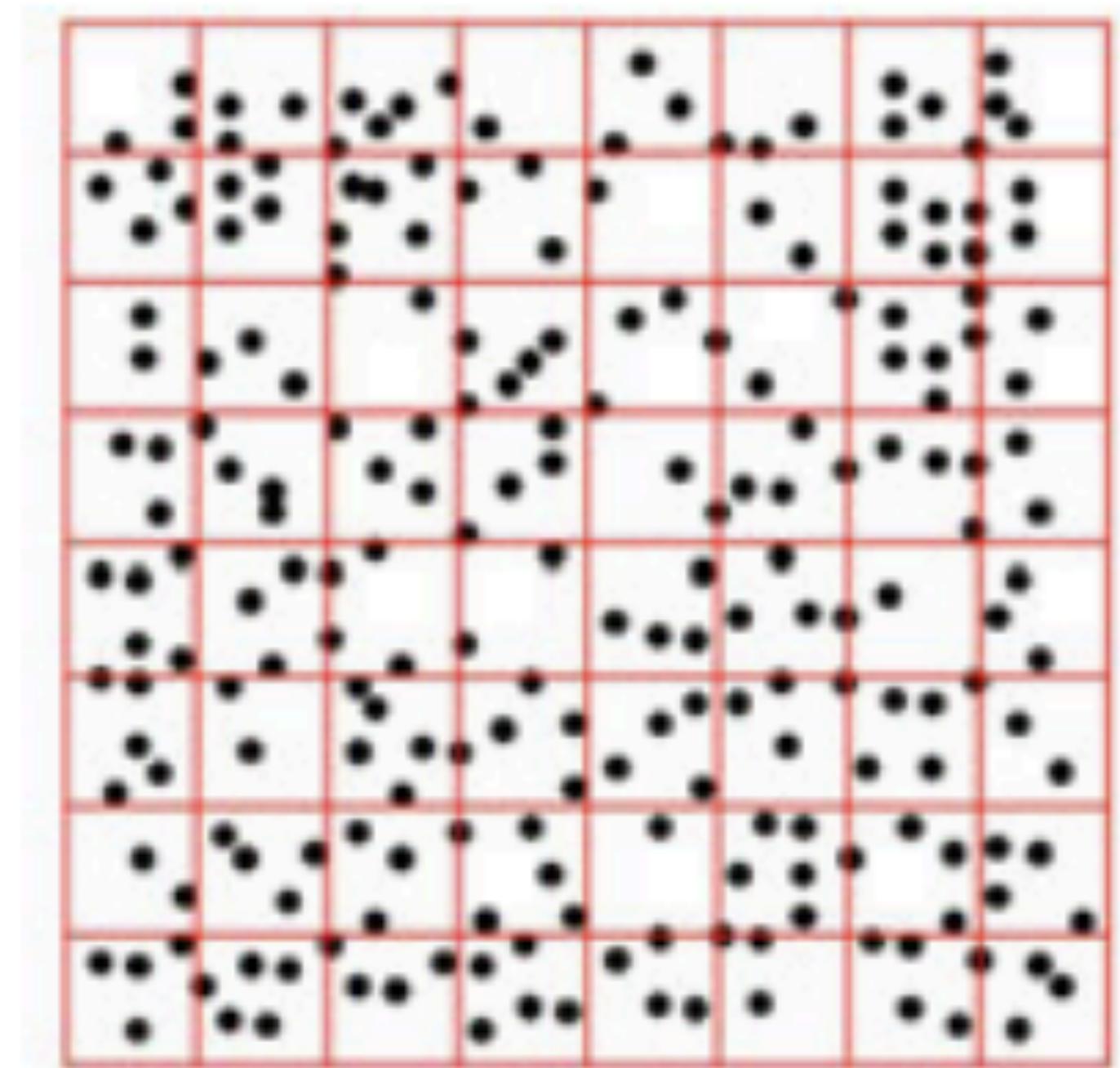
# Idea 2: Hierarchical Decomposition

- Partition the domain hierarchically until **each leaf box contains  $O(1)$  number of points**

