

# ArborX: a performance portable geometric search library

Andrey Prokopenko (ORNL)

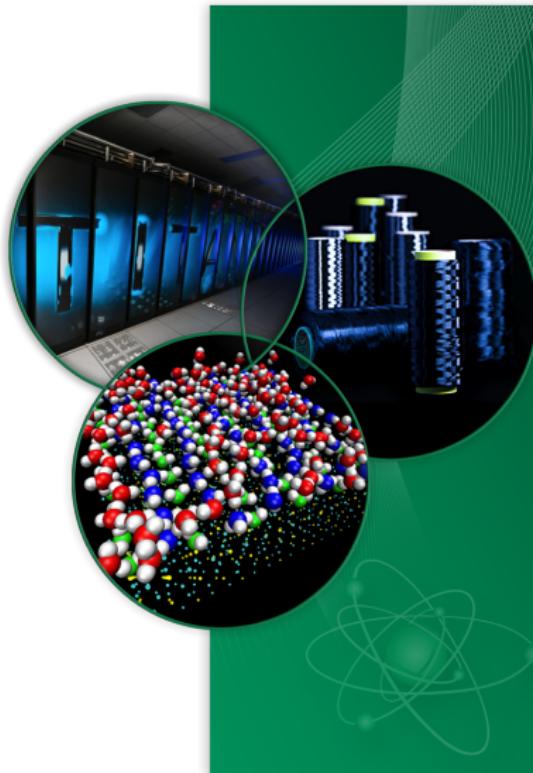
Daniel Arndt (ORNL)

Damien Lebrun-Grandié (ORNL)

Bruno Turcksin (ORNL)

Kokkos tea-time

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# Introduction

# What is ArborX?

ArborX is an open-source **performance portable geometric search library** based on MPI+Kokkos.

**Geometric search:** find geometric objects that are close in some sense.

- **Search**

- k-nearest neighbors (k-NN)
- Range (radius search, intersections)

- **Ray Tracing**

- **Clustering algorithms**

- Minimum spanning tree (Euclidean MST)
- Density based clustering (DBSCAN, HDBSCAN\*)

- **Interpolation**

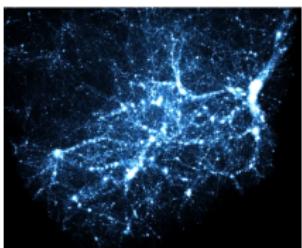
- Moving least squares (MLS)

<https://github.com/arborx/ArborX>

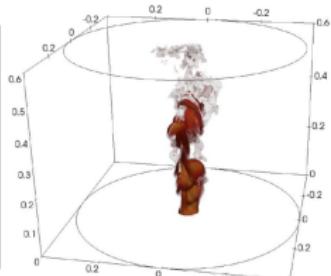


# Who uses ArborX?

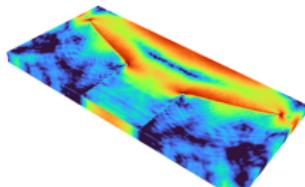
- **NimbleSM** contact mechanics
- **ALEGRA** shock hydrodynamics
- **LGRT** Lagrangian grid reconnection
- **deal.II** finite element library
- **MCRT** thermal radiation
- **Picasso** particle-in-cell
- **HACC/CosmoTools** clustering (dark matter)
- **Cabana** particle-based simulations
- **Adamantine** additive manufacturing
- **STK mesh** SIERRA/Trilinos meshing



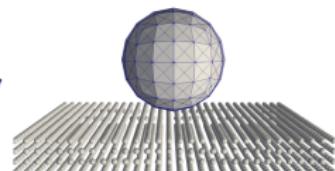
Cosmology (Credits: Nicholas Frontiere, ANL)



Combustion (Credits: Nicolas Tricard, UConn)



Additive manufacturing  
(Credits: Sam Reeve, ORNL)



Contact mechanics (Credits: Nicolas Morales, SNL)

# Why use ArborX?

- Fast
- Flexible interface
- Performance portable (Kokkos)
- Modern C++
- Actively developed
- Both on-node and distributed



# Who is developing ArborX?

Core development team

- Daniel Arndt
- Damien Lebrun-Grandié
- Andrey Prokopenko
- Bruno Turcksin

Most are also Kokkos developers.



