PARALLEL ID3

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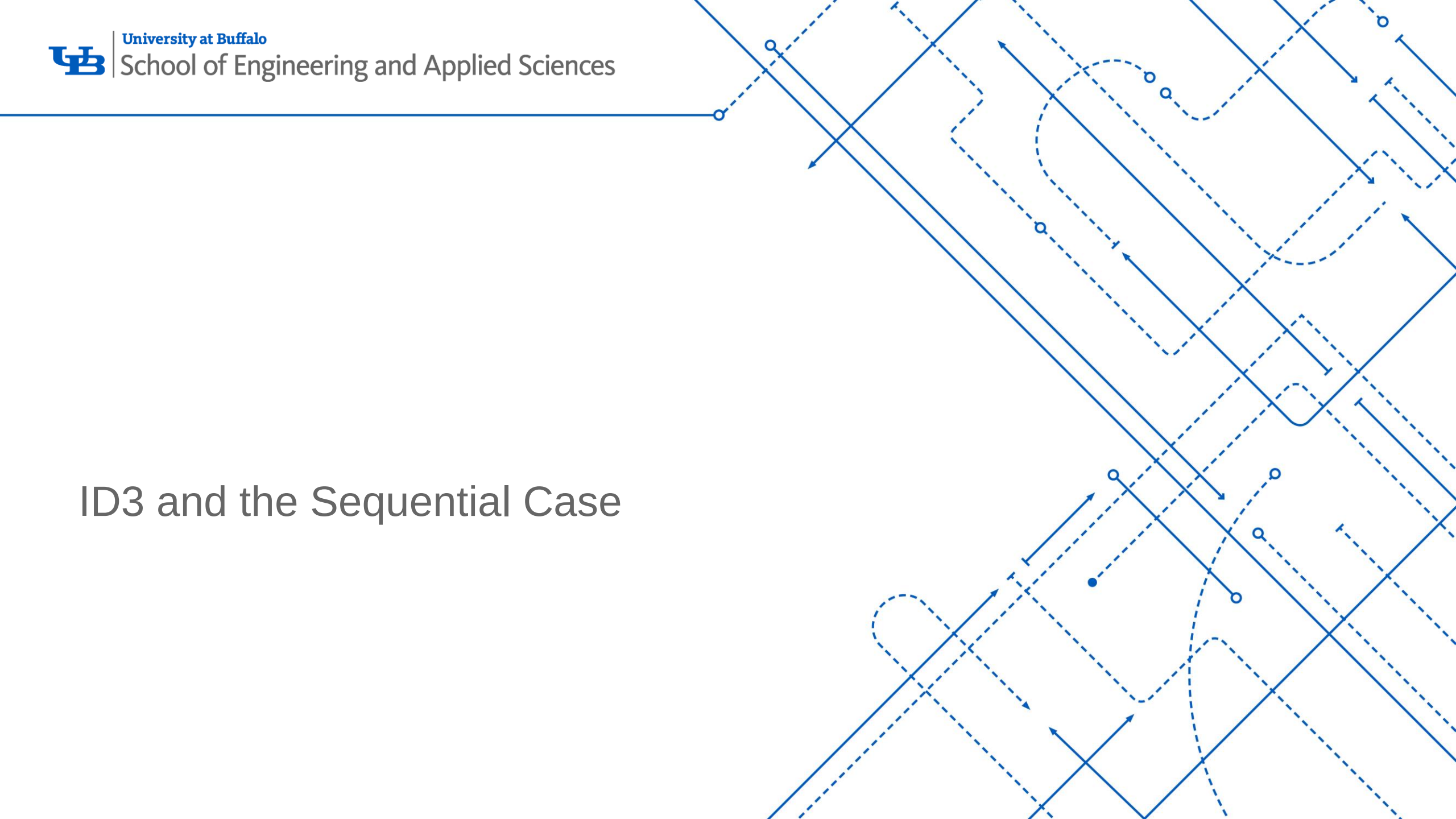
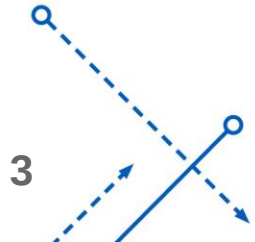


ID3 and the Sequential Case

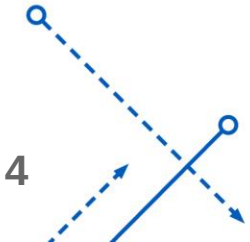
ID3

- Decision tree classifier
- Works on *k-ary* categorical data
- Goal of ID3 is to maximize information gain at each split
  - Same as minimizing the difference in entropy before and after splitting on a feature
- Produces a tree which represents each class as a disjunction of conjunctions (of features)
- Can think of it as producing multiple DNF expressions, one for each class



Sequential Performance Analysis (Worst-Case)

