

HPCHadoop: MapReduce on Cray X-series

Scott Michael
Research Analytics
Indiana University

Cray User Group Meeting
May 7, 2014



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY

Outline

- **Motivation & Design of HPCHadoop**
- HPCHadoop demo
- Benchmarking Methodology
- Benchmark Results
- Future Work



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



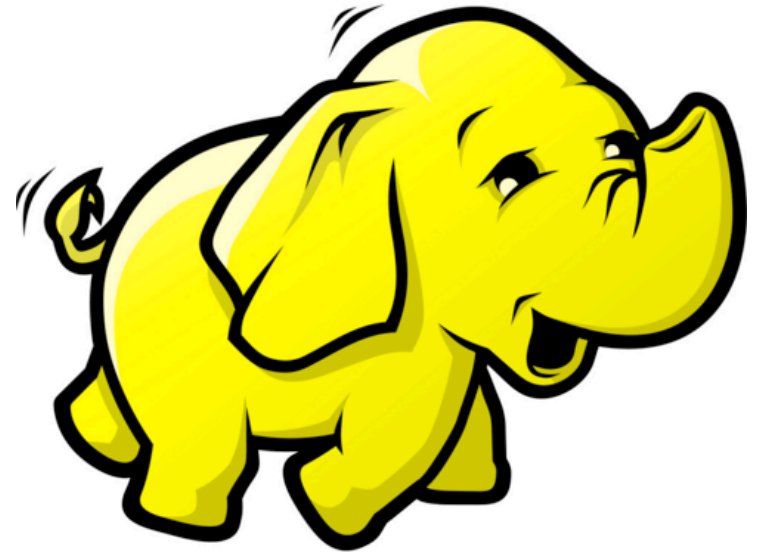
**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY



Why Hadoop on a Cray?

- Many users have heard about Big Data and Hadoop and want to try it out
- Some users already have Hadoop code
- Being a relatively simple framework, Hadoop can lower the barrier to entry for distributed computing
- At IU departmental resources can be scarce, and HPC resources are “free” to faculty



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY

Why Hadoop on a Cray?

MPI/OpenMP



MapReduce/Hadoop



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY



Hadoop is all Java, right?



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY

Hadoop is all Java, right?

- The Hadoop framework is Java based
- But Map and Reduce functions can be written in any language and streamed to the framework via Hadoop streaming
- For certain types of data reduction and analysis Hadoop can be a good fit
 - Astronomical image analysis
 - Medical image analysis
 - Genome analysis



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY

Java just runs everywhere, right?

- There are two major challenges in deploying Hadoop on a traditional HPC resource
 - Shared scheduling
 - Hadoop's "shared nothing" architecture
- The framework has to address these issues *and* be easy to configure and run



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY



Java just runs everywhere, right?

- Hadoop is generally deployed across an entire cluster that doesn't change or only changes infrequently
- HPC Hadoop takes information from the scheduler, configures and launches a Hadoop instance on your nodes
- HDFS can be instantiated on node local disks, or
- HDFS can be set up on a shared file system



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY



- Motivation & Design of HPCHadoop
- **HPCHadoop demo**
- Benchmarking Methodology
- Benchmark Results
- Future Work



