High-Performance Big Data Processing Tools for Neuroscience and A Demo on Chameleon Cloud

Breakout Session at ACNN (Sept. 2016)

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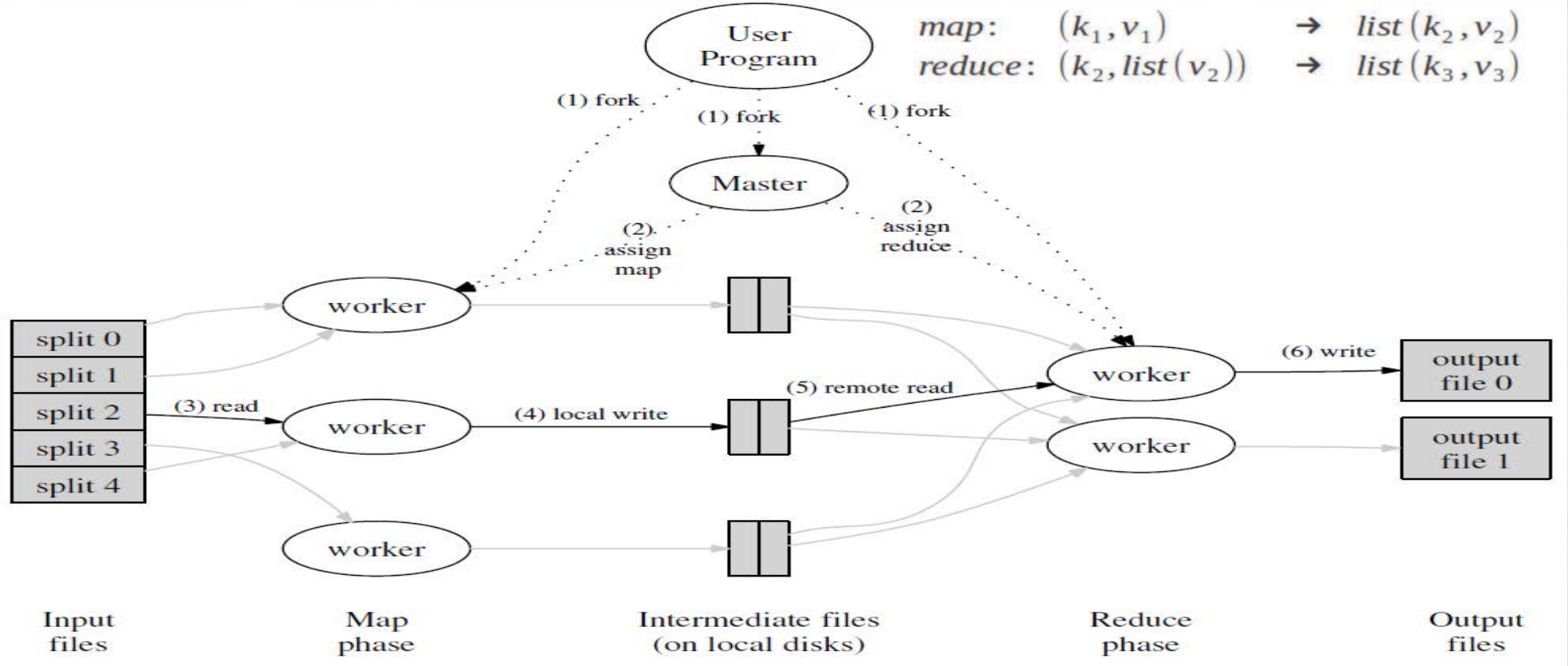
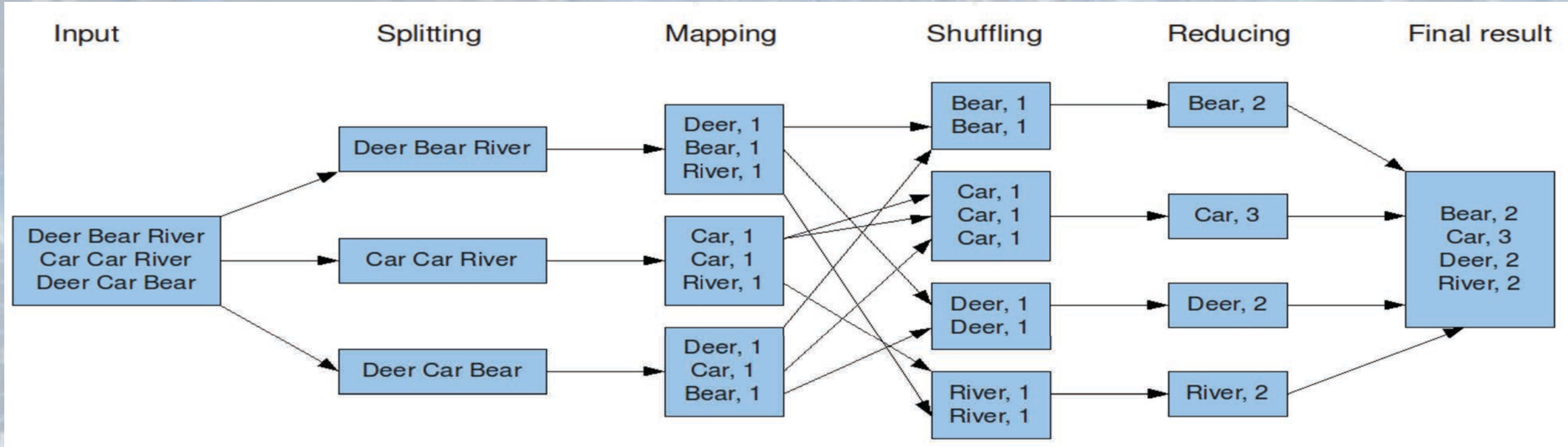
The MapReduce Model



J. Dean and S. Ghemawat. *MapReduce: Simplified Data Processing on Large Clusters*. In *Proceedings of the 6th Symposium on Operating Systems Design & Implementation (OSDI'04)*, 2004.

WordCount Execution

- The overall execution process of WordCount in MapReduce



Word Count in Hadoop!

```
public class WordCount {
 public static class Map extends Mapper<LongWritable, Text, Text, IntWritable> {
    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();
    public void map(LongWritable key, Text valu   Contex  ontext) throws IOException, InterruptedException {
        String line = value.toString();
        StringTokenizer tokenizer =
        while (tokenizer.hasMoreToken
            word.set(tokenizer.nex
            context.write(word, one);
        }
    }
 }
 public static class Reduce extends Reducer<Text, IntWritable, Text, IntWritable> {
    public void reduce(Text key, Iterator<IntWritable> values, Context context)
      throws IOException, Inte  uptedException {
        int  = 0;
        while
        }
        context.wri  y,  IntWr  ble(sum));
    }
 }
}
```