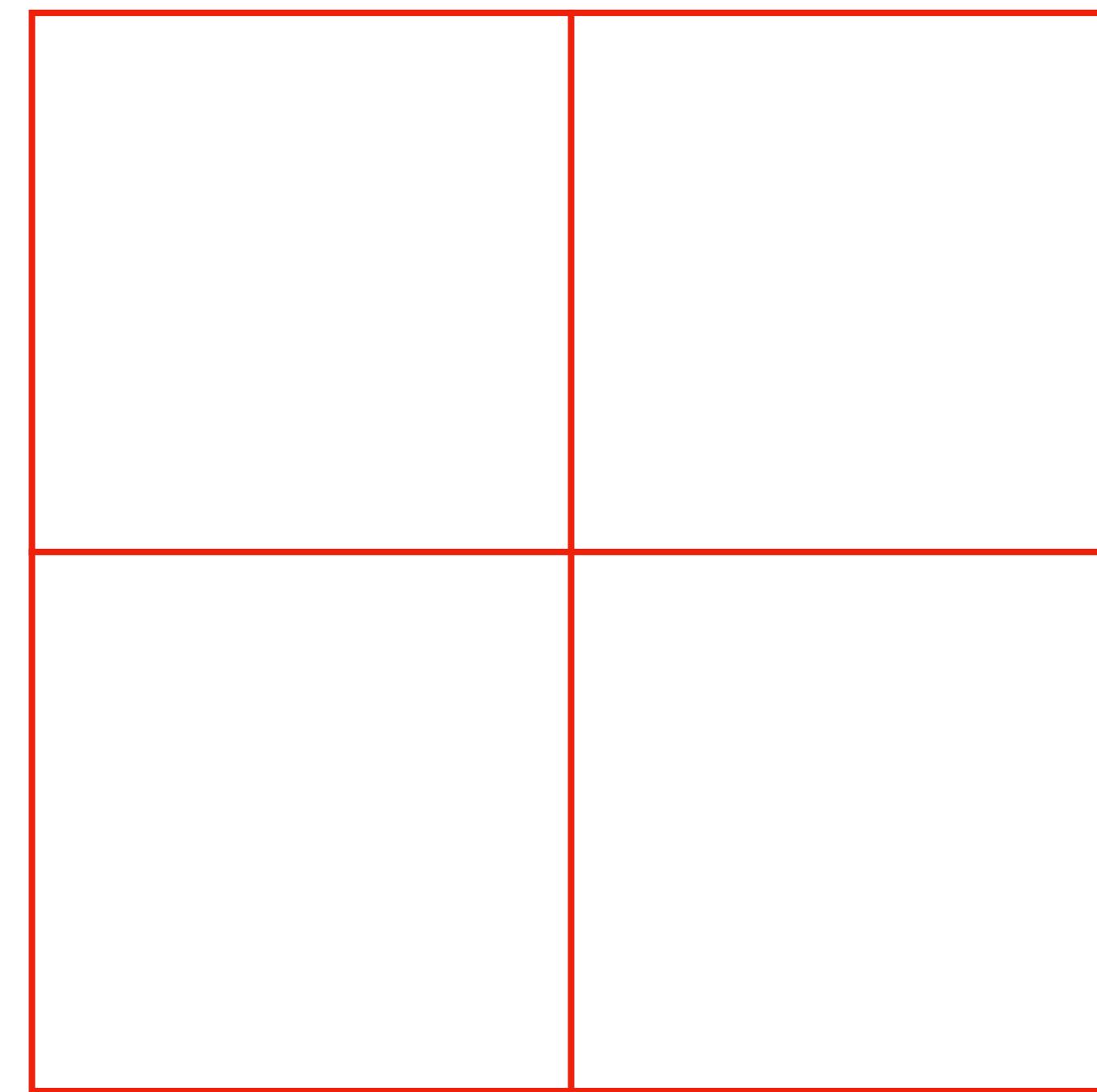


# Idea 2: Hierarchical Decomposition

- Partition the domain hierarchically until **each leaf box contains  $O(1)$  number of points**
- $N = \# \text{ points}$
- $\# \text{ levels} = O(\log_4 N)$
- $\# \text{ boxes on level } \ell = O(4^\ell)$
- Total # boxes =  $O(N)$