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services

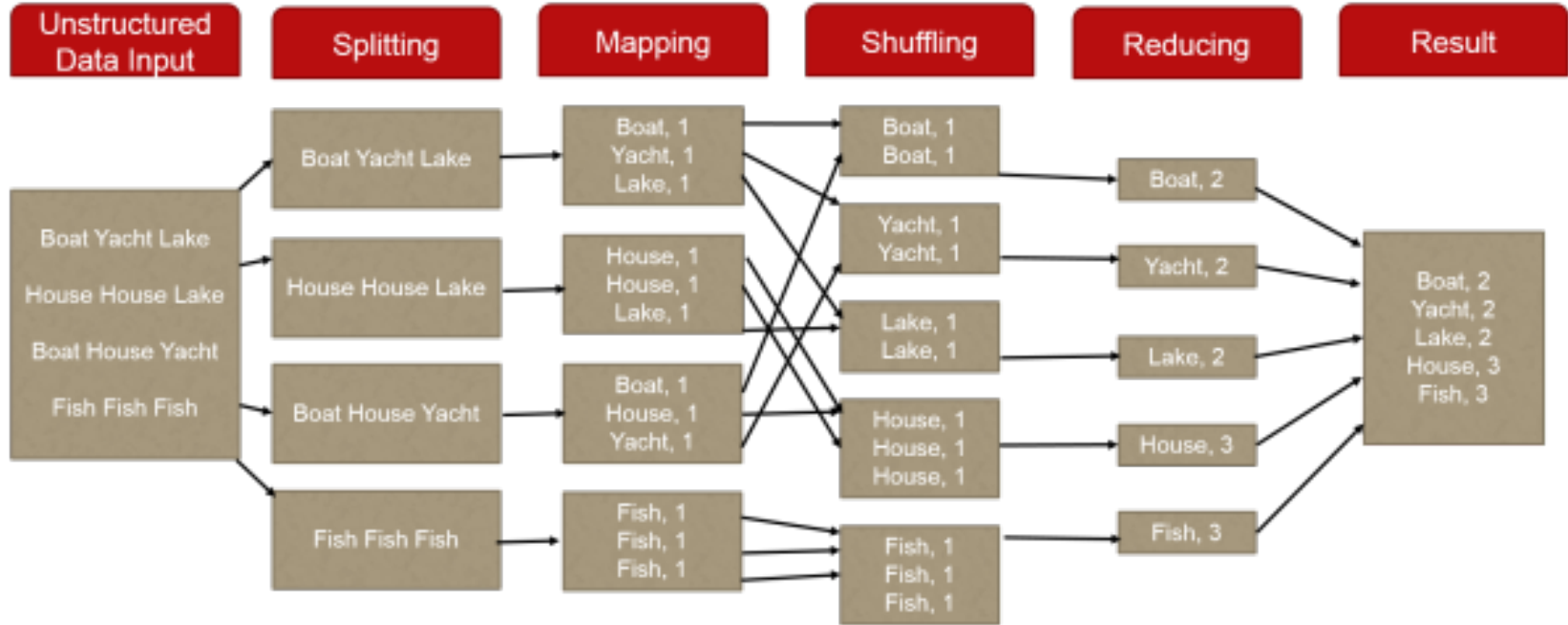


**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY



Wordcount Example



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY

Just two functions

map: $(k_1, v_1) \rightarrow list(k_2, v_2)$

```
public void map(LongWritable key, Text value,
OutputCollector<Text, IntWritable> output, Reporter
reporter) throws IOException {
    String line = value.toString();
    StringTokenizer tokenizer = new StringTokenizer(line);
    while (tokenizer.hasMoreTokens()) {
        word.set(tokenizer.nextToken());
        output.collect(word, one);
    }
}
```



RESEARCH
TECHNOLOGIES

INDIANA UNIVERSITY
University Information Technology Services



PERVASIVE TECHNOLOGY
INSTITUTE

INDIANA UNIVERSITY

Just two functions

reduce: $(k_2, list(v_2)) \rightarrow list(k_3, v_3)$

```
public static class Reduce extends MapReduceBase
implements Reducer<Text, IntWritable, Text, IntWritable>
{
    public void reduce(Text key, Iterator<IntWritable>
values, OutputCollector<Text, IntWritable> output,
Reporter reporter) throws IOException {
        int sum = 0;
        while (values.hasNext()) {
            sum += values.next().get();
        }
        output.collect(key, new IntWritable(sum));
    }
}
```



RESEARCH
TECHNOLOGIES

INDIANA UNIVERSITY
University Information Technology Services



PERVASIVE TECHNOLOGY
INSTITUTE

INDIANA UNIVERSITY

To the Terminal...

- Three configuration files need to be modified
 - `conf/env.sh`
 - `conf/hadoop_commands.sh`
 - PBS script
- Set inputs and outputs
- Set up a directory for HDFS



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY



- Motivation & Design of HPCHadoop
- HPCHadoop demo
- **Benchmarking Methodology**
- Benchmark Results
- Future Work



RESEARCH
TECHNOLOGIES

INDIANA UNIVERSITY
University Information Technology Services



PERVASIVE TECHNOLOGY
INSTITUTE

INDIANA UNIVERSITY



Many Choices in Benchmarks

- There are many “standard” Hadoop benchmarks, but there is a lot of parameter space to explore
- We settled on the Intel Hadoop Benchmarking Suite called HiBench <https://github.com/intel-hadoop/hibench>
- Benefits & Drawbacks
 - Standard Suite gets you many benchmarks
 - Framework can get in the way and insists on HDFS for some benchmarks



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY

Intel HiBench Suite

- HiBench gives a broad sampling of potential Hadoop workloads by including: Bayes, DFSIOE, Kmeans, Nutchindex, Pagerank, Terasort, and Wordcount
- The HiBench framework is relatively easy to set up and run, though it has a very large number of tunables
- We decided at minimum to optimize the numbers of mappers/reducers and input data size
 - Mapper/reducer ratio -- 4:3
 - Input data size -- 2.5x default data size



