MapReduce I

Big Data Management

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

1. Facilitate scalability 2. Hide parallelism
3. Exploit Data Locality 4. Balance workload
5. Resilient to failure 6. Fine grained fault tolerance

1. Query optimizer and execution manager replaced by map reduce
2. storage complexity replaced by hadoop

1. is generic and supported in many storage system like MongoDB, HBase, CouchDB
2. Programming paradigm is computationally complete
3. Signature is complete
4. Criticized for being too low level

Understanding objectives

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

Application objectives

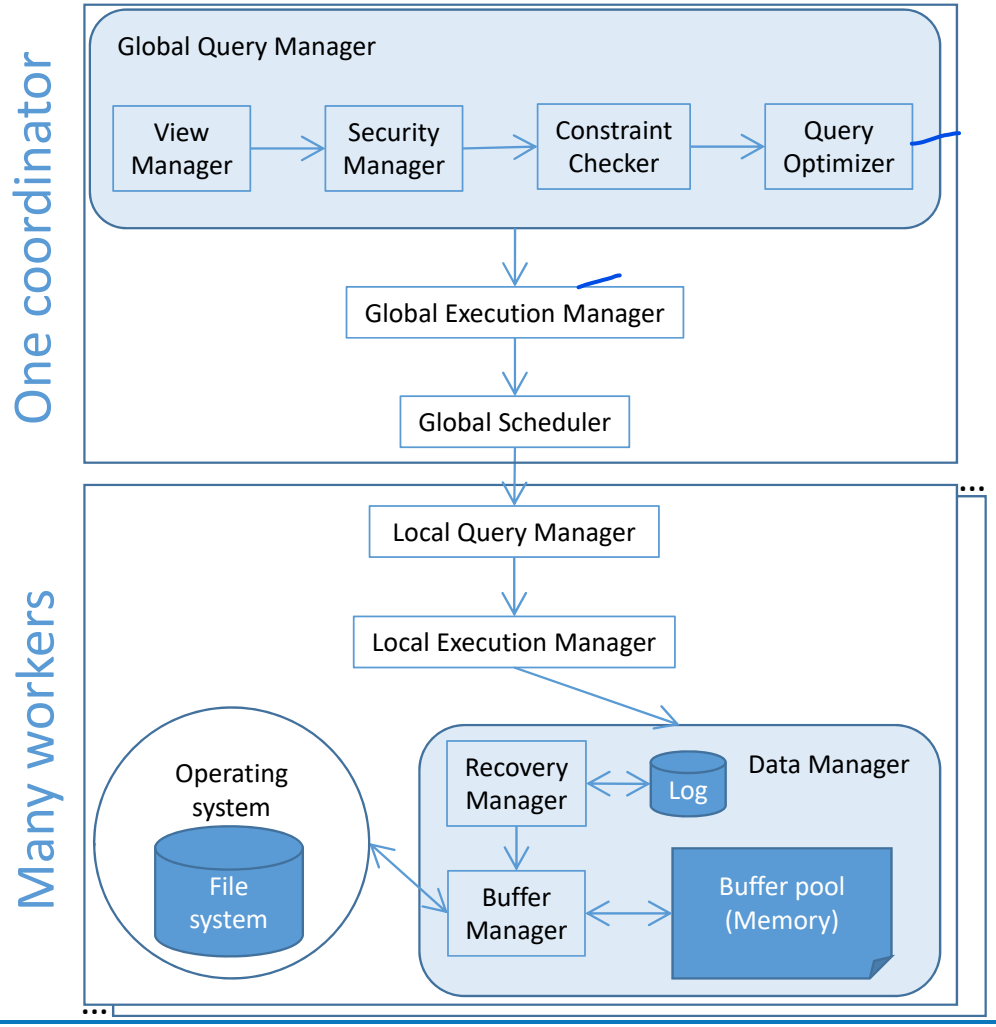
1. Identify the usefulness of MapReduce in a given use case
2. Define the key in the output of the map for a simple problem
3. Provide the pseudo-code of map and reduce functions for a simple problem

