k-Nearest Neighbors Classification using kd-Trees

Design of Parallel and High Performance Computing

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Introduction

- Algorithm - k-Nearest Neighbours (kNN)
  - Classification of a given Test Point - Output the most occurring class of the k nearest neighbours

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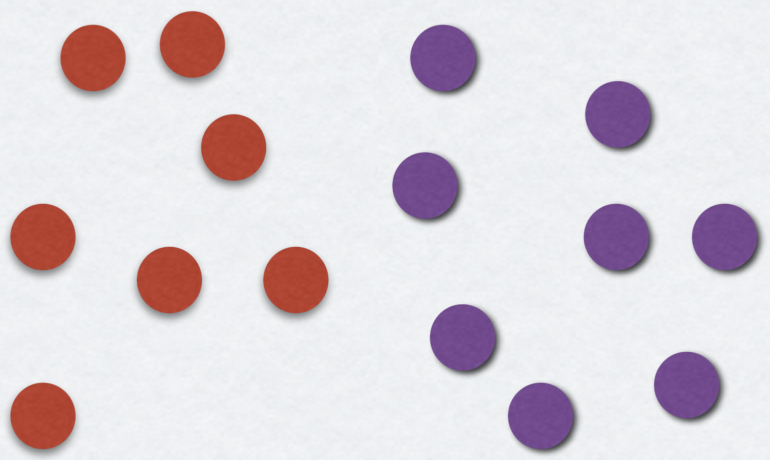

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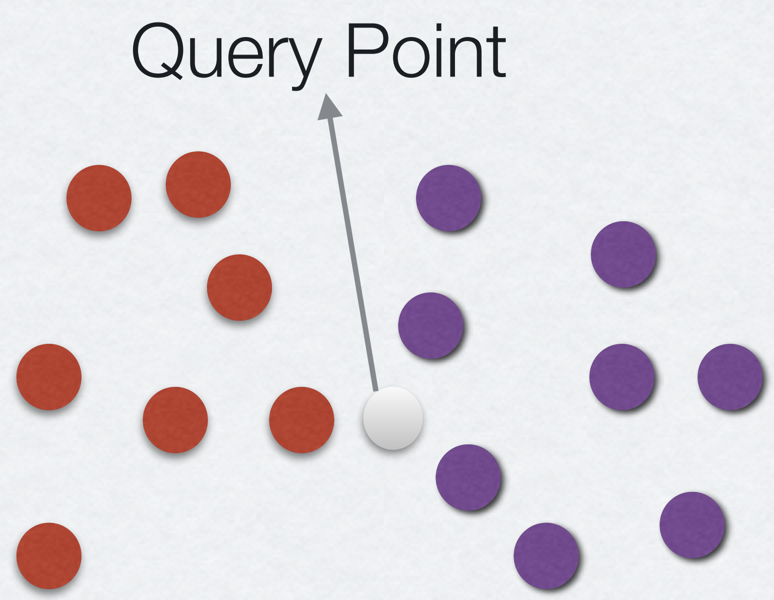

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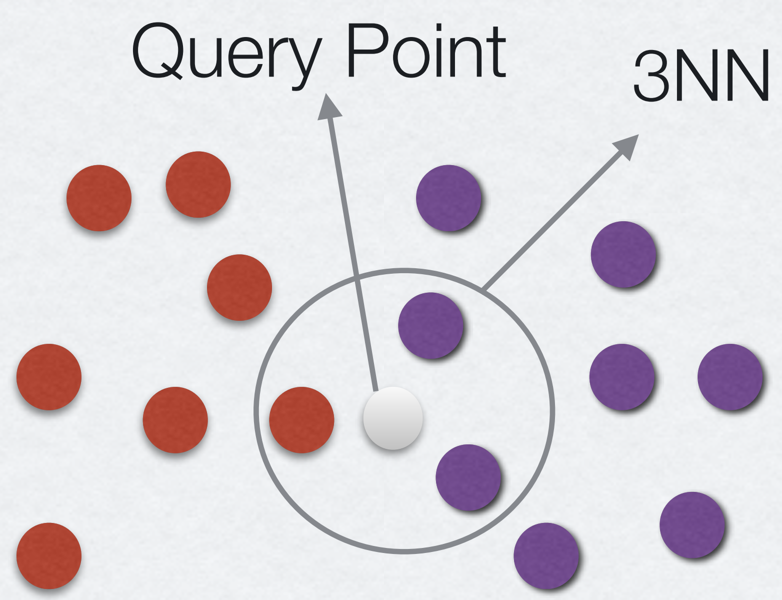

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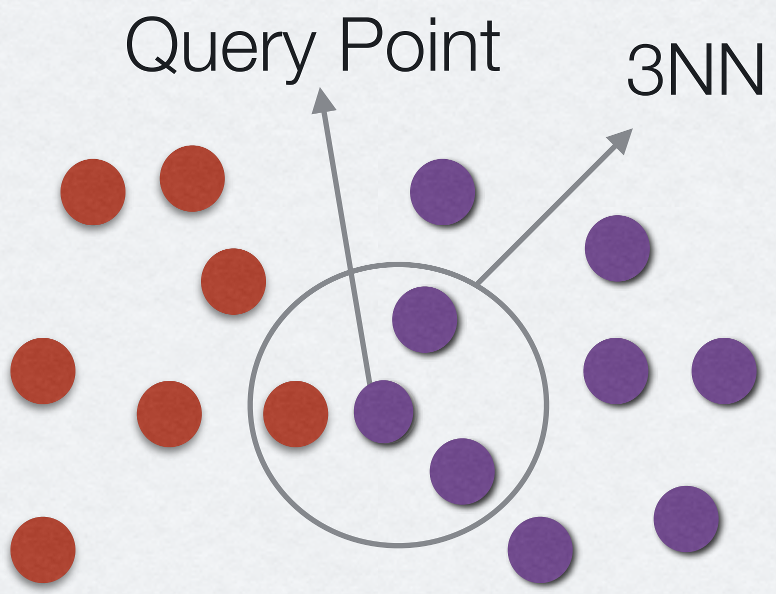

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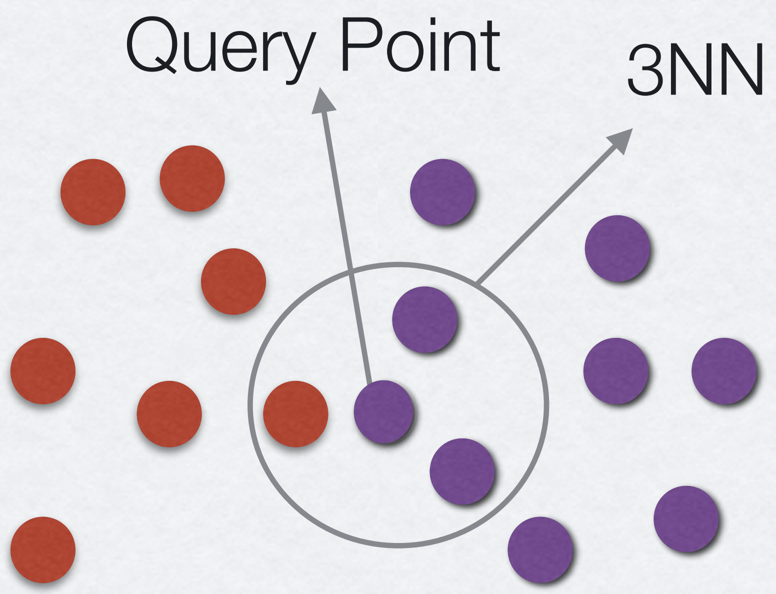

- kd-tree Implementation of kNN is used
  - kd-tree can do look up in O(log n), associated with additional overhead due to building the tree.

kd-Tree Construction

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- For each level of the tree, a dimension is chosen for splitting the data points.
- For each dimension an average of value of that dimension for all data points are taken and that point is used to split the tree at that level. This process is repeated recursively.

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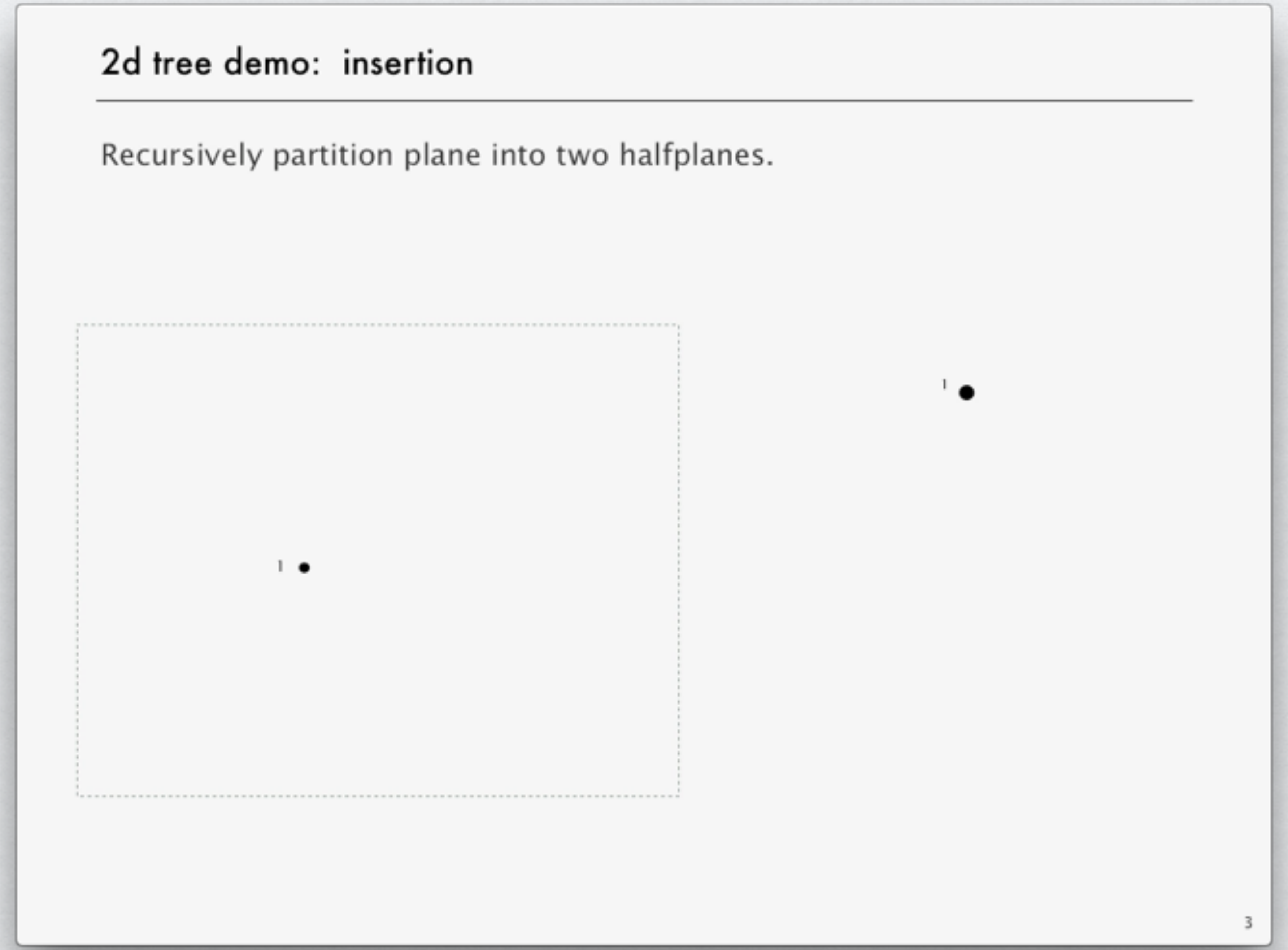

