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
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
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>
                }
            }

            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>
                    }

                    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);
                    }
                }
            }
    }

    public static void main(String[] args) throws Exception {
        Configuration conf = new Configuration();
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    }
}

• 48 lines of code not including library import lines

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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

```plaintext
1 input = LOAD 'input.txt' AS (line:chararray);
2 words = FOREACH input GENERATE FLATTEN(TOKENIZE(line)) AS word;
3 filWords = FILTER words BY word MATCHES '\w+';
4 wdGroups = GROUP filWords BY word;
5 wdCount = FOREACH wdGroups GENERATE group AS word, COUNT(filWords) AS count;
6 ordWdCnt = ORDER wdCount BY count DESC;
7 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

Pig’s Tuple-based (record-based) computation is slower than Hadoop. The execution time is about 2+ times slower compared to Hadoop. This is because Pig’s computation is based on tuple (record) operations, which is slower than Hadoop’s MapReduce model. The diagram illustrates the logical plan and actual data transformation, showing the overhead in each step. The performance comparison chart highlights the differences in execution time between Pig and Hadoop for the Wordcount operation on 0.5 GB of text data.
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
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
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
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

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

Pig+Harp K-means

1. centds = LOAD $hdfsInputDir using HarpKmeans('$initCentroidOnHDFS', '$numOfCentroids', '$numOfMappers', '$iteration', '$jobID', '$Comm') as (result);
2. STORE centroids INTO '$output';
K-means Performance

The diagram shows the performance of K-means with different data sizes and numbers of mappers. The x-axis represents the data size (in millions of data points times centroids size). The y-axis represents the total execution time in seconds.

- **Hadoop**
- **Harp**
- **Pig**
- **Pig+Harp**

The diagrams illustrate the performance for different mappers counts: 24 mappers, 48 mappers, and 96 mappers. The graph indicates that Pig+Harp generally performs better than the other systems, especially with larger data sizes and more mappers.

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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

![Graph showing K-means performance for different data points and centroids.](image)
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

```java
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';
```

---

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

---

Pig PageRank

Pig+Harp PageRank

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
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

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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.
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.
Q&A
Wordcount without tuple-based computation
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