Integrating Pig with Harp to Support Iterative Applications with Fast Cache and Customized Communication

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Outline

- Apache Hadoop and Pig background
- Performance issue
  – Pig's overhead
  – Pig in supporting iterative applications
- Solution
  – Pig with Harp (Pig+Harp) integration and performance
- Conclusion

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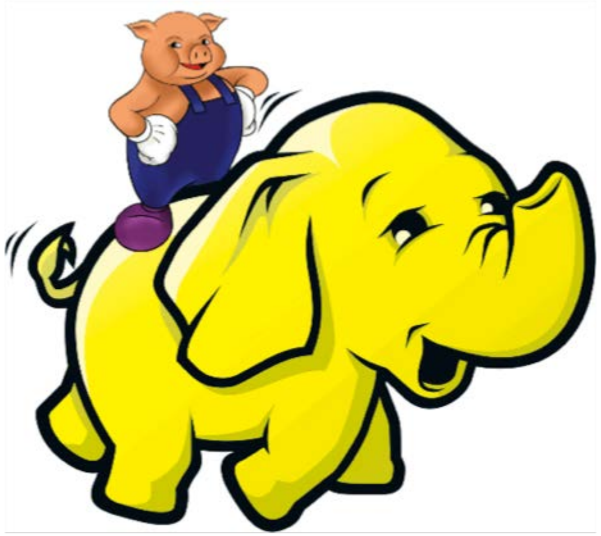
Hadoop and Pig

- Hadoop
  - Hadoop has been widely used by many fields of research and commercial companies
    - Machine Learning, Text Mining, Bioinformatics, etc.
    - Facebook, Amazon, LinkedIn, etc.
  - Java is one of the main stream languages for distributed systems
    - Apache Storm, Apache HBase, Apache Cassandra, etc.
- Pig
  - Procedural language and straightforward syntax
  - Runs directly on top of Hadoop
  - Automatic parallelism
  - Works with HDFS and HBase



Types of Pig Application

- Exact, Transform, Load (ETL)
  - Join, (Co)Group, Union, etc.
  - Raw Data analysis: daily log analysis
  - NoSQL Database queries
- Statistical data analysis
  - Means, median, standard deviation, etc.
- Data mining
  - K-means clustering

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WordCount Example in Hadoop

```java
public class WordCount {
  public static class Map
          extends Mapper<LongWritable, Text, Text, IntWritable>{
   private final static IntWritable one = new IntWritable(1); // type of output value
   private Text word = new Text();   // type of output key
   public void map(LongWritable key, Text value, Context context
               ) throws IOException, InterruptedException {
    StringTokenizer itr = new StringTokenizer(value.toString()); // line to string token
    while (itr.hasMoreTokens()) {
     word.set(itr.nextToken());    // set word as each input keyword
     context.write(word, one);     // create a pair <keyword, 1>
    }
   }
  }
```

Map

```java
  public static class Reduce
      extends Reducer<Text,IntWritable,Text,IntWritable> {
   private IntWritable result = new IntWritable();
   public void reduce(Text key, Iterable<IntWritable> values,
                     Context context
                     ) throws IOException, InterruptedException {
    int sum = 0; // initialize the sum for each keyword
    for (IntWritable val : values)
     { sum += val.get();  }
    result.set(sum);
    context.write(key, result); // create a pair <keyword, number of occurences>
   }
  }
```

Reduce

```java
  public static void main(String[] args) throws Exception {
    Configuration conf = new Configuration();
    String[] otherArgs = new GenericOptionsParser(conf, args).getRemainingArgs(); // get all
args
    for (int i = 0; i < otherArgs.length; i++)
                      System.out.println(i + " " +otherArgs[i]);
    Job job = new Job(conf, "wordcount");
    job.setJarByClass(WordCount.class);
    job.setMapperClass(Map.class);
    job.setReducerClass(Reduce.class);
    job.setInputFormatClass(TextInputFormat.class);
    job.setOutputFormatClass(TextOutputFormat.class);
    job.setCombinerClass(Reduce.class);
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);
    FileInputFormat.addInputPath(job, new Path(otherArgs[1]));
    FileOutputFormat.setOutputPath(job, new Path(otherArgs[2]));
    //Wait till job completion
    System.exit(job.waitForCompletion(true) ? 0 : 1);
  }
}
```

Driver

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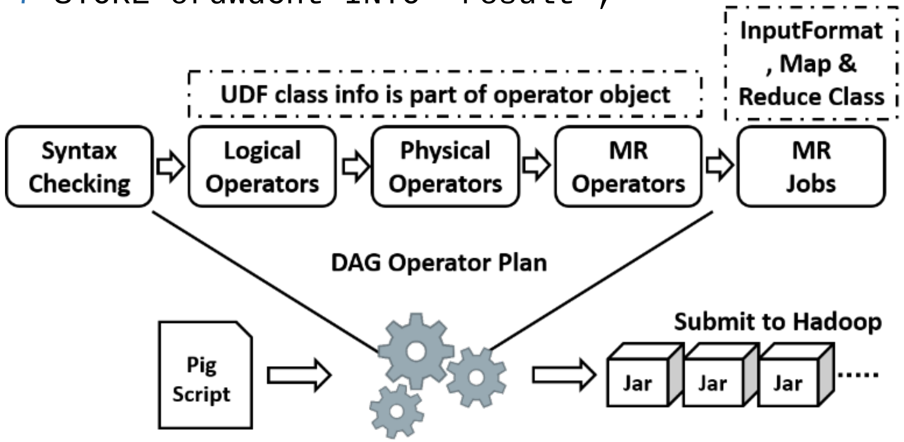
- 48 lines of code not including library import lines

