MapReduce I

Big Data Management

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

DTIM www.essi.upc.edu/dtim

Knowledge objectives

1. Enumerate several use cases of MapReduce
2. Explain 6 benefits of using MapReduce
3. Describe what the MapReduce is in the context of a DDBMS
4. Recognize the signature of Map and Reduce functions
5. Justify to which extent MapReduce is generic

Understanding objectives

1. Simulate the execution of a simple MapReduce algorithm from the user (agnostic of implementation details) perspective

Application objectives

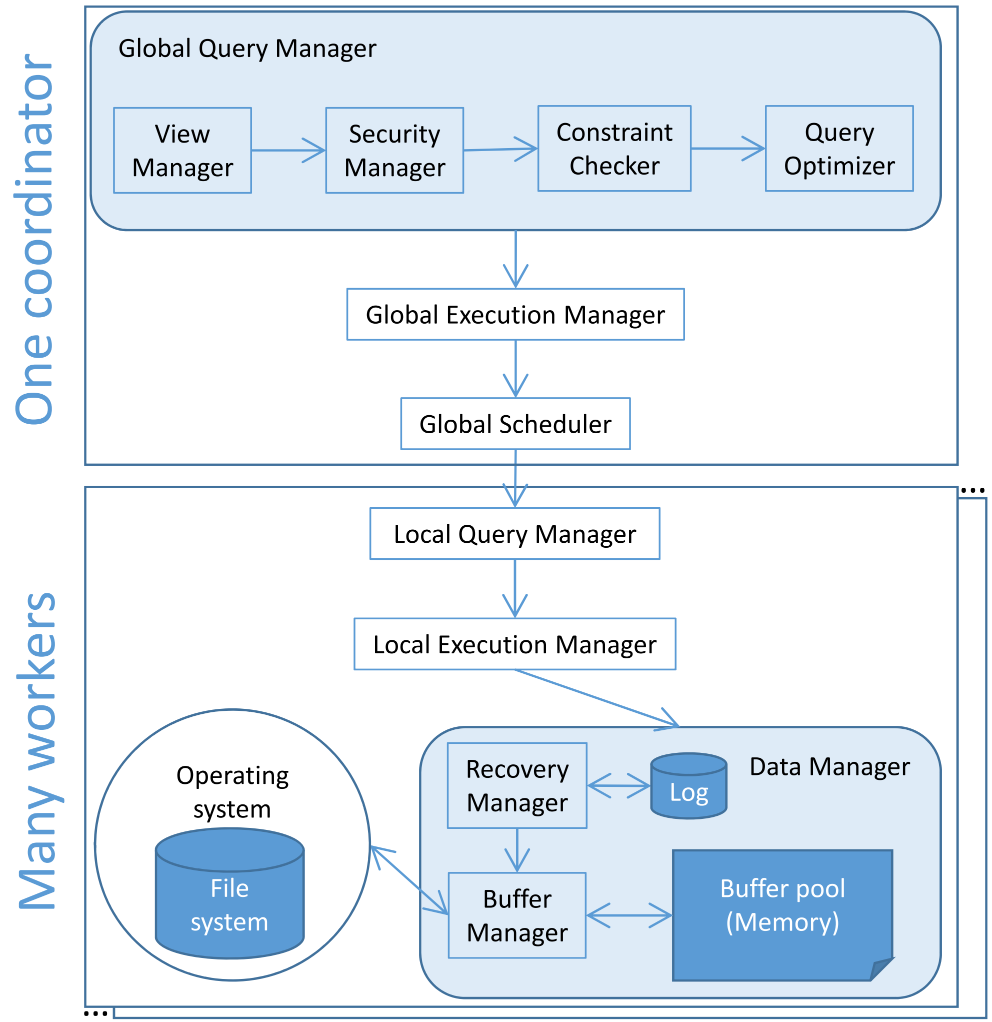
1. Identify the usefulness of MapReduce in a given use case
2. Define the key in the output of the map for a simple problem
3. Provide the pseudo-code of map and reduce functions for a simple problem