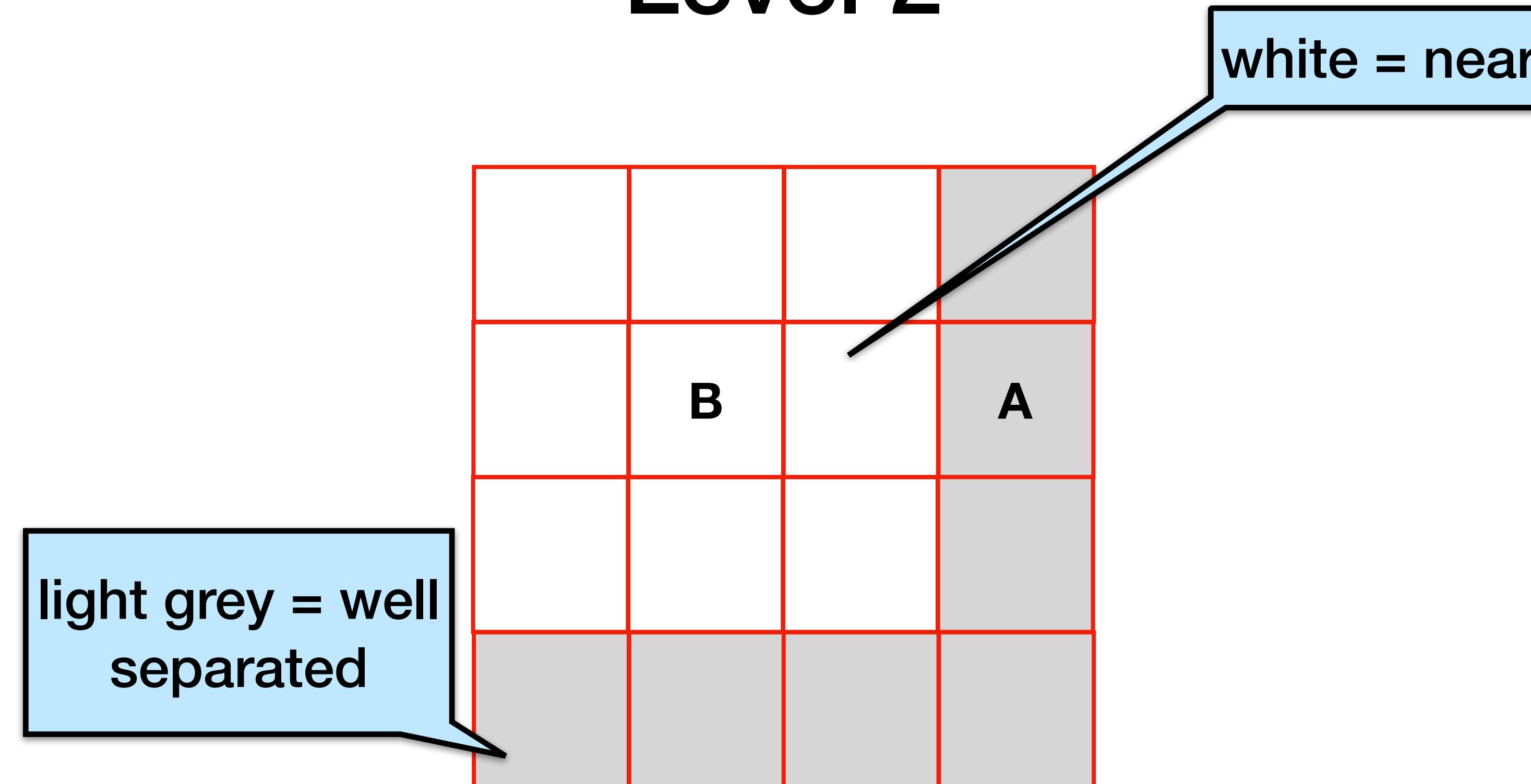


# Levels 0 and 1



At levels 0 and 1, the boxes are adjacent to each other, so **we cannot use the 3 step approximation** as the boxes are not well separated

## Level 2

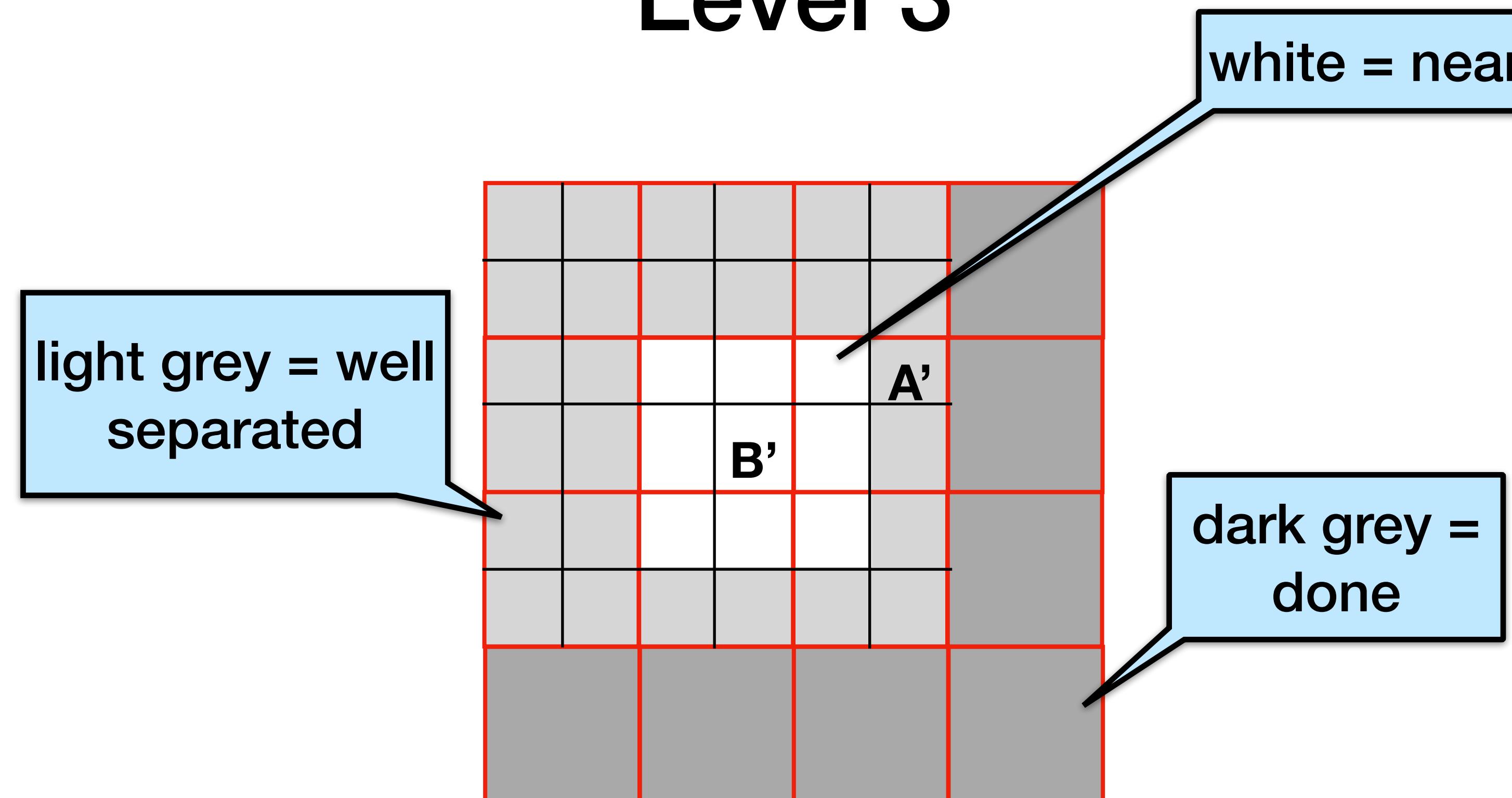


B and A are well separated, so use 3 step approximation for influence from B to A

Q: What about interaction with B its neighbors?