Pig WordCount

- Fewer lines of code
- Data is converted into Pig data types: bag, tuple and field.
- Data transformation is handled by built-in operators or UDF.
- Compile into Hadoop job(s) as jar file(s)
- DAG execution dataflow/pipeline
- Jobs are submitted sequentially

```
input     = LOAD 'input.txt' AS
            (line:chararray);
words     = FOREACH input GENERATE
            FLATTEN(TOKENIZE(line)) AS word;
filWords = FILTER words BY word MATCHES '\\w+';
wdGroups = GROUP filWords BY word;
wdCount  = FOREACH wdGroups GENERATE group AS
            word, COUNT(filWords) AS count;
ordWdCnt = ORDER wdCount BY count DESC;
STORE ordWdCnt INTO 'result';
```



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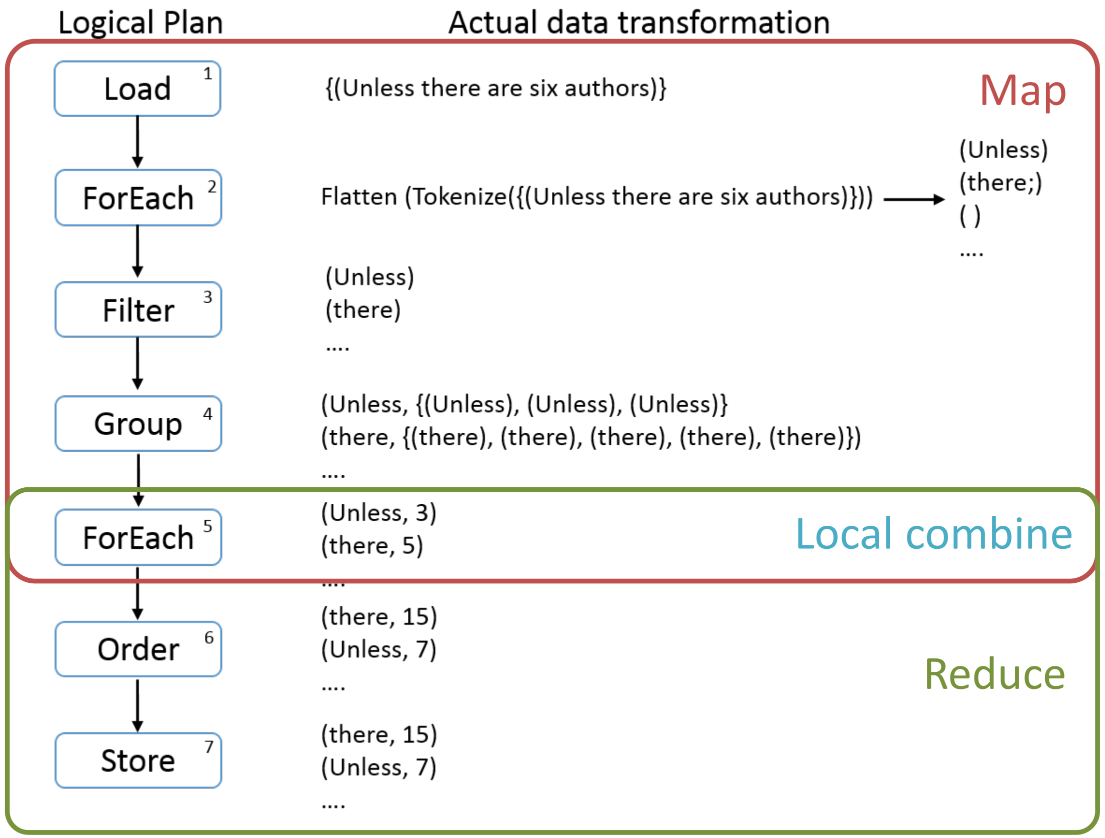
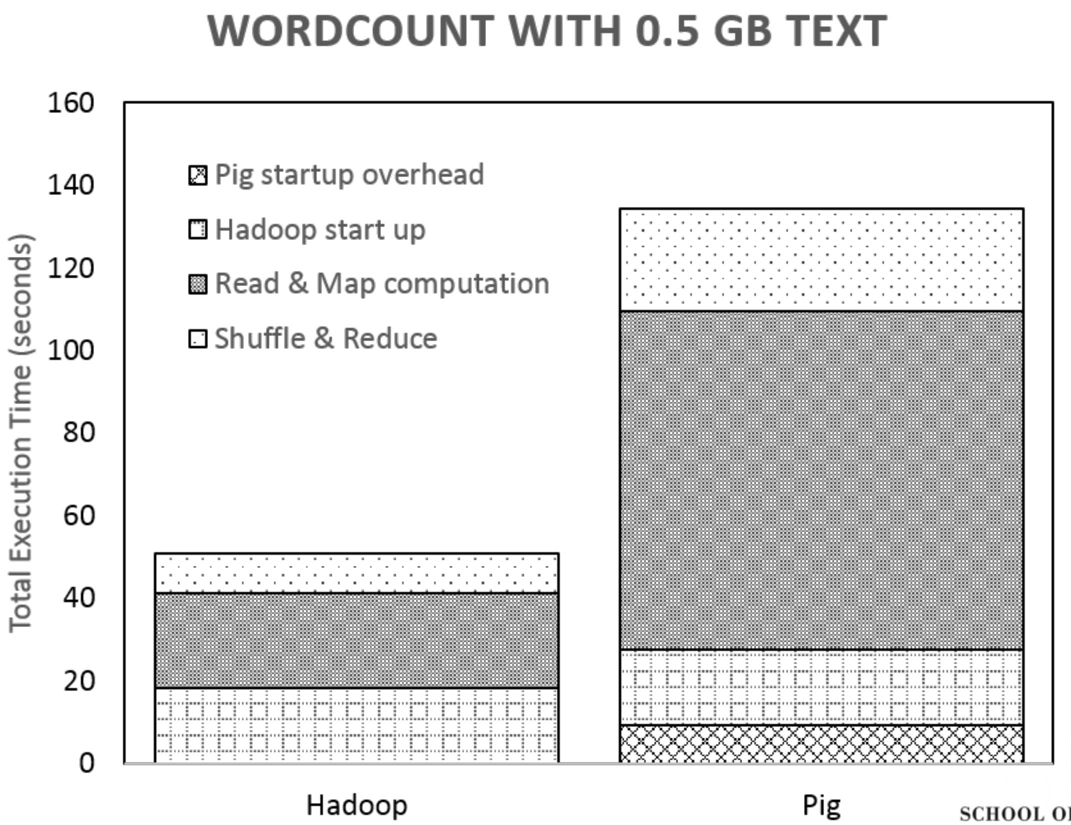
Pig's Computation Overhead