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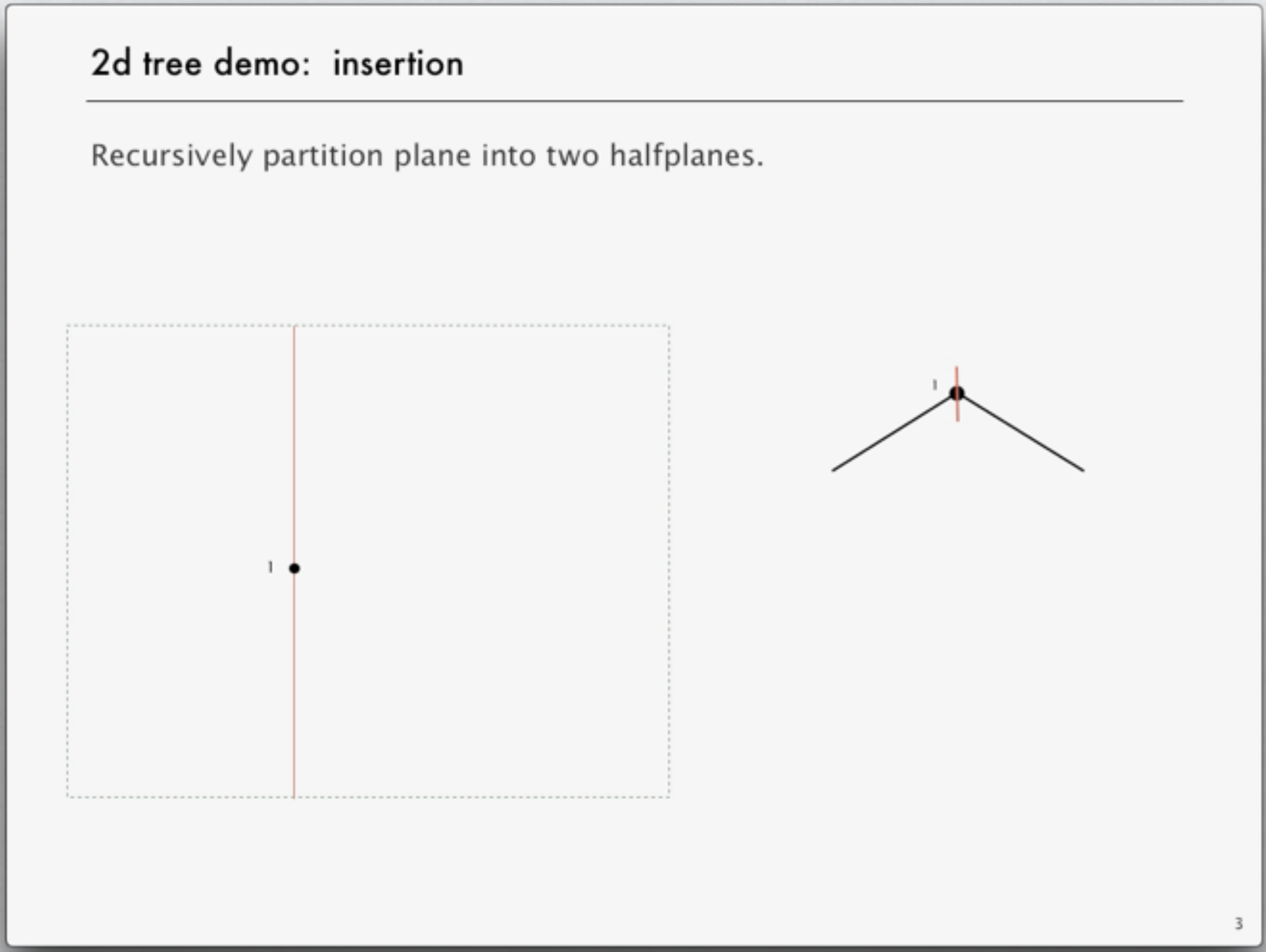

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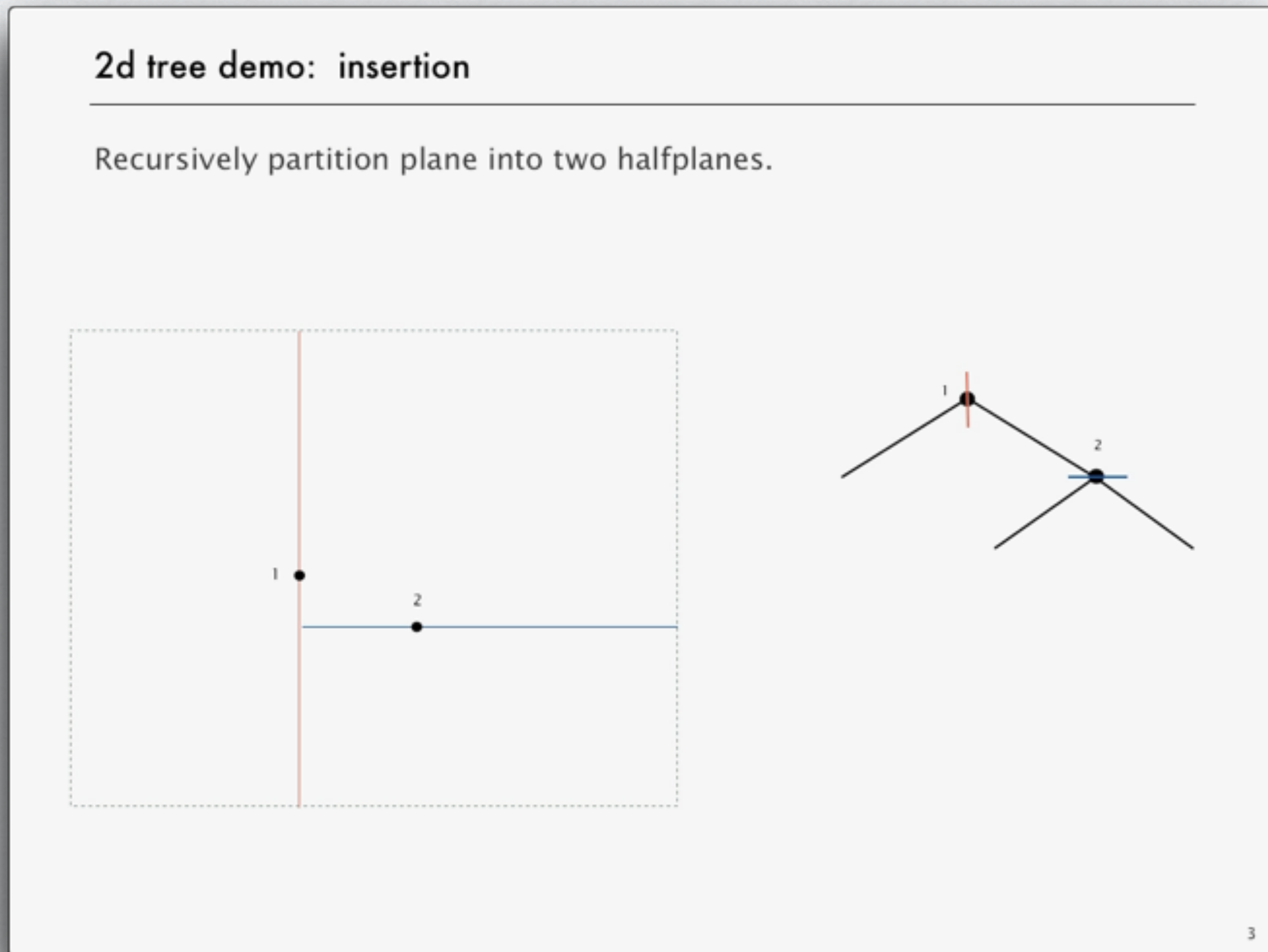

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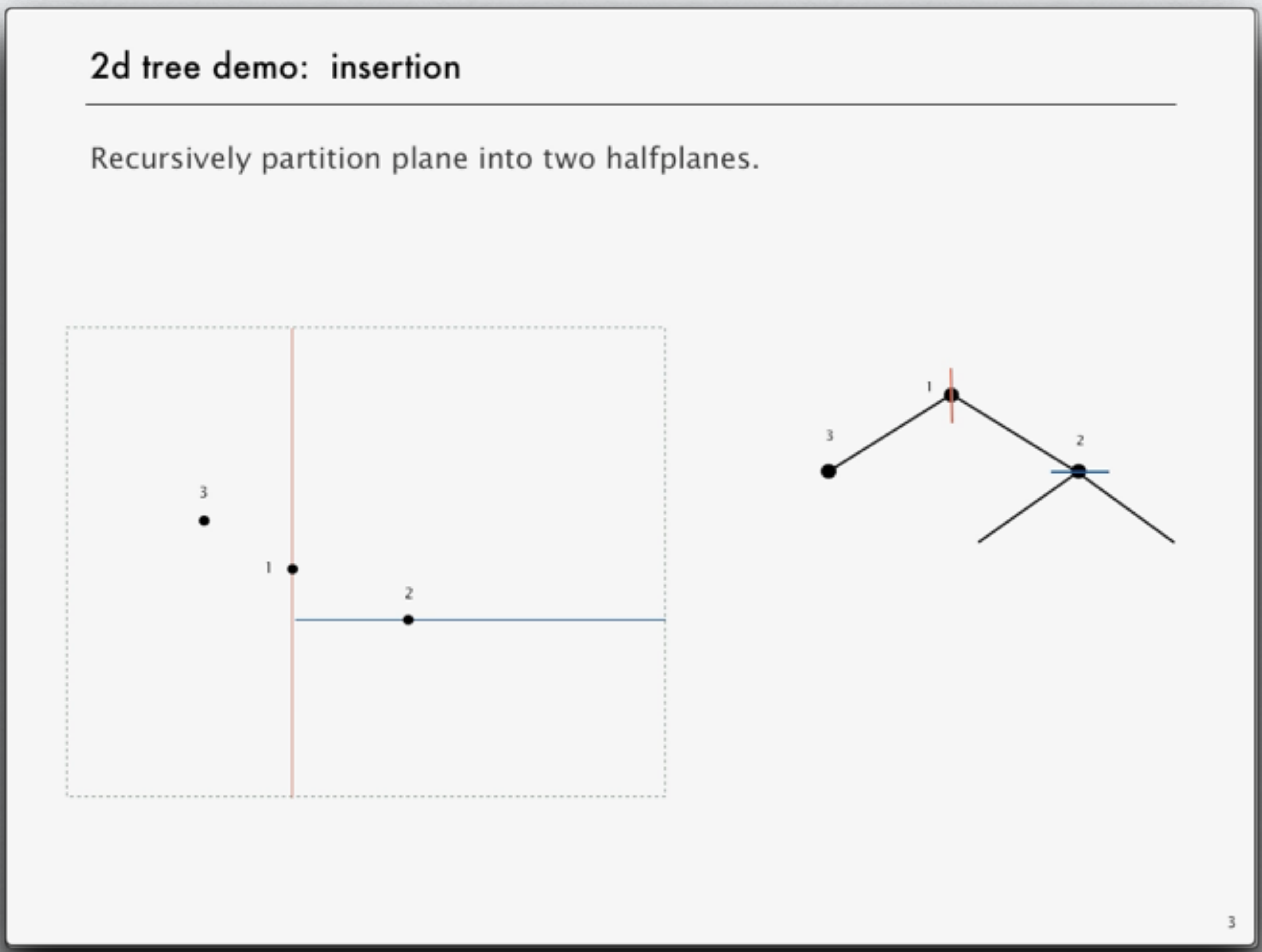