Distributed processing framework

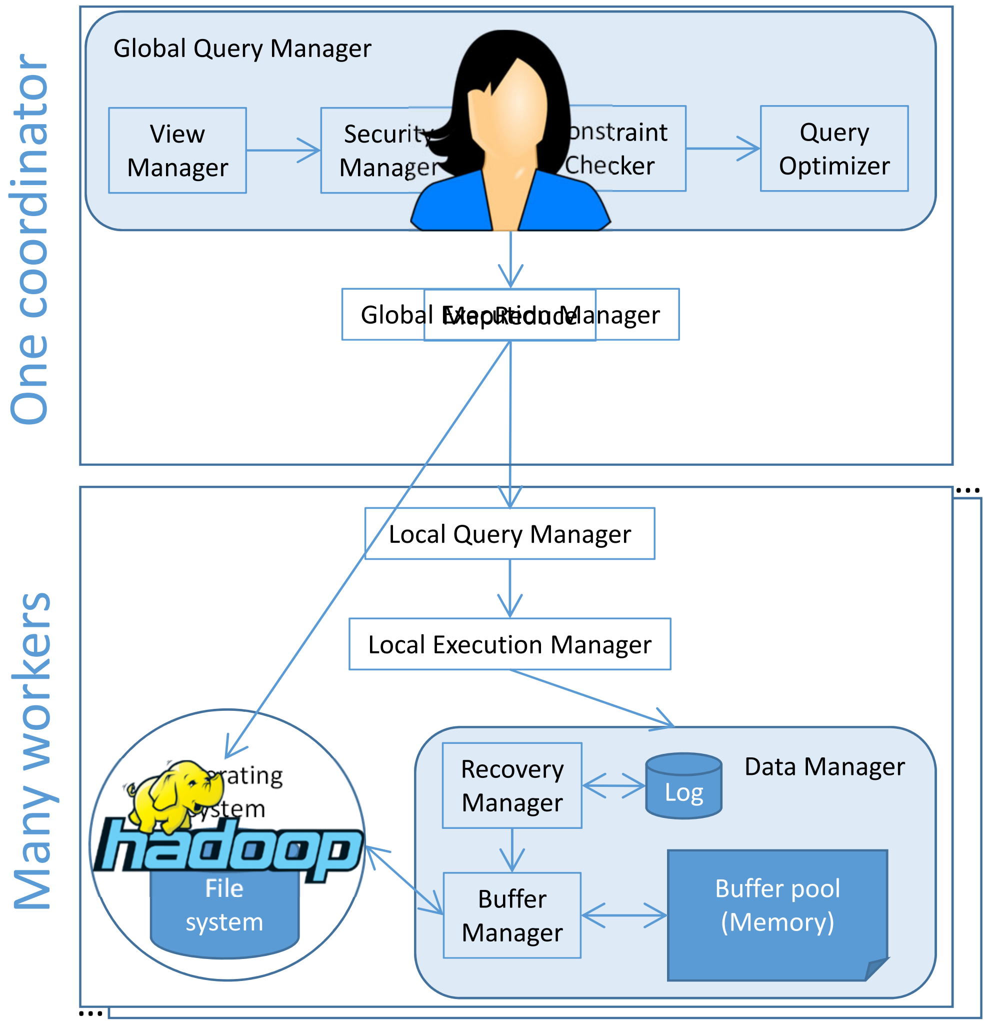
Origins

- Based on Google development
  - Conceived to compute the Page Rank
- Data processing framework
  - Facilitate scalability
  - Hidden parallelism
  - Transparent distribution
    - Exploit data locality
    - Balance workload
  - Resilience to failure
    - Fine grained fault tolerance
- Useful in any domain