Contributors:

- Ana Gainaru
- Wenjun Ge
- Piyush Sao
- Yohann Bosqued

# ArborX in the scientific stack

## Applications

Adamantine, ALLEGRA, HACC, MCRT, ...

Libraries

## Libraries

Cabana, deal.II, Picasso, ...

## ArborX

### Clustering algos

DBSCAN, HDBSCAN\*, MST, Dendrogram

### Interpolation

MovingLeastSquares

### Spatial indexes

BVH, BruteForce, DistributedTree

## Kokkos

## MPI (optional)

Hardware

E  
ry

# Why Kokkos?

Context: start of US DOE Exascale Computing Project in 2017

- Facing the unknown beyond Summit (Nvidia GPUs)
- SYCL not around at that time
- RAJA? Kokkos? Roll our own?

Join forces with Kokkos

- More than a programming model
- Ecosystem with debugging and profiling tools, math libraries, etc.
- Building a community

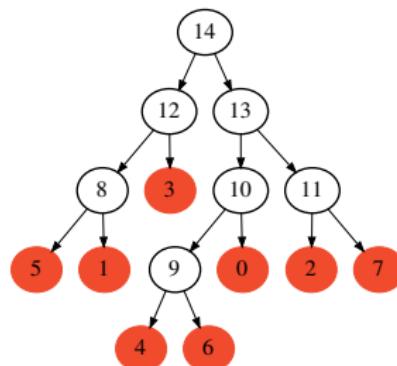
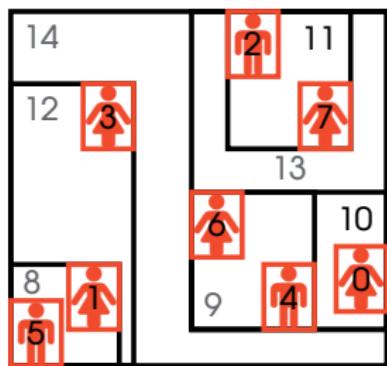


# Core concepts



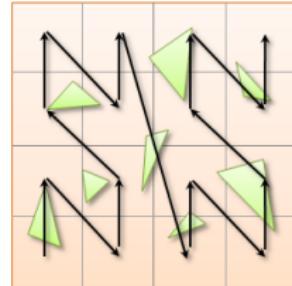
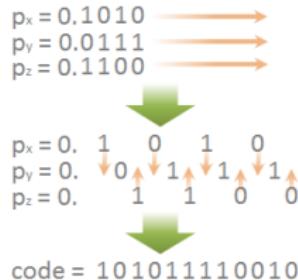
# Bounding volume hierarchy (BVH)

**Bounding volume hierarchy (BVH)** is a tree structure on a set of geometric objects, where each object is associated with a conservative bounding box.



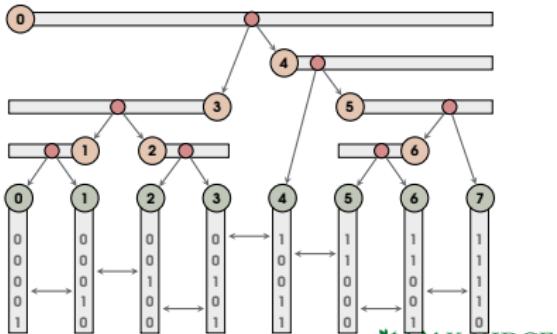
# Linear BVH

Impose order in which leaf nodes appear in the tree (Z-curve/Morton codes)



(courtesy of T. Karras, Nvidia)

- Each internal node is a linear range over leaf nodes
- The splits are determined according to the highest bit that differs between the Morton codes within the given range
- Can be constructed fully in parallel



# Two flavors of search

## Range search

Find all the data that satisfies a criteria (within certain distance, intersects, etc.)