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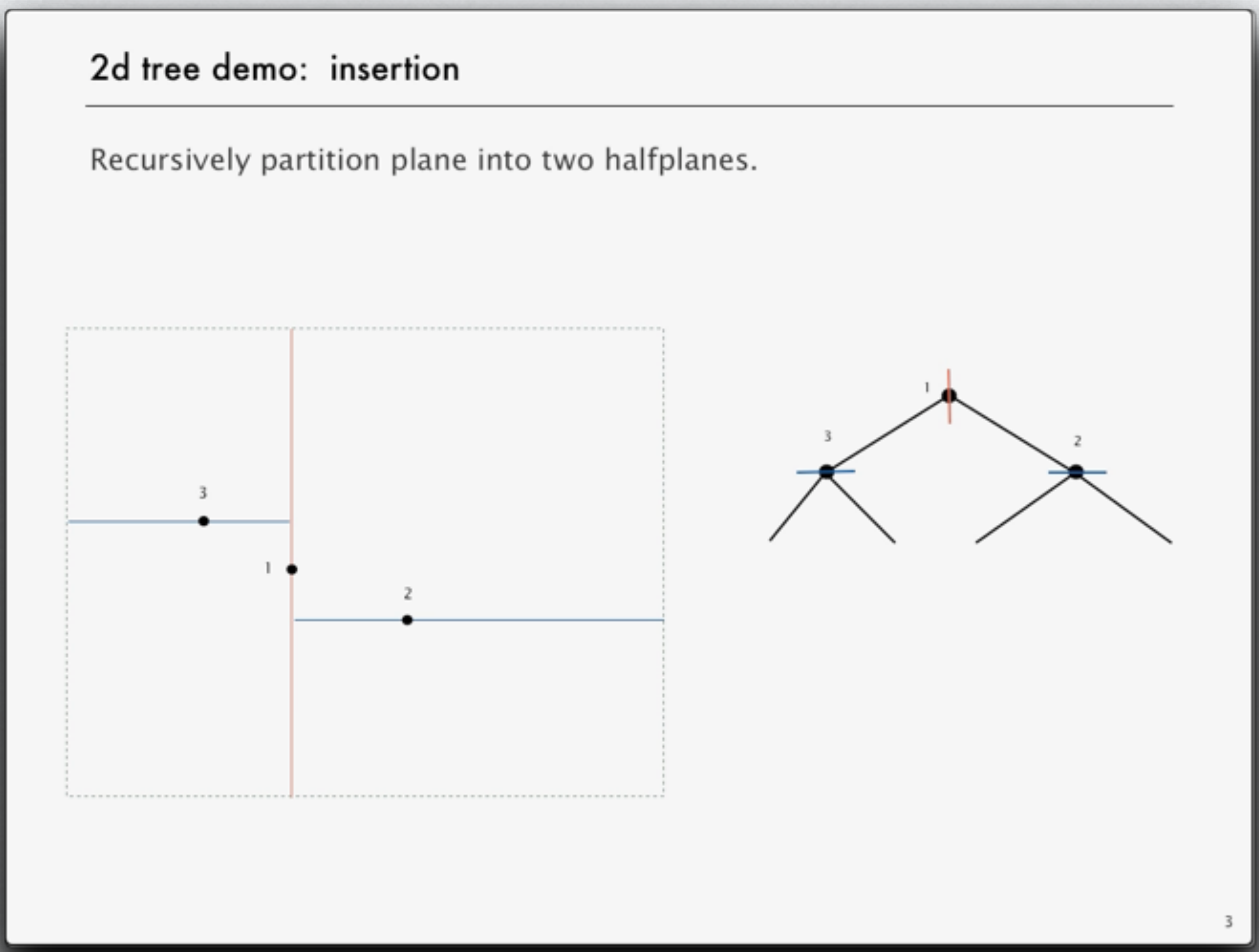

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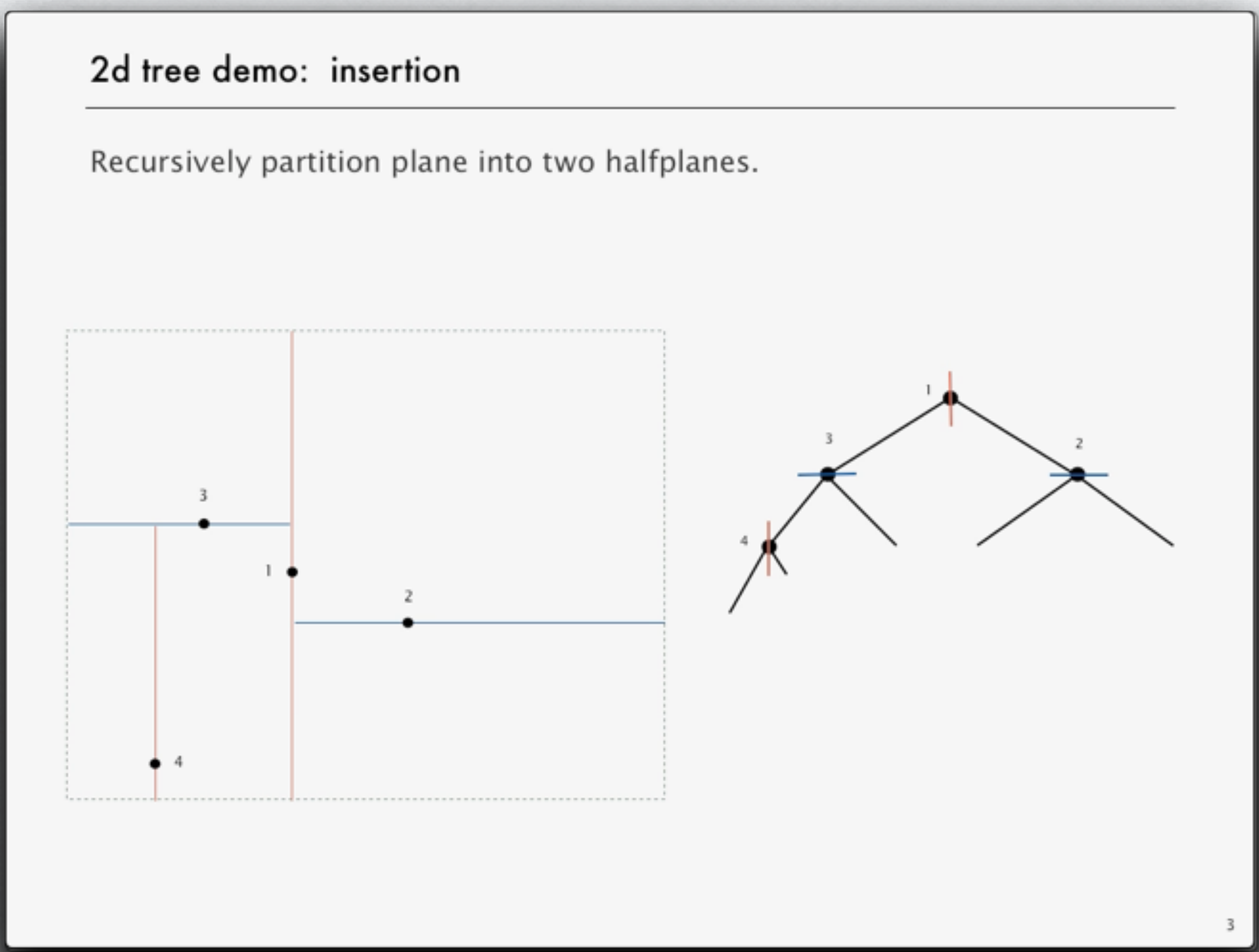

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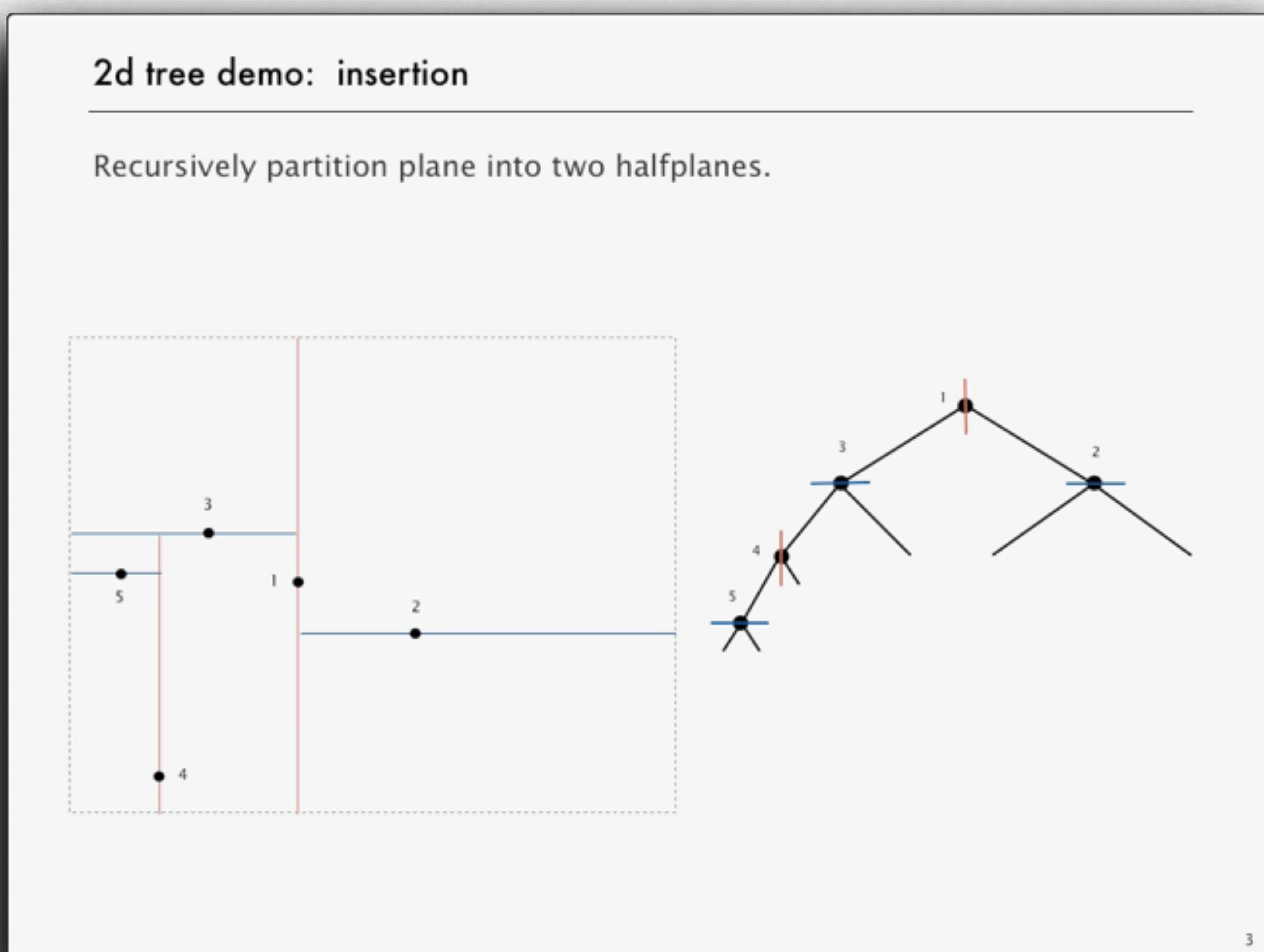