- Given D dimensional data with each dimension taking k categories
- Number of nodes $N = \frac{k^{D+1}-1}{k-1}$
- Number of observations $M = k^D$
- Since M and N are both of the same order, we can say performance is
- $O(NM) = O(N^2)$



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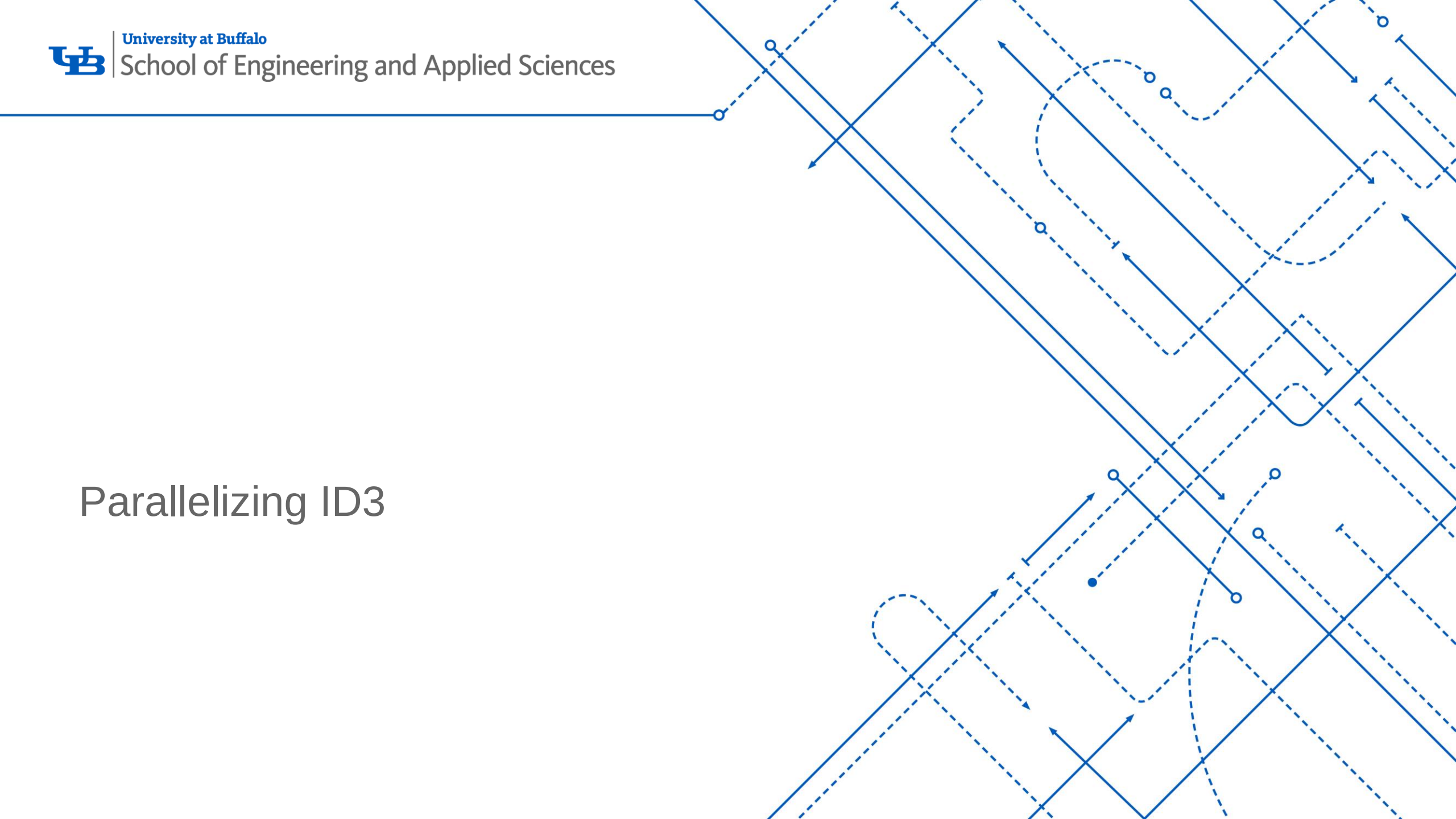
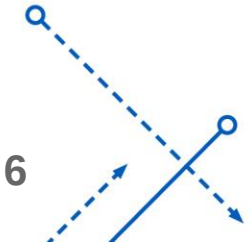
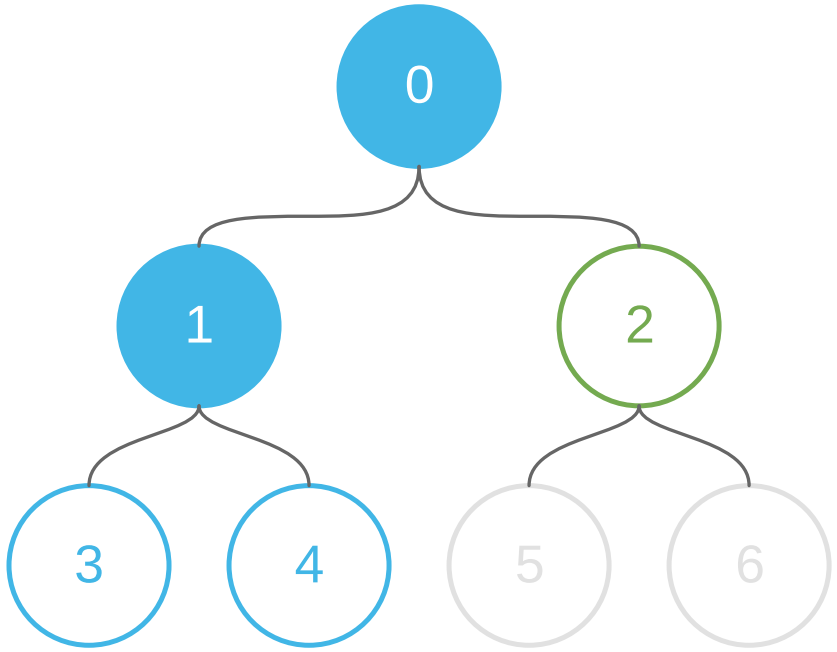