- Optimized stackless traversal
- Do two passes (count-and-fill) as the number of found object is not known *a priori*
- Multiple knobs to speed things up:
  - Early termination
  - Half traversal for pairs

## Nearest search

Find the predefined number of the closest neighbors to a given object.

- Single pass (know in advance how much memory is required)
- Use stack instead of priority queue



# Interface



# Concepts

- Search index is a container of values

Can be anything (integers, geometries, user types)

- Values are transformed to geometries through indexable getter

Could be user provided for custom, or default

- Bounding volumes can be customized (AABBs, kDOPs, OBBs)

AABB by default; could be user provided

```

template<typename MemorySpace,
         typename Value,
         typename IndexableGetter,
         typename BoundingVolume>
class BVH {
    template <typename ExecutionSpace, typename Values>
    BVH(ExecutionSpace const& space,
        Values const& values,
        IndexableGetter const& indexable_getter);

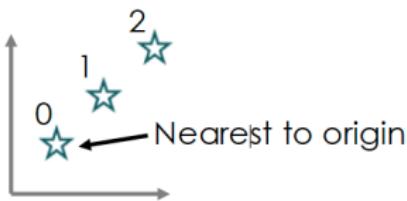
    template <typename ExecutionSpace, typename Predicates,
              typename Callback>
    void query(ExecutionSpace const& space,
               Predicates const& predicates,
               Callback const& callback) const;

    template <typename ExecutionSpace, typename Predicates,
              typename Callback,
              typename Values, typename Offsets>
    void query(ExecutionSpace const& space,
               Predicates const& predicates,
               Callback const& callback,
               Values& values,
               Offsets& offsets) const;
};


```



# "Hello, world!" in ArborX



```
#include <ArborX.hpp>
#include <Kokkos_Core.hpp>
int main(int argc, char *argv[]) {
    Kokkos::initialize(argc, argv);
    {
        Kokkos::DefaultExecutionSpace exec;
        // Build data structure
        ArborX::BoundingVolumeHierarchy bvh(
            exec, to_view({
                {1.f, 1.f}, // 0
                {2.f, 2.f}, // 1
                {3.f, 3.f} // 2
            }));
        // Perform the search
        bvh.query(exec, to_view(
            ArborX::Nearest(ArborX::Point{0.f, 0.f, 0.f})
        ), KOKKOS_LAMBDA(auto /*predicate*/,
                           auto point /*value*/) {
            printf("Nearest to origin is (%f, %f)\n",
                   point[0], point[1]);
        });
    }
    Kokkos::finalize();
    return 0;
}
```

Prints "Nearest to origin is (1, 1)"



# Access traits

- Customization point
- Opt-in mechanism to tell ArborX
  - where the data resides
  - how much of it
  - how to access
- Allowed to specialize for user-defined type

```
struct PointCloud {
    float *d_x, *d_y, *d_z;
    int N;
};

template <>
struct ArborX::AccessTraits<PointCloud>
{
    using memory_space = Kokkos::CudaSpace;

    static KOKKOS_FUNCTION
    std::size_t size(PointCloud const &cloud) {
        return cloud.N;
    }

    static KOKKOS_FUNCTION static ArborX::Point
    get(PointCloud const &cloud, std::size_t i) {
        return {{cloud.d_x[i], cloud.d_y[i], cloud.d_z[i]}};
    }
};
```



## User callbacks

Users may not care about the results themselves, or want a subset of the results.  
For example:

- Call a function on the results

May not need to store results, so less memory and single pass for spatial.