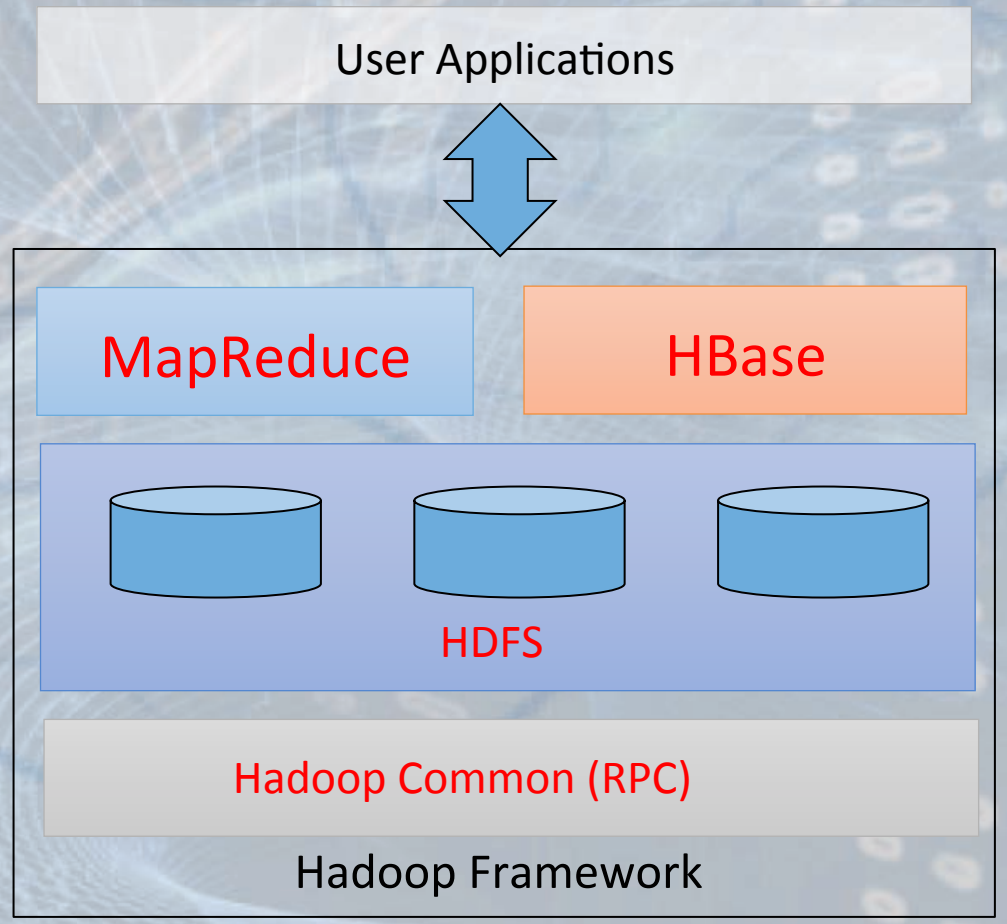
Productive

Scalable

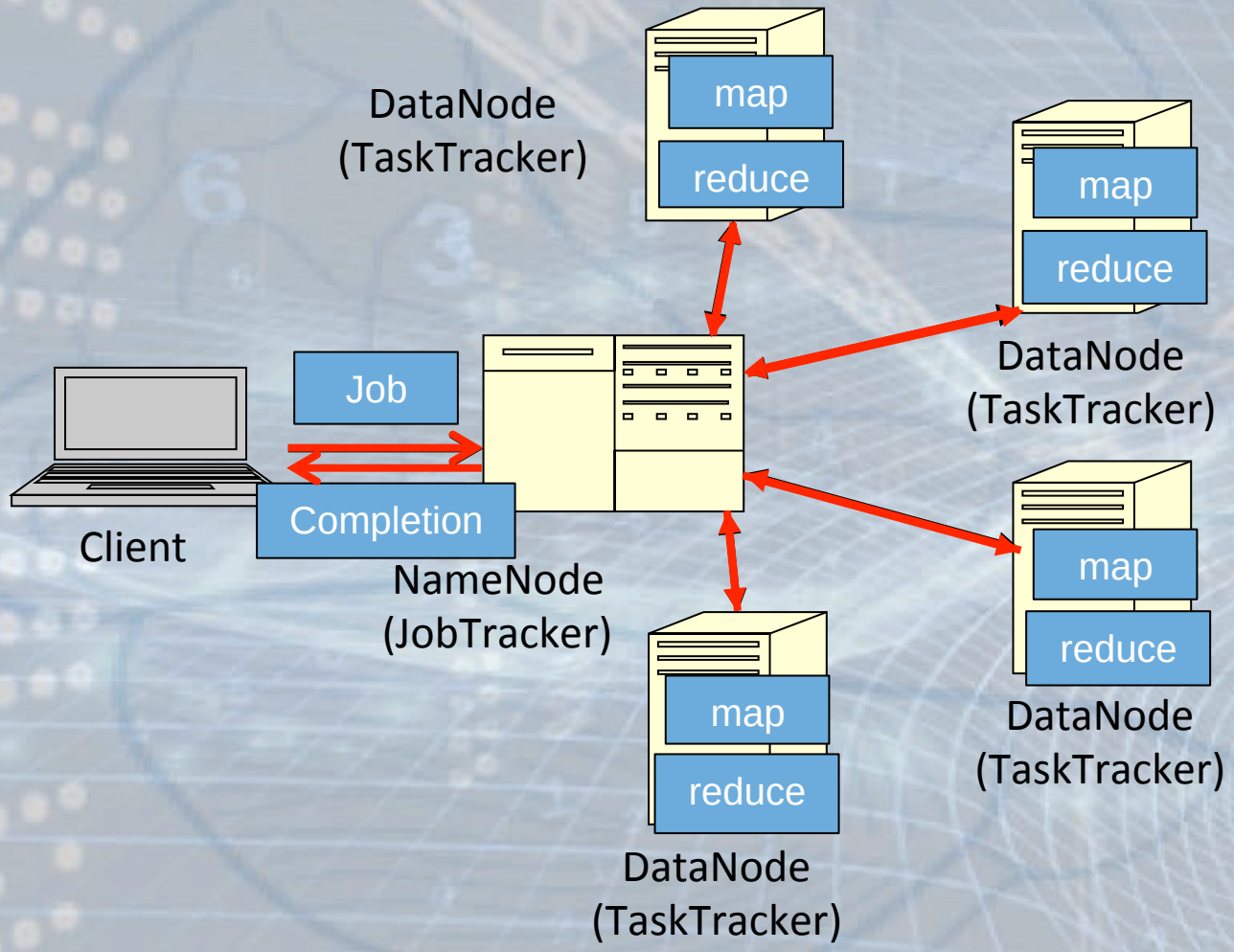
Fault-Tolerant

Big Data Processing with Hadoop Components

- Major components included in this tutorial:
  - MapReduce (Batch)
  - HBase (Query)
  - HDFS (Storage)
  - RPC (Inter-process communication)
- Underlying Hadoop Distributed File System (HDFS) used by both MapReduce and HBase
- Model scales but high amount of communication during intermediate phases can be further optimized

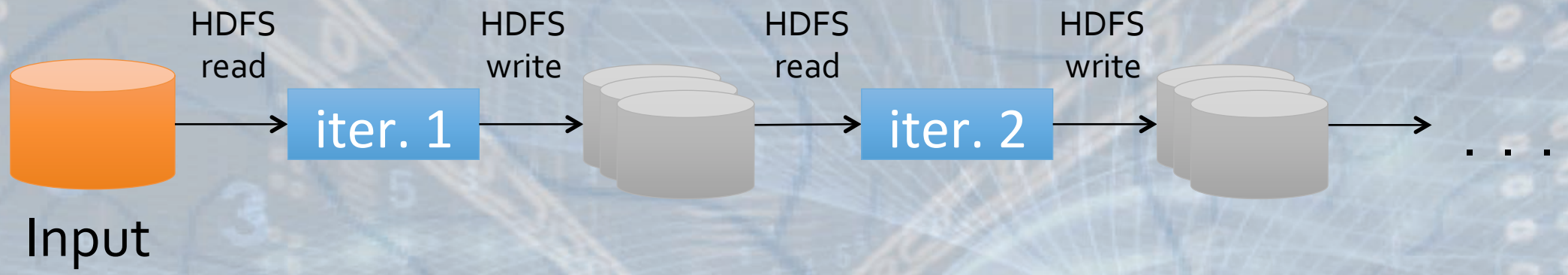


MapReduce Job Execution on Hadoop

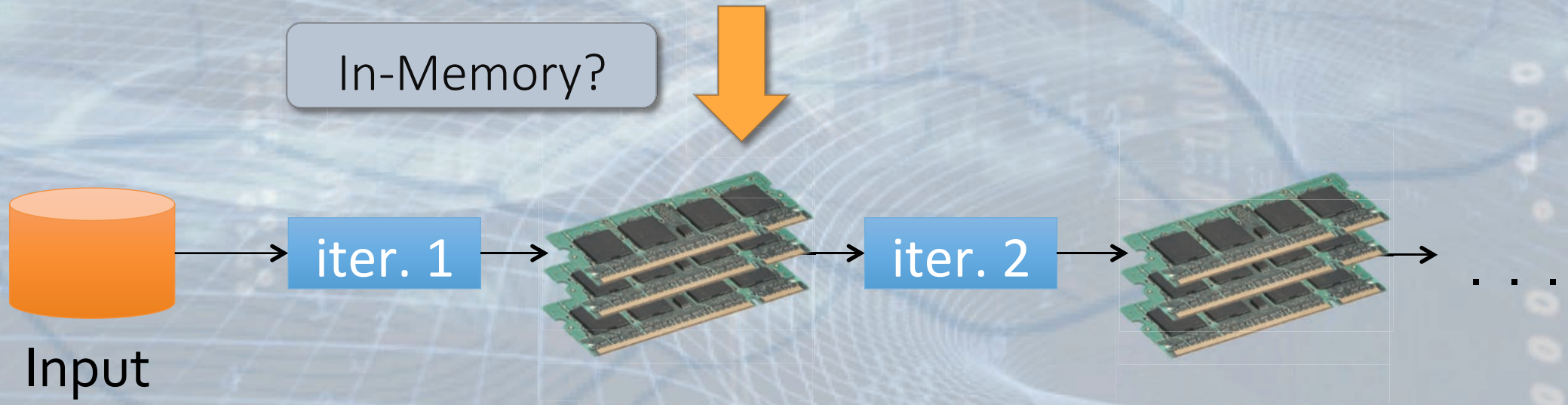


- Main Features
  - Replication (e.g. 3)
  - Data locality for Maps
  - HTTP-based Shuffle
  - Speculative execution
  - Independence among tasks
  - …
- Goals
  - Fault Tolerance
  - Scalability

Data Sharing Problems in MapReduce



Slow due to replication, serialization, and disk IO



10-100× faster than network and disk

RDD Programming Model in Spark

- Key idea: *Resilient Distributed Datasets* ***(RDDs)***
  - Immutable distributed collections of objects that can be cached in memory across cluster nodes
  - Created by transforming data in stable storage using data flow operators (map, filter, groupBy, …)
  - Manipulated through various parallel operators
  - Automatically rebuilt on failure
    - rebuilt if a partition is lost
- Interface
  - Clean language-integrated API in Scala (Python & Java)
  - Support R, distributed machine learning using MLlib
  - Can be used *interactively* from Scala console

RDD Operations

Transformations (define a new RDD)	Actions (return a result to driver)
map	reduce
filter	collect
sample	count
union	first
groupByKey	Take
reduceByKey	countByKey
sortByKey	saveAsTextFile
join	saveAsSequenceFile
…	…

More Information:

- https://spark.apache.org/docs/latest/programming-guide.html#transformations
- https://spark.apache.org/docs/latest/programming-guide.html#actions