- Go down one level in hierarchical decomposition

# Level 3

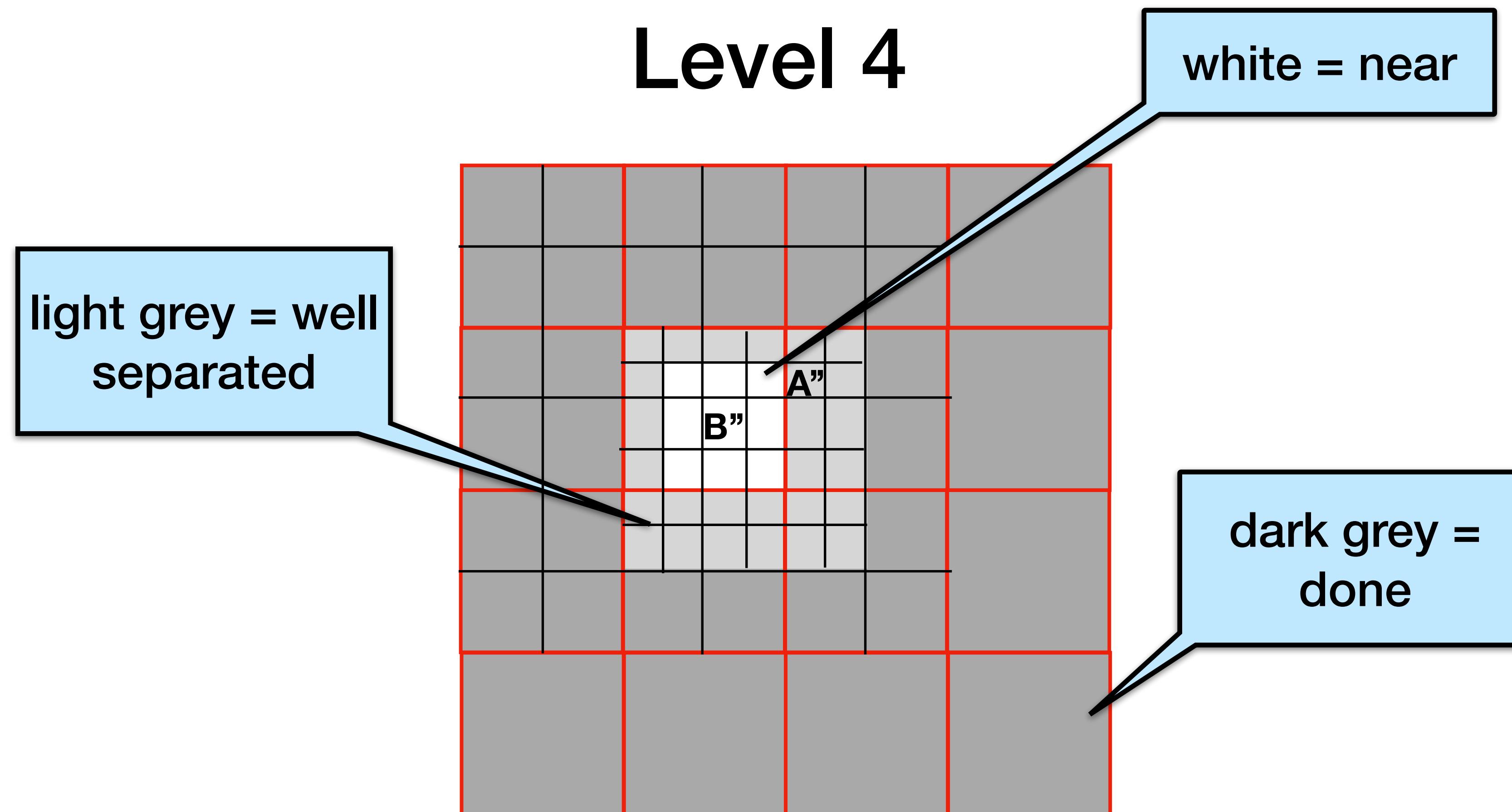


$B'$  and  $A'$  are well-separated

Use the 3-step approx. for the influence from  $B'$  to  $A'$

**Interaction list** of all  $B'$  = all such  $A'$ , at most  $6^2 - 3^2 = 27$  boxes

## Level 4



- $B''$  and  $A''$  are well-separated, so use 3-step approximation for influence from  $B''$  to  $A''$
- Q: influence from  $B''$  to neighbors?
  - Suppose we are at the leaf level, so we cannot keep going down
  - **Evaluate neighbor influence directly**

# Algorithm 1

1. For each box  $B$  in the tree, compute  $f_B = \sum_{x_j \in B} f_j$

2. For  $L = 2$  to last level

    for each box  $B$  at level  $L$

        for each  $A$  in  $B$ 's interaction list

$$u_A = u_A + G(c_A, c_B)f_B$$

O(1) boxes

3. for each box  $A$  in the tree

$$u_i = u_i + u_A \text{ for } x_i \in A$$

4. For each box  $B$  on the last level

$$u_i = u_i + \sum_{x_j \in \text{nghs}(B)} G(x_i, x_j)f_j, \text{ for } x_i \in B$$