- Pig's Tuple-based (record-based) computation is slower than Hadoop
  - Overall execution time is about 2+ times slower





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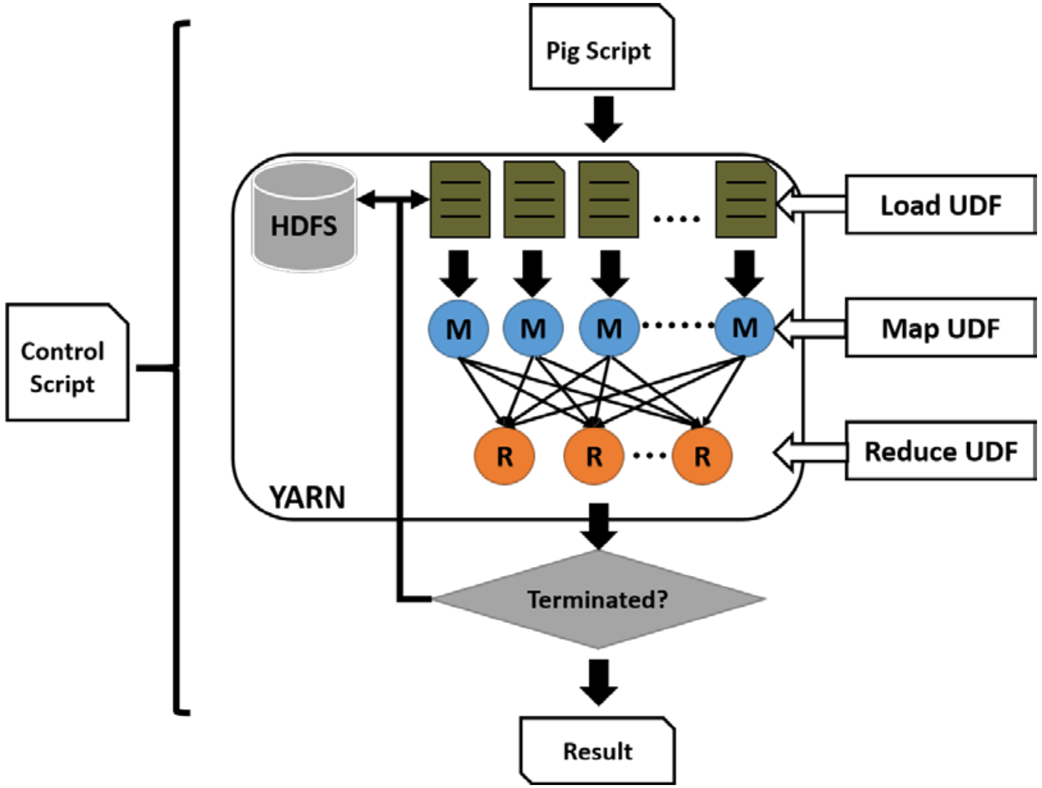
Pig and Iterative Applications

- Need a wrapper program to support conditional loop
- Intermediate results of iterations are mapped from disk to next iteration
  - Disk cache and Disk I/O are substantial
- Hadoop Jobs restart overhead
- No in-memory caching mechanism
- Data partitions are based on Pig Input Format
- Tuple-based data transformation/computation is slow



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Improvement?

- Avoid tuple-based computation
  - Easy fix by optimizing LOAD UDF
- Need loop-awareness support
- In-memory caching for reused data among iterations