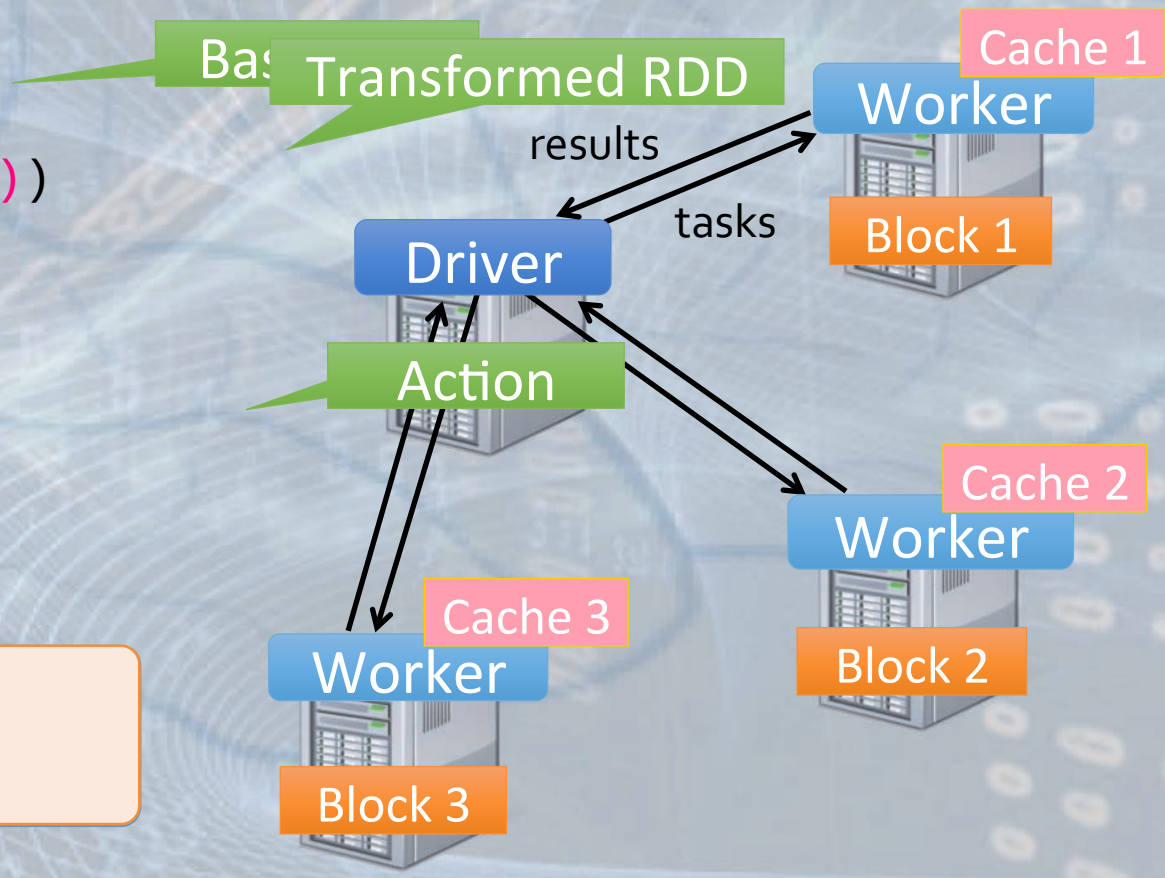
Example: Log Mining

Load error messages from a log into memory, then interactively search for various patterns

```
lines = spark.textFile(“hdfs://...”)
errors = lines.filter(_.startsWith(“ERROR”))
messages = errors.map(_.split(‘\t’)(2))
cachedMsgs = messages.cache()

cachedMsgs.filter(_.contains(“foo”)).count
cachedMsgs.filter(_.contains(“bar”)).count
. . .
```

Result: scaled to 1 TB data in 5-7 sec
(vs 170 sec for on-disk data)



Courtesy: https://spark.apache.org/

Example: Word Count in Spark!

```
val fi          extFile("hdfs:// ")

val cou         le.flatMap(line => line.split(" "))
                   .map(word => (word, 1))
                   .reduceByKey(_ + _)

counts.saveAsTextFile("hdfs://...")
```

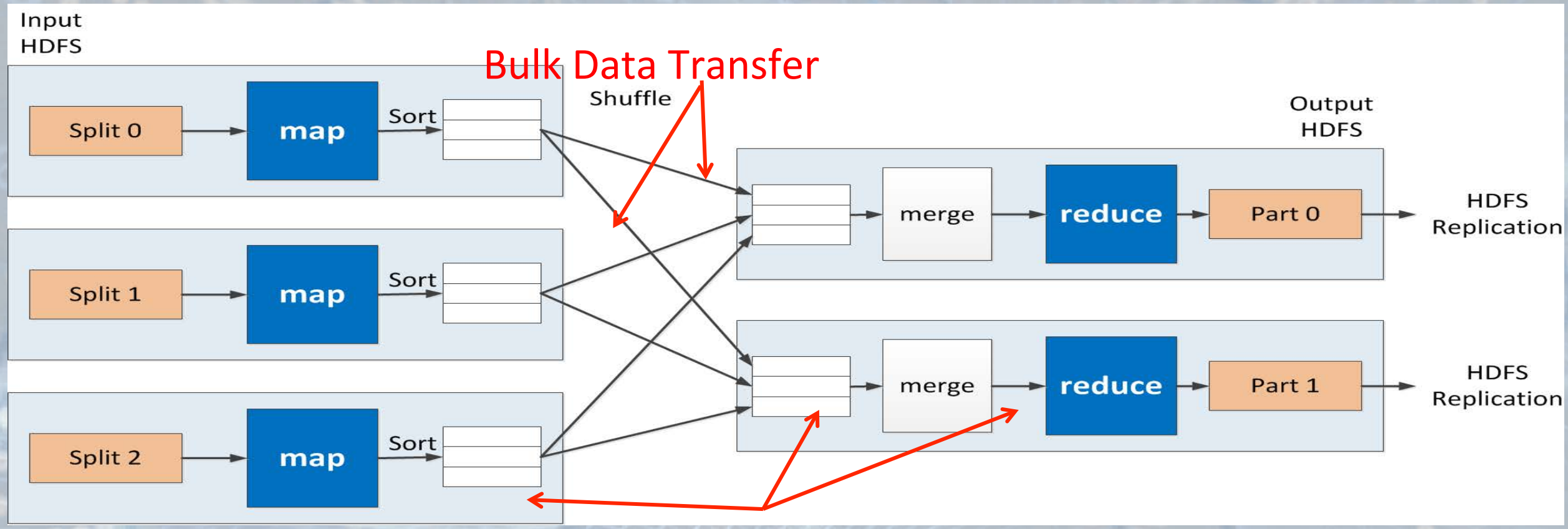
Productive

High-Performance

Scalable

Fault-Tolerant

Data Movement in MapReduce



- Map and Reduce Tasks carry out the total job execution
  - Map tasks read from HDFS, operate on it, and write the intermediate data to local disk
  - Reduce tasks get these data by shuffle from TaskTrackers, operate on it and write to HDFS
- Communication in shuffle phase uses HTTP over Java Sockets
- Similar bottlenecks exist in HDFS, RPC, Spark, HBase, Memcached, ec.

The High-Performance Big Data (HiBD) Project

- http://hibd.cse.ohio-state.edu
- RDMA for Apache Spark
- RDMA for Apache Hadoop 2.x (RDMA-Hadoop-2.x)
  - Plugins for Apache, Hortonworks (HDP) and Cloudera (CDH) Hadoop distributions
- RDMA for Apache HBase
- RDMA for Memcached (RDMA-Memcached)
- RDMA for Apache Hadoop 1.x (RDMA-Hadoop)
- OSU HiBD-Benchmarks (OHB)
  - HDFS, Memcached, and HBase Micro-benchmarks
- Users Base: 190 organizations from 26 countries
- More than 17,800 downloads from the project site
- RDMA for Impala (upcoming)

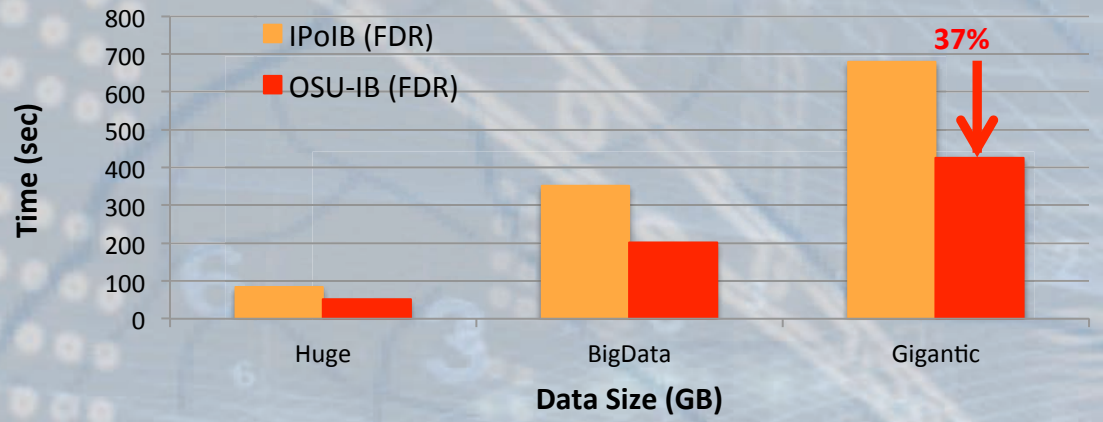
Available for InfiniBand and RoCE

HiBD
High-Performance Big Data

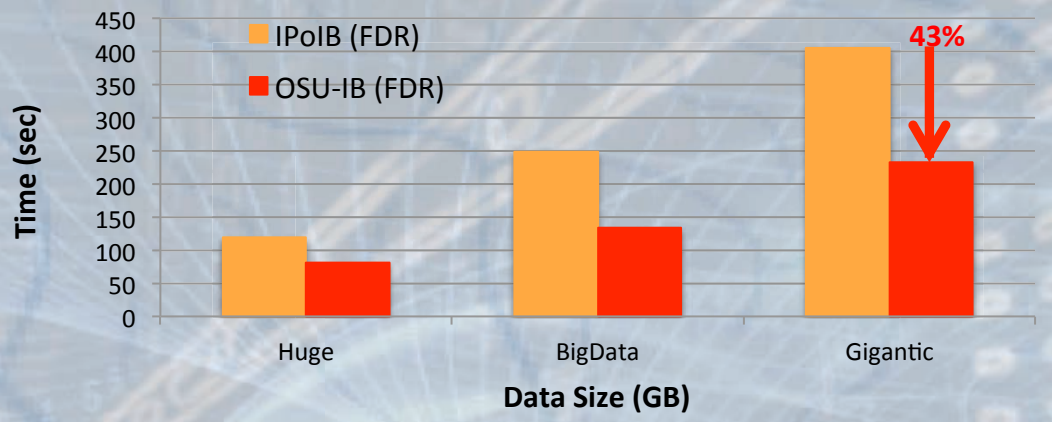
Network Based Computing Laboratory

The Ohio State University

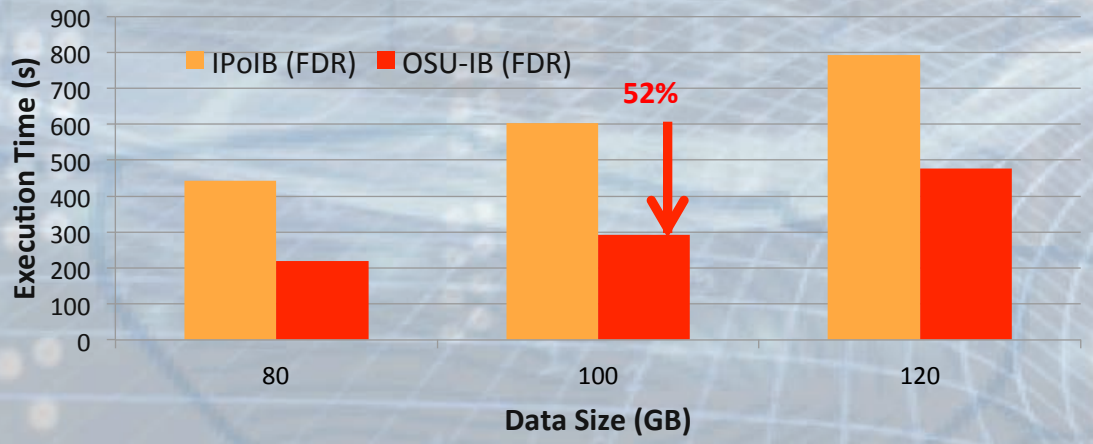
Performance Benefits of HiBD on PageRank, Sort, and TeraSort