## Step 1

1. For each box  $B$  in the tree, compute  $f_B = \sum_{x_j \in B} f_j$

For a given level  $\ell$ , there  $4^\ell$  boxes and  $O(N/4^\ell)$  points in each of the boxes at that level (assuming uniformity)

So the work to calculate the sum of all the masses at each level is  $O(N)$

for  $O(N \log N)$  total work

## Step 2

2. For  $L = 2$  to last level  
for each box  $B$  at level  $L$   
for each  $A$  in  $B$ 's interaction list

$$u_A = u_A + G(c_A, c_B)f_B$$

For a given level  $\ell$ , there  $4^\ell$  boxes and each has  $O(1)$  neighbors in the interaction list. So the work to do this approximation, assuming you have

already calculated  $f_B$ , is  $\sum_{\ell=0}^{\log_4 N} 4^\ell = O(N)$

# Algorithm 1 Analysis

1. For each box  $B$  in the tree, compute  $f_B = \sum_{x_j \in B} f_j$   $O(N \log N)$
2. For  $L = 2$  to last level
  - for each box  $B$  at level  $L$   $O(1)$  boxes
  - for each  $A$  in  $B$ 's interaction list  $O(N)$
$$u_A = u_A + G(c_A, c_B)f_B$$
3. for each box  $A$  in the tree  $O(N \log N)$ 
$$u_i = u_i + u_A \text{ for } x_i \in A$$
4. For each box  $B$  on the last level
  - $u_i = u_i + \sum_{x_j \in \text{ngths}(B)} G(x_i, x_j)f_j$ , for  $x_i \in B$   $O(N)$can we do better?  $\text{Total} = O(N \log N)$

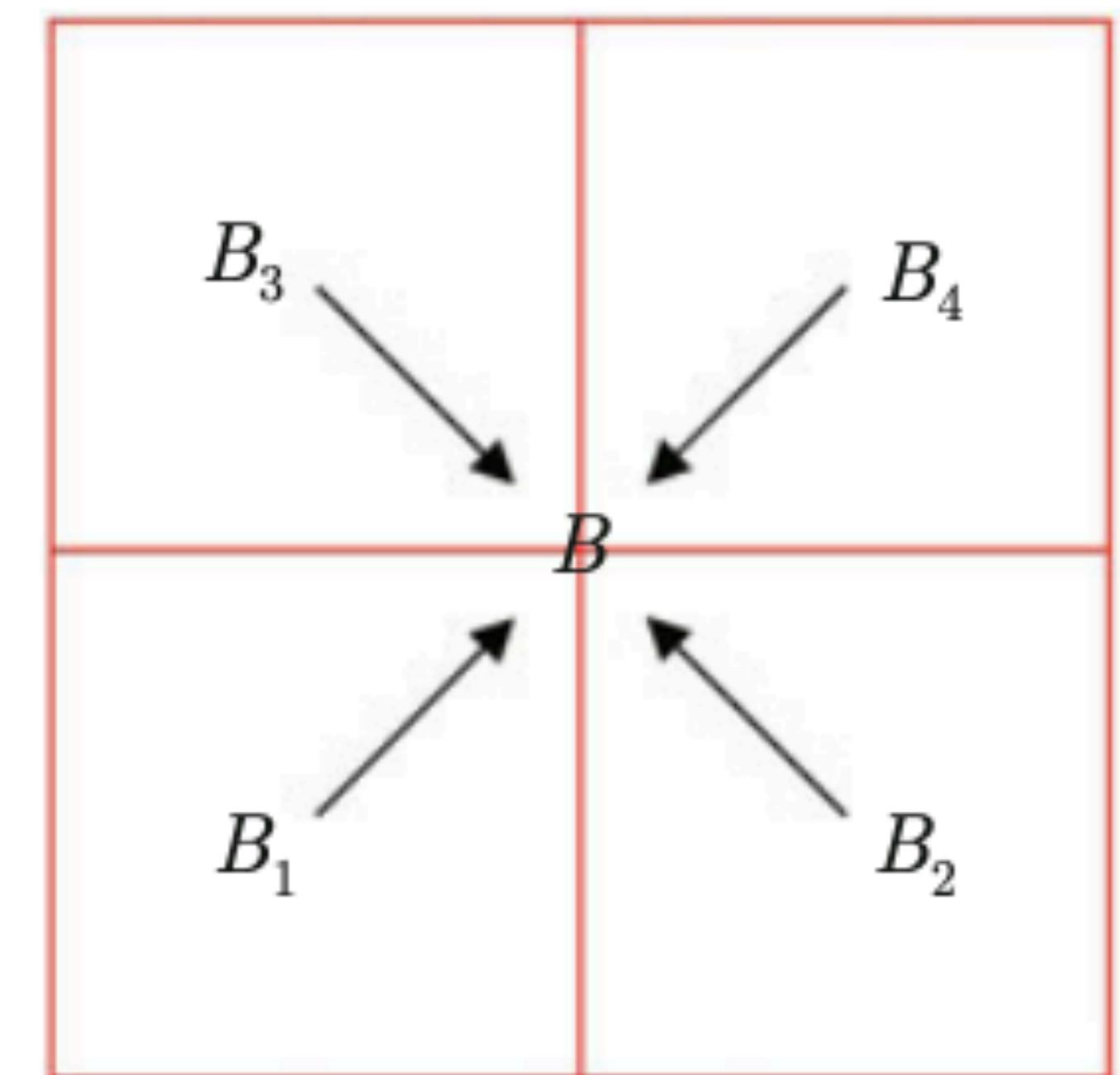
# Idea 3: reuse the computation

$$f_B = \sum_{x_j \in B} f_j = \sum_{x_j \in B_1} f_j + \sum_{x_j \in B_2} f_j + \sum_{x_j \in B_3} f_j + \sum_{x_j \in B_4} f_j = f_{B_1} + f_{B_2} + f_{B_3} + f_{B_4}$$