**Use case:** finding a particle with most neighbors (defined by a length), or particles with a lowest potential (calculated as a function of friends)

- Do results pruning

**Use case:** doing fine intersection search with the exact object geometry

- Use processor-local information

**Use case:** compute interpolation coefficients for results using mesh parts on a processor



# User callbacks

```
template <typename MemorySpace>
struct Callback {
    template <typename Query, typename Value>
    KOKKOS_FUNCTION
    void operator() (Query const &query, Value const& value) const {
        auto data = ArborX::getData(query);
        // do something
    }
};

template <typename MemorySpace>
struct CallbackWithOutput {
    template <typename Query, typename Value, typename Output>
    KOKKOS_FUNCTION
    void operator() (Query const &query, Value const& value, Output const &out) const {
        auto data = ArborX::getData(query);
        // store something as a result
        out({...});
    }
};
```



# Use case 1: DBSCAN

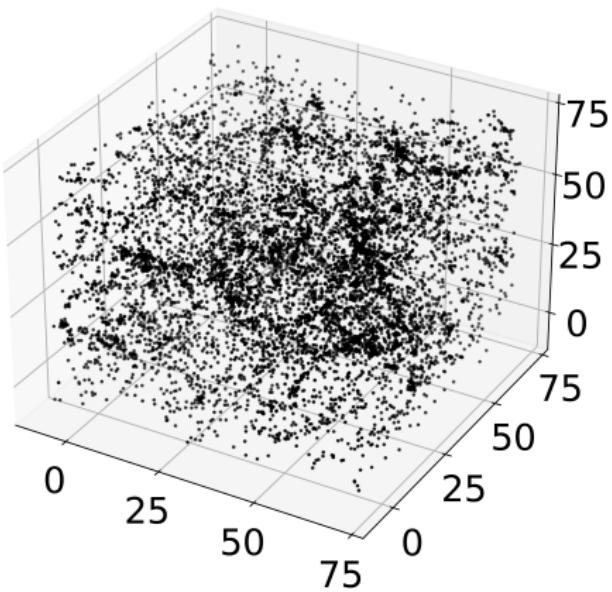


# Application

Cosmological simulation of the universe.

Data is massive. For example,  $3096^3$  particles running on 64 MPI ranks for a small run. In practice, 500M particles per GPU.

**Goal:** find dense regions of particles (halos) on each simulation time step.



# DBSCAN algorithm

**Clustering:** split a set of objects into disjoint classes (clusters), so that objects in each class are more similar to each other than to those in other classes.

**DBSCAN** is a clustering algorithm based on density.

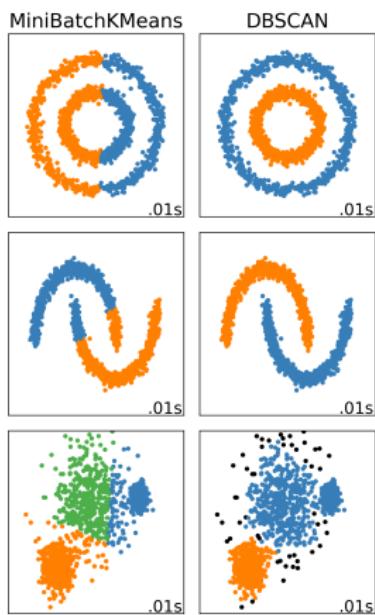
Main advantages:

- does not require to specify the number of clusters
- can find arbitrary shaped clusters
- has a notion of noise and is robust to outliers

It also has some disadvantages:

- not fully deterministic (border points)
- does not cope well with clusters of variable density
- choosing its parameters can be difficult

Ester et al. "A density-based algorithm for discovering clusters in large spatial databases with noise." In Kdd, 96(34), pp. 226-231. 1996



# DBSCAN algorithm

Given two parameters,  $\varepsilon$  and ***minpts***, DBSCAN separates all points into three classes:

- **core points**: have at least *minpts* neighbors within  $\varepsilon$
- **border points**: not core points, but have a core point within  $\varepsilon$
- **noise**: all other points

Any cluster consists of a combination of core points (at least one) and border points (possibly, none). Example below show *minpts* = 4.

