MANCHESTER 1824
The University of Manchester

COMP38120 Services on the Web: Workshop 3

Norman Paton, Sandra Sampaio

1

MANCHESTER 1824
The University of Manchester

Workshop Outline

- Today's workshop seeks to give you a flavour of web scale data processing, and covers:
  - Cloud services and big data.
  - The Map Reduce approach to big data processing:
    - The standard WordCount Example (in more detail).
    - Design patterns.
    - Writing of map reduce programs.

2

MANCHESTER 1824
The University of Manchester

Position in Workshop

- Big Data and the Cloud.
- MapReduce concepts.
- MapReduce design patterns.
- How MapReduce surfaces in Hadoop.

For reference – we won't get to this in the workshop.

3

MANCHESTER 1824
The University of Manchester

Web-Scale Data-Intensive Applications

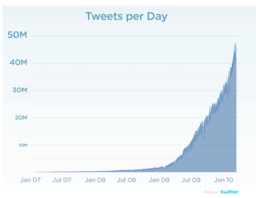
- An increasing number of applications are extremely data intensive; data intensive applications include:
  – web indexing: there are estimated to be over 45 billion pages (www.worldwidewebsize.com/).
  – social media: there are in the region of 500 million tweets per day.
  – instruments: CERN "sifts" around 30 petabytes a year; an Airbus A350 has 6000 sensors that produce 2.5Tb per day.
- So, the trends are that *the ability to capture and store data is overwhelming the ability to process what is stored*.

4

MANCHESTER 1824
The University of Manchester

Size not the only challenge

- Change and unpredictability are also challenging (https://blog.twitter.com/official/en_us/a/2010/measuring-tweets.htm).
- However, note that twitter's growth rate has dropped a lot:
  – 2009: 900%
  – 2013: 32%
  – Now: past the peak?



5

MANCHESTER 1824
The University of Manchester

Cloud Services for Web-Scale Data-Intensive Applications

- Data-intensive processing is beyond the capability of any individual machine and requires clusters.
- Volatile demand means that it is not surprising that a significant number of companies are opting to "rent" cloud resources, rather than investing in the running of giant data centres, which not everyone has the expertise to manage.
- There is no single model of big data processing:
  – Long running tasks: Batch (e.g. map reduce), Streaming (e.g. Storm).
  – Interactive tasks: Lookup (e.g. NoSQL Databases), Search (household names).

MANCHESTER 1824
The University of Manchester

Big Data and Parallelism

- It is not practical to address big data problems in serial; just scanning the data from disc takes much too long.
- Relevant disc trends:
  - Disc capacity has been following Moore's law: http://en.wikipedia.org/wiki/Moore%27s_law.
  - Disc speed has not kept up, especially for seeks (which need physical head movements).
- Thus it has become viable to store more and more data (on more and more discs), but accessing the data in a way that reflects these trends means scanning in parallel. Map Reduce emerged in this context.

7

MANCHESTER 1824
The University of Manchester

Big Data and the Web

- The archetypal big data problem in the web involves search. The challenges include:
  - Crawling the web to obtain the raw material over which the indexes are constructed (highly distributed, offline).
  - Constructing the indexes from the crawled data so that the data can be searched efficiently (batch processing, in the data centre).
  - Searching the indexes (interactive response times, in the data centre).
- So, there is not a single processing model for big data, but we will focus on a popular one that applies to many applications, namely map reduce (batch processing, in the data centre).

8

MANCHESTER 1824
The University of Manchester

Position in Workshop

- Cloud Services.
- MapReduce concepts.
- MapReduce design patterns.
- HowMap Reduce surfaces in Hadoop.

9

Map Reduce

- *Map Reduce* is a scalable programming model, originally developed by Google for tasks such as index building.
- In Map Reduce:
  - applications are developed using two simple, functional operations (*map* and *reduce*) … and a few other supporting players;
  - the infrastructure supports the running of Map Reduce applications in parallel on potentially huge data sets on potentially numerous commodity machines.
- *Hadoop* is a widely used open source implementation of map reduce (hadoop.apache.org).