Idea: Compute  $f_B$  from its children

$O(1)$  cost

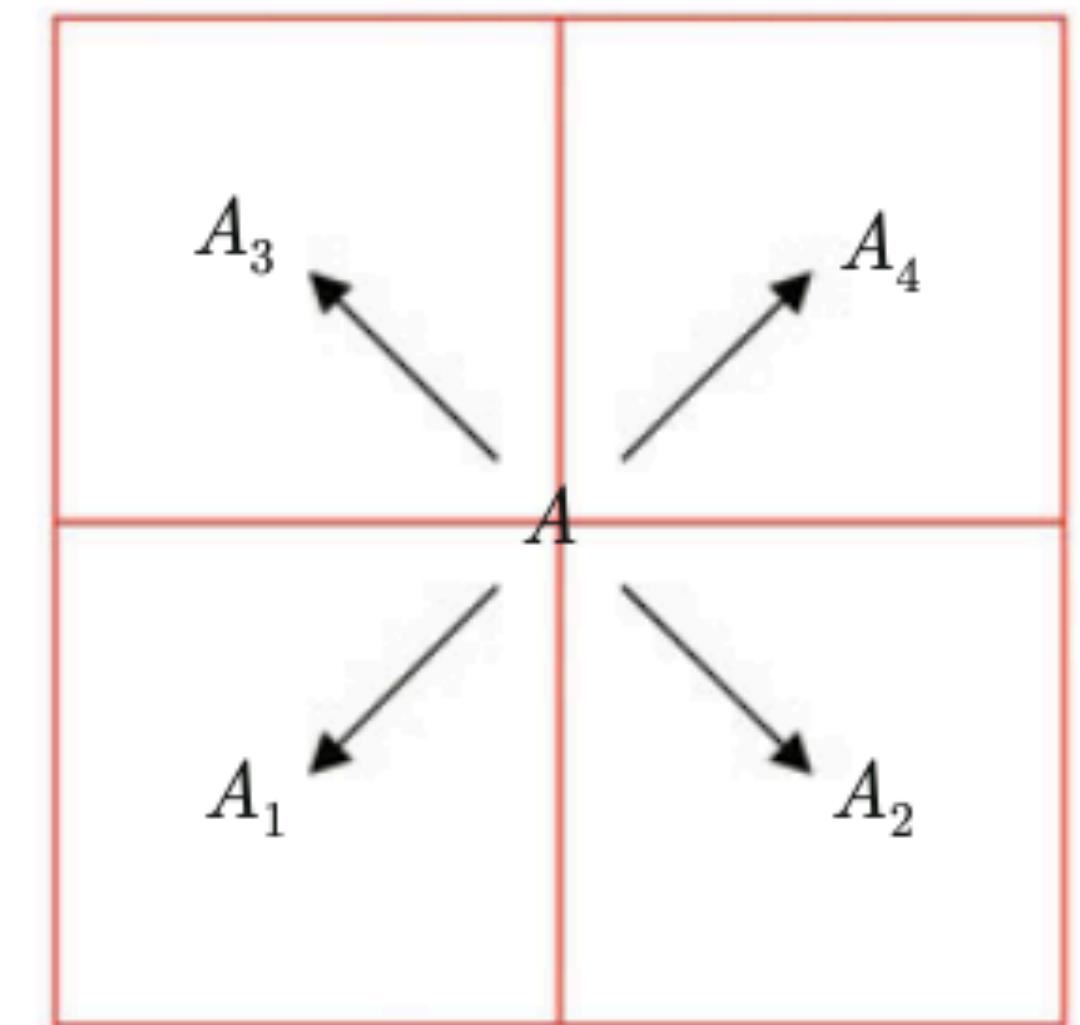
But you have to traverse the quadtree bottom-up



# Idea 3: reuse the computation

$$u_i = u_i + u_A, \text{ for } x_i \in A$$

- Similarly, add  $u_A$  to only its children - gradually pass down to the lower generations
- $O(1)$  cost
- Traverse quadtree top down



## Algorithm 2 (FMM)

1. Go up the tree, for each box B

if B is a leaf box,  $f_B = \sum_{x_j \in B} f_j$

else,  $f_B = f_{B_1} + f_{B_2} + f_{B_3} + f_{B_4}$

2. Same as step 2 of algorithm 1

3. Go down the tree, for each box A

if A is a leaf box,  $u_i = u_i + u_A$ , for  $x_i \in A$

else,  $u_{A_1} = u_{A_1} + u_A$ , same for  $A_2, A_3, A_4$

4. Same as step 4 of algorithm 1

## Algorithm 2 (FMM)

1. Go up the tree, for each box B

if B is a leaf box,  $f_B = \sum_{x_j \in B} f_j$

$O(N)$

else,  $f_B = f_{B_1} + f_{B_2} + f_{B_3} + f_{B_4}$

2. Same as step 2 of algorithm 1

$O(N)$

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if A is a leaf box,  $u_i = u_i + u_A$ , for  $x_i \in A$