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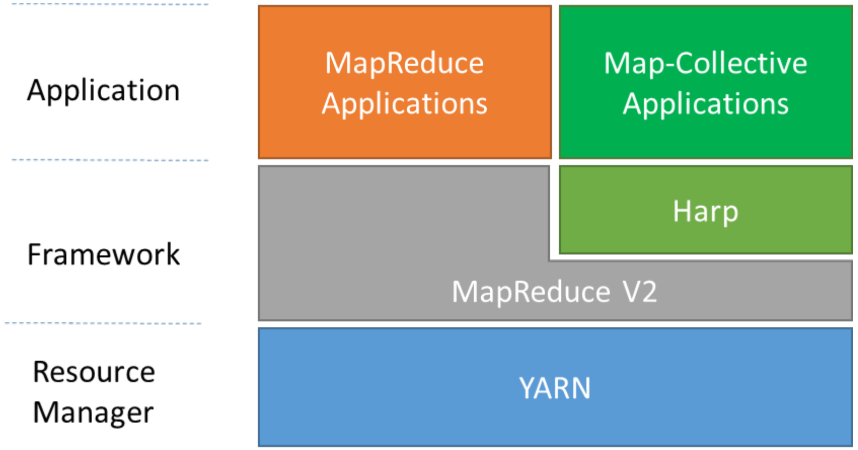
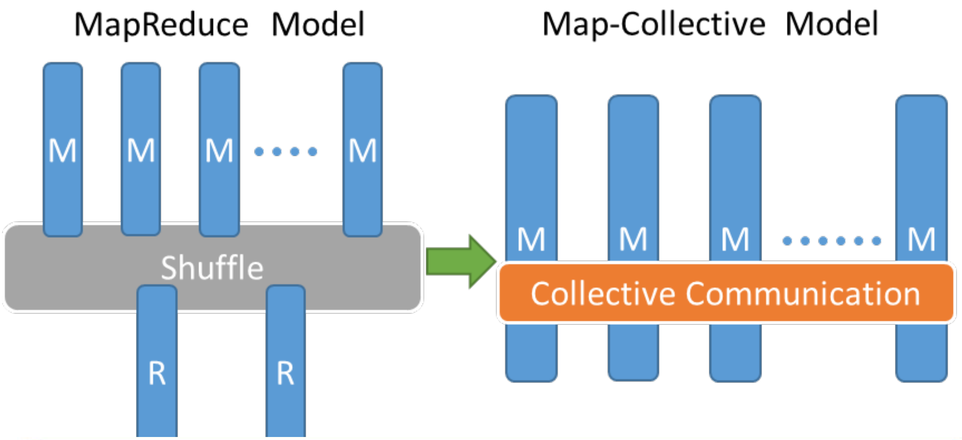
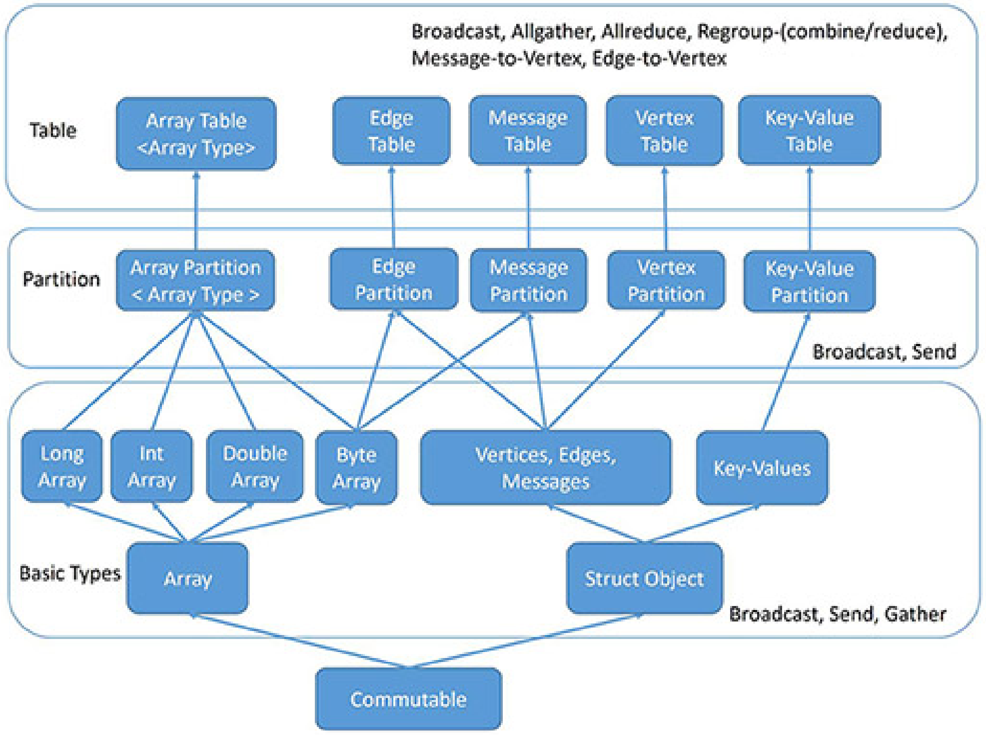
Harp: A Hadoop Plugin

- Plug-and-play Hadoop plugin
- Enable loop awareness for iterative applications
- Multi-thread and Multi-process computing
- In-memory object caching
- MPI-like and graph collective communication
- Pure Java implementation



