Big Data Analytics

4. Map Reduce I

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Outline

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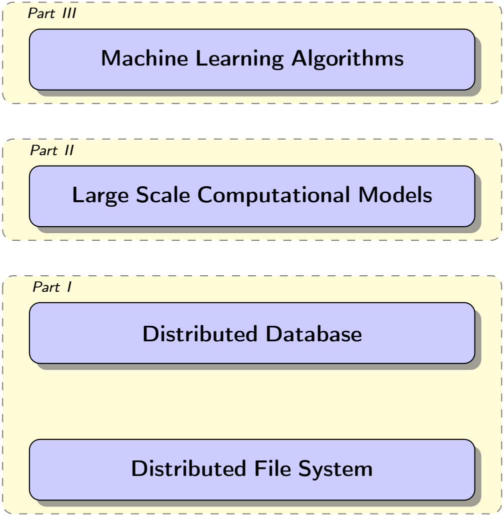
Overview


Part III
Machine Learning Algorithms
Part II
Large Scale Computational Models
Part I
Distributed Database
Distributed File System

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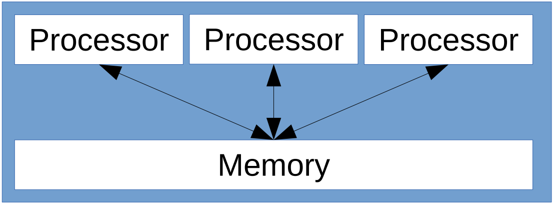
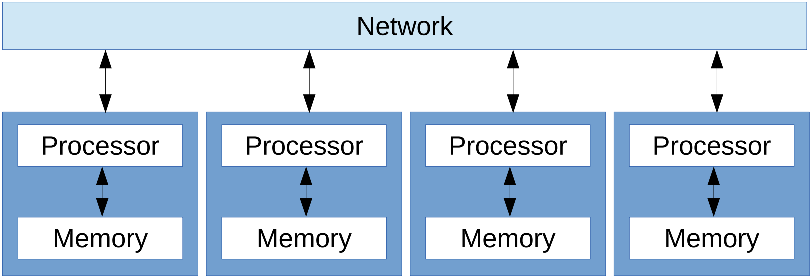
- We have a number of computers at our disposal
- We want our analytics software to take advantage of all this computing power
- When programming we want to focus on understanding our data and not our infrastructure

Shared Memory Infrastructure



Distributed Infrastructure



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Parallel Computing principles

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- Speedup $s(T, p)$ of a task T by using p processors:
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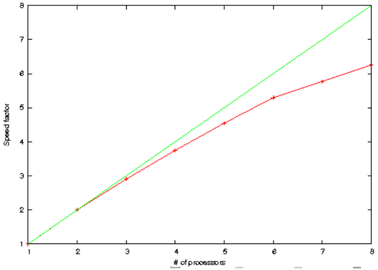
  - **Speedup** is given by:

$$s(T, p) = \frac{t(T, 1)}{t(T, p)}$$



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- Algorithms should increase efficiency with problem size

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For each processor p:

1. lock(d_i)
2. process(d_i)
3. unlock(d_i)

Word Count Example

Given a corpus of text documents

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pooled from a set W of possible words.

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the task is to generate word counts for each word in the corpus

Word Count - Shared Memory

Shared vector for word counts: $c \in \mathbb{R}^{|W|}$

$c \leftarrow \{0\}^{|W|}$

Each processor:

1. access a document $d \in D$
2. for each word w_i in document d:
   2.1 lock(c_i)
   2.2 $c_i \leftarrow c_i + 1$
   2.3 unlock(c_i)

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- Inefficient in a distributed scenario
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- Possible long waiting times for a piece of data because of the lock mechanism

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For each processor p:

1. For each $d \in \pi(D, p)$
   1.1 process(d)
2. Communicate results

Word Count - Message passing

We need to define two types of processes:

1. Slave - counts the words on a subset of documents and informs the master
2. Master - gathers counts from the slaves and sums them up

Word Count - Message passing

Slave:
Local memory:

subset of documents: $\pi(D, p) := \{d_p, \ldots, d_{p+\frac{n}{p}-1}\}$

address of the master: addr_master

local word counts: $c \in \mathbb{R}^{|W|}$

1. $c \leftarrow \{0\}^{|W|}$
2. for each document $d \in \pi(D, p)$
   for each word w_i in document d:
   $c_i \leftarrow c_i + 1$
3. **Send message** send(addr_master, c)

Word Count - Message passing

Master:

Local memory:

1. **Global word counts:** $c^{\text{global}} \in \mathbb{R}^{|W|}$
2. **List of slaves:** S

$c^{\text{global}} \leftarrow \{0\}^{|W|}$

$s \leftarrow \{0\}^{|S|}$

For each received message (p, c^p)

1. $c^{\text{global}} \leftarrow c^{\text{global}} + c^p$
2. $s_p \leftarrow 1$
3. if $||s||_1 = |S|$ return c^{global}

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- Implementations like OpenMPI only provide services to exchange messages