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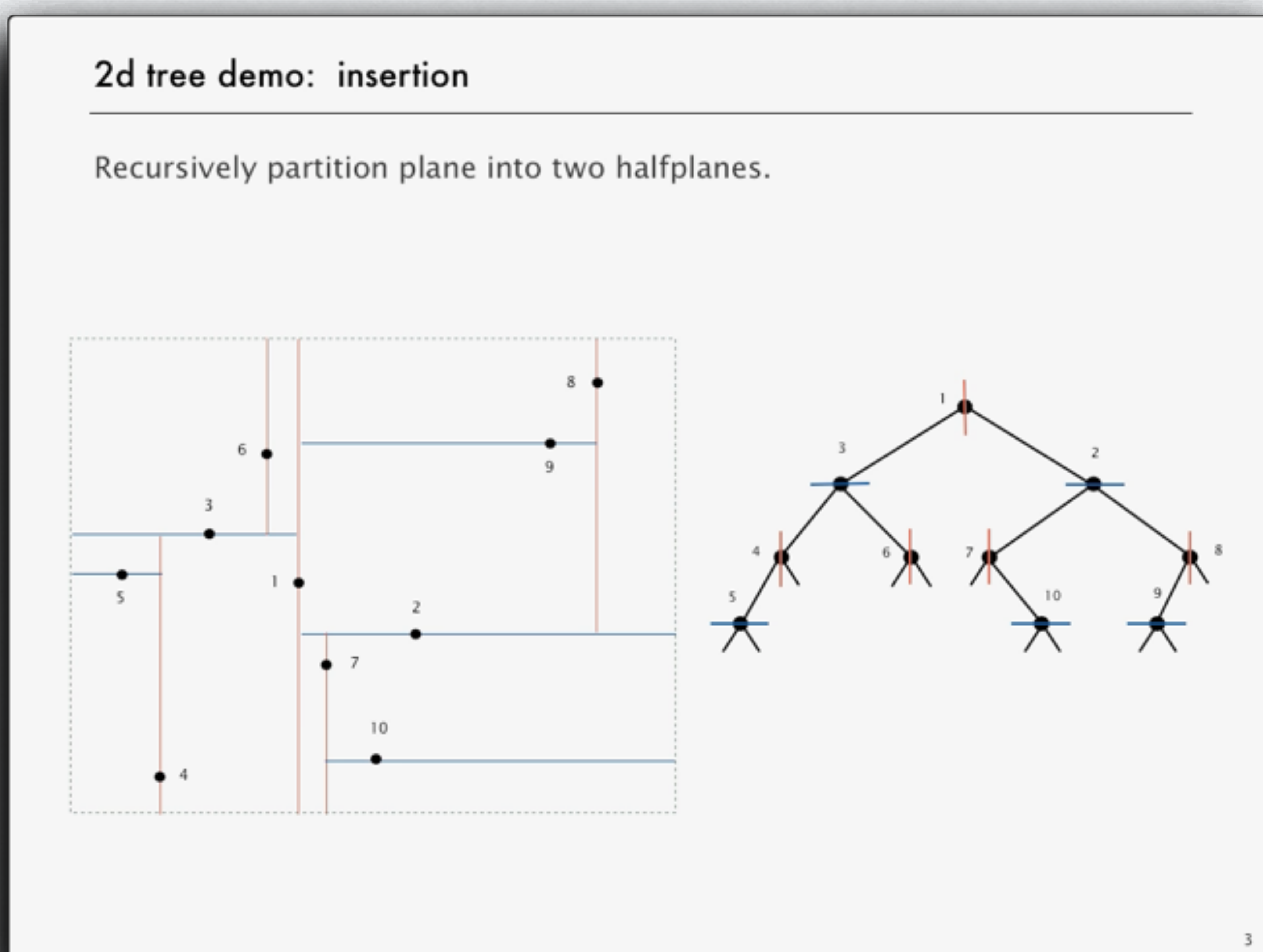
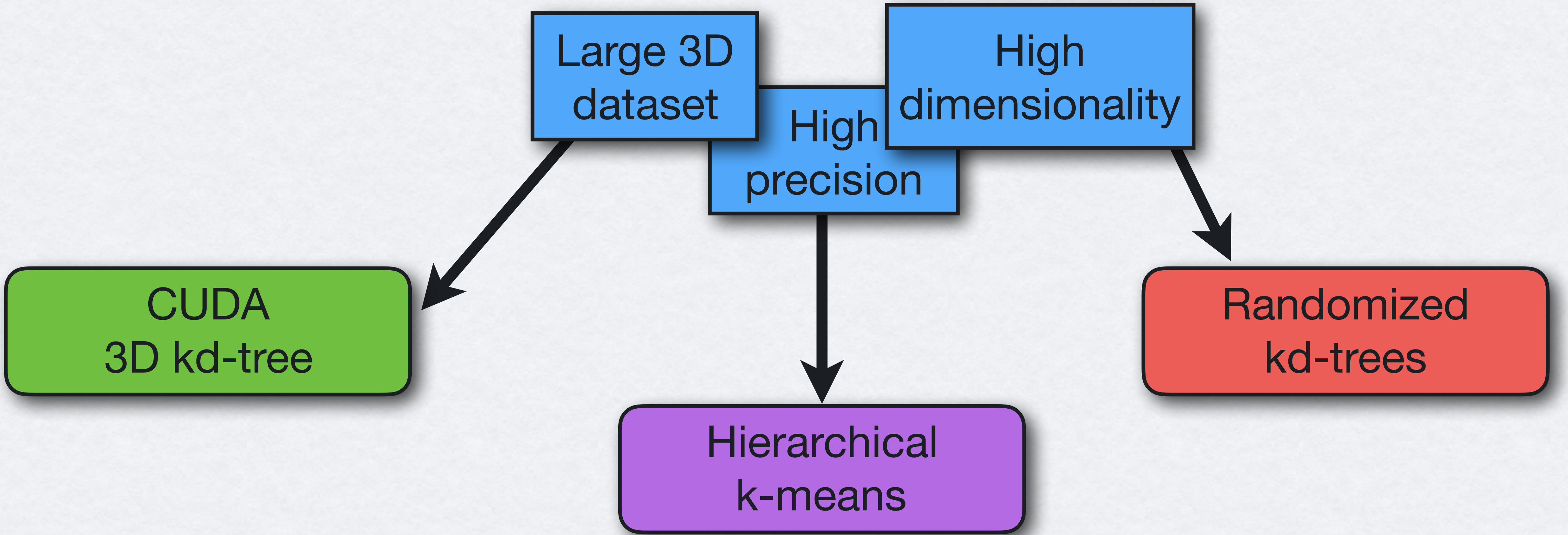


FLANN

Fast **L**ibrary for **A**pproximate **N**earest **N**eighbor by Marius Muja and David G. Lowe (http://www.cs.ubc.ca/research/flann/).

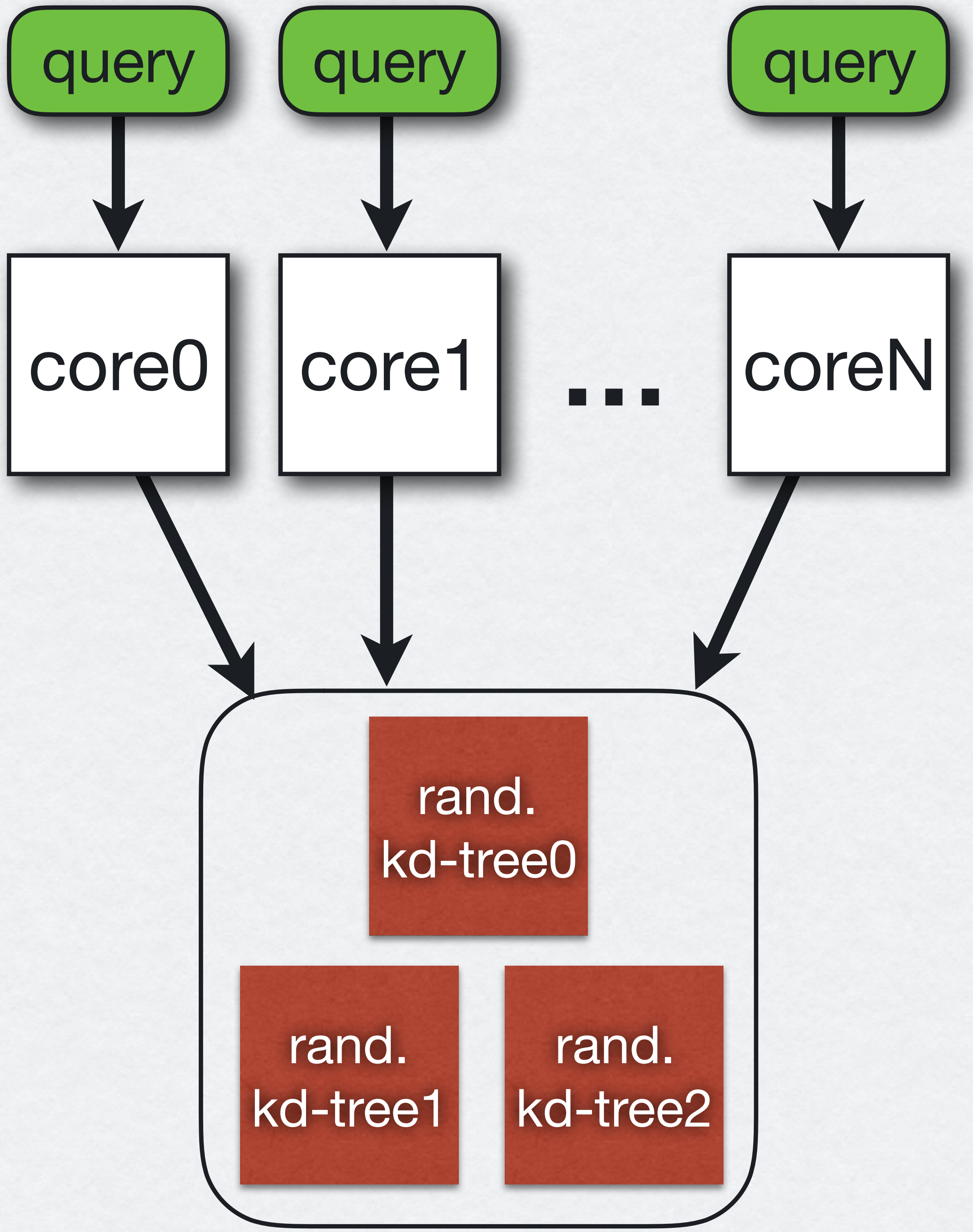
Implements different NN algorithms suitable for different input:



Widely used, in particular in Computer Vision application.