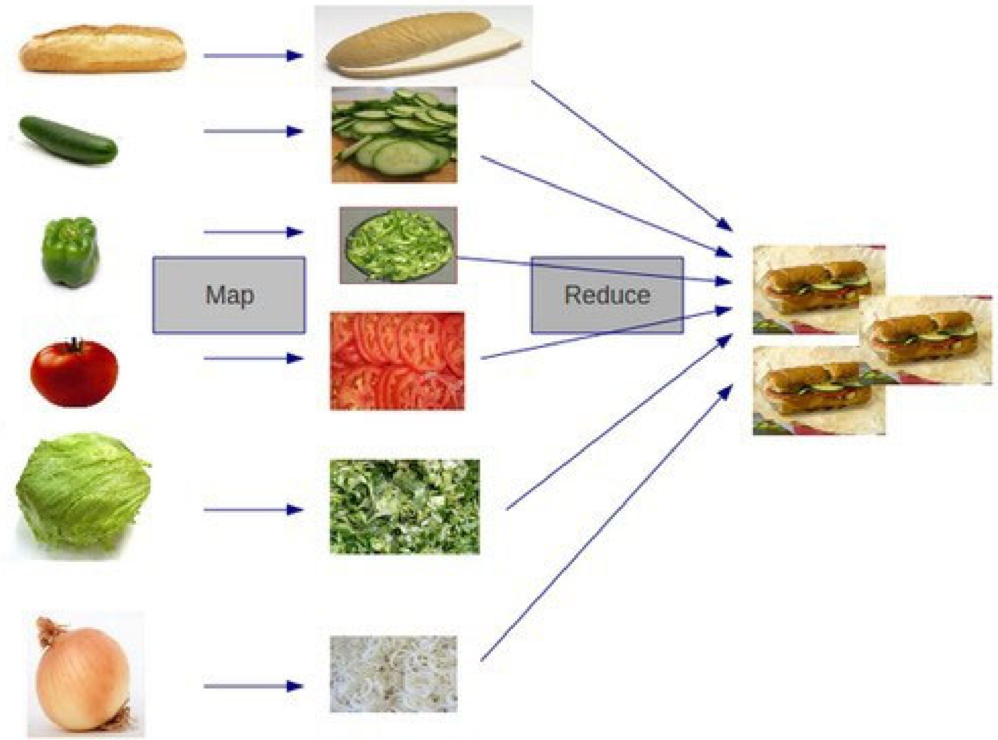
MapReduce as a DDBMS component



MapReduce as a DDBMS component



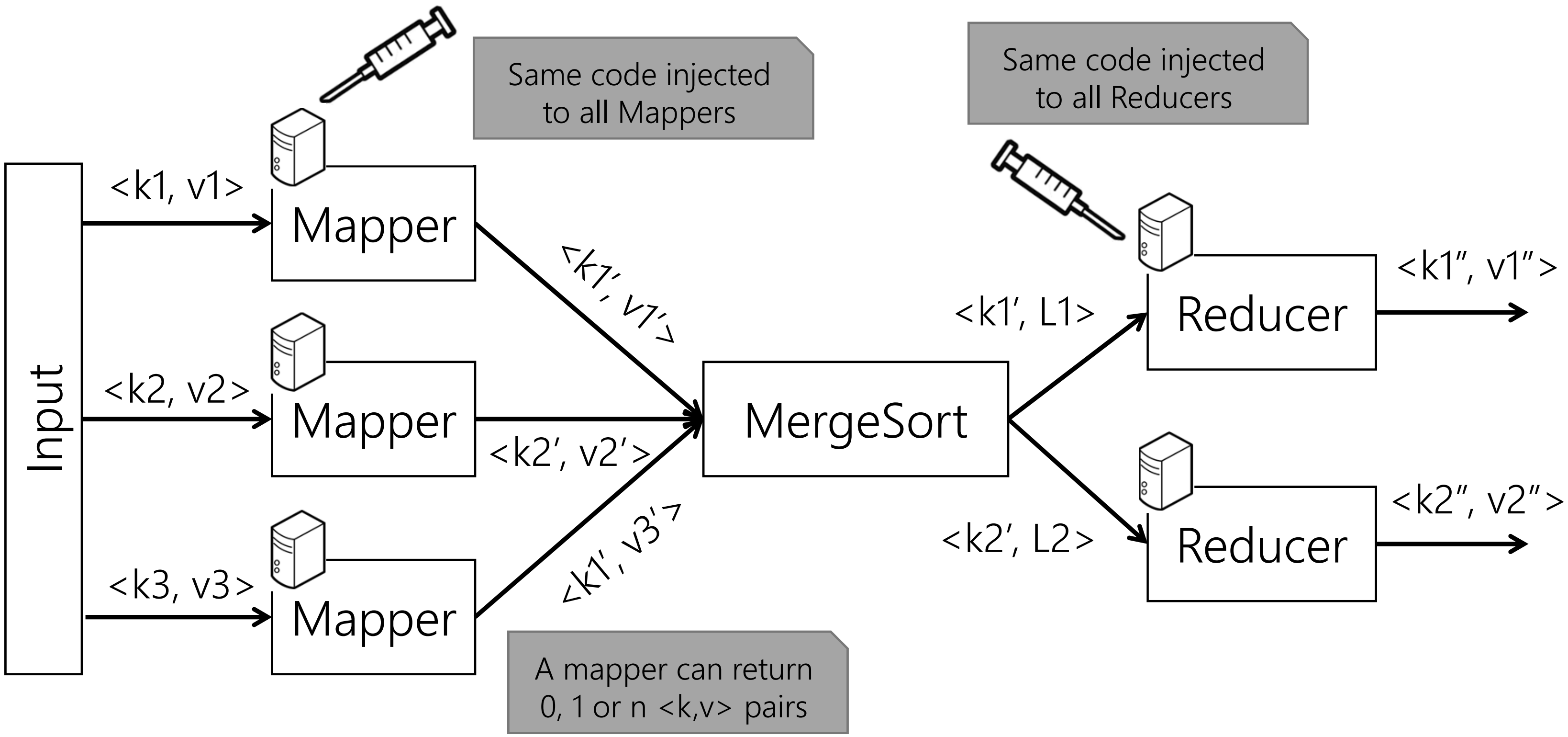
Chain production



By Mohamed Nabeel

Components and use

The MapReduce framework



The MapReduce framework in detail

1. Input: read input from a DFS
2. Map: for each input <key_{in}, $value_{in}$>
   - generate zero-to-many <key_{map}, $value_{map}$>
3. Partition: assign sets of <key_{map}, $value_{map}$> to reducer machines
4. Shuffle: data are shipped to reducer machines using a DFS
5. Sort&Merge: reducers sort their input data by key
6. Reduce: for each key_{map}
