Large Scale Data Processing

Hadoop

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Word Count Example

The goal of this example is to count the number of distinct words in a given text.

```
class MAPPER
  method MAP(docID a, doc d)
     for all term t in doc d do
       EMIT(term t, count 1)
```

The MAP method takes an input pair and produces a set of intermediate <key,value> pairs. Then all the intermediate values associated with the same intermediate key are grouped by the MapReduce library (shuffle phase).

Word Count Example

```
class REDUCER
  method REDUCE(term t, counts[c1,c2,...])
    sum = 0
    for all count c in counts[c1,c2,...] do
        sum = sum + c
    EMIT(term t, count sum)
```

The REDUCE method receives an intermediate key and a set of values for that key merging together these values to form a smaller set of values.

Word Count Example

Suposse we are give the following input file:

```
We are not what
we want to be,
but at least
we are not what
we used to be.
```

The MapReduce job consists of the following:

```
Map(doc_id, record) --> [(word, 1)]
Reduce(word, [1,1,...]) --> (word, count)
```

In the map phase the text is tokenized into words. Then a <word,1> pair is formed with these words.

```
<we, 1>; <are, 1>; <not, 1>; <what, 1>; ....
```

Remember that <key, value> pairs are generated in parallel on many machines. Each task has a little part of the overall Map input

Word Count Example

Considering our input text, in preparation for the reduce phase all the "we" pairs are grouped togheter, all the "what" pairs are grouped togheter, etc.

```
<we, 1> <we, 1> <we, 1> <we, 1> -- > <we, [1,1,1,1]>
<are, 1> <are, 1>                -- > <are, [1,1]>
<not, 1> <not, 1>                -- > <not, [1,1]>
...
```

In the reduce phase a reduce function is called once for each key. The reduce phase also sorts the output into increasing order by key as follows:

```
<are, 2>; <at, 1>; <be, 2>; <but, 1>; <least, 1>; <not, 2>; <to, 2>;
<used, 1>; <want, 1>; <we, 4>; <what, 2>
```

Like in the map phase, the reduce phase is also run in parallel. Each machine is assigned a subset of the keys to work on. The results are stored into a separate file.

Word Count::The Map source code

```
public class Map extends MapReduceBase implements Mapper<LongWritable, Text,
                                                                Text, IntWritable> {
  private final static IntWritable one = new IntWritable(1);
  private Text word = new Text();
  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);
    }
  }
}
```

- LongWritable, Text, Text and IntWritable are Hadoop specific data types designed for operational efficiency. All these data types are based out of Java data types; LongWritable is the equivalent for long, IntWritable for int and Text for String.
- Mapper<LongWritable, Text, Text, IntWritable> refers to the data type of input and output key value pairs. The input key (LongWritable) is a default value, the input value (Text) is a line. The output is of the format <word,1> hence the data type of the ouput is Text and IntWritable.

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                 Reporter reporter) throws IOException {
    String line = value.toString();
    StringTokenizer tokenizer = new StringTokenizer(line);
    while (tokenizer.hasMoreTokens()) {
      word.set(tokenizer.nextToken());
      output.collect(word, one);
    }
  }
}
```

- In the map method **map(LongWritable key, Text value, OutputCollector<Text, IntWritable> output, Reporter reporter)**
- The first two parameters refer to the data type of the input to the mapper.
- The third parameter **OutputCollector<Text, IntWritable> output** does the job of taking the output data from the mapper. The Reporter is used to report the task status internally in Hadoop environment.

```
public 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));
 }
}
```

- Considering Text, IntWritable, Text, IntWritable, the first two refers to data type of the input (<we,1>) to the reducer. The last two refers to data type of the output (<we,#occurrences>).
- In the reduce method **reduce(Text key, Iterator<IntWritable> values, OutputCollector<Text, IntWritable> output, Reporter reporter)**
- The input to reduce method from the mapper after the sort and shuffle phase is of the format <we,[1,1,1,1]>

Word Count::The driver

```
public static void main(String[] args) throws Exception {
   JobConf conf = new JobConf(WordCount.class);
   conf.setJobName("wordcount");

   conf.setOutputKeyClass(Text.class);
   conf.setOutputValueClass(IntWritable.class);

   conf.setMapperClass(Map.class);
   conf.setCombinerClass(Reduce.class);
   conf.setReducerClass(Reduce.class);

   conf.setInputFormat(TextInputFormat.class);
   conf.setOutputFormat(TextOutputFormat.class);

