

MONICALIAN SILVERSILY

MongoDB

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MongoDB

- Last week we looked at MongoDB, a popular Document Database
- This week we will discuss the Mongo aggregation framework



Aggregation in SQL

- Recall that aggregation in a RDBMS uses the GROUP BY clause in a SELECT statement
- Groups rows of data into a single row
 - Typically paired with an aggregation function such as SUM() or COUNT()

```
SELECT
        tracks.AlbumId,
        title,
        SUM(Milliseconds) AS length
FROM
        tracks
INNER JOIN albums ON albums. AlbumId = tracks. AlbumId
GROUP BY
        tracks.AlbumId
HAVING
        length > 60000000;
```

- Aggregation in MongoDB is similar in some ways, and distinct in others
- Here is an example that aggregates the orders collection

- In Mongo, aggregations are done in stages
- In this example
 - Stage 1 A Match Stage
 - All documents matching the given filter are passed through to the next stage
 - Stage 2 A Group Stage
 - All documents that passed the match stage are grouped by some set of attributes

- Here the match stage is picking out all orders whose status is "A"
- And the group stage is grouping by the cust_id field, and computing a sum of the amount field

- While this may appear superficially similar to the GROUP BY clause in SQL, it is in fact more general
- An aggregation can consist of any number of stages
- Each stage can transform or filter documents to be passed on to the next stage

- Stage types
 - There are many different stage types
 - \$match matchesdocuments
 - \$group groups documents
 - \$sort sorts documents
 - \$limit limits the number of documents
 - Etc.

- Stages can be in any order
- Here the \$group stage and the \$match stage are reversed
 - This \$match stage is acting like a HAVING clause in SQL: it applies to the aggregate

```
db.sales.aggregate(
    // First Stage
      $group :
          _id : "$item",
          totalSaleAmount: { $sum: { $multiply: [ "$price", "$quantity" ] } }
     // Second Stage
       $match: { "totalSaleAmount": { $gte: 100 } }
```

- Most stage types can appear multiple times in a an aggregation pipeline
 - Here we group twice
 - Once to sum up all the population by city in a zipcode database
 - And then we group that info again by the state, using an average to get the average population of cities in a state

- The MongoDB aggregation pipeline is inspired by the Unix pipe concept
- You connect an arbitrary number of commands together to produce the desired results

```
🙉 🖨 🗊 rishabh@rishabh: ~/GFG
rishabh@rishabh:~/GFGS cat result.txt
Rajat Dua
                     ECE
                            9.1
Rishabh Gupta
                     CSE
                            8.4
Prakhar Agrawal
                            9.7
Aman Singh
                            7.9
Rajat Dua
                            9.1
Rishabh Gupta
                            8.4
Aman Singh
                            7.9
Naman Garq
                            9.4
rishabh@rishabh:~/GFG$ sort result.txt | uniq
Aman Singh
                             7.9
Naman Garq
                            9.4
Prakhar Agrawal
                            9.7
                            9.1
Rajat Dua
                     ECE
Rishabh Gupta
                            8.4
rishabh@rishabh:~/GFGS
```

- Mongo also supports the Map/Reduce programming model
- Map/Reduce is a
 programming model for
 processing large sets of data
 in a distributed manner
 - Cluster Friendly



- Concept has been patented by Google and was widely used there
 - As an intern I ported various batch processing jobs to the google Map/Reduce infrastructure
 - It was alright



According to Wikipedia:

"By 2014, Google was no longer using MapReduce as their primary big data processing model"



- Nonetheless, the idea has had a large influence on the Big Data world
- Many open source implementations now
 - Hadoop is the most popular one that I am aware of



- Map/Reduce algorithm
 - Data is read as an input
 - A function then maps each piece of input to a key/value pair
 - Partition: each key/value pair is sent to a *Reducer* based on the mapp value



- Map/Reduce algorithm
 - The reducer sorts the input and then processes it using its reduce function
 - This reduce function produces zero or more outputs
 - This output is finally written to stable storage

