# Processing of massive data sets II

Krzysztof Dembczyński

Intelligent Decision Support Systems Laboratory (IDSS)
Poznań University of Technology, Poland

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# Review of previous lectures

- Mining of massive datasets.
- Evolution of database systems.
- Dimensional modeling.
- Processing of massive data sets I:
  - Physical storage and data access
  - Materialization, denormalization and summarization

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# Outline

# Motivation

- Computational burden $\rightarrow$ divide and conquer

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- Horizontal vs. vertical vs. chunk partitioning.

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- From the perspective of the application, however, a partitioned table is identical to a non-partitioned table.

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  - Composite Partitioning: partitions data using the range method, and within each partition, subpartitions it using the hash or list method.

# Data partitioning

- **Example**:

```
CREATE TABLE sales_list (
  salesman_id NUMBER(5),
  salesman_name VARCHAR2(30),
  sales_state VARCHAR2(20),
  sales_amount NUMBER(10),
  sales_date DATE)
  PARTITION BY LIST(sales_state)
  (
    PARTITION sales_west VALUES('California', 'Hawaii'),
    PARTITION sales_east VALUES ('New York', 'Virginia'),
    PARTITION sales_central VALUES('Texas', 'Illinois')
    PARTITION sales_other VALUES(DEFAULT)
  )
);
```

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- "Divide and conquer" approach to data management.

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  - The join operation can be performed on smaller tables.

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  - If data is partitioned on date, simply delete or compress the oldest partitions.

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- Similarly one can generalize hash-join to the so-called partitioned hash-join.

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  - Move-code-to-data

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- Simple – allow users to quickly write efficient parallel code.

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- How to implement these procedures for efficient execution in a distributed system?
- How much can we gain by such implementation?
- Let us focus on the word count problem ...

# Word count

- Count the number of times each word occurs in a set of documents:

*Do as I say, not as I do.*

| Word | Count |
|---|---|
| as | 2 |
| do | 2 |
| i | 2 |
| not | 1 |
| say | 1 |

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```
define wordCount as Multiset;

for each document in documentSet {
    T = tokenize(document);

    for each token in T {
        wordCount[token]++;
    }

}

display(wordCount);
```

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sendToSecondPhase(wordCount);
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  - Second step:

```
define totalWordCount as Multiset;

for each wordCount received from firstPhase {
   multisetAdd (totalWordCount, wordCount);
}
```

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  - Ensure fault tolerance.

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  - Map: the map function is written to convert input elements to key-value pairs.
  - Reduce: the reduce function is written to take pairs consisting of a key and its list of associated values and combine those values in some way.

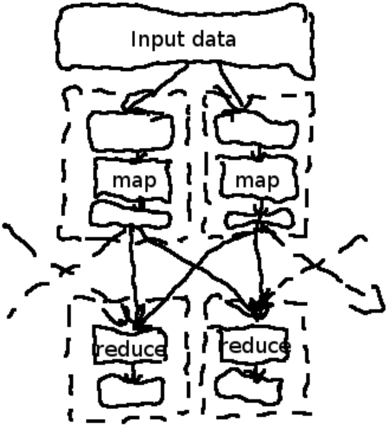
# MapReduce

- The complete data flow:

| | Input | Output |
|---|---|---|
| map | `(<k1, v1>)` | `list(<k2, v2>)` |
| reduce | `(<k2, list(<v2>)` | `list(<k3, v3>)` |

# MapReduce

Figure: The complete data flow



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  - The list of key-value pairs is broken up and each individual key-value pair, `<k1,v1>`, is processed by calling the map function of the mapper (the key `k1` is often ignored by the mapper).

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  - The framework asks the reducer to process each one of these aggregated key-value pairs individually.

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- **Combiner** – perform local aggregation (the reduce step) on the map node.
- **Partitioner** – divide the key space of the map output and assign the key-value pairs to reducers.

## WordCount in MapReduce

- Map:
  - For a pair `<k1,document>` produce a sequence of pairs `<token,1>`, where `token` is a token/word found in the document.

```
map(String filename, String document) {
    List<String> T = tokenize(document);

    for each token in T {
      emit ((String)token, (Integer) 1);
    }

}
```

# WordCount in MapReduce

- Reduce
  - For a pair `<word, list(1, 1, ..., 1)>` sum up all ones appearing in the list and return `<word, sum>`, where `sum` is the sum of ones.

```
reduce(String token, List<Integer> values) {
    Integer sum = 0;