Xeon Phi

All cores query one set of random kd-trees



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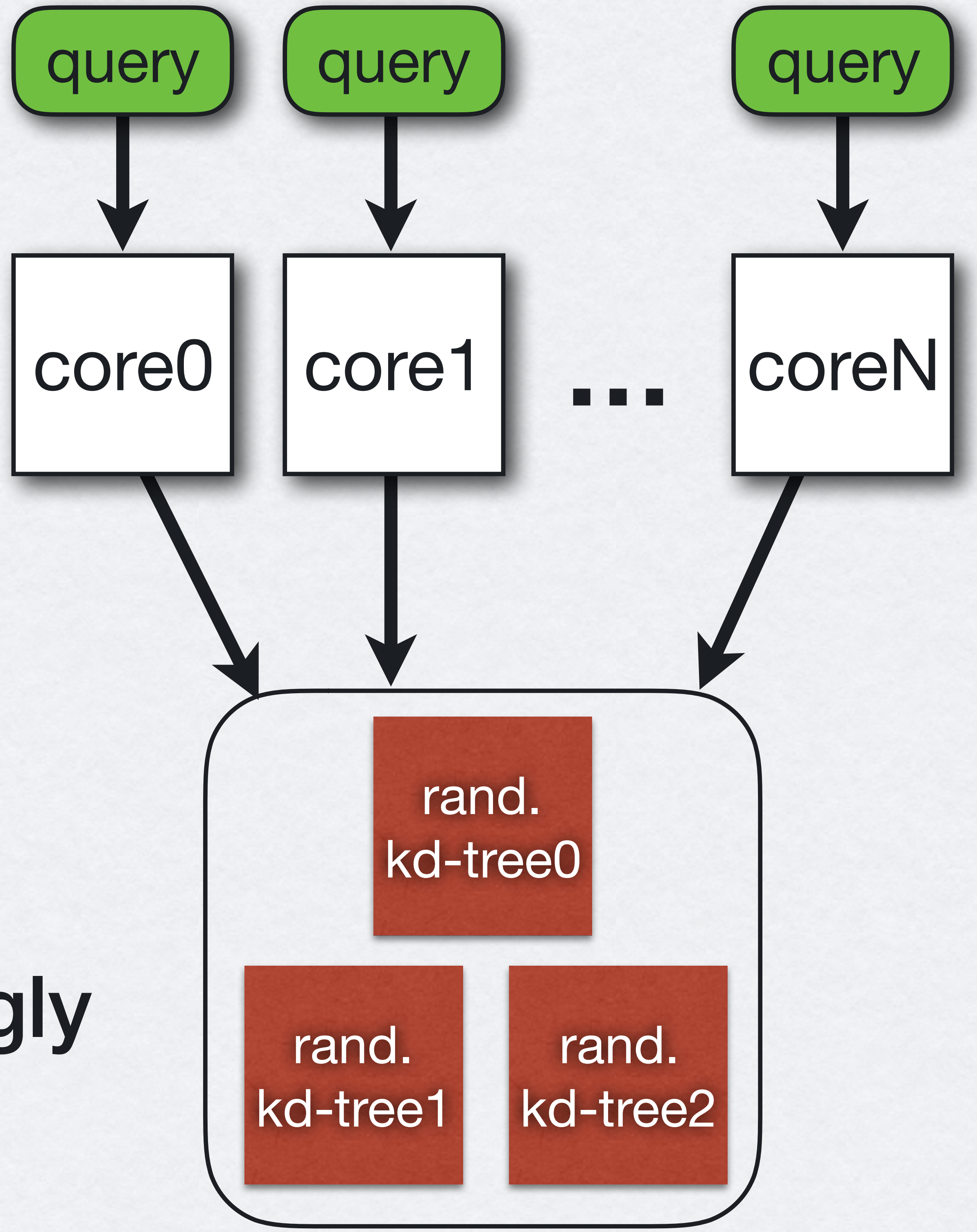

Pros

- O(log n) complexity
- Embarrassingly parallel

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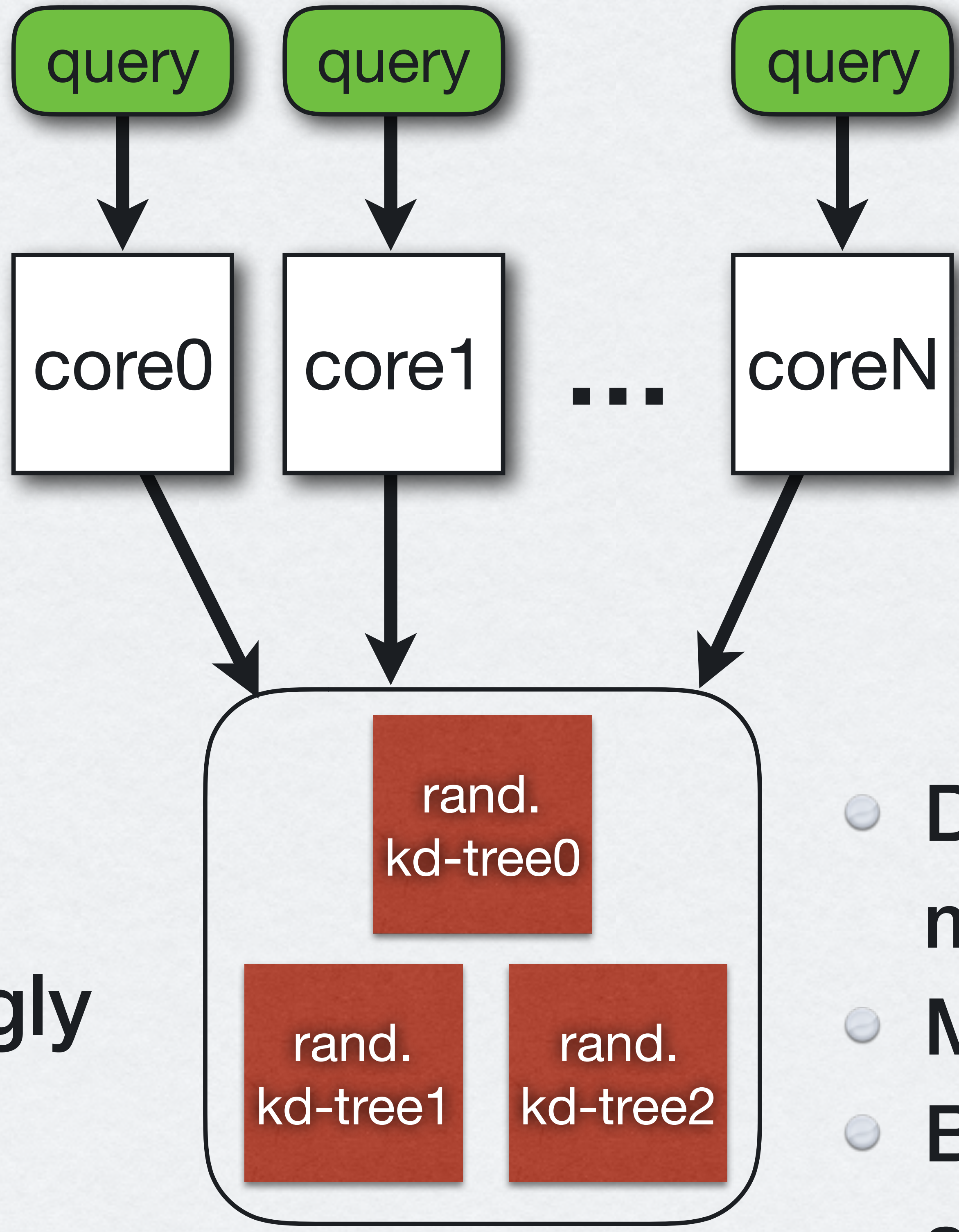

Pros

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Cons

- Discontiguous memory access
- Memory bound
- Best suited for approximate

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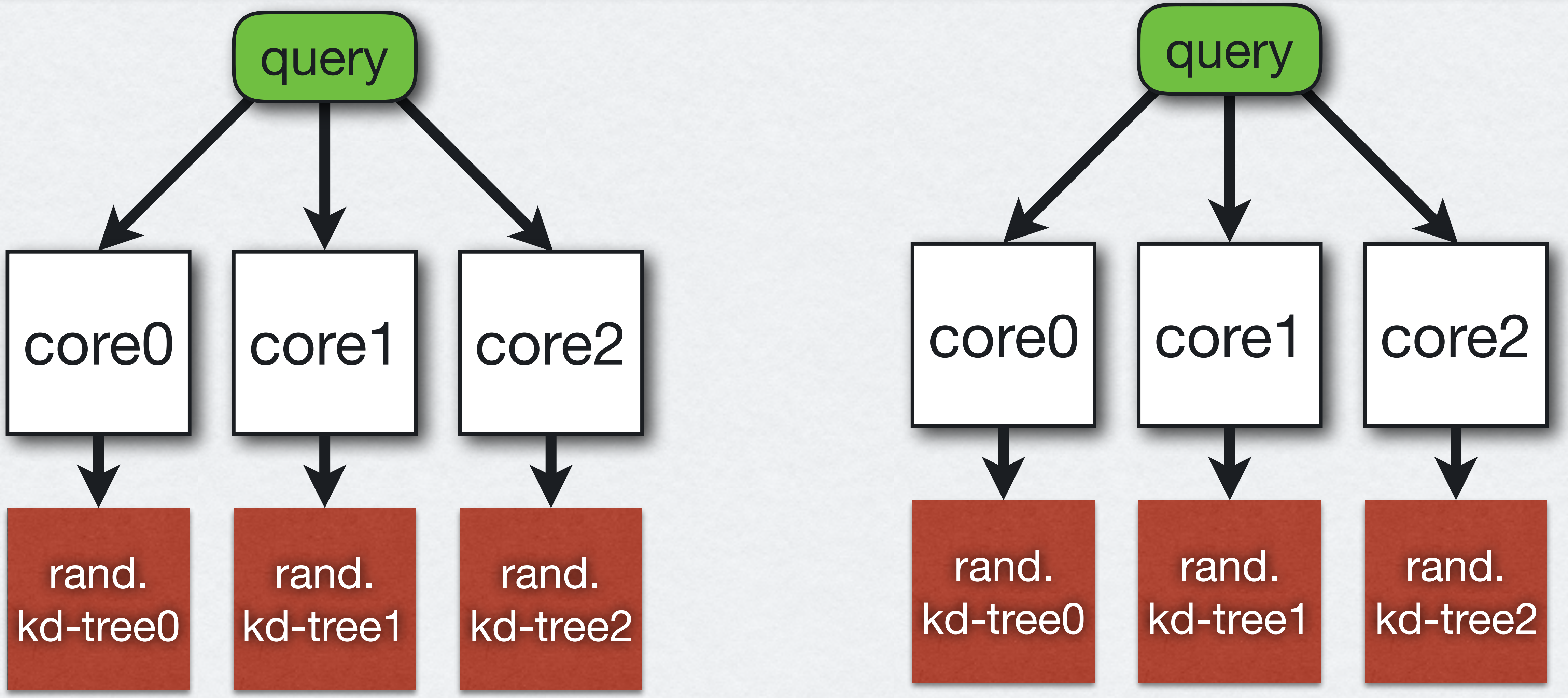
Random kd-trees distributed on cores