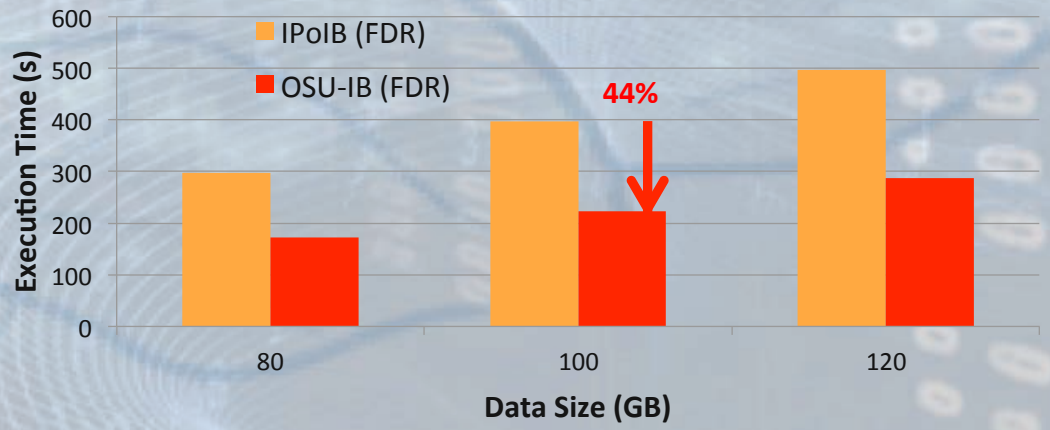
SDSC Comet 32 Worker Nodes, 768 cores
PageRank Total Time



SDSC Comet 64 Worker Nodes, 1536 cores
PageRank Total Time



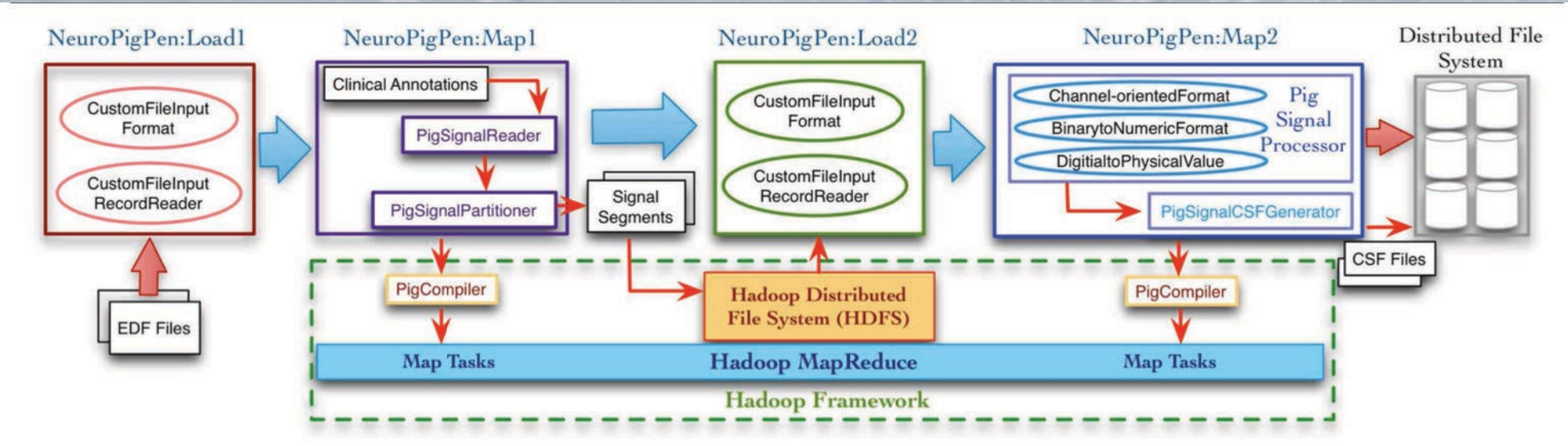
TACC Stampede 32 Worker Nodes,
Sort Total Time



TACC Stampede 32 Worker Nodes,
TeraSort Total Time

A Case Study with NeuroPigPen

- **NeuroPigPen Toolkit[1]:** a data management toolkit using Hadoop Pig for processing electrophysiological signals in Neuroscience applications
  - Dr. Sahoo, etc., Case Western Reserve University



The data processing workflow supported by the NeuroPigPen toolkit modules consists of multiple steps with EDF files as input and CSF files as output. The Load functions in the toolkit extend the Hadoop FileInputFormat and FileInputRecordReader classes to support signal data. The Map functions in the toolkit are automatically compiled into MapReduce tasks by the Apache Pig compiler. The intermediate and final results are stored in Hadoop Distributed File System (HDFS), which provides a reliable and scalable storage platform for signal data.

1. Sahoo SS, Wei A, Valdez J, Wang L, Zonjy B, Tatsuoka C, Loparo KA, Lhatoo SD. NeuroPigPen: a Data Management Toolkit using Hadoop Pig for Processing Electrophysiological Signals in Neuroscience Applications, http://www.ncbi.nlm.nih.gov/pubmed/27375472

Demo on NSF Supported Chameleon Cloud

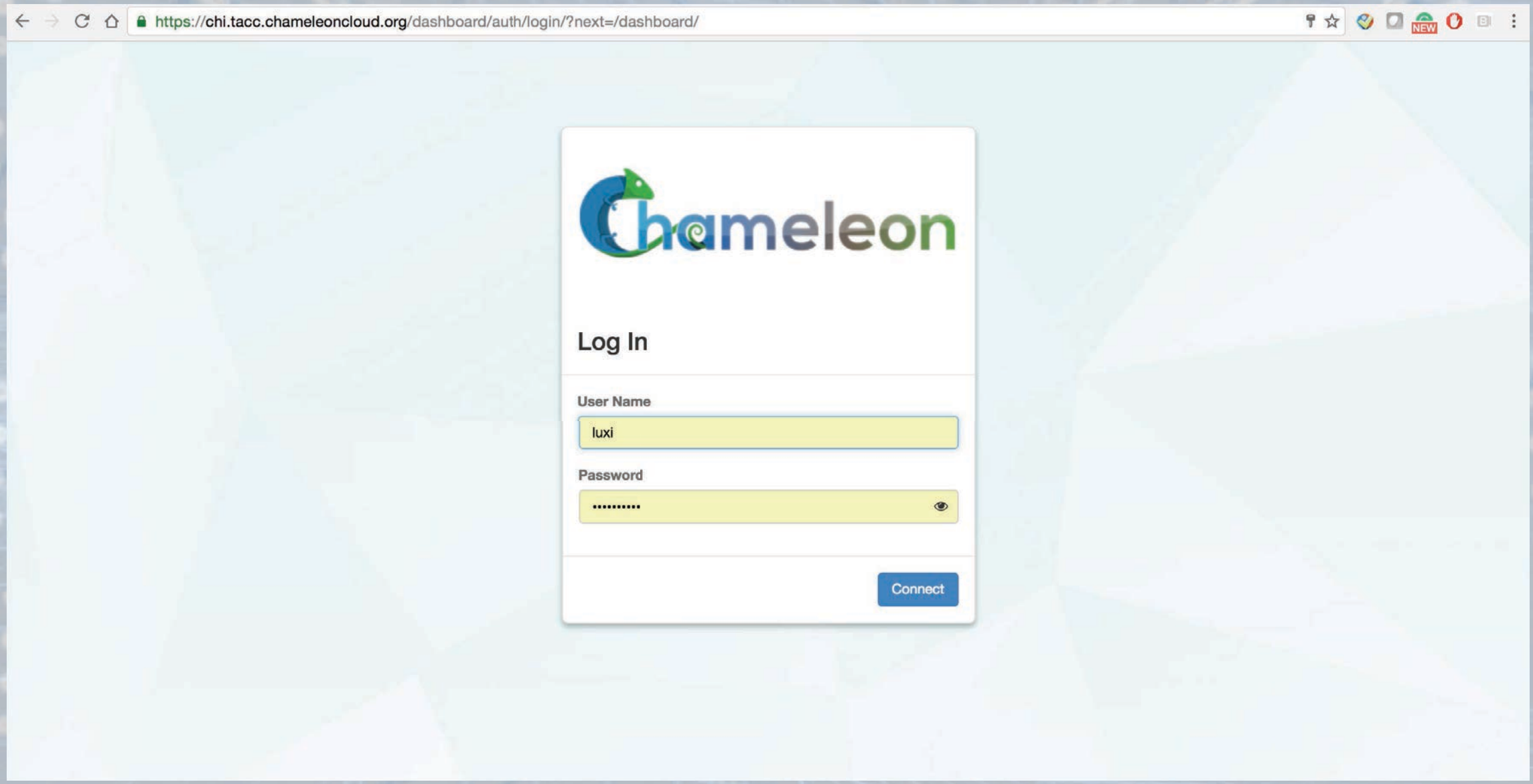
- Five InfiniBand bare-metal nodes (with SR-IOV support) on Chameleon Cloud
- 25 VMs in total, 6 VMs per node
- RDMA-Hadoop appliance available on Chameleon Cloud
  - Pre-installed OS, drivers, and software packages
  - Automatically configuration
- Deployment of virtual machines
- RDMA-Hadoop examples
  - RandomWriter
  - Sort