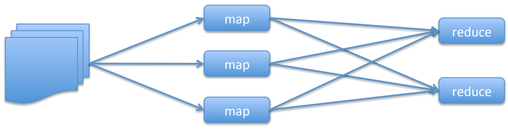
Map Reduce Functions

- The map and reduce functions are defined as:
  - map(key_1, $value_1$) -> [(key_2,$value_2$)]
  - reduce(key_2,list of values $value_2$) -> [(key_3, $value_3$)]
- where:
  - map, given a key key_1 and a value $value_1$, generates a collection of key-value pairs (key_2,$value_2$).
  - reduce, given a key key_2 output by map, and a collection of *all* the values $value_2$ associated with that key, returns a new collection of key-value pairs.

Word Count Example

- The standard map reduce example program counts the number of occurrences of each word in a document (although this is in some ways a toy task, it is relevant to web indexing).

Word Count at Runtime



the reduce operation, given the id of a document and the document, emits a collection of key-value pairs …	the reduce operation, given the id of	(the, 1) (reduce, 1) (the, 1) …	(the, [1,1,1]) (reduce,[1]) …	(the, 3) (reduce, 1) …
	a document and the document, …	(the, 1) (document, 1) … …	(of, [1,1]) (pairs,[1]) …	(of, 2) (pairs, 1) …

13

Word Count Map

- Recall the description of map:
  - map(key_1, $value_1$) -> [(key_2,$value_2$)]
  - map, given a key key_1 and a value $value_1$, generates a collection of key-value pairs (key_2,$value_2$).
- In WordCount:
  - key_1 is the identifier of the document (not used).
  - $value_1$ is the document (or part of the document).
  - key_2 is a word from the document.
  - $value_2$ is an occurrence count for key_2.

14

Map Pseudo-Code

- The map operation, given the *id* of a document and the *document* (or part of the document), emits a collection of key-value pairs, where the key is a term in the document and the value is a (partial) count of the number of occurrences of the word in the document.

```
map(documentId key1, document value1) {
  for each term t in value1 do
    emit(term t, count 1)
}
```

15

MANCHESTER 1824
The University of Manchester

Map Example Inputs/Outputs

Input to map

the reduce operation, given the id of

Output from map

- <the, 1>
- <reduce, 1>
- <operation, 1>
- <given, 1>
- <the, 1>
- <id, 1>
- <of, 1>

16

MANCHESTER 1824
The University of Manchester

Word Count Reduce

- Recall the description of reduce:
  - reduce(key_2, list of values $value_2$) -> [(key_3, $value_3$)]
  - reduce, given a key key_2 output by map, and a collection of *all* the values $value_2$ associated with that key, returns a new collection of key-value pairs.
- In WordCount:
  - key_2 is a term from the document processed by map.
  - $value_2$ is a list of (partial) counts of occurrences of key_2 from map.
  - key_3 is the same as key_2.
  - $value_3$ is the total occurrence count for key_3.

17

MANCHESTER 1824
The University of Manchester

Reduce Pseudo-Code

- The reduce operation, given a term and a list of partial counts of the term from map, emits a collection of key-value pairs, where the key is the term and the value is the sum of the partial counts.

```
reduce(term key2, list of count value2) {
  sum = 0
  for each count in value2 do
    sum = sum + count;
  emit(term key2, count sum)
}
```

18

Map Example Inputs/Outputs

Input to reduce
- <the, [1, 1, 1]>

Output from reduce
- <the, 4>

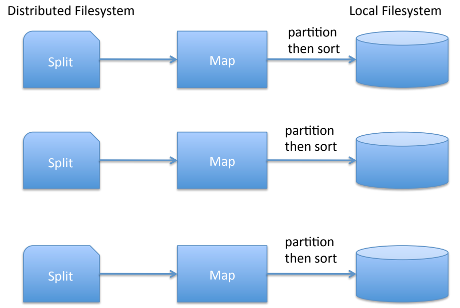
What Actually Happens?