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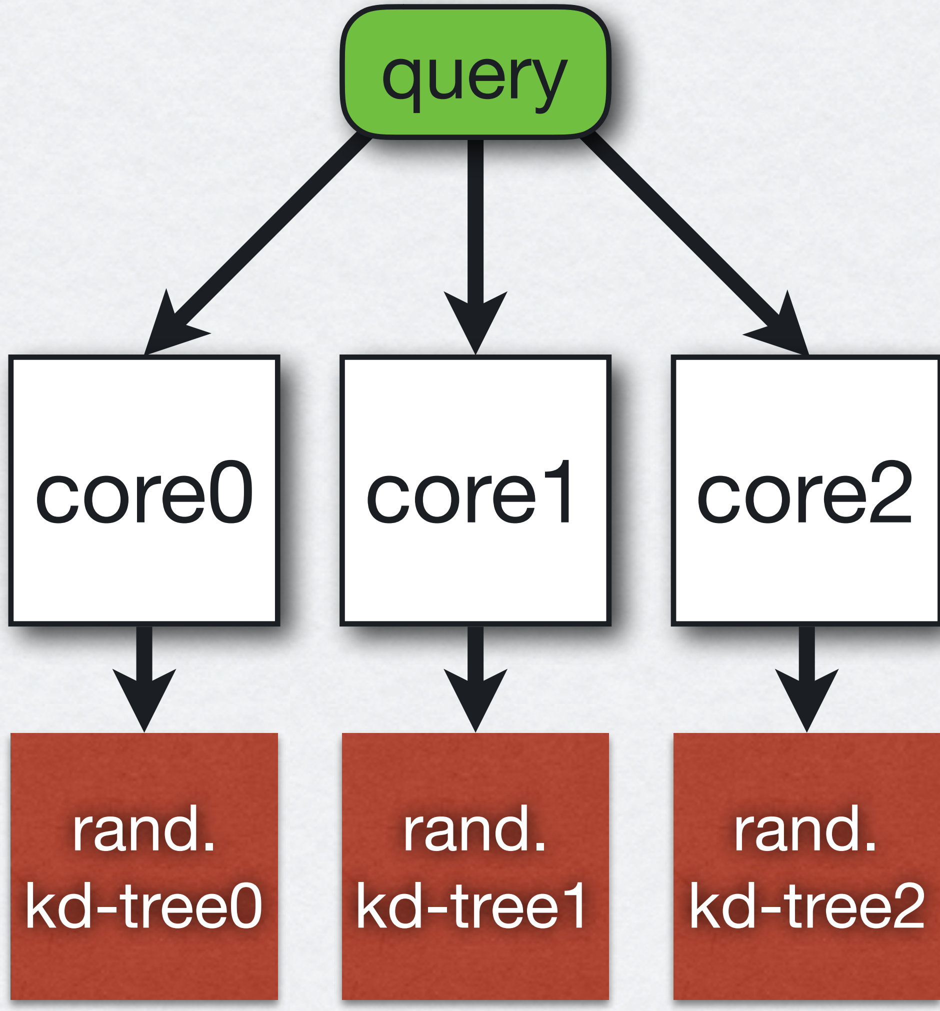

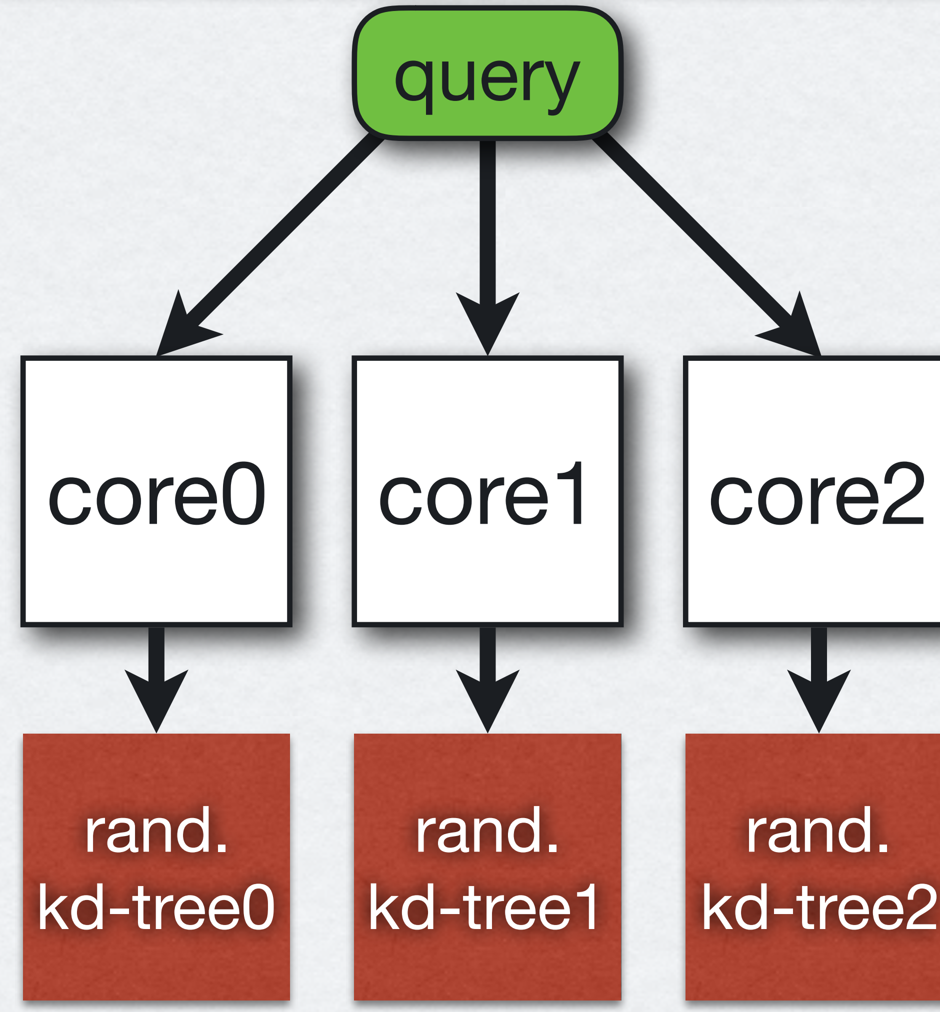

Pros

- Keep entire tree in L1 or L2 cache
- Still O(log n)

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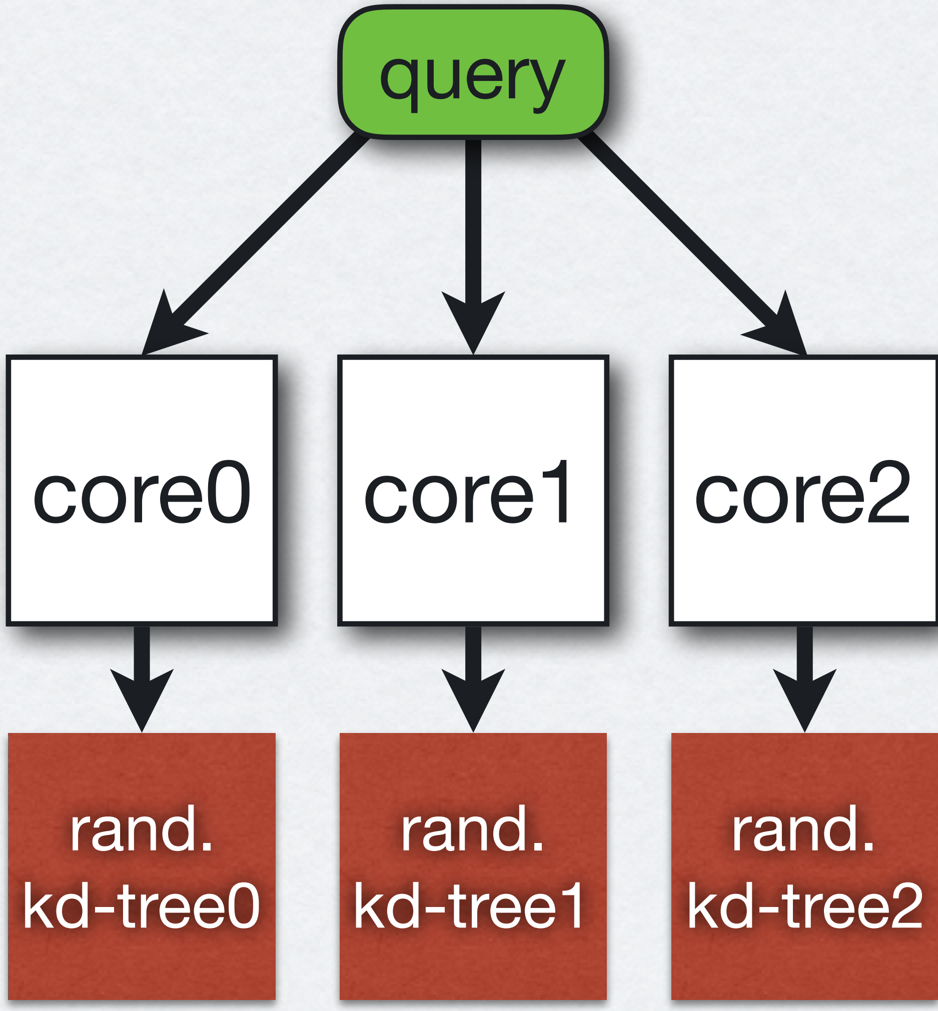