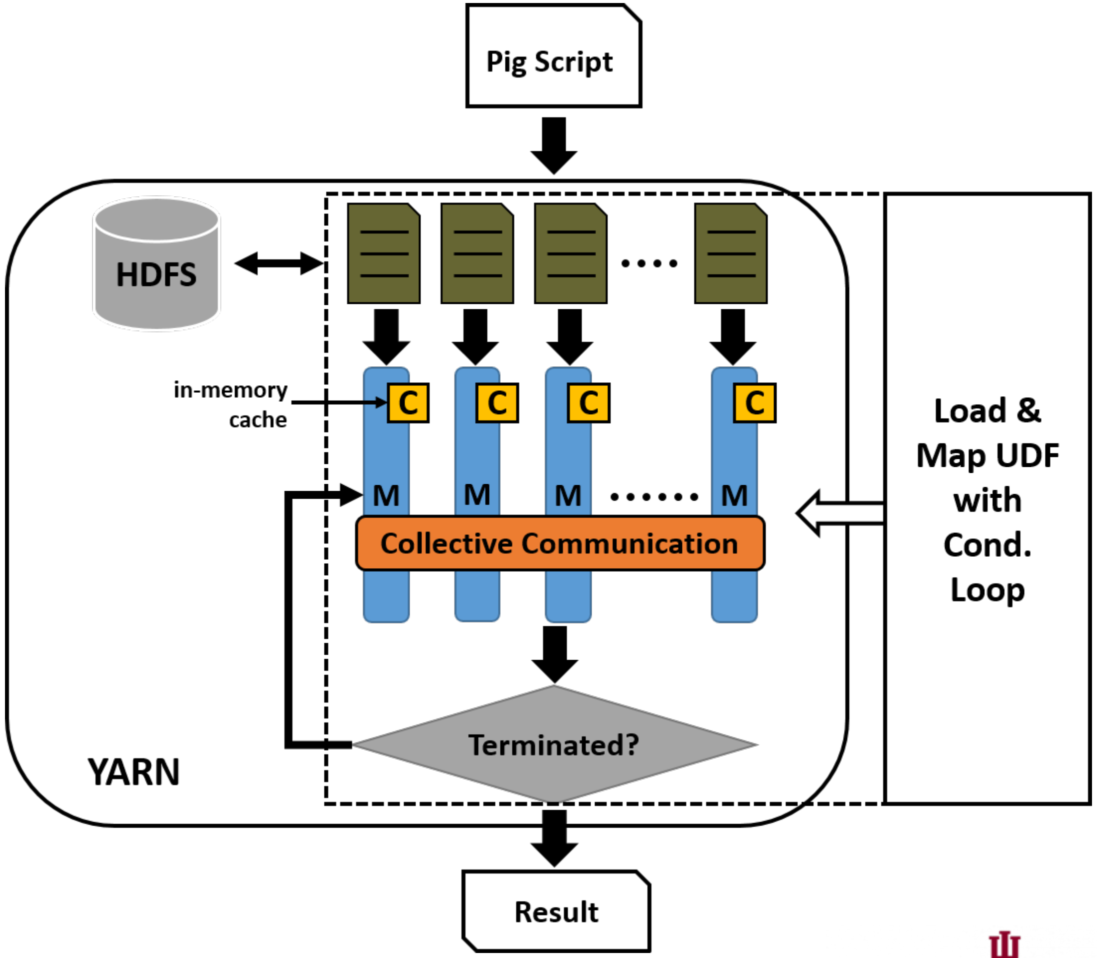




*Apache Harp project: http://salsaproj.indiana.edu/harp

Solution: Pig+Harp

- Replace default mapper interface with Harp's MapCollective long-running mapper
- Read once, Compute many
- In-memory objects caching in LOAD & MAP stages' UDF
- Shuffle data by calling Harp's collective communication API
- UDF controls loop termination
- No-hassle plugins
  - Same as general Pig if collective communication is not written in UDF



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Applications and Benchmarking

- Madrid Cluster (before update)
  - 8-node cluster with an extra head node
  - 4 x AMD Opteron 8356 2.30GHz with 4 cores
  - 16GB RAM per node
  - 1Gbps Ethernet network
  - Red Hat Enterprise 6.5s
- Hadoop 2.2.0
- Harp 0.1.0
- Pig 0.12.0
- K-means clustering on large dataset
  - Fixed computation ratios (50 Billion 4D data points computation per node) but various memory and communication usage aspects
- PageRank
  - Strong scaling test on a dataset with 2 million random vertices

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K-means

- Pig K-means
  - An external python loop-control wrapper
  - Data points and centroids are reloaded each iteration
  - Batch computation right after data loading
  - Default GROUP BY aggregation
- Pig+Harp K-means
  - Extends from Pig's LOAD interface
  - Reads data as file directly from HDFS.
  - Data points and centroids are cached as in-memory objects
  - Batch computation right after data loading
  - Sync intermediate centroids by using AllReduce communication

Pig K-means

```
raw     = LOAD $hdfsInputDir using
          PigKmeans('$centroids',
          '$numOfCentroids') AS (datapoints);
dptsBag = FOREACH raw GENERATE
          FLATTEN(datapoints) as dptInStr;
dpts    = FOREACH dptsBag GENERATE
          STRSPLIT(dptInStr, ',', 5) AS
          splitedDP;
grouped = GROUP dpts BY splitedDP.$0;
newCens = FOREACH grouped GENERATE
          CalculateNewCentroids($1);
STORE newCens INTO 'output';
```

Pig+Harp K-means

```
centds = LOAD $hdfsInputDir using
         HarpKmeans('$initCentroidOnHDFS',
         '$numOfCentroids', '$numOfMappers',
         '$iteration', '$jobID', '$Comm') as
         (result);
STORE centroids INTO '$output';
```

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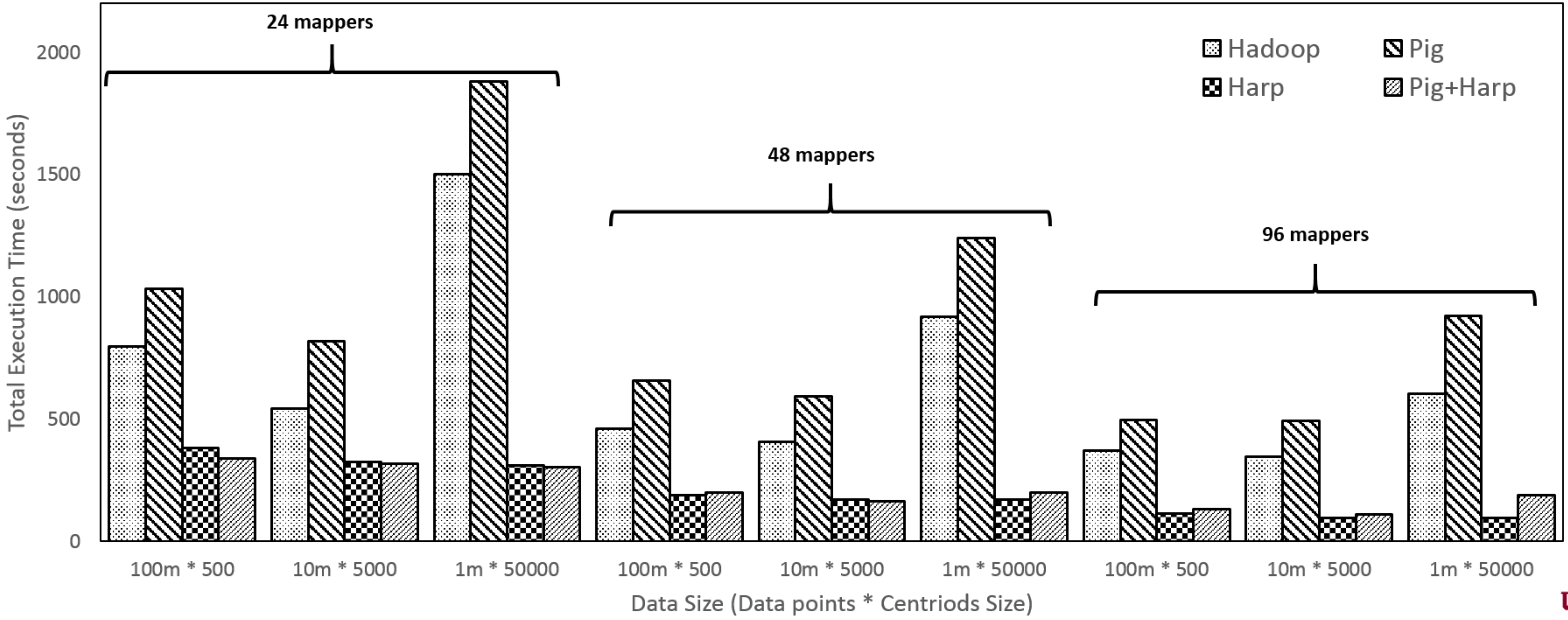
K-means Performance