    for each value in values {
        sum = sum + value;
    }

    emit ((String)token, (Integer) sum);
}
```

## Matrix-vector Multiplication

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- The matrix-vector multiplication is defined as:

$$\boldsymbol{A}\boldsymbol{x} = \boldsymbol{v},$$

where $\boldsymbol{v} = (v_1, \ldots, v_n)$ and

$$v_i = \sum_{j=1}^{m} a_{ij} x_j.$$

## Matrix-vector multiplication

- Let us first assume that $m$ is large, but not so large that vector $\boldsymbol{x}$ cannot fit in main memory, and be part of the input to every Map task.
- The matrix $\boldsymbol{A}$ is stored with explicit coordinates, as a triple $(i, j, a_{ij})$.
- We also assume the position of element $x_j$ in the vector $\boldsymbol{x}$ will be stored in the analogous way.

# Matrix-vector multiplication

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# Matrix-vector multiplication

- **Map**: each map task will take the entire vector $\boldsymbol{x}$ and a chunk of the matrix $\boldsymbol{A}$. From each matrix element $a_{ij}$ it produces the key-value pair $(i, a_{ij}x_j)$. Thus, all terms of the sum that make up the component $v_i$ of the matrix-vector product will get the same key.

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# Matrix-vector multiplication

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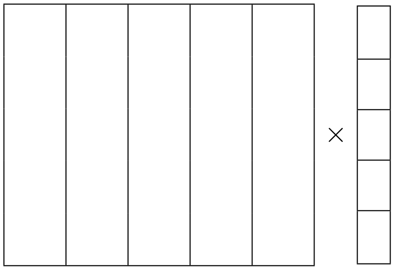
- **Reduce**: a reduce task has simply to sum all the values associated with a given key $i$. The result will be a pair $(i, v_i)$ where:

$$v_i = \sum_{j=1}^{m} a_{ij}x_j.$$

# Matrix-Vector Multiplication with Large Vector $v$

## Matrix-Vector Multiplication with Large Vector $v$

- Divide the matrix into vertical stripes of equal width and divide the vector into an equal number of horizontal stripes, of the same height.



- The $i$th stripe of the matrix multiplies only components from the $i$th stripe of the vector.
- Thus, we can divide the matrix into one file for each stripe, and do the same for the vector.

## Matrix-Vector Multiplication with Large Vector $v$

- Each Map task is assigned a chunk from one the stripes of the matrix and gets the entire corresponding stripe of the vector.
- The Map and Reduce tasks can then act exactly as in the case where Map tasks get the entire vector.

# Outline

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  - and Spark Streaming.
- For more check `https://spark.apache.org/`

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- Hadoop works in a master/slave architecture for both distributed storage and distributed computation.
- Hadoop Distributed File System (HDFS) is responsible for distributed storage.

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- To play with Spark there is no need to install HDFS ...
- But, you can try to play around with HDFS.

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- View the files in the distributed filesystem:

```
hdfs dfs -ls /user/myname/
hdfs dfs -cat /user/myname/data.txt
```

# WordCount in Hadoop

```java
import java.io.IOException;
import java.util.StringTokenizer;

import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.Mapper;
import org.apache.hadoop.mapreduce.Reducer;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;

public class WordCount {

 public static class TokenizerMapper
      extends Mapper<Object, Text, Text, IntWritable>{

    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();

    public void map(Object key, Text value, Context context
                    ) throws IOException, InterruptedException {
      StringTokenizer itr = new StringTokenizer(value.toString());
      while (itr.hasMoreTokens()) {
        word.set(itr.nextToken());
        context.write(word, one);
      }
    }
  }
  (...)
```

# WordCount in Hadoop

```java
(...)
public static class IntSumReducer
     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;
     for (IntWritable val : values) {
       sum += val.get();
     }
     result.set(sum);
     context.write(key, result);
   }
 }

 public static void main(String[] args) throws Exception {
   Configuration conf = new Configuration();
   Job job = Job.getInstance(conf, "word count");
   job.setJarByClass(WordCount.class);
   job.setMapperClass(TokenizerMapper.class);
   job.setCombinerClass(IntSumReducer.class);
   job.setReducerClass(IntSumReducer.class);
   job.setOutputKeyClass(Text.class);
   job.setOutputValueClass(IntWritable.class);
   FileInputFormat.addInputPath(job, new Path(args[0]));
   FileOutputFormat.setOutputPath(job, new Path(args[1]));
   System.exit(job.waitForCompletion(true) ? 0 : 1);
 }
}
```

# WordCount in Spark

- The same code is much simpler in Spark
- To run the Spark shell type: `./bin/spark-shell`
- The code

```
val textFile = sc.textFile("~/data/all-bible.txt")
val counts = (textFile.flatMap(line => line.split(" "))
                 .map(word => (word, 1))
                 .reduceByKey(_ + _))
counts.saveAsTextFile("~/data/all-bible-counts.txt")
```

Alternatively:

```
val textFile = spark.read.textFile("~/data/all-bible.txt")
val wordCounts = textFile.flatMap(line => line.split(" ")).groupByKey(identity).
     count()
```

# Matrix-vector multiplication in Spark

- The Spark code is quite simple:

```
val x = sc.textFile("~/data/x.txt").map(line => {val t = line.split(","); (t(0).
    trim.toInt, t(1).trim.toDouble)})
val vectorX = x.map{case (i,v) => v}.collect
val broadcastedX = sc.broadcast(vectorX)
val matrix = sc.textFile("~/data/M.txt").map(line => {val t = line.split(","); (t
    (0).trim.toInt, t(1).trim.toInt, t(2).trim.toDouble)})
val v = matrix.map { case (i,j,a) => (i, a * broadcastedX.value(j-1))}.reduceByKey(
    _ + _)
v.toDF.orderBy("_1").show
```

# Outline

# Summary

- Computational burden $\rightarrow$ data partitioning, distributed systems.
- Data partitioning
- New data-intensive challenges like search engines.
- MapReduce: The overall idea and simple algorithms.
- Spark: MapReduce in practice.

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