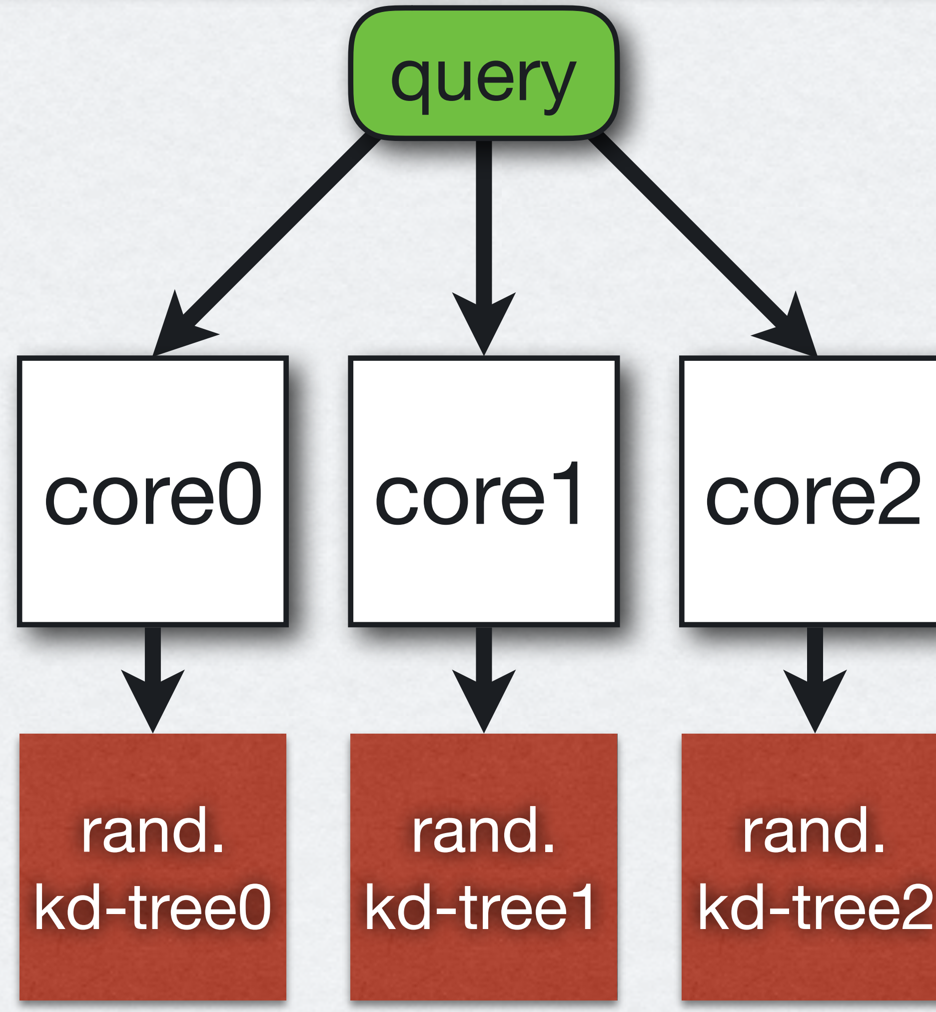

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Cons

- Requires synchronization
- Limited tree size

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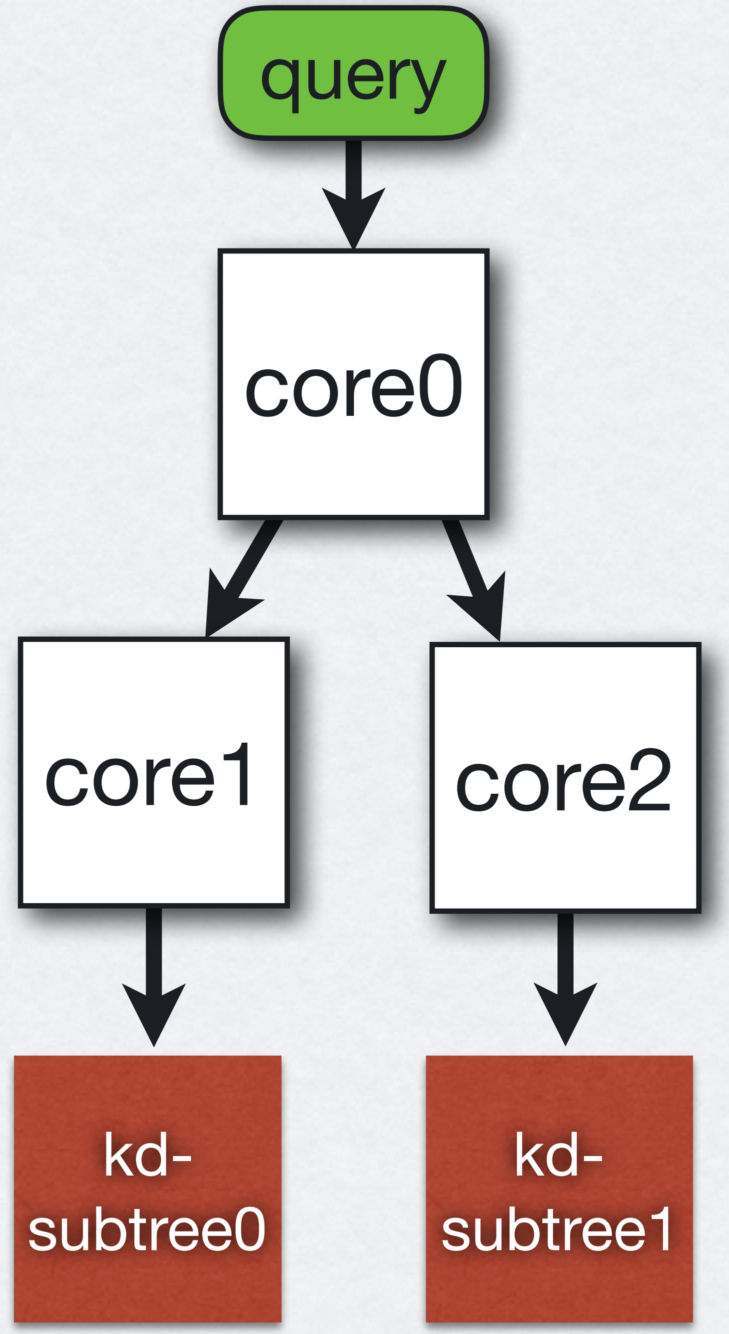
Single distributed complete tree



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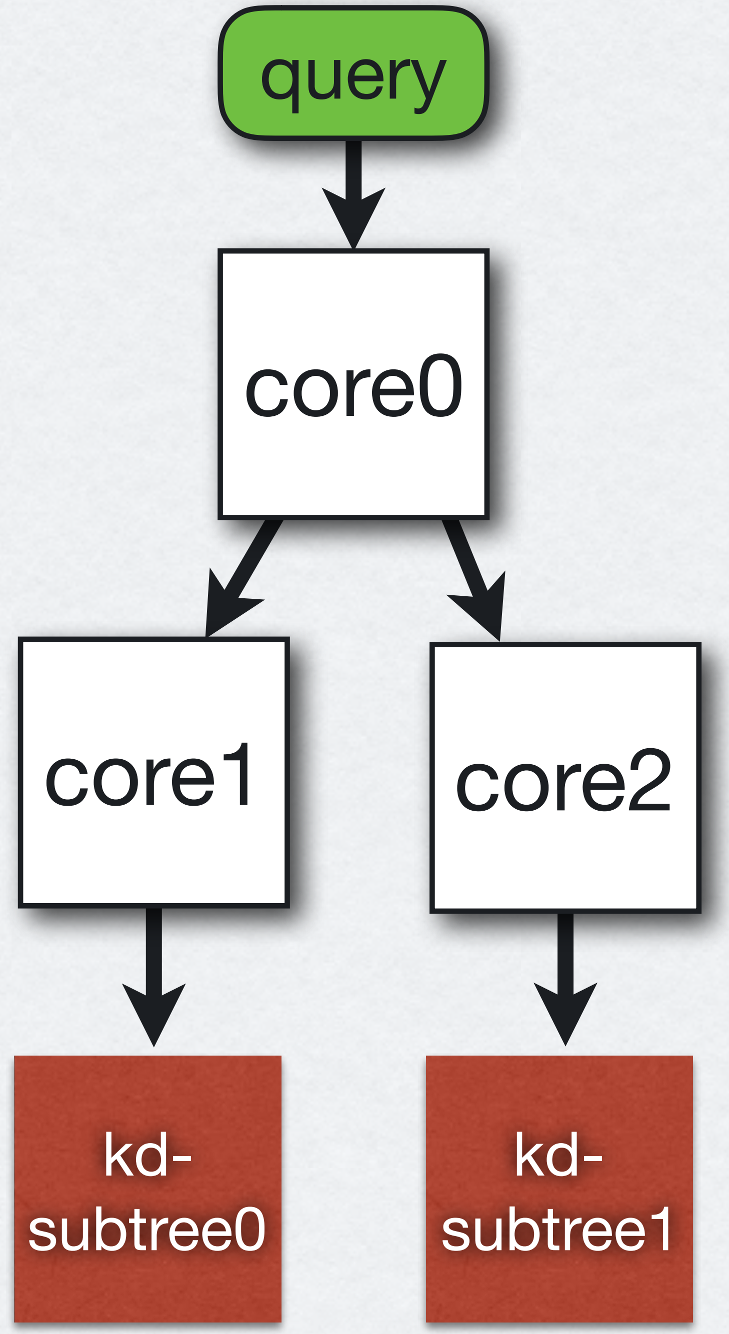

Pros

- Exact solution
- O(log n)
- Keep subtrees in L1/L2 cache

Xeon Phi

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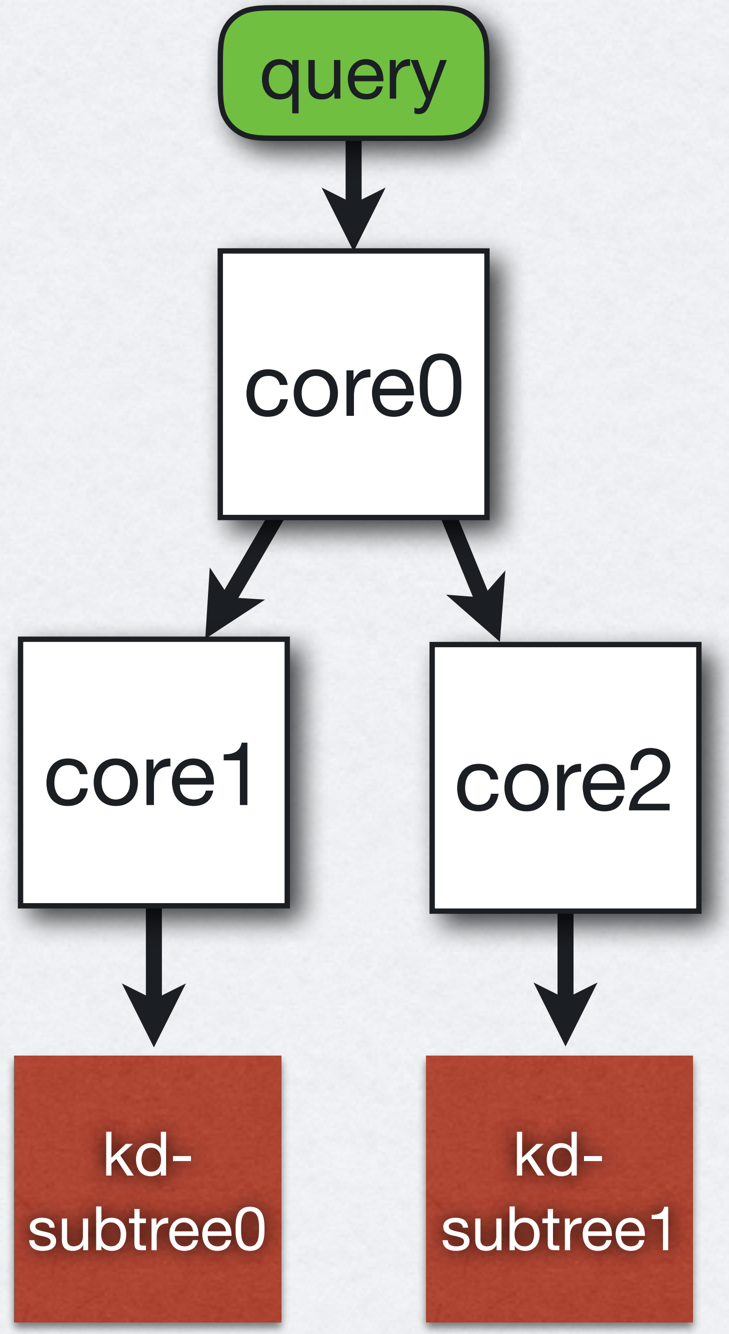