NSF Chameleon Cloud: A Powerful and Flexible Experimental Instrument

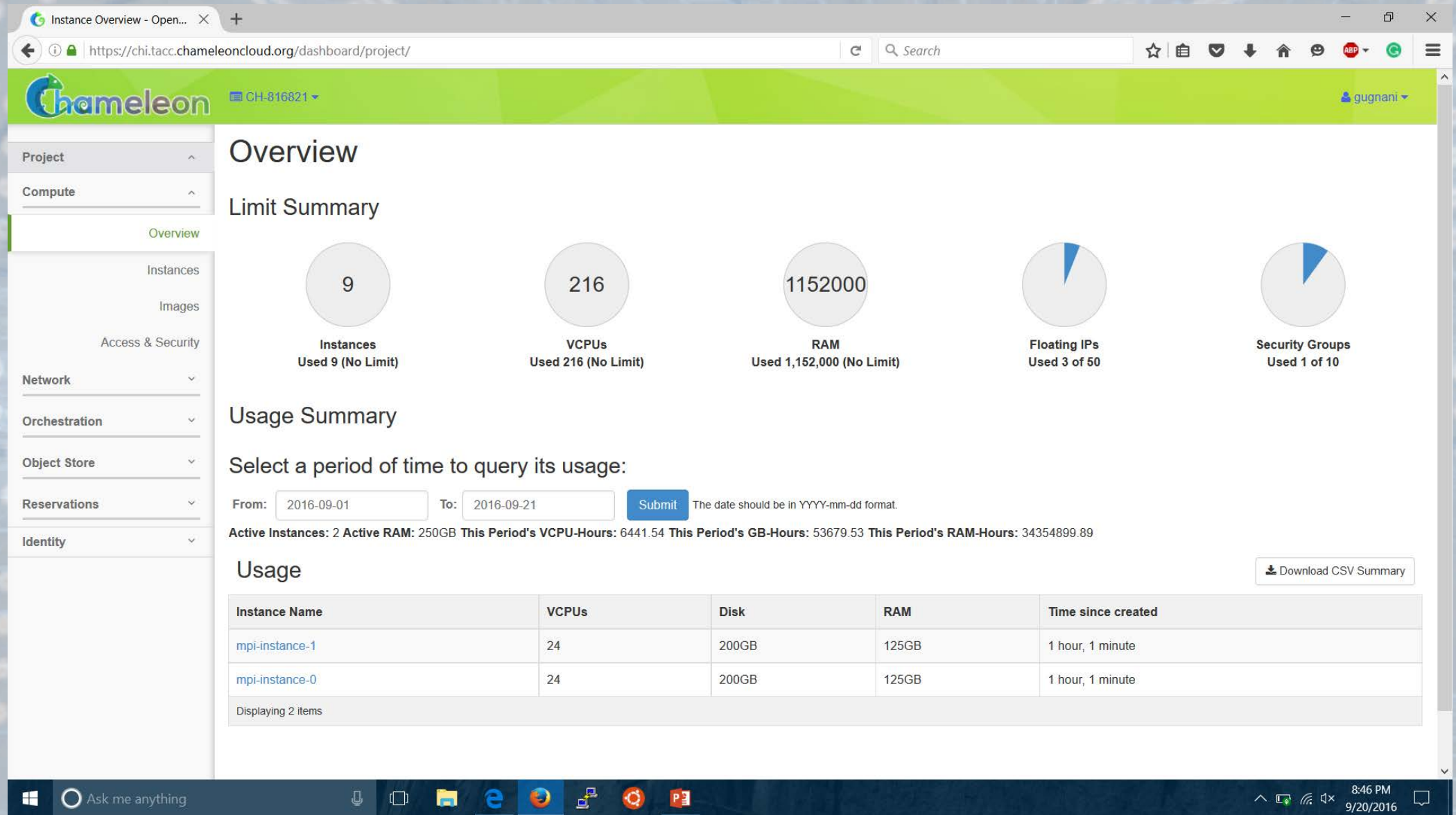
- Large-scale instrument
  - Targeting Big Data, Big Compute, Big Instrument research
  - ~650 nodes (~14,500 cores), 5 PB disk over two sites, 2 sites connected with 100G network
- Reconfigurable instrument
  - Bare metal reconfiguration, operated as single instrument, graduated approach for ease-of-use
- Connected instrument
  - Workload and Trace Archive
  - Partnerships with production clouds: CERN, OSDC, Rackspace, Google, and others
  - Partnerships with users
- Complementary instrument
  - Complementing GENI, Grid'5000, and other testbeds
- Sustainable instrument
  - Industry connections

http://www.chameleoncloud.org/

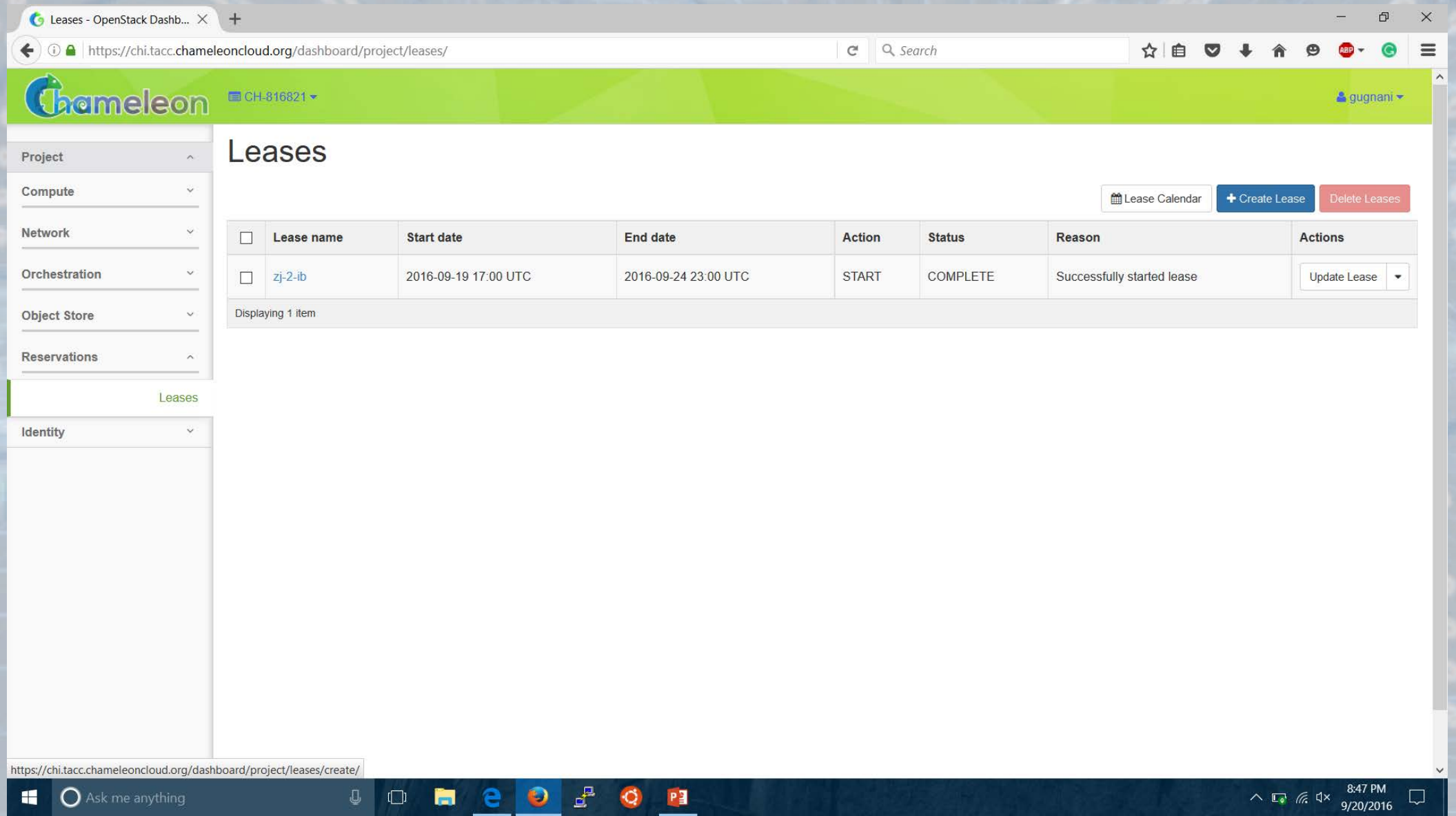
Demo - Login to Chameleon



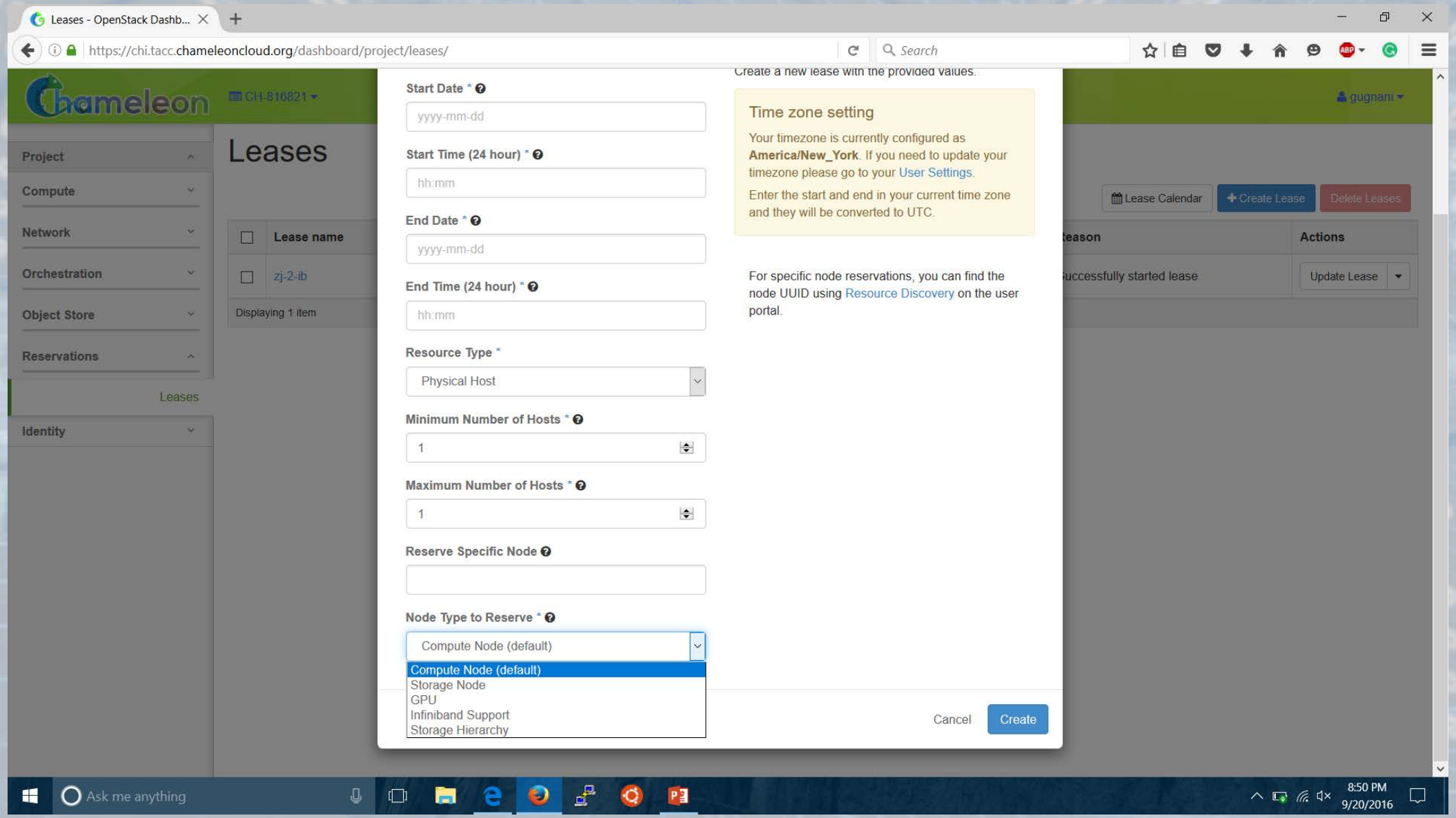
Demo – Overview of Your Chameleon Resources