Parallelizing ID3

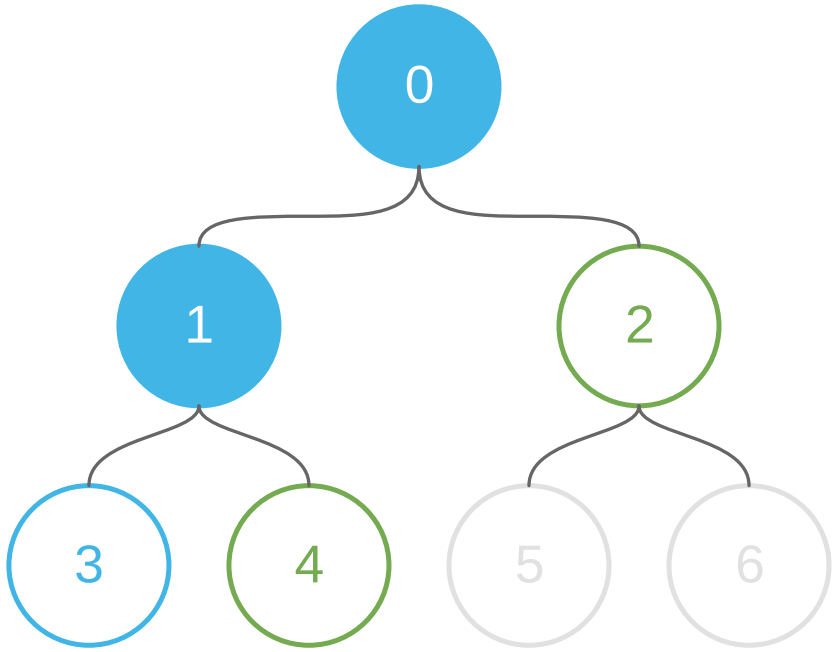
Parallelization of ID3

- “Divide and conquer” is the obvious approach, but it has a major flaw
- If the data is unbalanced, then a large amount of CPU time is wasted
- Solution: add a master processor and send out individual tasks to free processors whenever it is possible to do so
- Overhead is larger than divide and conquer with one processor forced to delegate, but tree imbalance no longer affects speedup
- Implemented using Intel MPI and C++ 11





Divide & Conquer Approach (Four Steps)



Master & Workers Approach (Three Steps)

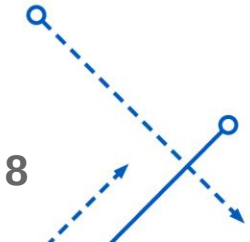
Master-Worker ID3 Algorithm

Master:

compute the topology of the perfect binary tree (maximum size scenario)
for-each un-computed node, if there are no unresolved dependencies and there is a free worker,
send feature restrictions to worker, else break
wait for response from worker, on response, add new information to model, remove node from
working list, and if it's a leaf, remove descendants from un-computed list
goto for-each until completion

Worker:

wait for feature vector from master
remove invalid observations from list of all observations
compute correct ID3 decision
send decision to master



Worst-Case Performance Analysis of Master-Worker ID3

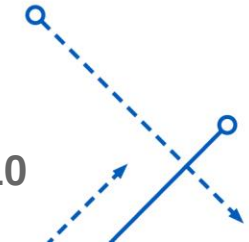
- Pre-processing work done by master $O(Nlog_k N)$
- Time to send tasks to workers $O(logP) \approx O(1)$
- Time to process data from workers $O\left(log_k^2 N\right)$