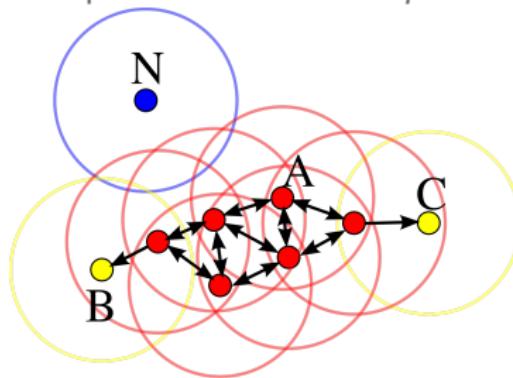


Image by Chire, Wikimedia Commons, distributed under CC BY-SA 3.0

# F-DBSCAN (sparse)

**Focus:** use parallel neighbor computation to minimize data and thread divergence on GPUs. Two phases: *preprocessing* and *main*.

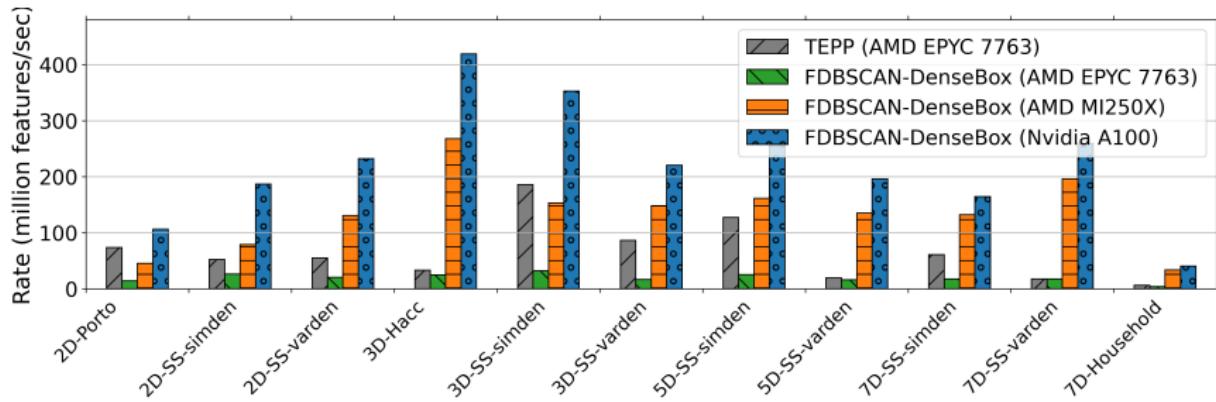
- Use tree structure for search (e.g., kd-tree or BVH)
- Determine core points in preprocessing (terminate early)
- Implicit edges, execute **UNION** on collision

```

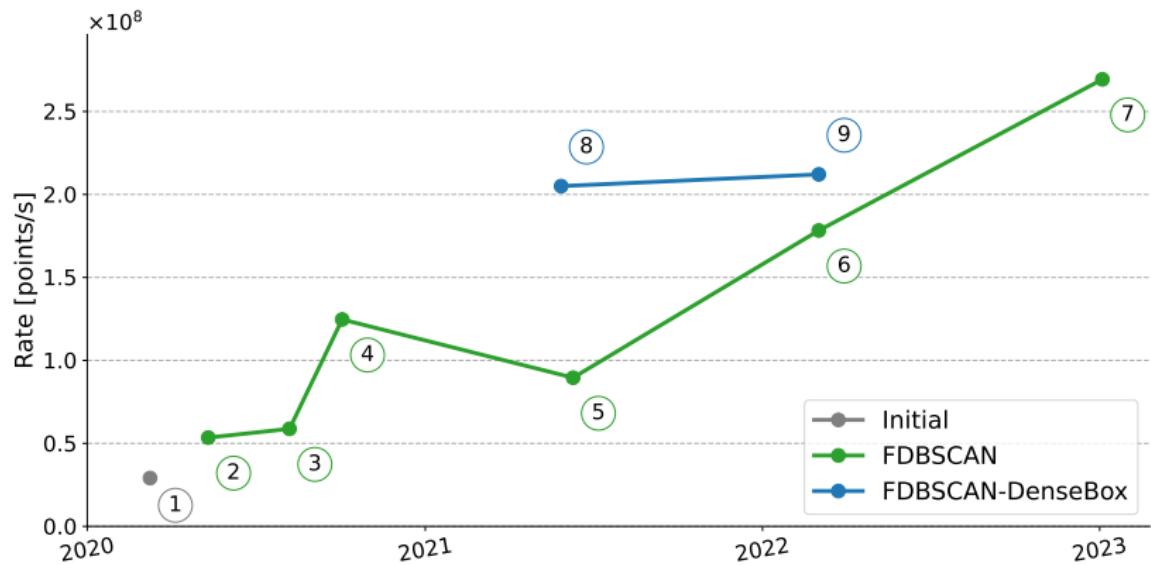
procedure F-DBSCAN( $X, minpts, \varepsilon$ )
if  $minpts > 2$  then
    for each point  $x \in X$  in parallel do
        determine whether  $x$  is a core point
    for each pair of points  $x, y$ 
        such that  $dist(x, y) \leq \varepsilon$  in parallel do
            if  $x$  is a core point then
                if  $y$  is a core point then
                    Union( $x, y$ )
                else if  $y$  is not yet a member of any cluster then
                    critical section:
                        mark  $y$  as a member of a cluster
                    mark  $y$  as a member of a cluster
                    Union( $x, y$ )
                
```