Distributed processing framework

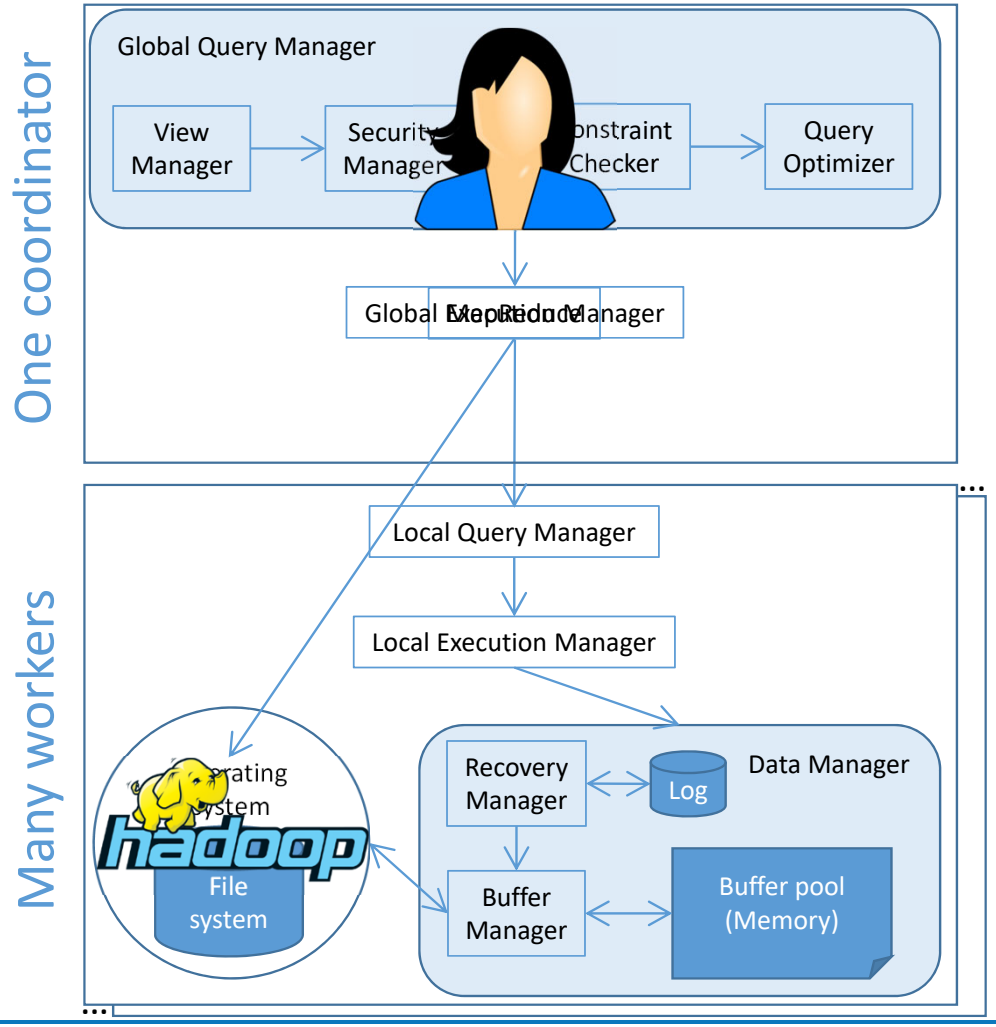
Origins

- 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

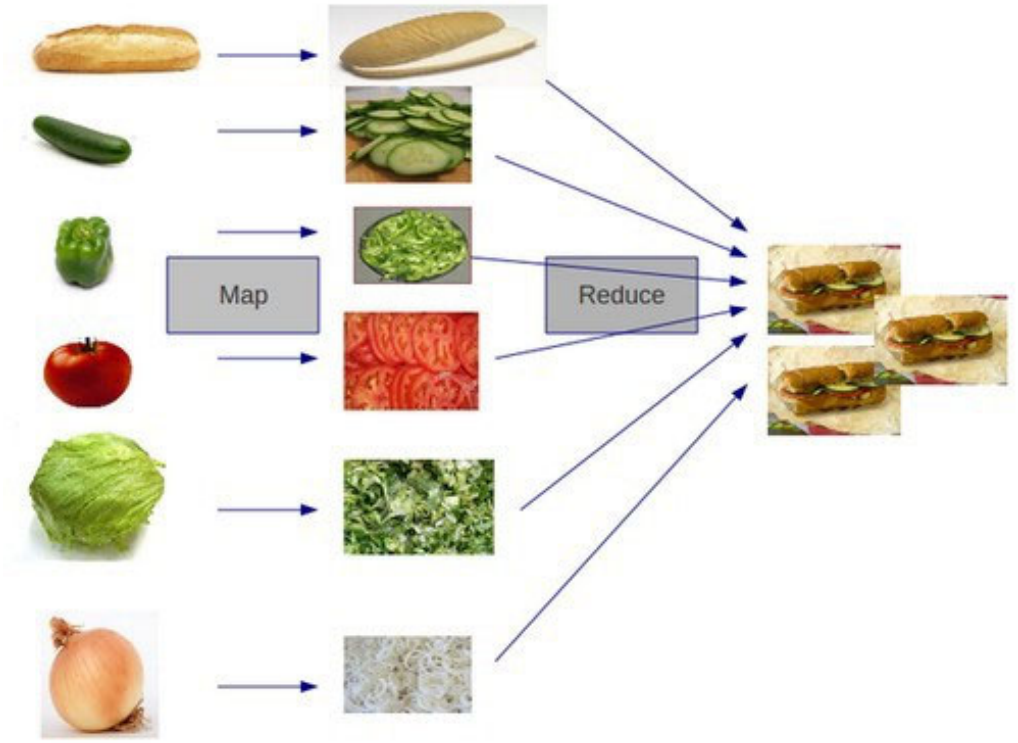
MapReduce as a DDBMS component