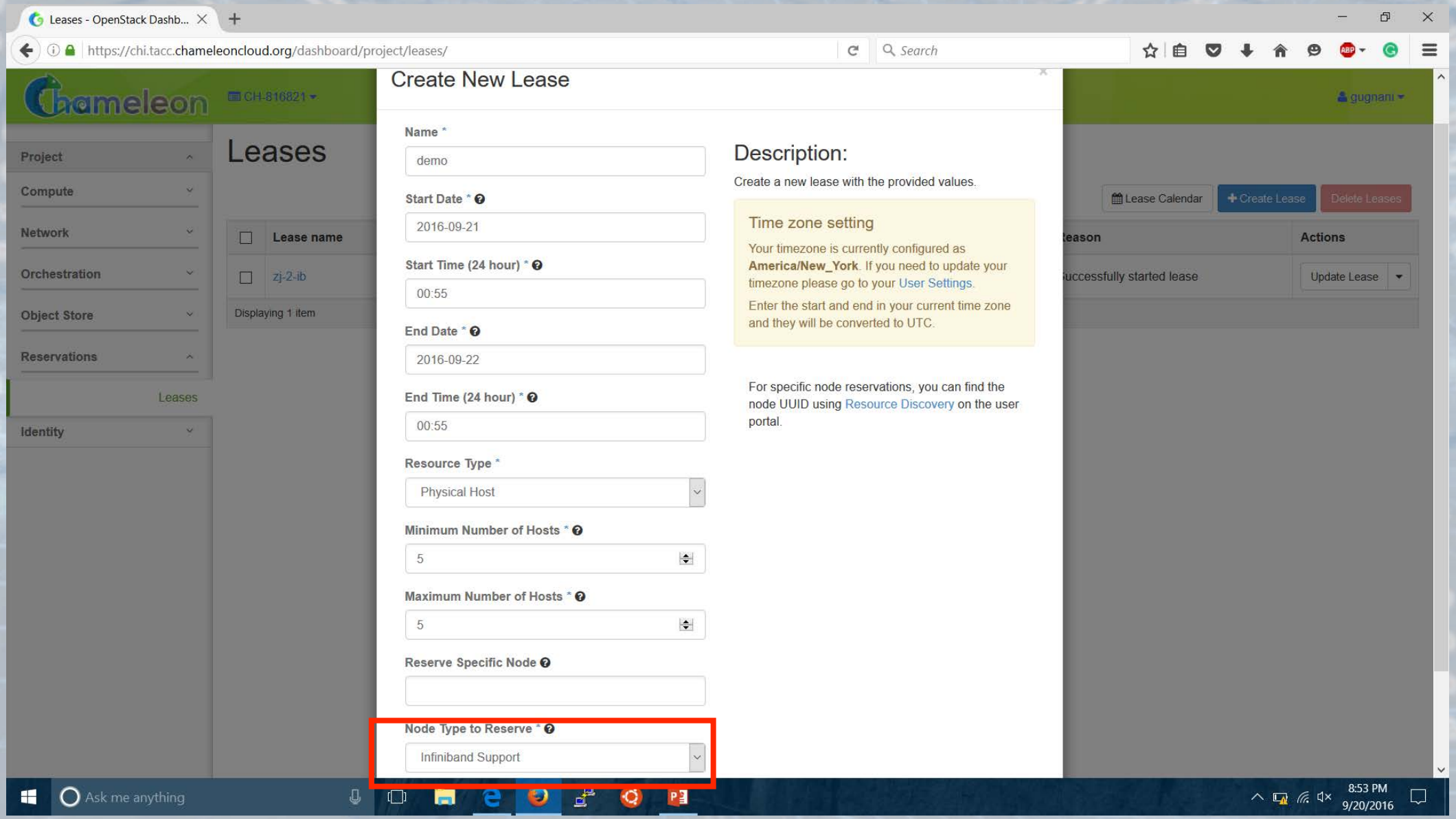
Demo – Create Your Lease



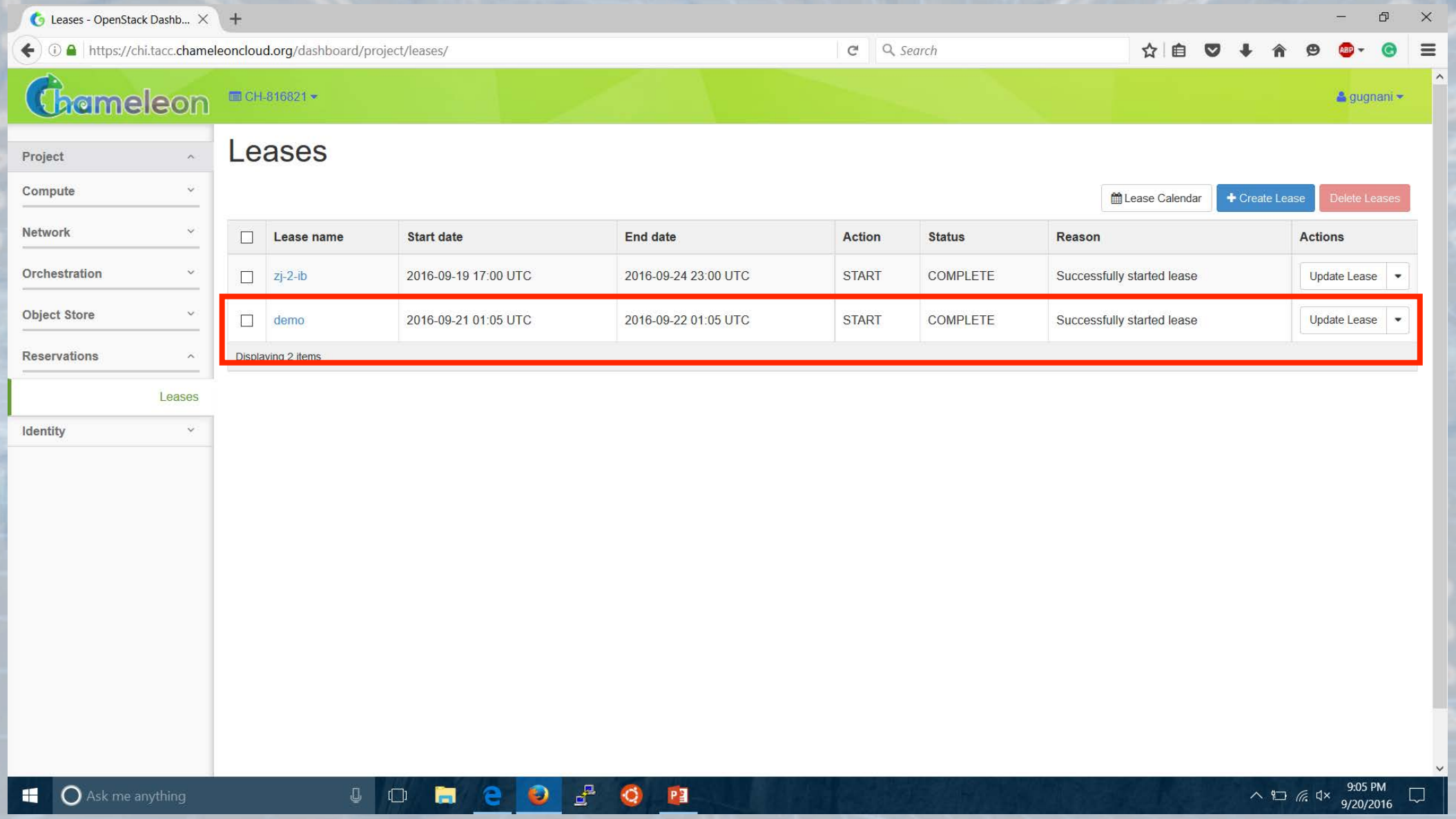
Demo – Create Your Lease



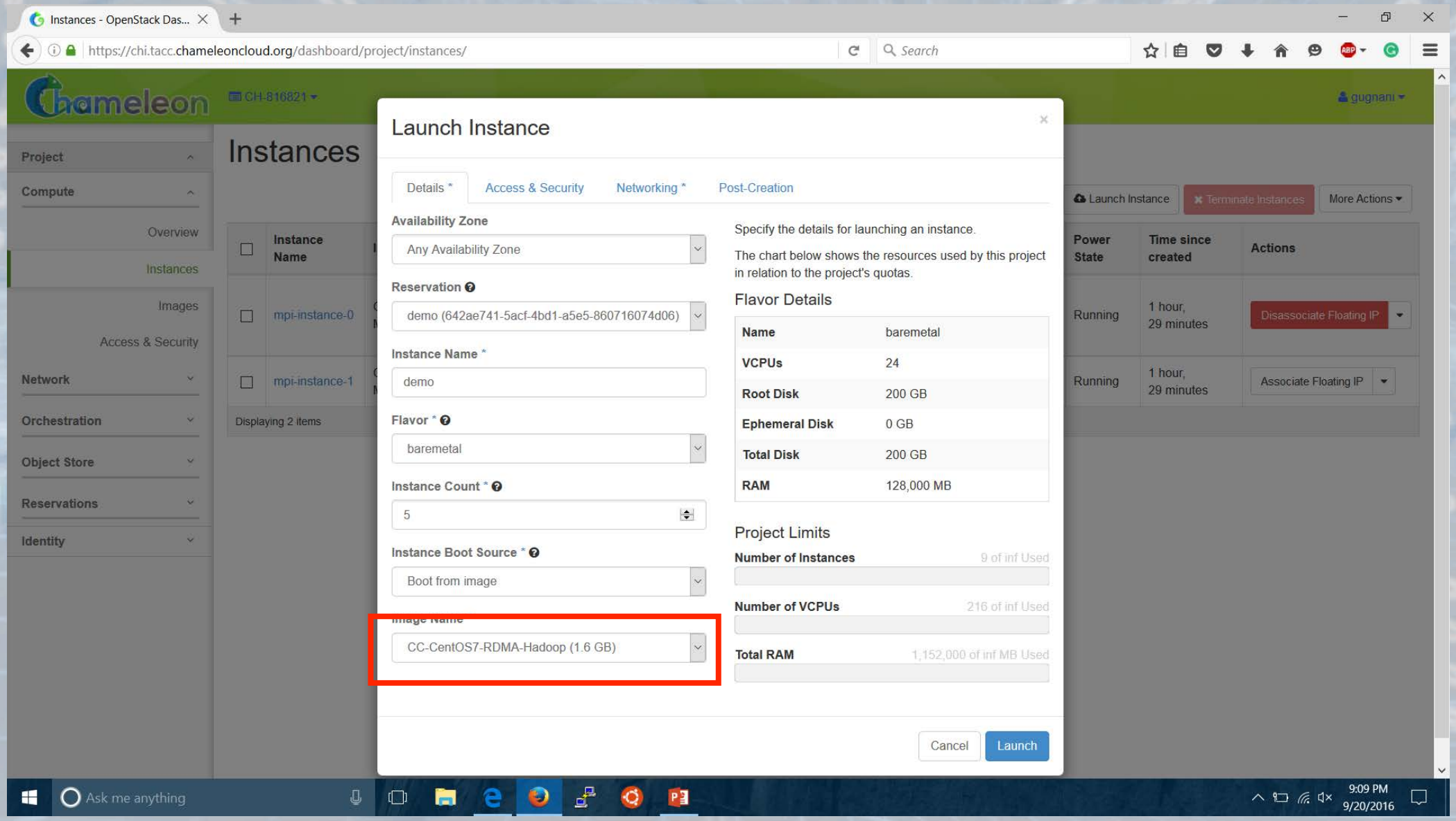
Demo – Create Your Lease



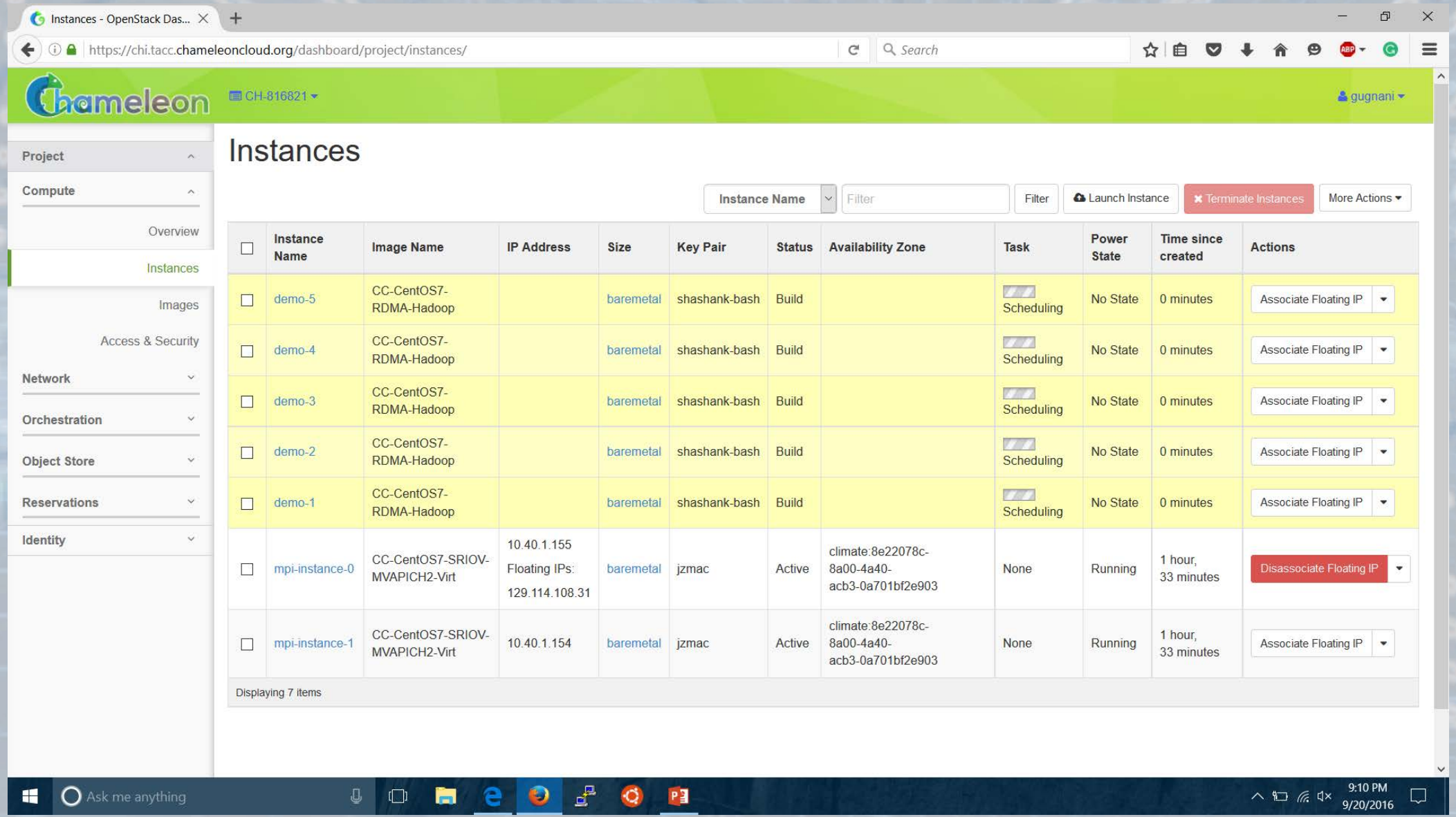
Demo – Create Your Lease



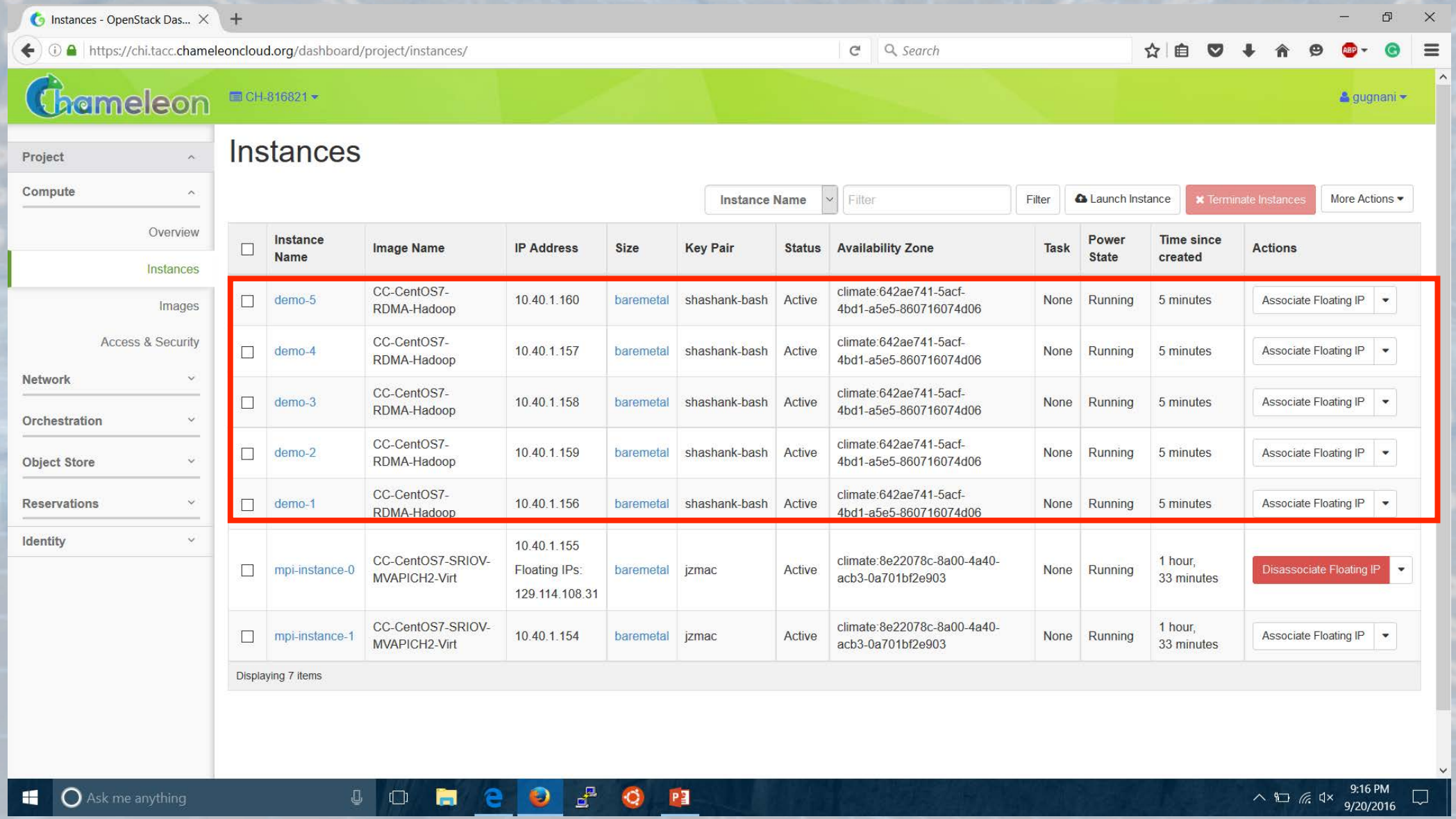
Demo – Launch Your Instances



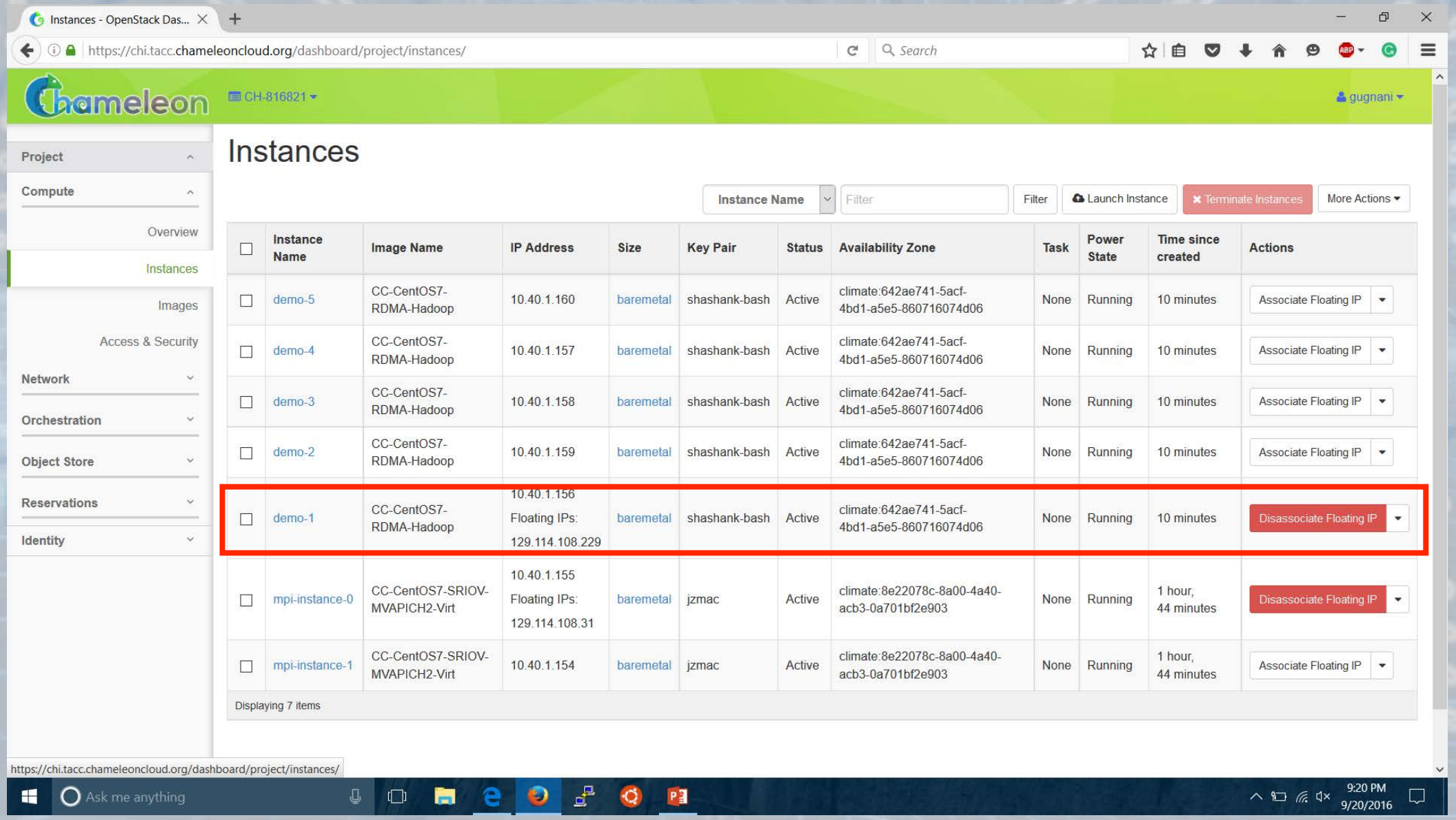
Demo – Launch Your Instances



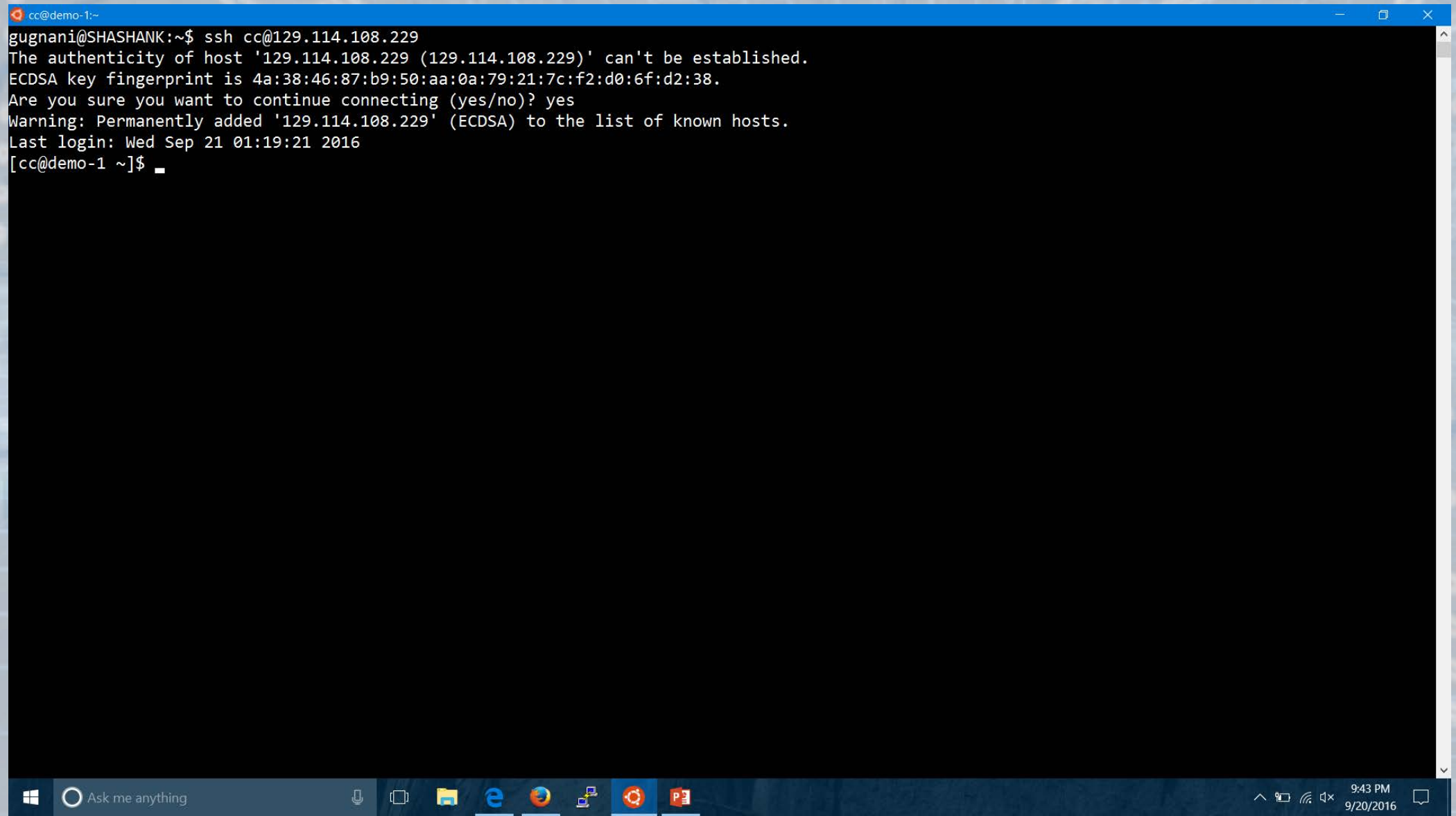
Demo – Launch Your Instances



Demo – Associate Floating IP



Demo – Login to Your Instances



Demo – Play with Your Hadoop on Chameleon Cloud

- ssh cc@129.114.108.229
- cd rdma-hadoop-2.x-0.9.8/
- ./sbin/start-all.sh
- bin/hdfs dfsadmin –report