$O(N)$

else,  $u_{A_1} = u_{A_1} + u_A$ , same for  $A_2, A_3, A_4$

4. Same as step 4 of algorithm 1

$O(N)$

Total =  $O(N)$

# Three Main Ideas So Far

- When things are far away, use 3-step procedure (low-rank approximation)
- Use hierarchical decomposition to identify what is far away and what is nearby
- Reuse computation to do calculation of the total mass

what about accuracy? not just the total mass, but the mass distribution

# Idea 4: Better Source/Target Representations

So far

- $f_B$  is the sum of charges in B
- $u_A$  is the potential at  $c_A$  from well-separated sources
- Low accuracy if A and B are not far

More generally

- $f_B$  is a **compact representation** of the charge for B in well-separated targets
- Similarly,  $u_A$  is a **compact representation** of the potential in A by well-separated targets
- Better accuracy requires better compact reps.
  - In 2D, treat x, y as points in the complex plane
  - $G(x, y) = \text{RE}(\ln(x-y))$

# More Fine-grained Representations

- In practice, to get good accuracy, we can use low-rank approximations rather than rank-1 approximations.
- Instead of representing  $f_B, u_A$  as a single value, represent them as a **series of coefficients rather than a single term** - first one is the initial approximation
- Keep  $p = \lg(1/\epsilon)$  for accuracy  $\epsilon$
- Calculating the total mass now goes to  $O(pn_B + pn_A)$ . Still linear if  $p = O(1)$

# Summary of FMM

- The FMM relies on 4 main ideas:
  - Low-rank interaction
  - Hierarchical decomposition
  - Reuse of computation
  - More accurate compact representation for  $f_B$  and  $u_A$
- So far we assumed the points are uniform, if they are not, adaptive algorithm is also available

# **Parallelizing BH, FMM, and related algorithms**

# Parallelizing Hierarchical N-Body Codes

Barnes-Hut, FMM and related algorithms have similar computational structure:

- 1) Build the QuadTree
- 2) Traverse QuadTree from leaves to root and build outer expansions  
(just (TM,CM) for Barnes-Hut)
- 3) Traverse QuadTree from root to leaves and build any inner expansions  
(FMM only)
- 4) Traverse QuadTree to accumulate forces for each particle

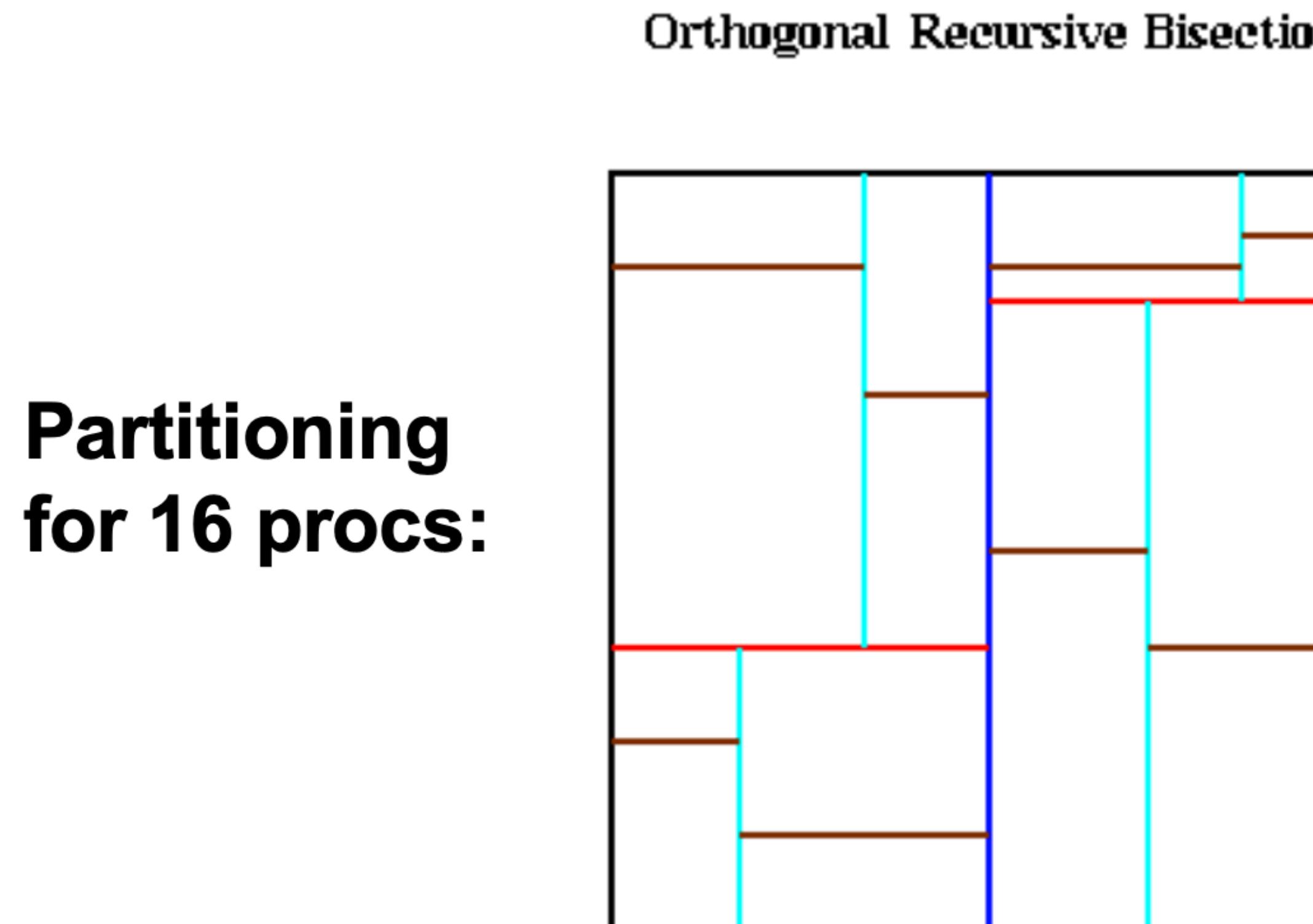
# Parallelizing Hierarchical N-Body Codes