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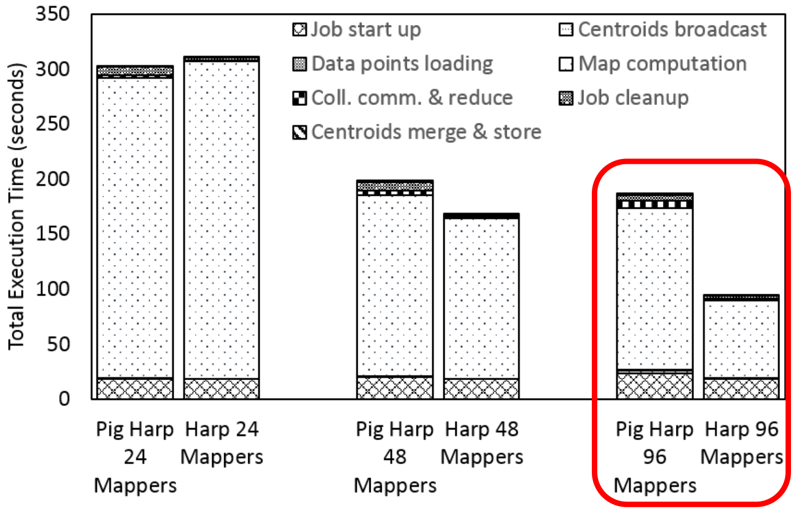
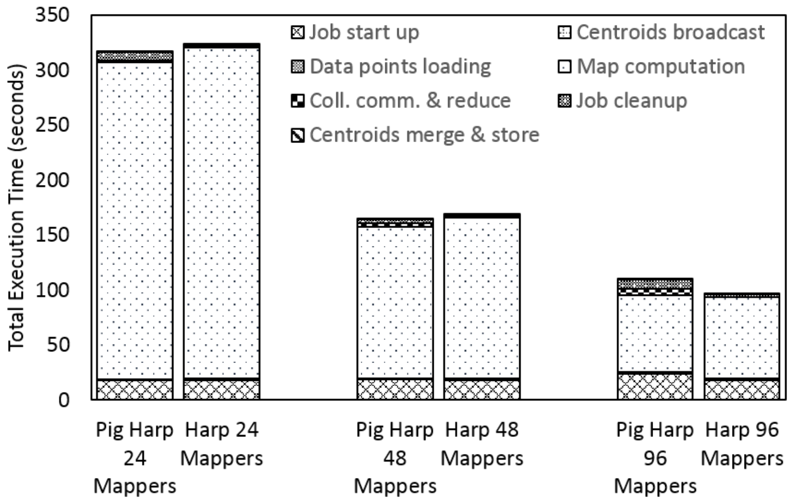
K-means Performance (cont.)

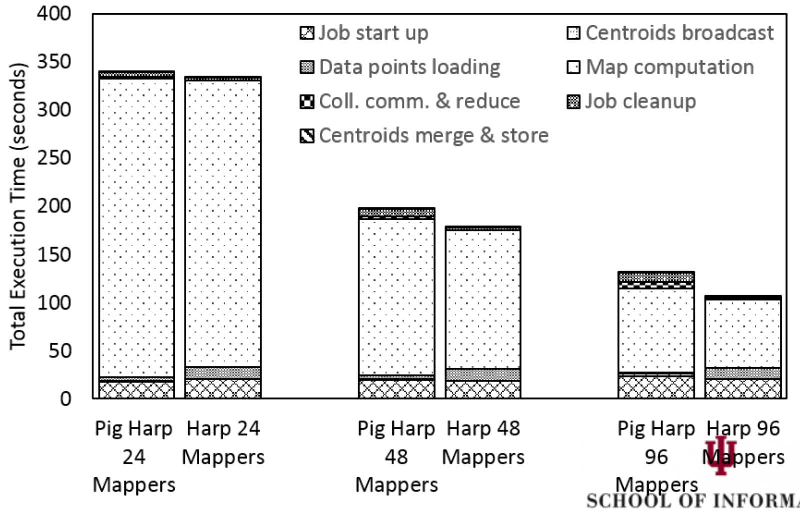
- Harp K-means is written in multi-thread model; meanwhile, Pig+Harp is written in multi-process model
- Pig+Harp 1m 50K 96 mappers runs 2 times slower than Harp’s multi-thread computation
  - L2 & L3 cache effect of in-memory caching