- Reduce the set of observations $O(DM) \approx O(N)$
- Maximum time to compute ID3 decision $O(DM) \approx O(N)$

- Overall theoretical time complexity $O\left(Nlog_k N + \frac{N^2}{P}\right)$

Synthetic Benchmarks

- Tested on UB CCR systems with Intel Xeon E5645 processors
- Tested using 1, 2, 4, 8, and 11 workers plus one master
- 15 binary datasets with 2^2 through 2^{16} observations
- Full datasets have each observation as its own class in order to force a perfect binary tree (worst-case scenario)
- Fractional datasets have the value of one feature determine the class (if 1st feature is 0, then the class is 0, otherwise each value has a unique class)
- Times used exclude I/O and the initial time to transfer data to all processors, sequential overhead and all other MPI operations included



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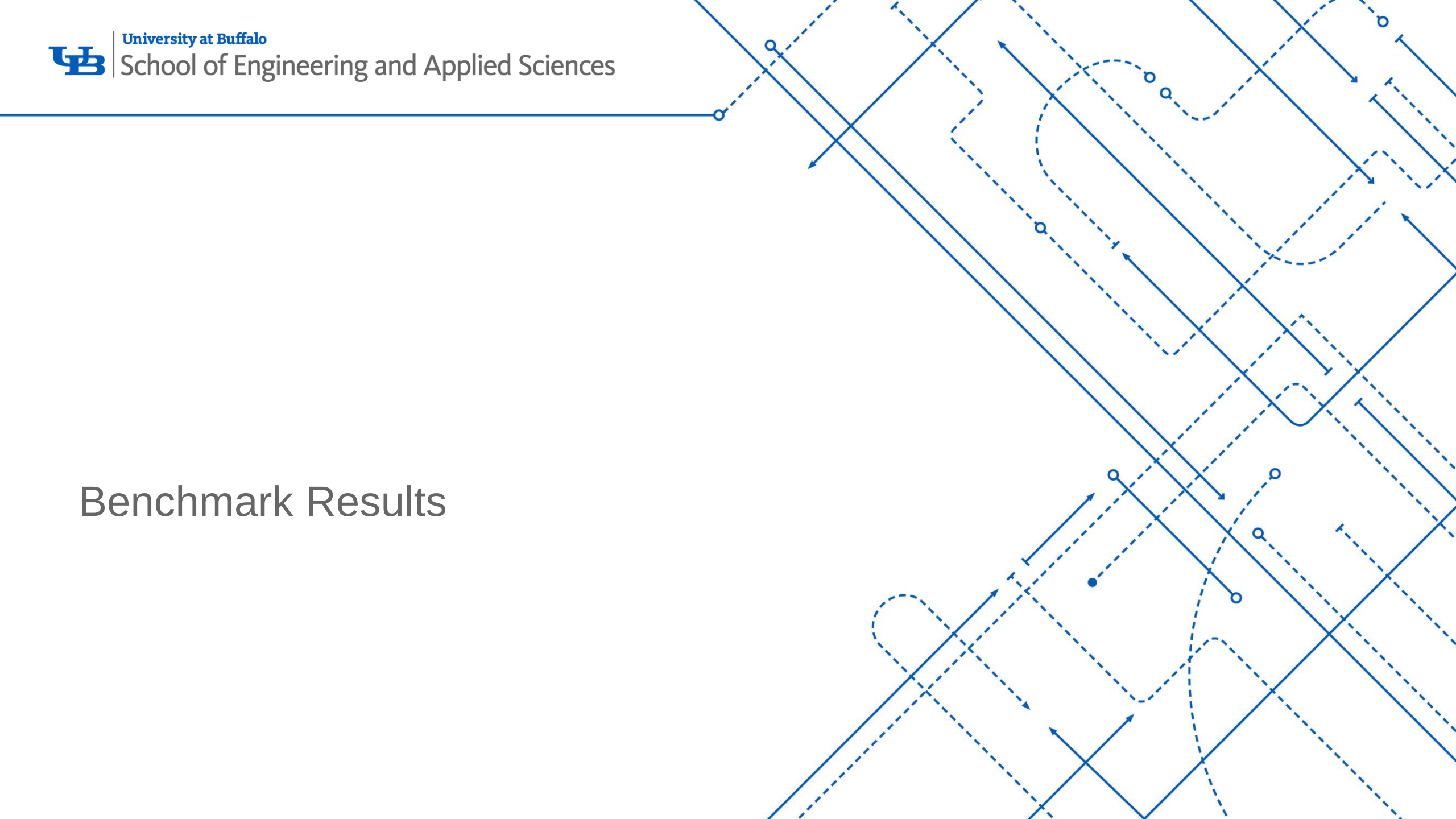
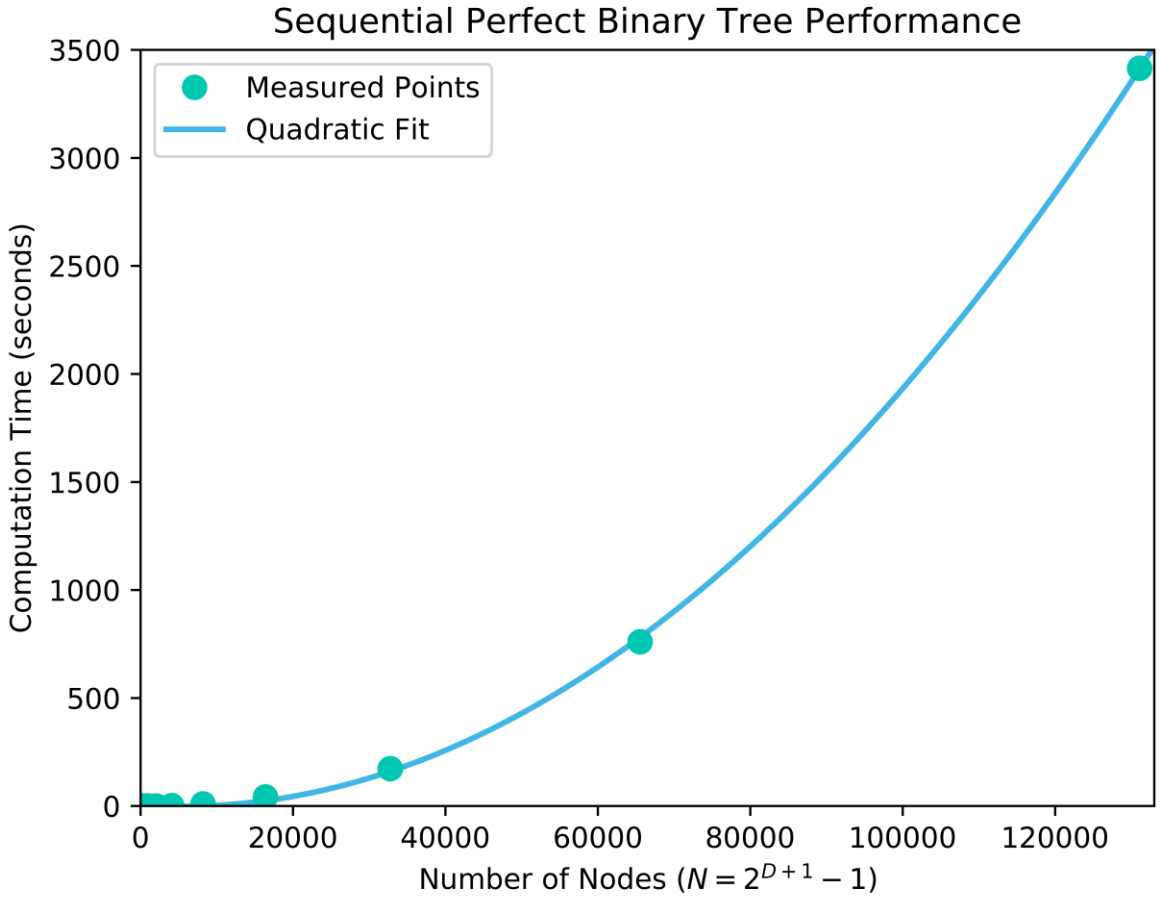
Benchmark Results