One parallelization scheme will work for them all [Blackston and Suel, SC '97]

- Assign regions of space to each processor
- Regions may have different shapes, to get load balance
  - Each region will have about  $N/p$  particles
- Each processor will store part of Quadtree containing all particles (=leaves) in its region, and their ancestors in Quadtree
  - Top of tree stored by all processors, lower nodes may also be shared
- Each processor will also store adjoining parts of Quadtree needed to compute forces for particles it owns
  - Subset of Quadtree needed by a processor called the **Locally Essential Tree (LET)**
- Given the LET, all force accumulations (step 4)) are done in parallel, without communication

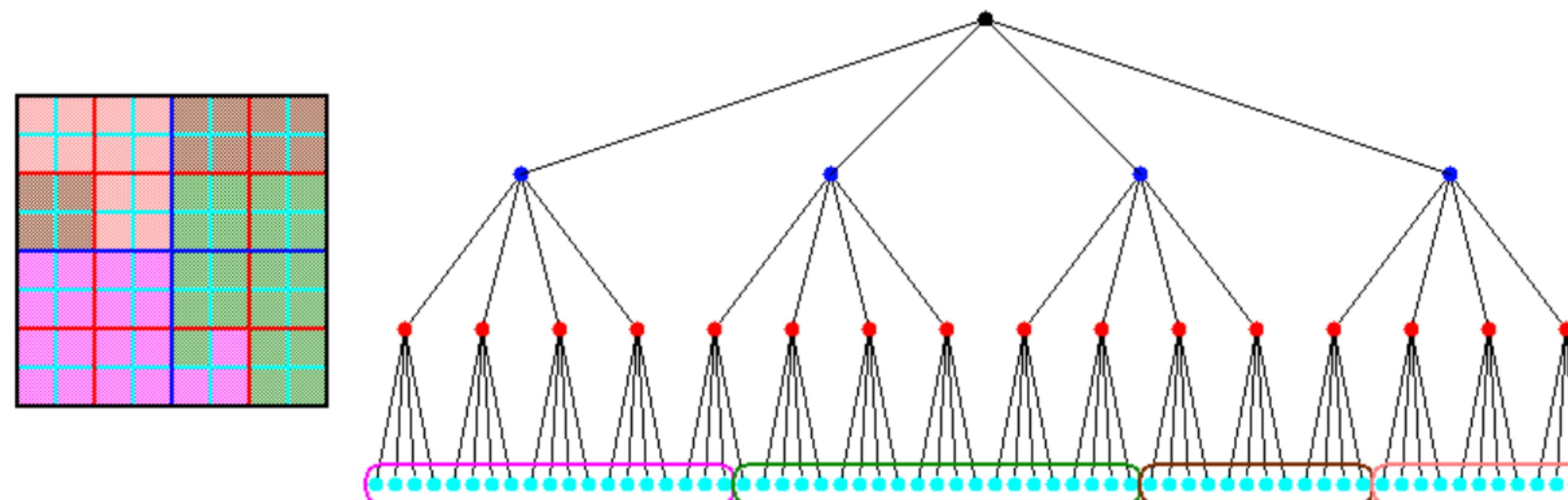
# Load Balancing Scheme 1: Orthogonal Recursive Bisection (ORB) [Warren and Salmon, SC '92]

- Recursively split region along axes into regions containing equal numbers of particles



# Load Balancing Scheme 2: Costzones

- **Called Costzones for Shared Memory**
  - PhD thesis, J.P. Singh, Stanford, 1993
- **Called “Hashed Oct Tree” for Distributed Memory**
  - Warren and Salmon, Supercomputing 93
- **We will use the name Costzones for both; also in Pbody**
- **Idea: partition QuadTree instead of space**
  - Estimate work for each node, call total work  $W$



# Example Performance Results

- **512 Proc Intel Delta**
  - Warren and Salmon, Supercomputing 92, Gordon Bell Prize
  - 8.8 M particles, uniformly distributed
  - .1% to 1% RMS error, Barnes-Hut
  - 114 seconds = 5.8 Gflops
    - Decomposing domain 7 secs
    - Building the OctTree 7 secs
    - Tree Traversal 33 secs
    - Communication during traversal 6 secs
    - Force evaluation 54 secs
    - Load imbalance 7 secs
  - Rises to 160 secs as distribution becomes nonuniform