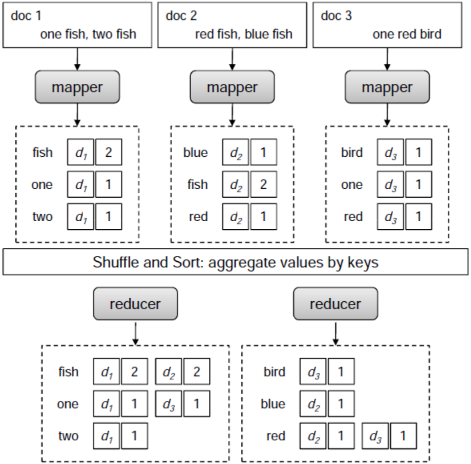
   FileInputFormat.setInputPaths(conf, new Path(args[0]));
   FileOutputFormat.setOutputPath(conf, new Path(args[1]));

   JobClient.runJob(conf);
}
```

Compilation and run

```
$ mkdir classes
$ javac -classpath /usr/share/hadoop/hadoop-core-0.20.204.0.jar -d classes/ *.java
$ jar -cvf wordcount.jar -C classes/ .
$ hadoop dfs -ls input/
$ hadoop jar wordcount.jar org.myorg.WordCount input/ output/
$ hadoop dfs -cat output/part-00000
```

Exercise::Inverted index



Pseudocode

```
class MAPPER
  method MAP(docID n, doc d)
     H = new AssociativeArray

     for all term t in doc d do
       H{t} = H{t}+1

     for all term t in H do
       EMIT(term t, posting <n,H{t}>)


class REDUCER
  method REDUCE(term t, posting [<n1,f1>,<n2,f2>....])
     P = new List

     for all posting <docid,f> in postings [<n1,f1>,<n2,f2>....] do
         Append(P,<docid,f>)
     Sort(P)
     EMIT(term t, postings P)
```

Custom Data Types

- In Hadoop we are free to define our own data types. In the above pseudocode we must implement an object that represents a posting composed of an document identifier and a term frequency.
- The object marshaled to or from files and across the network must obey the Writable interface, which allows Hadoop to read and write the data in a serialized form for transmission.
- The Writable interface requires two methods:

```
public interface Writable {
     void readFields(DataInput in);
     void write(DataOutput out);
}
```

- The **readFields()** method initializes all of the fields of the object on data contained in the binary stream **in**. The **write()** method reconstructs the object to the binary stream **out**.

Custom Data Types

- The most important contract between **readFields()** and **write()** methods is that they read and write the data in the same order.
- The following code implements a class usable by Hadoop:

```
public class point2D implements Writable {
    private IntWritable x;
    private IntWritable y;
    public point2D(IntWritable x, IntWritable y){
       this.x = x;
       this.y = y;
    }
    public point2D(){
       this(new IntWritable(),new IntWritable());
    }
    public void write(DataOutput out) throws IOException {
        x.write(out);
        y.write(out);
    }
    public void readFields(DataInput in){
        x.readFields(in);
        y.readFields(in);
    }
 }
```

Custom Key Types

If we want to emit custom objects as keys they must implement a stricter interface, WritableComparable.

```
public class point2D implements WritableComparable {
    private IntWritable x;
    private IntWritable y;
    public point2D(IntWritable x, IntWritable y){
       this.x = x;
       this.y = y;
    }
    public point2D(){
       this(new IntWritable(),new IntWritable());
    }
    public void write(DataOutput out) throws IOException {
        x.write(out);
        y.write(out);
    }
    public void readFields(DataInput in){
        x.readFields(in);
        y.readFields(in);
    }
    public int compareTo(point2D other){
        return Float.compare(distanceFromOrigin,other.distanceFromOrigin);
    }
 }
```

- The **setOutPutKeyClass()** and **setOutPutValueClass()** methods control the output types for the map and reduce functions, which are often the same.
- If the map and reduce functions are different, you can set the types emitted by the mapper with the **setMapOutPutKeyClass()** and **setMapOutPutValueClass()** methods. These implicitly set the input types expected by the reducer.

Partitioning Data

- Partitioning is the process of determining which reducer instance will receive which intermediate keys and values.
- It is necessary that for any key, regardless of which mapper instance generated it, the destination partition is the same.
- Hadoop determines when the job starts how many partitions it will divide the data into. If ten reduce tasks are to be run, then ten partitions must be filled.
- The Partitioner defines one method which must be filled:

```
public interface Partitioner extends JobConfigurable{
    int getPartition(K key, V value, int numPartitions);
}
```

- After implementing the Partitioner interface, we must use the **JobConf.setPartitionerClass()** method to tell Hadoop to use the custom Partitioner in the job.