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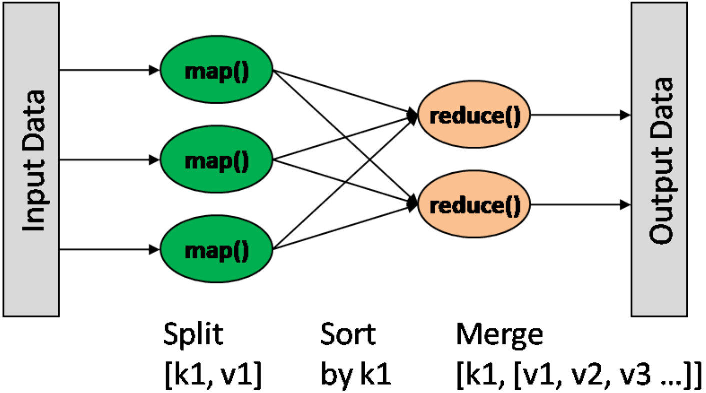
- Builds on the distributed message passing paradigm
- Considers the data is partitioned over the nodes
- Pipelined procedure:
  1. Map phase
  2. Reduce phase
- High level abstraction: programmer only specifies a *map* and a *reduce* routine

Map-Reduce



- No need to worry about how many processors are available
- No need to specify which ones will be mappers and which ones will be reducers

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- Examples:

Key	Value
document	array of words
document	word
user	movies
user	friends
user	tweet

The Paradigm - Formally

Given

- A set of input keys I
- A set of output keys O
- A set of input values X
- A set of intermediate values V
- A set of output values Y

We can define:

$$\text{map} : I \times X \rightarrow \mathcal{P}(O \times V)$$

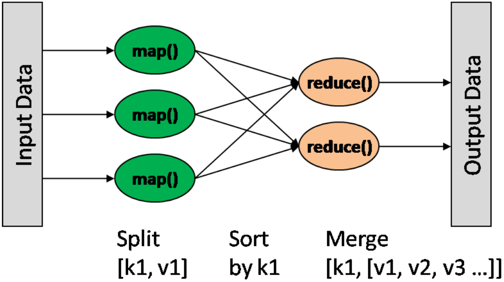
and

$$\text{reduce} : O \times \mathcal{P}(V) \rightarrow O \times Y$$

where $\mathcal{P}$ denotes the powerset

The Paradigm - Informally

1. Each mapper transforms some key-value pairs into a set of pairs of an output key and an intermediate value
2. all intermediate values are grouped according to their output keys
3. each reducer receives some pairs of a key and all its intermediate values
4. each reducer for each key aggregates all its intermediate values to one final value



Word Count Example

Map:

- Input: document-word list pairs
- Output: word-count pairs

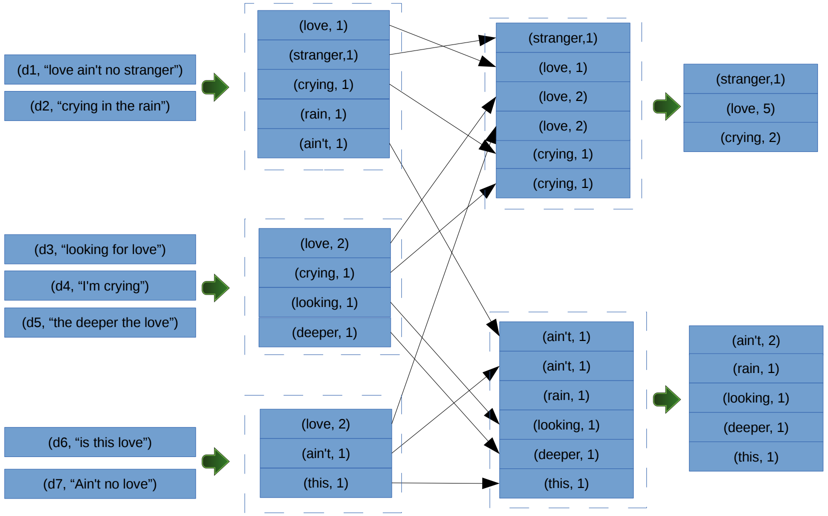
$$(d_k, \text{``}w_1, \ldots, w_m'') \mapsto [(w_i, c_i)]$$

Reduce:

- Input: word-(count list) pairs
- Output: word-count pairs

$$(w_i, [c_i]) \mapsto (w_i, \sum_{c \in [c_i]} c)$$

Word Count Example



Mappers Reducers

Map

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

Reduce

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

Execution snippet

```
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);
    }
}
```

Considerations

- Maps are executed in parallel
- Reduces are executed in parallel
- Bottleneck: Reducers can only execute after all the mappers are finished

Fault tolerance

When the master node detects node failures:

- Re-executes completed and in-progress map()
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When the master node detects particular key-value pairs that cause mappers to crash:

- Problematic pairs are skipped in the execution

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- Time for performing the task with Map-reduce:

$$t_{MR}(T, p) = \frac{wD}{p} + 2K\frac{\sigma D}{p}$$

K - constant for representing the overhead of IO operations (reading and writing data to disk)

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$$
\begin{aligned}
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&= \frac{wD}{wD + 2K\sigma D} \\
&= \frac{wD\frac{1}{wD}}{wD\frac{1}{wD} + 2K\sigma D\frac{1}{wD}} \\
&= \frac{1}{1 + 2K\frac{\sigma}{w}}
\end{aligned}
$$

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- High speedups can be achieved with large number of processors
- If σ is high (too much intermediate data) the efficiency deteriorates
- In many cases σ depends on p