1m data points 50k centroids



10m data points 5k centroids



100m data points 500 centroids

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PageRank

- Pig PageRank
  - An external java loop-control wrapper
  - PageRank adjacent matrix is reloaded each iteration
  - Compute with built-in operators except data loading
  - Tuple-based computation

- Pig+Harp PageRank
  - Extend from Pig's LOAD interface
  - Reads data as file directly from HDFS
  - Data points are cached as in-memory objects
  - Batch computation right after loading
  - Sync intermediate page rank values by using AllGather communication

```
1 raw       = LOAD '$InputDir' USING
              CmLoader('$noOfURLs','$itrs') as
              (source,pagerank, out:bag{});
2 prePgRank = FOREACH raw GENERATE FLATTEN(out)
              as source, pagerank/SIZE(out) as
              pagerank;
3 newPgRank = FOREACH (COGROUP raw by source,
              prePgRank by source OUTER)GENERATE
              group as source, (1-$dpFactor) +
              $dpFactor*(SUM(prePgRank.pagerank)
              IS NULL?0:SUM(prePgRank.pagerank))
              as pagerank, FLATTEN(raw.out)
              as out;
4 STORE newPgRank INTO '$outputFile';
```

Pig PageRank

```
1 pagerank = LOAD '$InputDir' using
             HarpPageRank('$totalUrls',
             '$numMaps', '$itrs', '$jobID')
             as (result);
2 STORE pagerank INTO '$output';
```

Pig+Harp PageRank

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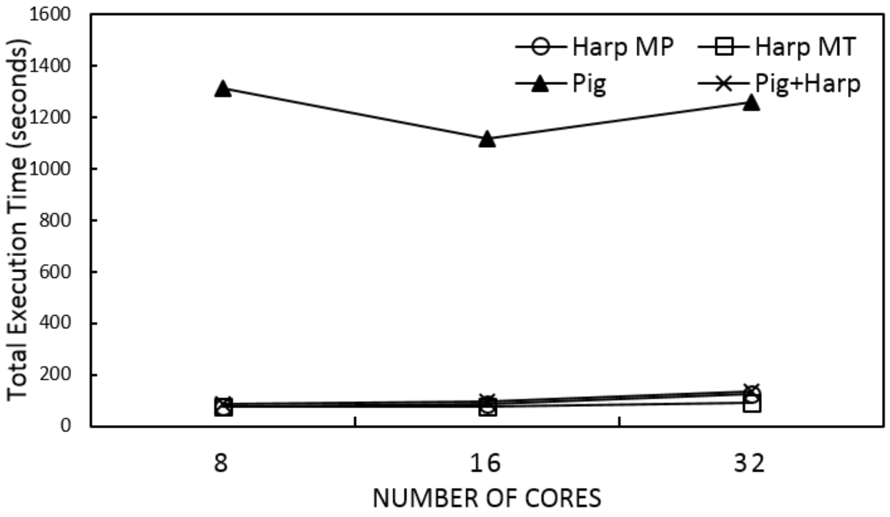
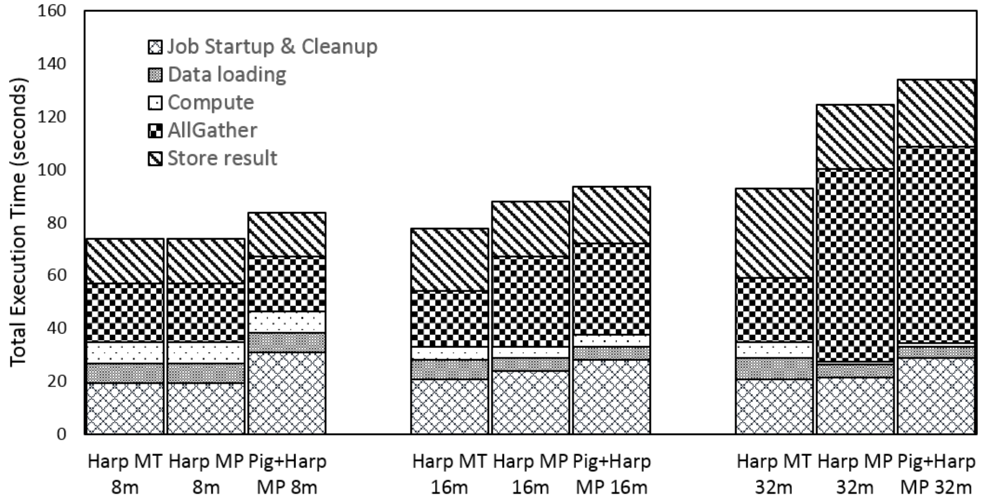
PageRank

- Pig+Harp is 5 times faster than native Pig
  - Tuple-based computation
  - Data type conversion time between bags and fields
- Harp's multi-thread shows the advantage in AllGather communication for larger partitions.
  - 2 layer synchronization
  - In-node sync and cross-node sync





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Lines of code for K-means and PageRank

- Same lines of code for core algorithm
- Zero lines of code for wrapper in Pig+Harp approach

	Hadoop K-means	Pig K-means	Harp K-means	Pig+Harp K-means
K-means	36	36	39	39
Load & Format	261	250	499	662
Reduce / Comm.	142	56	34	34
Pig	0	10	0	3
Driver / Wrapper	341	40	176	0
Total lines	780	393	748	738

	Pig PageRank	Harp PageRank	Pig+Harp PageRank
PageRank	1	56	56
Load & Format	50	386	494
Reduce / Comm.	0	4	4
Pig	4	0	3
Driver / Wrapper	70	90	0
Total lines	125	536	557

Conclusion

- A trend of using Apache high level languages for data analytics
- Leverage Apache open source building blocks to maximize the usage of existing features such as expressiveness of data type and data structure, automatic parallelization for applications, and algorithms.
- Easy-to-use Hadoop and Pig plugin written in Java.
- Pig+Harp saves the jobs restart overheads; by utilizing Harp, it provides in-memory objects caching and fast communication for data shuffling.
- Pig+Harp suggests minimizing tuple-based computation by batch computation and replacing data aggregation by writing customized collective communication in UDF.