- bin/mapred job -list-active-trackers
- ./bin/hdfs dfs -ls /
- bin/hadoop jar share/hadoop/mapreduce/hadoop-mapreduce-examples-*.jar randomwriter -Dmapreduce.randomwriter.mapsperhost=4 -Dmapreduce.randomwriter.bytespermap=1000 /rw-output
- ./bin/hdfs dfs -ls /
- bin/hadoop jar share/hadoop/mapreduce/hadoop-mapreduce-examples-*.jar sort /rw-output /sort-output
- ./bin/hdfs dfs -ls /
- ./sbin/stop-all.sh

Conclusion

- Overview of MapReduce Programming Model and Hadoop Architecture
- Overview of RDD Programming Model and Spark Architecture
- Overview of HiBD project: accelerating Big Data processing middleware (e.g., Spark, Hadoop, Memcached) by taking advantage of HPC technologies, such as InfiniBand/RDMA, SSD, etc.
- A case study with NeuroPigPen
- Demo of RDMA-Hadoop on NSF supported Chameleon Cloud
- Soliciting collaboration with other groups
  - Interested in exploring BigData processing requirements from Neuroscience researchers
  - We can explore how to collaborate further

Thank You!

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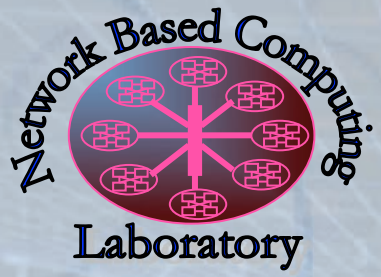

Network-Based Computing Laboratory
http://nowlab.cse.ohio-state.edu/

MVAPICH

The MVAPICH2 Project
http://mvapich.cse.ohio-state.edu/

HiBD
High-Performance
Big Data

The High-Performance Big Data Project
http://hibd.cse.ohio-state.edu/

Computational Neuroscience Network (ACNN)





http://www.NeuroscienceNetwork.org/ACNN_Workshop_2016.html