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY

Benchmark Hardware

- Big Red II
 - Cray XE6/XK7
 - 32 cores/node (XE6)
 - 64 GB mem/node (XE6)
- Quarry
 - Intel based gigabit cluster
 - 8 cores/node
 - 16 GB mem/node
- Data Capacitor II
 - 5 PB Lustre filesystem



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY



- Motivation & Design of HPCHadoop
- HPCHadoop demo
- Benchmarking Methodology
- **Benchmark Results**
- Future Work



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



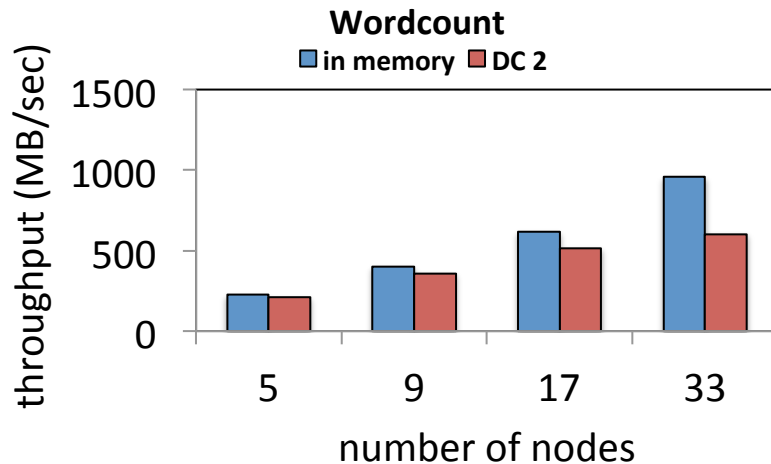
**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY

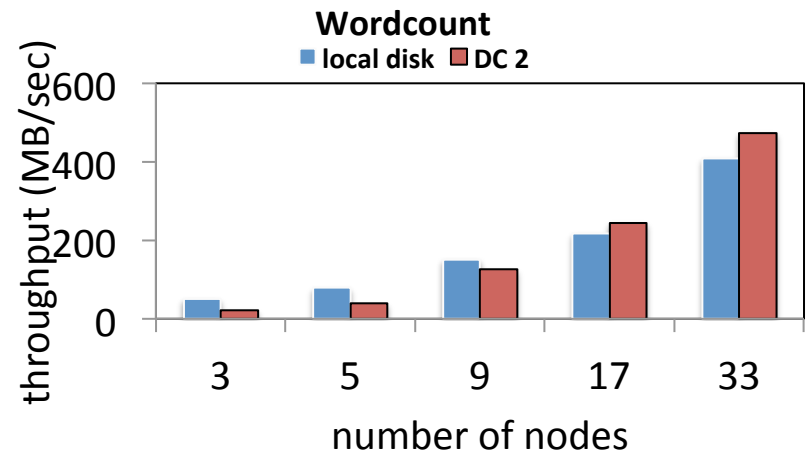


Some Results

- In all 20 runs of HiBench across the two machines; 160 individual benchmark results