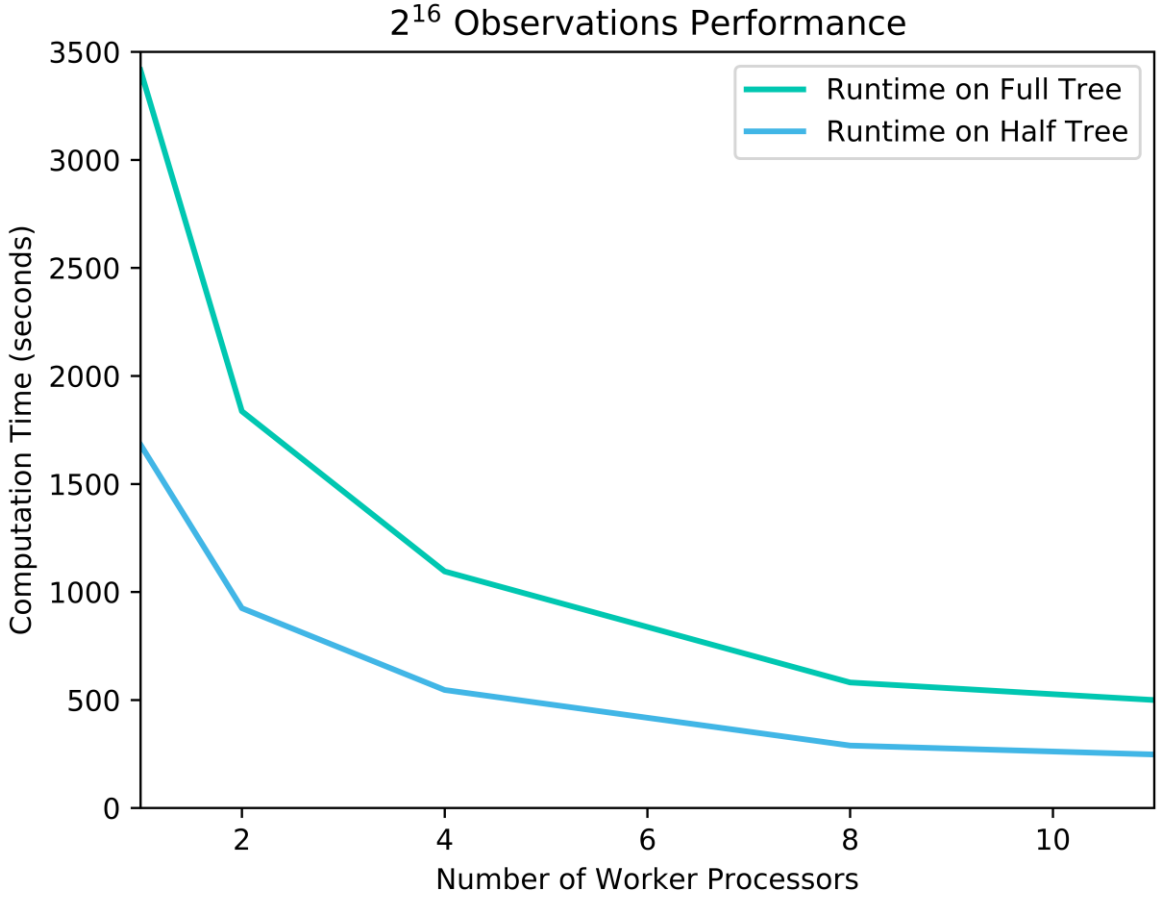
Sequential Performance

- Predicted performance of $O(N^2)$
- Performance measured using two processors (one master and one worker)
- Fit curve using scipy.optimize.curve_fit



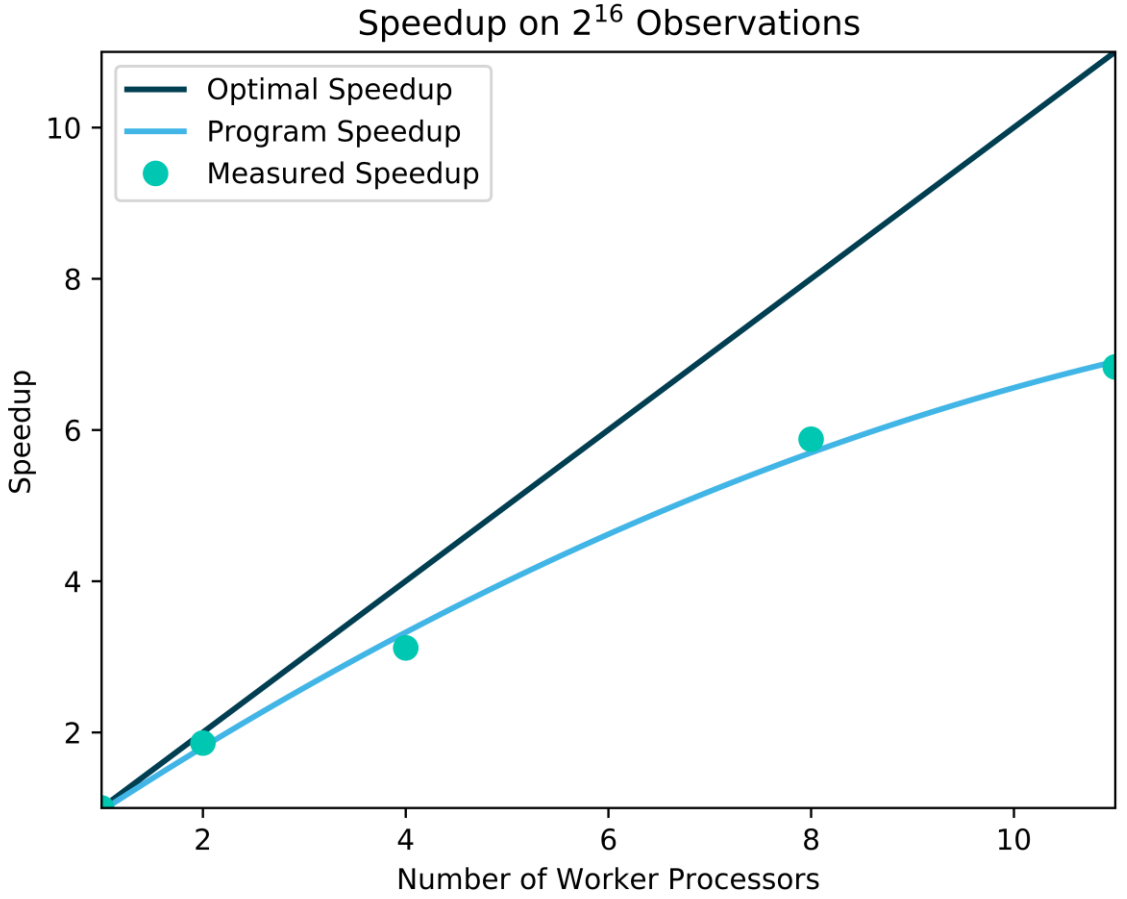
Parallel Performance On Different Tree Constructions