# Results: performance portability



# Results: application proxy performance improvement



# Use case 2: Euclidean minimum spanning tree (EMST)

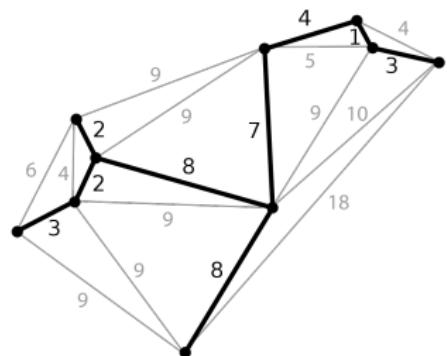


# Euclidean minimum spanning tree

A **minimum spanning tree (MST)** is a subgraph of a weighted undirected graph that connects all the vertices together, without any cycles and with the minimum possible total edge weight.

A **Euclidean MST (EMST)** is a MST of the distance graph of a set of points, i.e., a graph where each pair of vertices are connected by an edge of weight equal to the Euclidean distance between them.

Applications: data clustering (e.g., HDBSCAN\*), Euclidean traveling salesman problem, wireless network connectivity, computational fluid dynamics, etc.



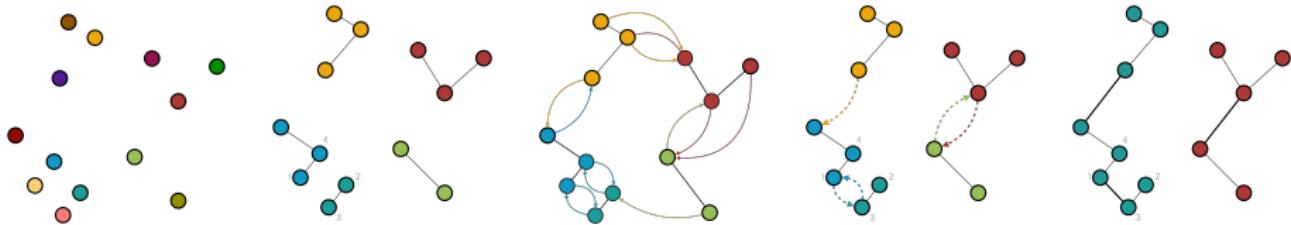
c/o Wikipedia

**Our goal:** fast EMST

computation for large (10M+) dataset of low-dimensional data.