   - the set $value_{map}$ is processed to produce zero-to-many <key_{red}, $value_{red}$>
7. Output: writes the result of reducers to the DFS

Formal definition

- Single input
  - Data are represented as <key, value> pairs
    - Value can be anything (structured or not)
- Functional programming
  - Map phase, for each input <key, value> a function *f* is applied that returns a multiset of new <key, value> pairs:

$$f(\langle k, v\rangle) \mapsto \{\langle k_1, v_1\rangle, \ldots, \langle k_n, v_n\rangle\}$$

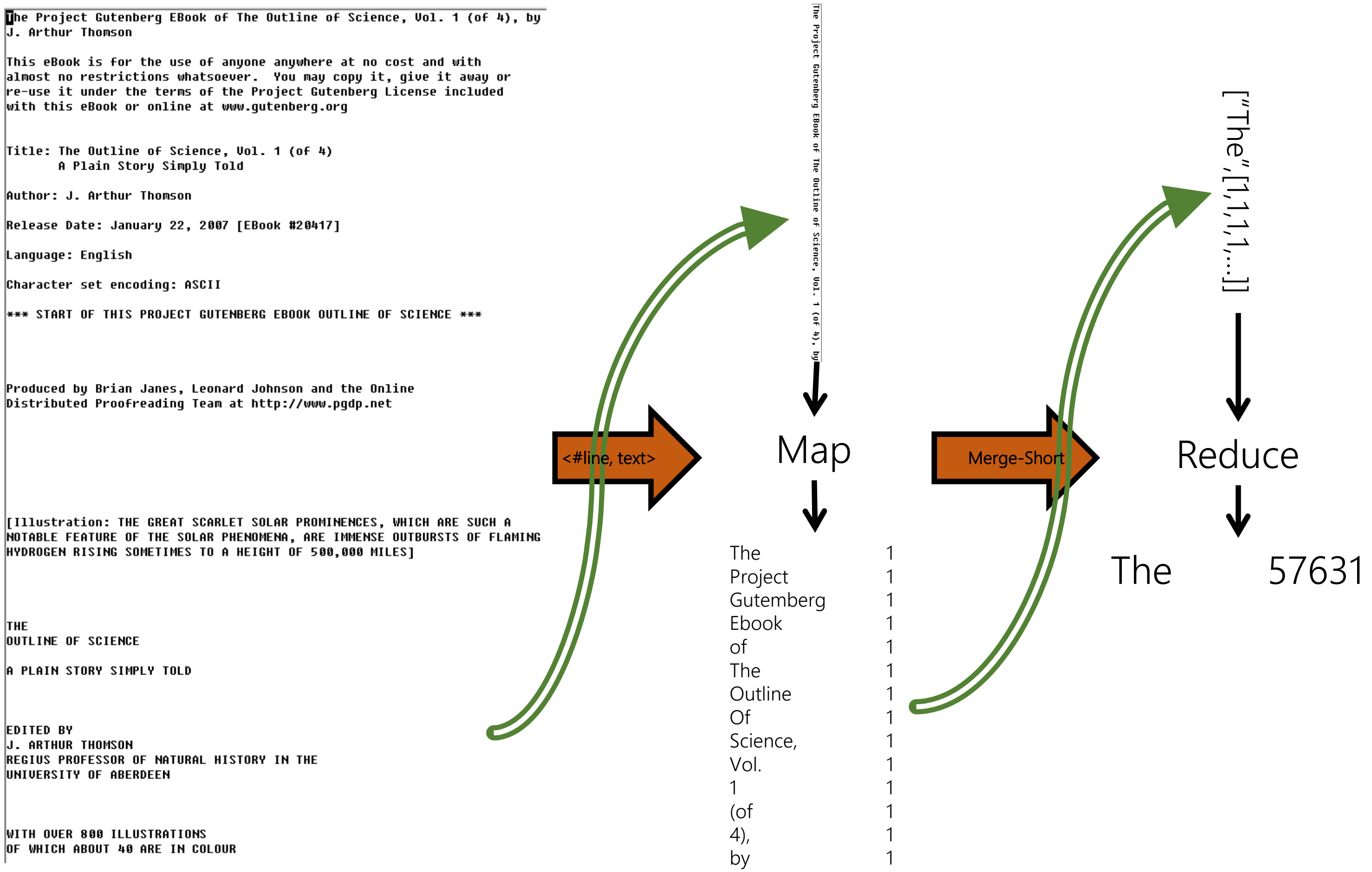
  - Reduce phase, all pairs with the same key are grouped and a function *g* is applied, which returns also a multiset of new <key, value> pairs:

$$g(\langle k, \{v_1, \ldots, v_n\}\rangle) \mapsto \{\langle k_1, v_1\rangle, \ldots, \langle k_m, v_m\rangle\}$$

MapReduce examples

Word count

Word count example



The Project Gutenberg EBook of The Outline of Science, Vol. 1 (of 4), by
J. Arthur Thomson

This eBook is for the use of anyone anywhere at no cost and with
almost no restrictions whatsoever. You may copy it, give it away or
re-use it under the terms of the Project Gutenberg License included
with this eBook or online at www.gutenberg.org

Title: The Outline of Science, Vol. 1 (of 4)
       A Plain Story Simply Told

Author: J. Arthur Thomson

Release Date: January 22, 2007 [EBook #20417]

Language: English

Character set encoding: ASCII

*** START OF THIS PROJECT GUTENBERG EBOOK OUTLINE OF SCIENCE ***

Produced by Brian Janes, Leonard Johnson and the Online
Distributed Proofreading Team at http://www.pgdp.net

[Illustration: THE GREAT SCARLET SOLAR PROMINENCES, WHICH ARE SUCH A
NOTABLE FEATURE OF THE SOLAR PHENOMENA, ARE IMMENSE OUTBURSTS OF FLAMING
HYDROGEN RISING SOMETIMES TO A HEIGHT OF 500,000 MILES]

THE
OUTLINE OF SCIENCE

A PLAIN STORY SIMPLY TOLD

EDITED BY
J. ARTHUR THOMSON
REGIUS PROFESSOR OF NATURAL HISTORY IN THE
UNIVERSITY OF ABERDEEN

WITH OVER 800 ILLUSTRATIONS
OF WHICH ABOUT 40 ARE IN COLOUR

WordCount Code Example

```
public void map(LongWritable key, Text value) {
    String line = value.toString();
    StringTokenizer tokenizer = new StringTokenizer(line);
    while (tokenizer.hasMoreTokens()) {
        write(new Text(tokenizer.nextToken()), new IntWritable(1));
    }
}

public void reduce(Text key, Iterable<IntWritable> values) {
    int sum = 0;
    for (IntWritable val : values) {
        sum += val.get();
    }
    write(key, new IntWritable(sum));
}
```

WordCount Code Example

```
public void map( Key , Value ) {
Blackbox
      write( Key , Value );
   }
}

public void reduce( Key , Values ) {
Blackbox
   write( Key , Value );
}
```