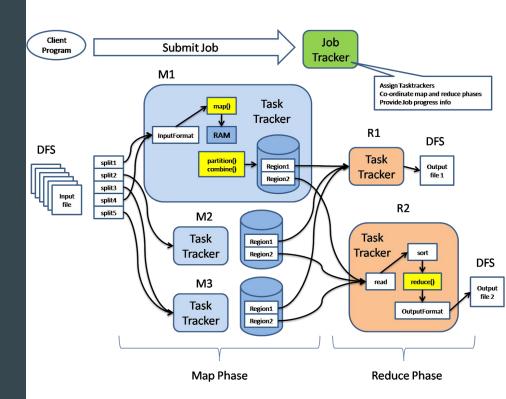


- There is controversy if this is a unique or even "good" idea
- It is taken from the functional programming concepts of the same names
- Many distributed computing researchers felt it was not a new idea, nor particularly flexible



Hadoop Map/Reduce

- Hadoop infrastructure
 - Client submits a job
 - Job is split into multiple mappers
 - Mappers partition and combine data
 - Reducers (optionally) read combined data and reduce to a final value



- Job Setup
 - Configure the map reduce job
 - Submit it to the JobTracker

```
//Main function
public static void main(String args[])throws Exception {
   JobConf conf = new JobConf(ProcessUnits.class);
   conf.setJobName("max eletricityunits");
   conf.setOutputKeyClass(Text.class);
   conf.setOutputValueClass(IntWritable.class);
   conf.setMapperClass(E EMapper.class);
   conf.setCombinerClass(E EReduce.class);
   conf.setReducerClass(E EReduce.class);
   conf.setInputFormat(TextInputFormat.class);
   conf.setOutputFormat(TextOutputFormat.class);
   FileInputFormat.setInputPaths(conf, new Path(args[0]));
   FileOutputFormat.setOutputPath(conf, new Path(args[1]));
   JobClient.runJob(conf);
```

- Mapper
 - Split value on tabs
 - Take the first value as year
 - Scan to end for last value
 - Parse as integer for average price for this row
 - Collect into a group based on the year

```
//Mapper class
public static class E EMapper extends MapReduceBase implements
Mapper<LongWritable ,/*Input key Type */
Text.
                    /*Input value Type*/
Text.
                   /*Output key Type*/
IntWritable>
                    /*Output value Type*/
   //Map function
   public void map(LongWritable key, Text value,
   OutputCollector<Text, IntWritable> output,
   Reporter reporter) throws IOException {
      String line = value.toString();
      String lasttoken = null;
      StringTokenizer s = new StringTokenizer(line, "\t");
      String year = s.nextToken();
      while(s.hasMoreTokens()) {
         lasttoken = s.nextToken();
      int avgprice = Integer.parseInt(lasttoken);
      output.collect(new Text(year), new IntWritable(avgprice));
```

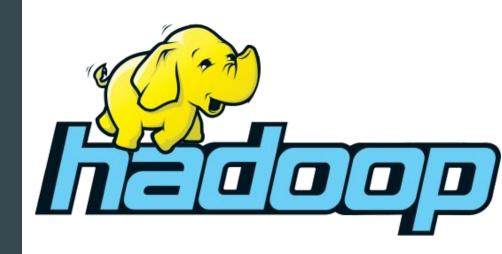
- Reduce
 - Iterate over input grouping
 - Filter out anything with an average price less than 30

```
//Reducer class
public static class E_EReduce extends MapReduceBase implements Reducer< Text, IntWrita

//Reduce function
public void reduce( Text key, Iterator <IntWritable> values,
OutputCollector<Text, IntWritable> output, Reporter reporter) throws IOException {
   int maxavg = 30;
   int val = Integer.MIN_VALUE;

   while (values.hasNext()) {
      if((val = values.next().get())>maxavg) {
         output.collect(key, new IntWritable(val));
      }
   }
}
```