# Borůvka's algorithm



- a Initial state (each component having a single vertex).
- b The state after a few Borůvka iterations.
- c Closest neighbors from a different component for each vertex.
- d The shortest outgoing edge for each component.
- e The new components after the merge (the initial state of the next Borůvka iteration).

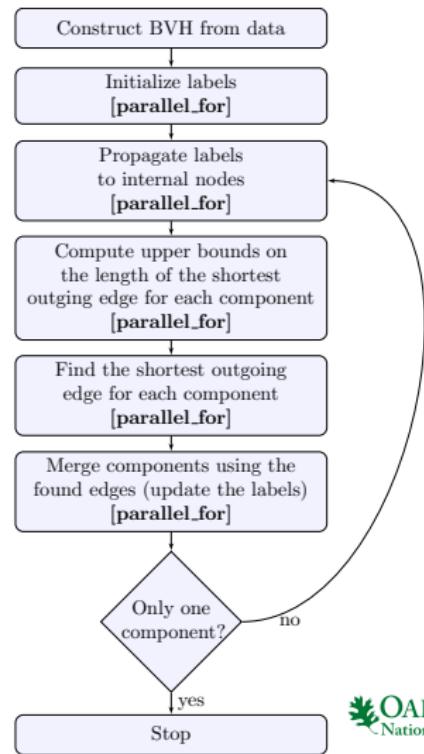
# The single-tree algorithm overview

The Boruvka's algorithm is iterative. Each iteration consists of two phases:

- ➊ find the shortest outgoing edge for each component (**expensive!**)
- ➋ merge components

Finding the shortest outgoing edge: a **nearest-neighbor** problem with a **constraint** (the neighbor is from a different component). **Two optimizations** are necessary to prune the number of distance calculations:

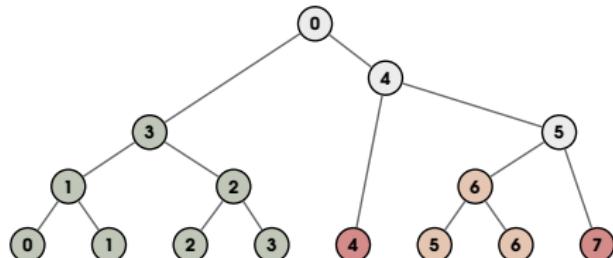
- skipping nodes in the same component (**subtree skipping**)
- maintaining an **upper bound** on the distance of the outgoing edge candidates



# Subtree skipping

**Goal:** Reduce the number of tree nodes encountered during the traversal.

- Leaf node labels are component membership of the data points.
- Propagate the labels from the leaf nodes to the internal nodes.  
Same labels of children → parent label. Different labels of children → invalid parent label. Done in a single bottom up traversal
- Skip subtrees of the same label as query during the traversal.