Pros

- Exact solution
- O(log n)
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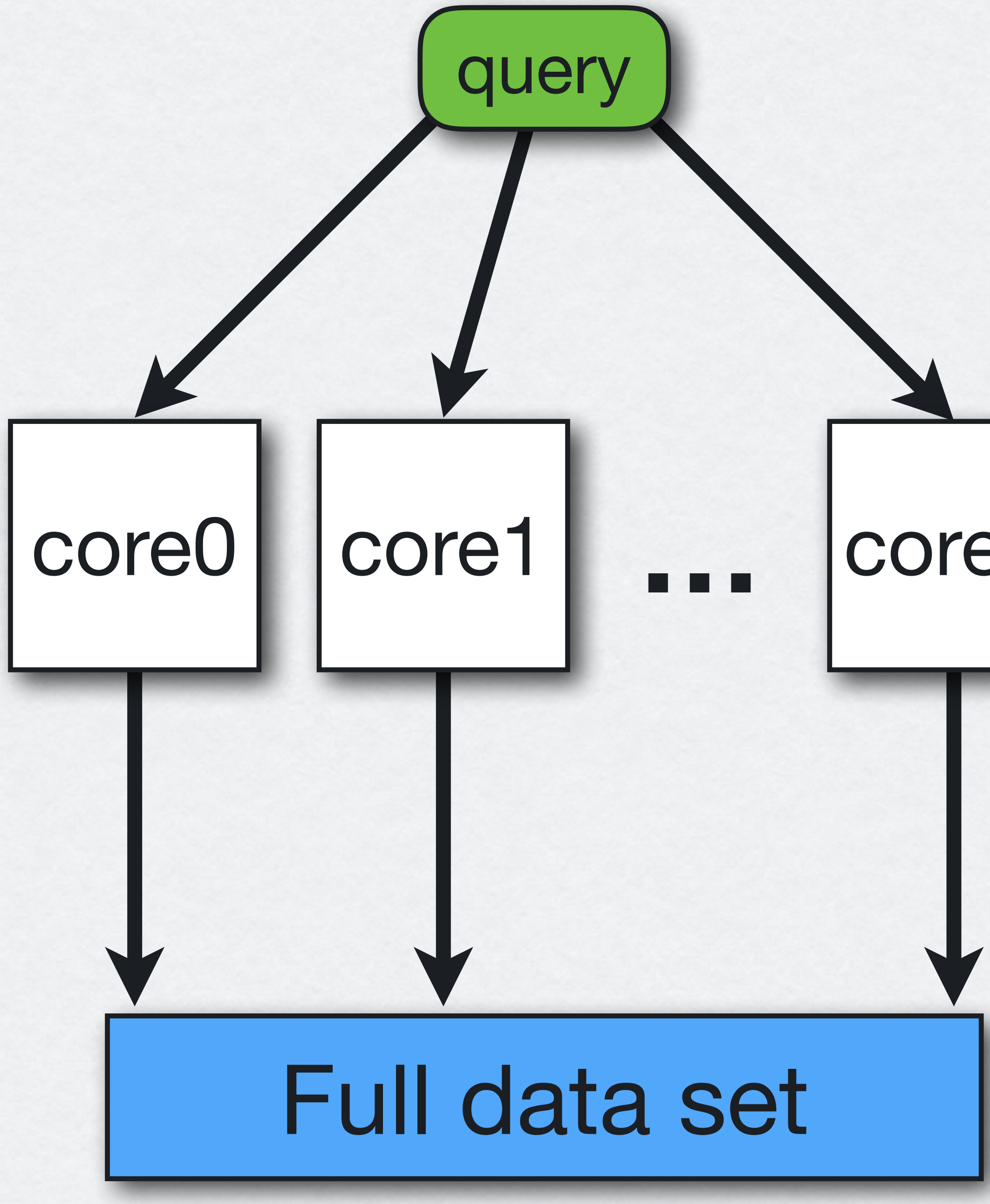
Cons

- Communication costs
- Load imbalance
- Requires extensive tweaking

Xeon Phi



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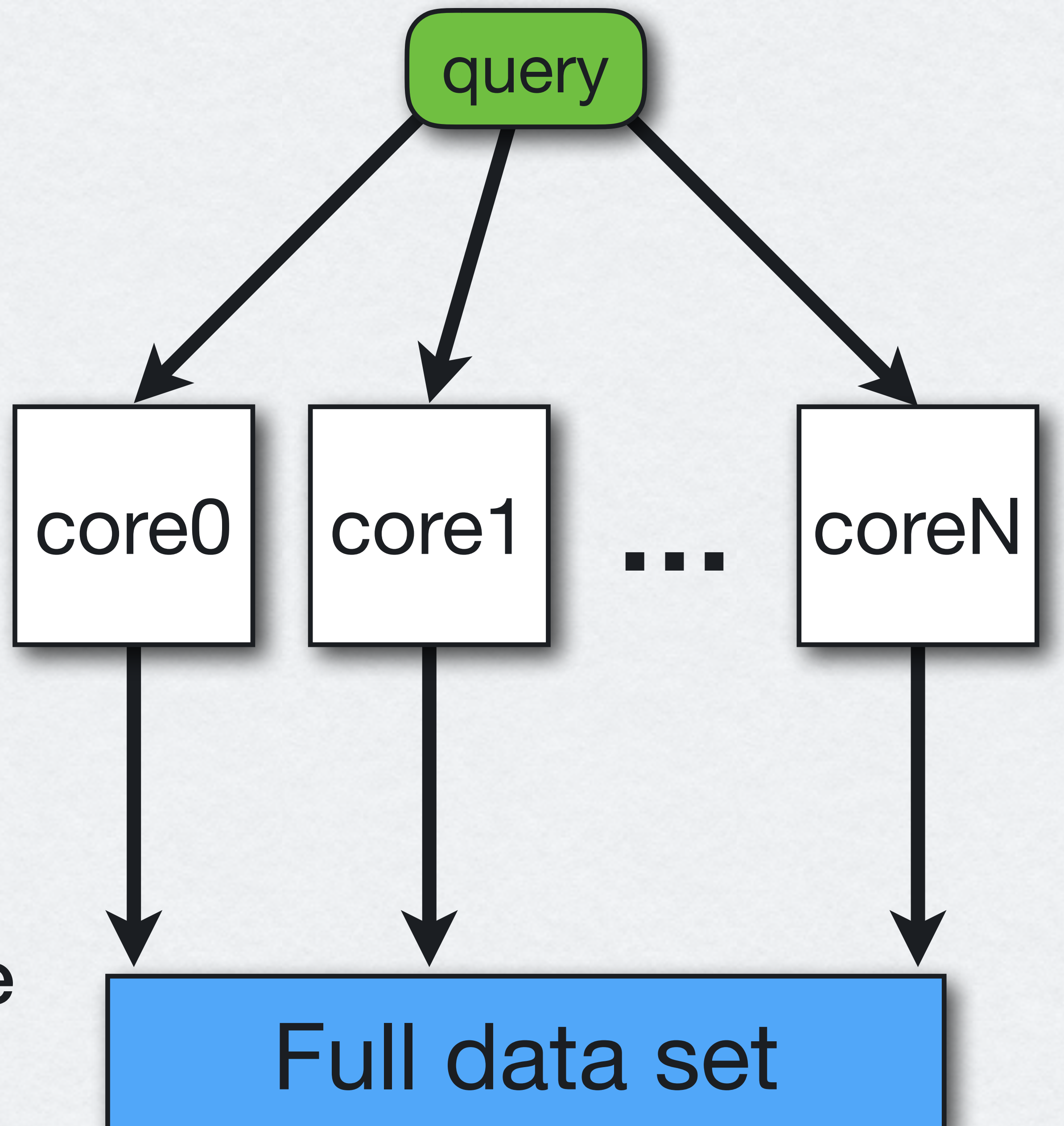

Pros

- Exact solution
- High hardware utilization
- Use highly optimized matrix library

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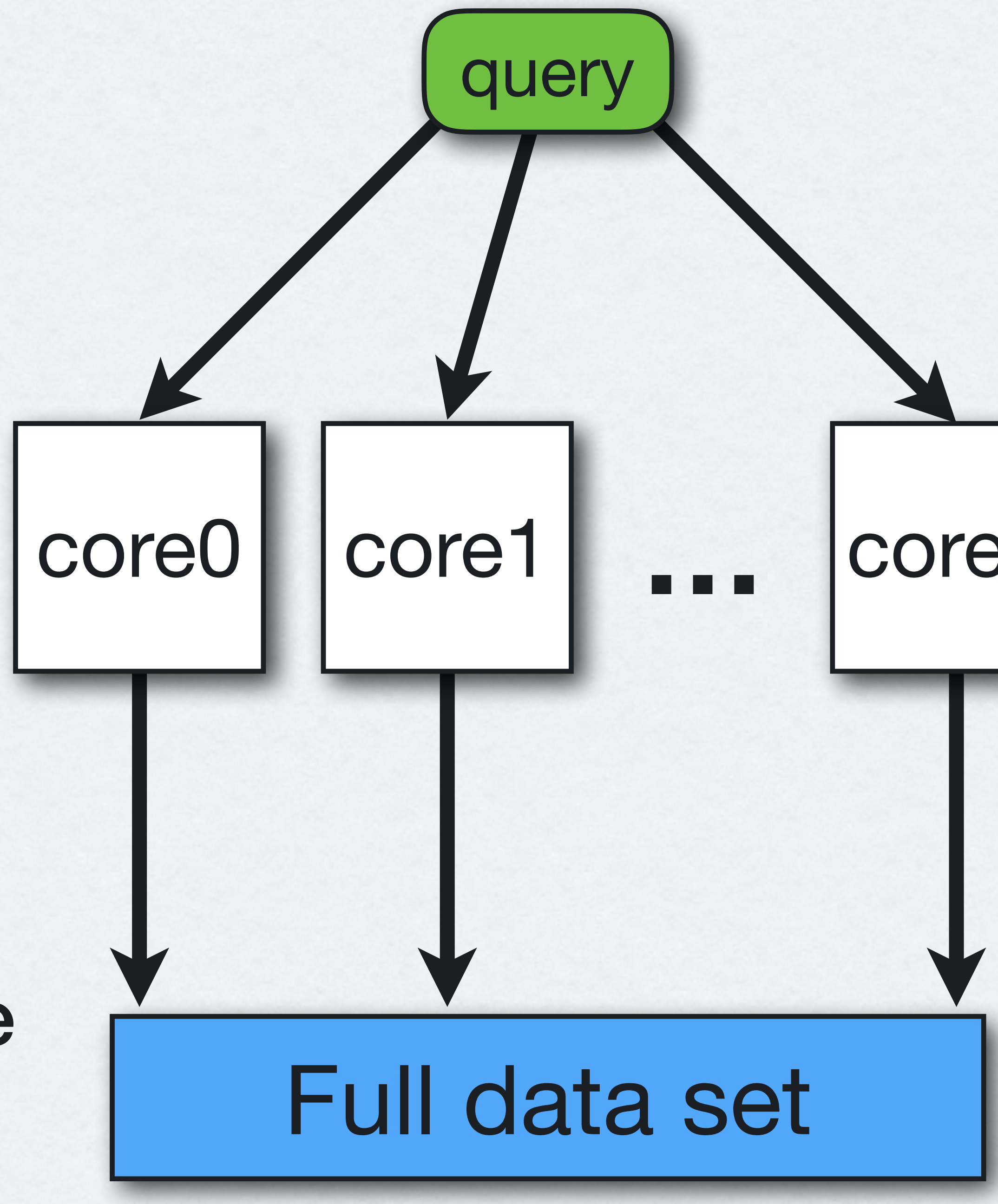

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- High hardware utilization
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Cons

- O(n) complexity

Results of Current Tests

SIFT Data Set

- Linear search vs. kd-tree search is identical (using 128-dimensional SIFT data, compared to exact k-neighbors)

- Speed up of kd-tree search using median splitting compared to linear search (1’000’000 base vectors, 10’000 query vectors)

3-Dimensional Data			
k	t_{linear}	t_{kd}	Improvement
10	16.89s	0.21s	78.6x
50	18.70s	1.20s	15.6x
100	16.02s	2.89s	5.6x
500	20.40s	15.82s	1.3x
1000	31.63s	32.51s	1.0x

128-Dimensional Data			
k	t_{linear}	t_{kd}	Improvement
10	356.7s	446.0s	0.8x
50	368.5s	621.1s	0.6x
100	310.0s	526.4s	0.6x
500	713.3s	744.5s	1.0x
1000	721.2s	563.0s	1.3x

Run on 1 Brutus node with four 12-core AMD Opteron 6174 CPUs and 64 GB of RAM
GCC 4.8.2 -std=c++11 -O3 -g

Milestones

- Naive kNN search ☑
- kd-Tree kNN search ☑
- Randomized approximate kd-Trees on CPU ☐
- Parallelize tree build and kNN search ☐
- Tuning to Xeon Phi ☐