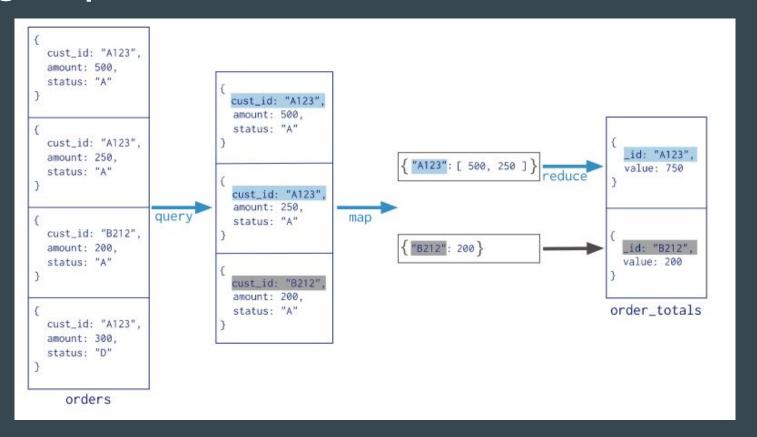
- Not a super interesting
 MapReduce but it gives you
 the flavor
- Hadoop is very mature and widely used in industry
- And they have a good logo



- In MongoDB, collections have a mapReduce() function available directly on them
- This function takes three arguments
 - A map function
 - A reduce function
 - A query/output pair

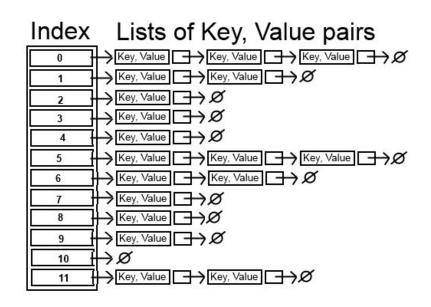
- The map function takes inputs from the collection and maps them to a particular key
- The reduce function takes a particular key and all the values mapped to it, and transforms them to a new, final value

- query allows a
 pre-MapReduce filter to be
 applied to documents
- out allows you to specify an output collection (or inline)



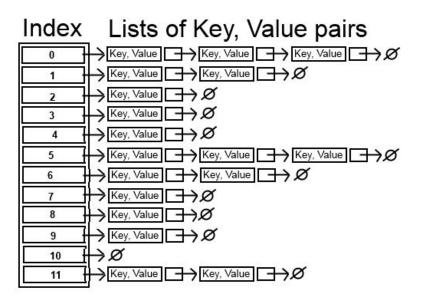
MapReduce & Hash Tables

- MapReduce works, in part, as a sort of network aware hash table
- Recall how a hash table works
 - A key is hashed to a particular index
 - A linked list (or similar) is
 maintained for each hash bucket



MapReduce & Hash Tables

- MapReduce suffers from many of the same pathological cases as Hashtables
 - E.g. What if everything maps to the same index?



MapReduce & SQL

- As we have discussed, aggregation in Mongo is similar but not identical to the GROUP BY functionality offered in SQL
- This table shows a rough correspondence between SQL feature and stage type

SQL Terms, Functions, and Concepts	MongoDB Aggregation Operators
WHERE	\$match
GROUP BY	\$group
HAVING	\$match
SELECT	<pre>\$project</pre>
ORDER BY	\$sort
LIMIT	\$limit
SUM()	\$sum
COUNT()	\$sum
	\$sortByCount

MapReduce & SQL

- Keep in mind, though: Mongo allows multiple instances of most stage types
 - More like the Unix pipeline than traditional SQL and RDBMS implementations

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Mongo Aggregation

- MongoDB provides an aggregation framework similar in some ways to what is available in SQL
- Mongo Aggregation has stages rather than a fixed syntax
- A stage has a particular stage type that provides a particular type of functionality
 - Sorting, grouping, etc.
- Stages can be chained together, like a Unix pipeline
- Most stage types can appear more than once in a mongo aggregation
- Mongo also provides a MapReduce API that can be used for aggregation calculations



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