MapReduce examples

Common friends

Friends in common example

- In a social network (e.g., Facebook), we aim to compute the friends in common for every pair of users
  - This is a value that does not frequently change, so it can be precomputed
- Friends are stored as

Person -> [List of friends]

  - A → B C D
  - B → A C D E
  - C → A B D E
  - D → A B C E
  - E → B C D

Friends in common – Map task

- For every friend in the list, the mapper will generate a <k,v>
  - Key: the input key concatenated with one friend <u>in alphabetical order</u>
  - Value: the whole list of friends
- Keys will be sorted, a pair of friends go to the same reducer

A → B C D
(A B) → B C D
(A C) → B C D
(A D) → B C D

B → A C D E
(A B) → A C D E
(B C) → A C D E
(B D) → A C D E
(B E) → A C D E

C → A B D E
(A C) → A B D E
(B C) → A B D E
(C D) → A B D E
(C E) → A B D E

…

Friends in common – Reduce task

- Reducers receive two lists of friends per pair of people

(A B) → (B C D) (A C D E)
(A C) → (B C D) (A B D E)
(A D) → (B C D) (A B C E)
…

- The reduce function intersects the lists of values and generates the same key

(A B) → (C D)
(A C) → (B D)
(A D) → (B C)
…

- … when D visits A's profile we can lookup (A D) to see their common friends

Relational algebra in MapReduce

MapReduce Generality

- Supported in many store systems
  - HBase, MongoDB, CouchDB, etc.
- Programming paradigm is computationally complete
  - Any data process can be adapted to it
    - Some tasks better adapt to it than others
    - Not necessarily efficient
      - Optimization is very limited because of lack of expressivity
- Signature is closed
  - Iterations can be chained
    - Fault tolerance is not guaranteed in between
    - Resources are released to be just requested again
- Criticized for being too low-level
  - APIs for Ruby, Python, Java, C++, etc.
  - Attempts to build declarative languages on top
    - SQL-like
      - HiveQL
      - Cassandra Query Language (CQL)

Relational operations: Projection

$$\pi_{a_{i_1},\dots,a_{i_n}}(T) \Rrightarrow \begin{cases} \texttt{map}(\text{key } k, \text{value } v) \mapsto [(\texttt{prj}_{a_{i_1},\dots,a_{i_n}}(k \oplus v), 1)] \\ \texttt{reduce}(\text{key } ik, \text{vset } ivs) \mapsto [(ik)] \end{cases}$$

Relational operations: Cross Product

$$
T \times S \Rightarrow \begin{cases}
\texttt{map}(\text{key } k, \text{value } v) \mapsto \\
\begin{cases} [(\mathrm{h}_T(k) \bmod D, k \oplus v)] & \text{if input}(k \oplus v) = T, \\ [(0, k \oplus v), .., (D-1, k \oplus v)] & \text{if input}(k \oplus v) = S. \end{cases} \\
\texttt{reduce}(\text{key } ik, \text{vset } ivs) \mapsto \\
\Big[\texttt{crossproduct}(T_{ik}, S) \mid \\
\quad T_{ik} = \{iv \mid iv \in ivs \wedge \text{input}(iv) = T\}, \\
\quad S = \{iv \mid iv \in ivs \wedge \text{input}(iv) = S\}\Big]
\end{cases}
$$

Closing

Summary

- MapReduce usefulness and benefits
- MapReduce programming model
  - Expressivity
- Relational algebra in MapReduce

References

- J. Dean et al. *MapReduce: Simplified Data Processing on Large Clusters*. OSDI'04
- A. Pavlo et al. *A Comparison of Approaches to Large-Scale Data Analysis*. SIGMOD, 2009
- J. Dittrich et al. *Hadoop++: Making a Yellow Elephant Run Like a Cheetah (Without It Even Noticing)*. Proc. VLDB Endow. 3(1-2), 2010
- M. Stonebraker et al. *MapReduce and parallel DBMSs: friends or foes?* Communication of ACM 53(1), 2010
- S. Abiteboul et al. *Web data management*. Cambridge University Press, 2011
- A. Rajaraman et al. *Mining massive data sets*. Cambridge University Press, 2012
- P. Sadagale and M. Fowler. *NoSQL distilled*. Addison-Wesley, 2013