- The whole point of MapReduce is that it scales out (to more nodes). First some terminology:
  - A MapReduce *job* is the unit of work to be performed (the data and the program).
  - A MapReduce job consists of several map and reduce *tasks.*
  - A *task tracker* tracks the progress of each of the map or reduce tasks on a node, and keeps the job tracker informed of progress.
  - A *job tracker* coordinates the different tasks.

Map Side

- In terms of map:
  - A map *task* is created for each *split* (i.e. part – often a 64Mb filesystem block) of the input.
  - Wherever possible, the map task will be run on the node where the input data is stored.
  - The map task runs on the split, generating key-value pairs.
  - The output of the map is partitioned into groups that reflect their reduce node, normally by hashing.
  - The partitions are sorted by key.
  - When the output has been written, the task tracker informs the job tracker.

Map side



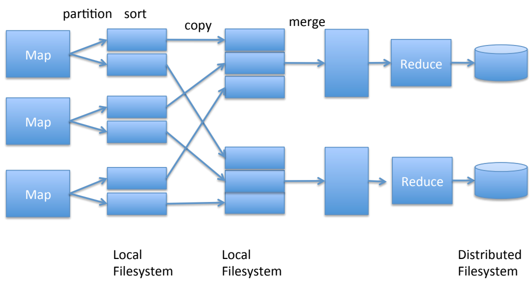
22

Reduce Side

- In terms of reduce:
  - Reduce tasks are created, the task trackers of which poll the job tracker to find out which of the relevant map outputs are complete.
  - The relevant data is pulled over the network.
  - When all the map outputs have been copied the data is merged to produce the inputs for the reduce operation.
  - The reduce operation is run, writing its outputs to the distributed filesystem.

23

Reduce Side



24

MANCHESTER 1824
The University of Manchester

Activity - 1

- Now you will run a MapReduce job in the workshop.
- Your table will either be:
  - A node that runs a map (3).
  - A node that runs a reduce (2).
  - The job tracker (1).
- Mapper:
  - Someone acts as the task tracker.
  - Someone executes map().
  - Someone executes partition().
  - Someone sorts each partitions.
- Reducer:
  - Someone acts as the task tracker.
  - Someone merges incoming partitions.
  - Someone executes reduce().

25

MANCHESTER 1824
The University of Manchester

Position in Workshop

- Cloud Services.
- MapReduce concepts.
- MapReduce design patterns.
- How MapReduce surfaces in Hadoop.

26

MANCHESTER 1824
The University of Manchester

Basket Analysis in MapReduce

- Another web-scale, data-intensive application is Basket Analysis, where a customer accesses a Web application to shop for products. Each individual interaction by a customer is recorded with information about the value (price) of each basket of products that the customer purchases, as shown in the table on the next slide.
- A simple basket analysis involves calculating the average spent by each customer, considering all the recorded interactions by the customer.

27

MANCHESTER 1824
The University of Manchester

Basket Analysis

- Note that each customer is associated with a number of interactions, and for each interaction there is a basket value.

CustomerID	BasketValue (in £)
CID_001	26.00
CID_002	30.00
CID_001	40.00
CID_001	20.00
CID_002	35.00
CID_002	25.00
CID_001	10.00
CID_003	25.00
CID_002	35.00

Basket analysis results:
CID_001: 24.00
CID_002: 31.25
CID_003: 25.00

28

MANCHESTER 1824
The University of Manchester

Activity - 2

- Write the basket analysis application as a MapReduce program using pseudo-code.
- A solution to this activity will be made available in Blackboard.

29

MANCHESTER 1824
The University of Manchester

Design Patterns

- Design patterns are a means by which experience and good practice can be passed on.
- In MapReduce, design patterns capture features of implementations that either:
  - enable specific functionalities to be captured within the restrictions of MapReduce, or
  - enable more efficient processing than more naïve implementations.
- Here we discuss one example; for more see: Miner, Donald and Adam Shook, MapReduce design patterns: building effective algorithms and analytics for Hadoop and other systems, O'Reilly, 2012.