- Master-Worker architecture should have runtime proportional to number of nodes
- Performance curves show that at all measured times, runtime on the full-tree is twice that as on the half-tree
- On smaller test sets, effect is less pronounced due to the larger impact of sequential initialization



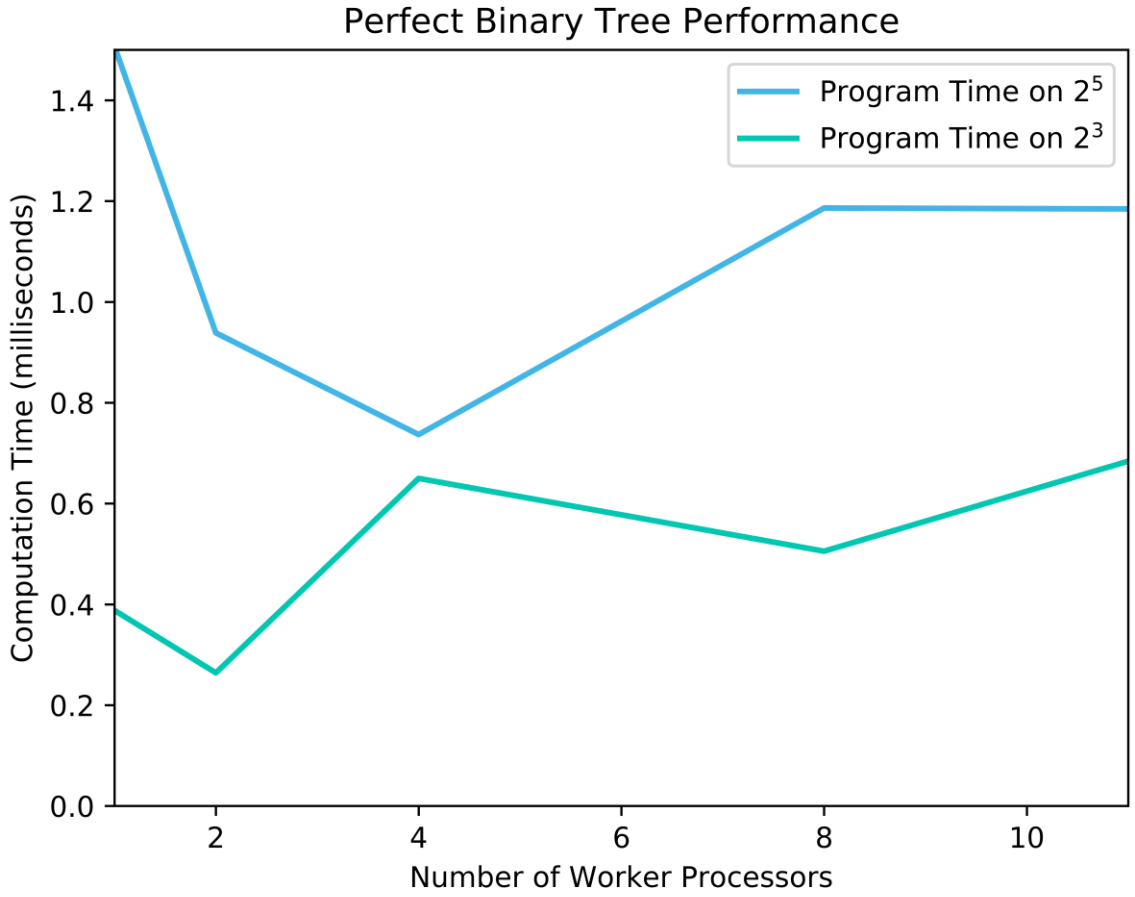
Parallel Speedup

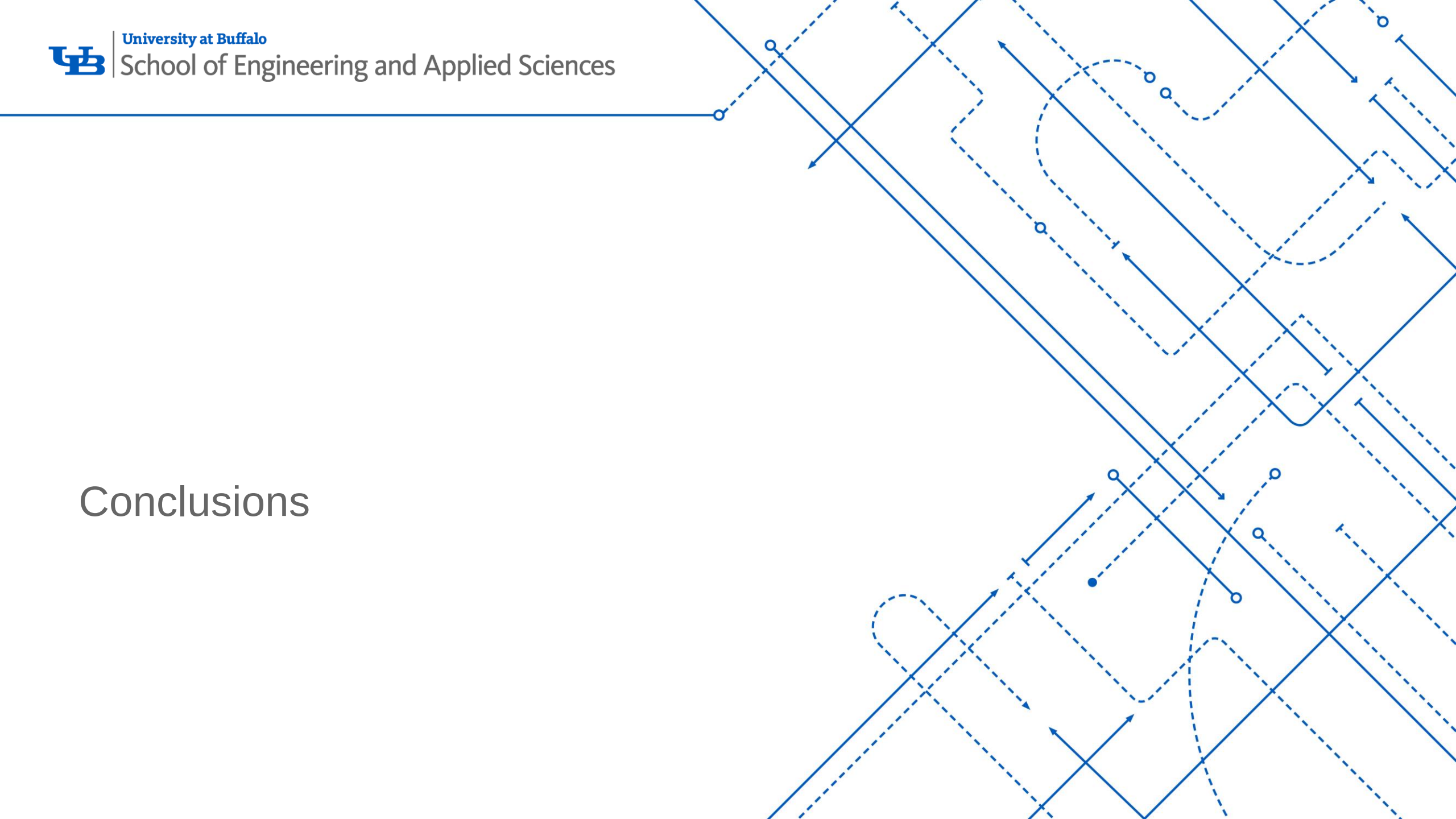
- Optimal speedup would be equal to the number of worker processors
- $O(1)$ overhead when sending a task to and $O\left(log_k^2 N\right)$ when receiving a result
- Inevitable queueing delays when multiple processors try to return simultaneously



Overhead Overtaking

- Even in cases where there are more tasks than processes, overhead can mean that fewer processors yield higher performance





Conclusions

Expectations Met and Unmet

- Sequential performance was as predicted
- Parallel speedup takes a large hit due to overhead, in part from having a single coordinator and frequent communication needs
- Improvement over simple divide and conquer in unbalanced datasets is linear to the reduction in nodes as expected

Future Improvements

- Reduce the $O(log_k^2 N)$ receiving overhead if at all possible
- Cluster individual processor tasks into multiple nodes instead of single nodes to reduce communication overhead, and reduce duplicate processing
- Dynamically create tree topology to reduce $O(Nlog_k N)$ initialization overhead in master processor