**Very important** on the **later** Borůvka iterations, when the components are large.

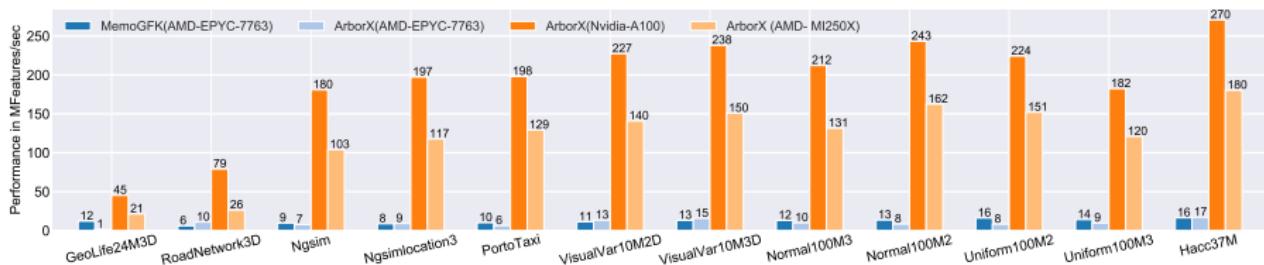
# Datasets

Name	Dim	Size	Description
<i>Ngsim</i>	2	~12,000,000	Car trajectories on three highways
<i>Ngsimlocation3</i>	2	~6,400,000	A subset of <i>Ngsim</i> (one highway)
<i>PortoTax</i>	2	~1,710,000	Taxi trajectories in Porto, Portugal
<i>RoadNetwork3</i>	2	~400,000	Road network of a Denmark province
<i>GeoLife24M3</i>	3	~24,000,000	User location data
<i>Hacc37M</i>	3	~37,000,000	Cosmological data from a simulation
<i>Hacc497M</i>	3	~497,000,000	Cosmological data from a simulation
<i>VisualVar10M2</i>	2	10,000,000	Synthetic data (Gan-Tao generator)
<i>VisualVar10M3</i>	3	10,000,000	Synthetic data (Gan-Tao generator)
<i>Normal100M2</i>	2	100,000,000	Normally distributed points
<i>Normal300M2</i>	2	300,000,000	Normally distributed points
<i>Normal100M2</i>	3	100,000,000	Normally distributed points



# Parallel performance

Performance comparison of the EMST implementations using AMD EPYC 7763 (64 cores), Nvidia A100 and AMD MI250X (single GCD<sup>1</sup>).

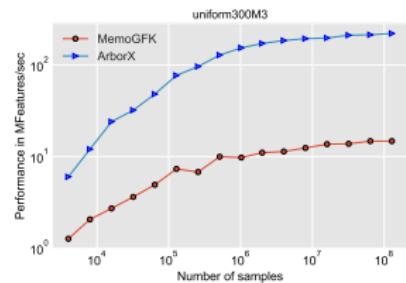
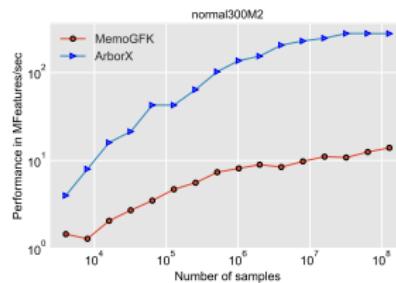
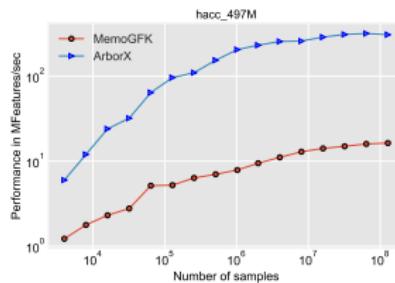


- ARBORX implementation is faster by 4-24× than MEMO GFK on Nvidia A100
- ARBORX multi-threaded implementation is within factor 0.5-2× of MEMO GFK (the fastest available multi-threaded implementation) (except GeoLife24M3D)
- ARBORX optimized for Nvidia A100 but not for AMD MI250X

<sup>1</sup>GCD = Graphics Complex Die

# Scaling

Effect of the dataset size on the parallel performance using AMD EPYC 7763 and Nvidia A100.



- Performance increases with the number of samples until reaching saturation
- Asymptotically linear complexity of the algorithms

# Future

# What does future hold?

- ArborX 2.0 (new interface!)
- Documentation!
- Performance improvements

OBB hierarchy, hierarchy structure optimization, low precision

- New indexes
  - Octree, kd-tree
- Approximate search
- Very high dimensional ( $\text{dim} > 10$ ) search

# Questions?

<https://github.com/arborx/ArborX>

prokopenkoav@ornl.gov