Big Red II Wordcount scalability



Quarry Wordcount scalability



RESEARCH
TECHNOLOGIES

INDIANA UNIVERSITY
University Information Technology Services



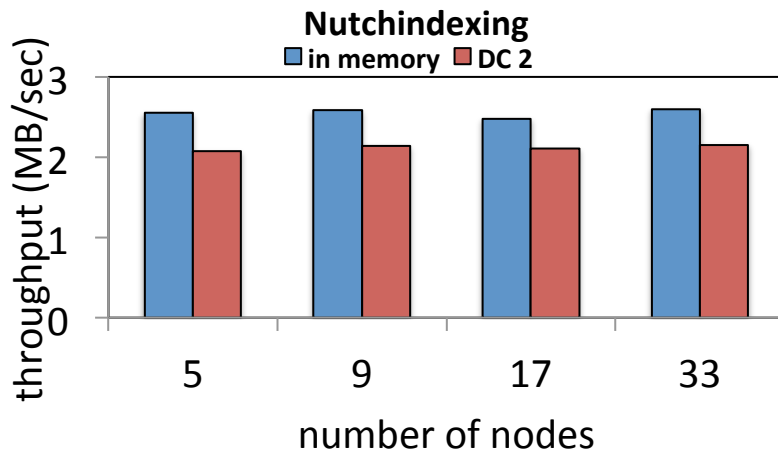
PERVASIVE TECHNOLOGY
INSTITUTE

INDIANA UNIVERSITY

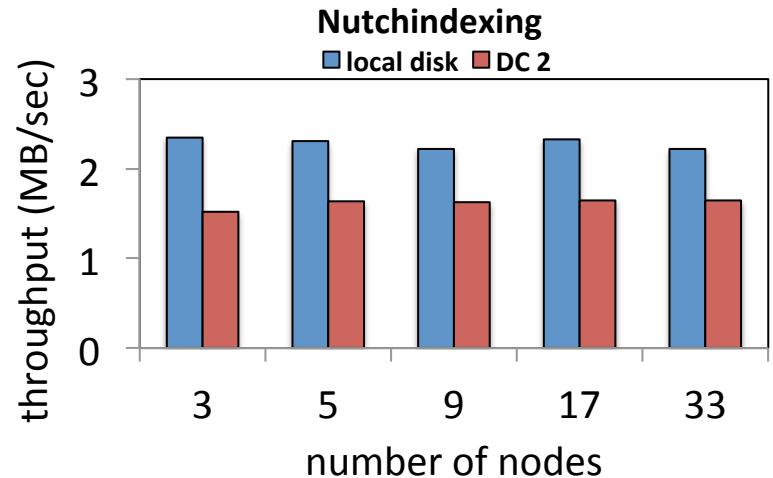


Not everything scales well

- This could be due to the algorithm, or simply require further optimization



Big Red II Nutchindexing scalability



Quarry Nutchindexing scalability



RESEARCH
TECHNOLOGIES

INDIANA UNIVERSITY
University Information Technology Services



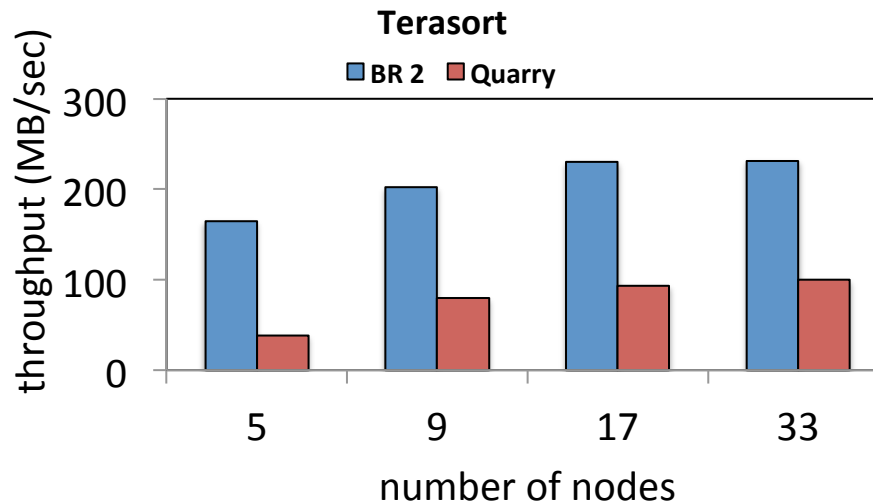
PERVASIVE TECHNOLOGY
INSTITUTE

INDIANA UNIVERSITY



X-series can perform well

- Comparing Cray X-series to gigabit connected cluster for Terasort up to 4.25x faster



Big Red II vs. Quarry for Terasort on Lustre



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY

- Motivation & Design of HPCHadoop
- HPCHadoop demo
- Benchmarking Methodology
- Benchmark Results
- **Future Work**



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY



Future Work

- Initial incarnation of HPC Hadoop is a proof of concept, several additional features are in the works
- Support for schedulers other than PBS
- Further optimization for HiBench and comparison to other MapReduce systems like MARIANE
- Support for native use of shared parallel file systems such as GPFS and Lustre
 - Have begun collaborating with Intel on their Lustre compatibility module



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY

Conclusions

- Hadoop is not for everyone and does not solve all “Big Data” problems
- However, for the problems that fit well into a Hadoop framework HPC resources are sometimes the only computational option for researchers
- HPC Hadoop allows for easy set up and launching of Hadoop jobs on batch scheduled systems including the Cray X-series



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY



Questions?

email questions to: **scamicha@iu.edu**

<https://github.com/scamicha/HPCHadoop>



**RESEARCH
TECHNOLOGIES**

INDIANA UNIVERSITY
University Information Technology Services



**PERVASIVE TECHNOLOGY
INSTITUTE**

INDIANA UNIVERSITY