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Future Work

- Link scientific data pipelines as an end-to-end solution in the context of using high-level languages to solve parallel computing problems.
- Investigate Apache Tez, compare to our approach, and optimize in-memory data caching between tasks.
- Benchmark applications at a larger scale.

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Q&A

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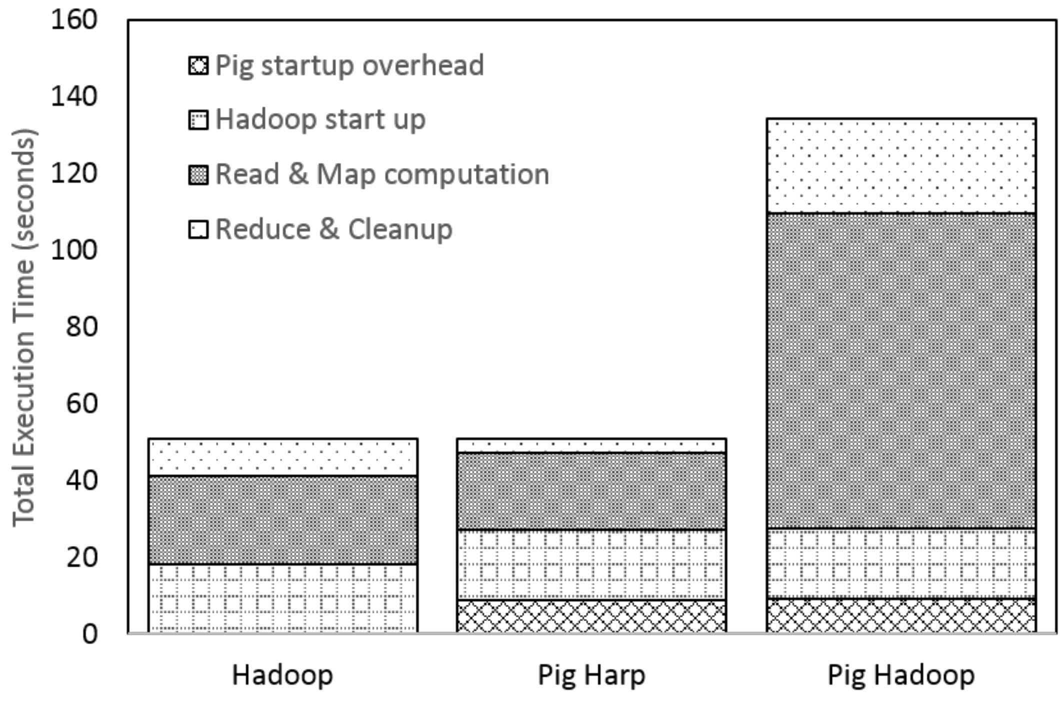
Wordcount without tuple-based computation



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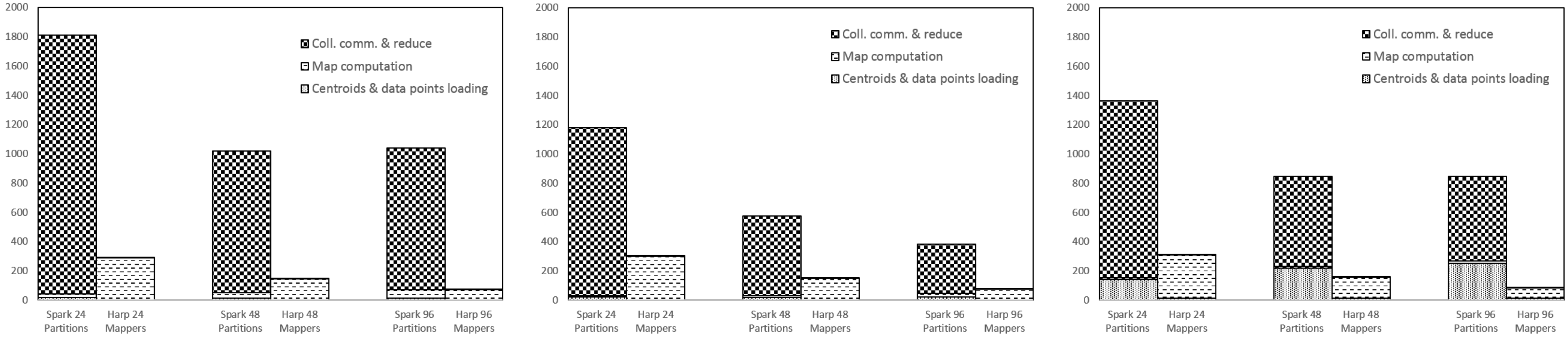
Harp 0.1.0 vs Spark 1.0.2

- Run Same K-Means clustering data with default Spark Mlib K-Means clustering
- Harp's data communication is highly optimized.
- Spark's computation and collectAsMap has less impact on the overall performance.
- Spark's reduceByKey operation takes much longer than usual with large data points as RDDs.
  - *Large intermediate data are shuffled to disk.



1m data points 50k centroids

10m data points 5k centroids

100m data points 500 centroids

*http://spark-summit.org/2014/training

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