30

MANCHESTER 1824
The University of Manchester

Summarisation

- In summarisation, additional work is carried out within mapper that seeks to reduce the amount of data written to disk and sent over the network to reduce.
- Word count example:
  - Instead of: <the, 1>, <the, 1>, <the, 1>.
  - Summarise as: <the, 3>

31

MANCHESTER 1824
The University of Manchester

Combiner Summarisation

- In Hadoop, as well as *map* and *reduce*, there is an optional *combiner.*
- The infrastructure may choose (or not) to call the combiner, so a developer cannot be sure combiner summarisations will run.
- For WordCount, the combiner can be the reduce operation, which given a collection of values with the same key, aggregates their value.
- Caution is required – only certain operations can perform summarisation without loss of information (they need to be *commutative* and *associative*). Also note that the result type of the reduce is the same as that of the map!

32

MANCHESTER 1824
The University of Manchester

In Mapper Summarisation

- Alternatively, summarisation can take place inside map.

```
map(documentId key1, document value1) {
  localCache = Hashmap(String -> Integer)
  for each term t in value1 do {
    count = 1;
    if (localCache.containsKey(t))
      count = localCache.get(t) + 1;
    localCache.put(t,count);
  }
  for each term t in localCache do
    emit(term t, localCache.get(t))
}
```

33

MANCHESTER 1824
The University of Manchester

Activity - 3

- Write the basket analysis application as a MapReduce program using pseudo-code, in which there is in-mapper summarisation.
- A solution to this activity will be made available in Blackboard.

34

MANCHESTER 1824
The University of Manchester

Position in Workshop

- Cloud Services.
- MapReduce concepts.
- MapReduce design patterns.
- How MapReduce surfaces in Hadoop.

35

MANCHESTER 1824
The University of Manchester

MapReduce in Hadoop

- In the labs, you will be writing MapReduce programs, specifically:
  - Making a small functionality change to a given WordCount implementation.
  - Developing a program to build a basic inverted index.
  - Augmenting the basic inverted index with additional functionality from *Documents on the Web*.

36

MANCHESTER 1824
The University of Manchester

Where will it run

- The principal focus will be on design and functionality, so you will develop using a *local job runner*.

37

MANCHESTER 1824
The University of Manchester

What does a program look like?

- You will compile a java class definition into a JAR, which hadoop can run.
- The framework knows about your code because you will extend or implement classes and interfaces that are provided by hadoop.

38

MANCHESTER 1824
The University of Manchester

WordCount Example: map/reduce

```
public class WordCount extends Configured implements Tool
{
   private static class MyMapper extends
         Mapper<LongWritable, Text, Text, IntWritable>
   {
      public void map(LongWritable key, Text value, Context context)
      { .... }
   }
   private static class MyReducer extends
         Reducer<Text, IntWritable, Text, IntWritable>
   {
      public void reduce(Text key, Iterable<IntWritable> values,
            Context context)
      { ....}
   }
}
```

39

MANCHESTER 1824
The University of Manchester

WordCount Example: run

```
public int run(String[] args) throws Exception
{
    job.setJobName(WordCount.class.getSimpleName());
    job.setJarByClass(WordCount.class);

    // Set the mapper and reducer classes
    job.setMapperClass(MyMapper.class);
    job.setReducerClass(MyReducer.class);

    // Set the output classes
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);

    // Set the input and output file paths
    FileInputFormat.setInputPaths(job, new Path(inputPath));
    FileOutputFormat.setOutputPath(job, new Path(outputPath));
   ...
}
```

40

MANCHESTER 1824
The University of Manchester

In the labs …

- You can largely ignore most of the material supplied in the word count case, and concentrate on the map, reduce and associated operations.
- You will, however, be asked to consider both performance and functionality aspects of your design, even if you run at small scale.
- There are lots of subtleties and complications we are not introducing or assessing, but hopefully you can get the big picture!

41

MANCHESTER 1824
The University of Manchester

References

- Tom White, Hadoop: The Definitive Guide, Fourth Edition, O'Reilly, 2015.

42

MANCHESTER 1824
The University of Manchester

Reading for this Week

- Chapters 1 and 2 (you won't need to follow the details of all the examples in Chapter 2) from:
  - Adam Shook, MapReduce design patterns: building effective algorithms and analytics for Hadoop and other systems, O'Reilly, 2012.

43