MapReduce as a DDBMS component



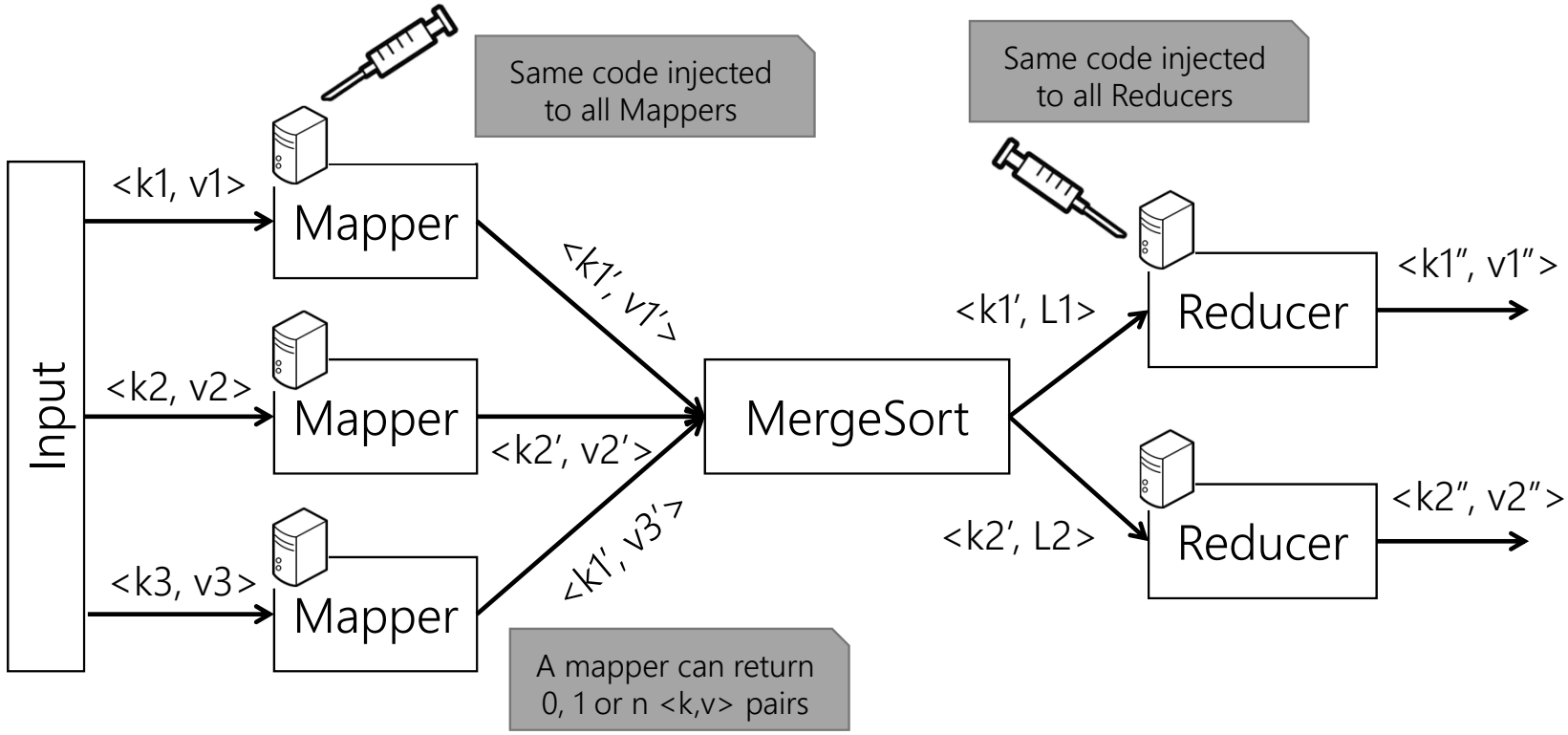
Chain production



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

data not shipped here

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

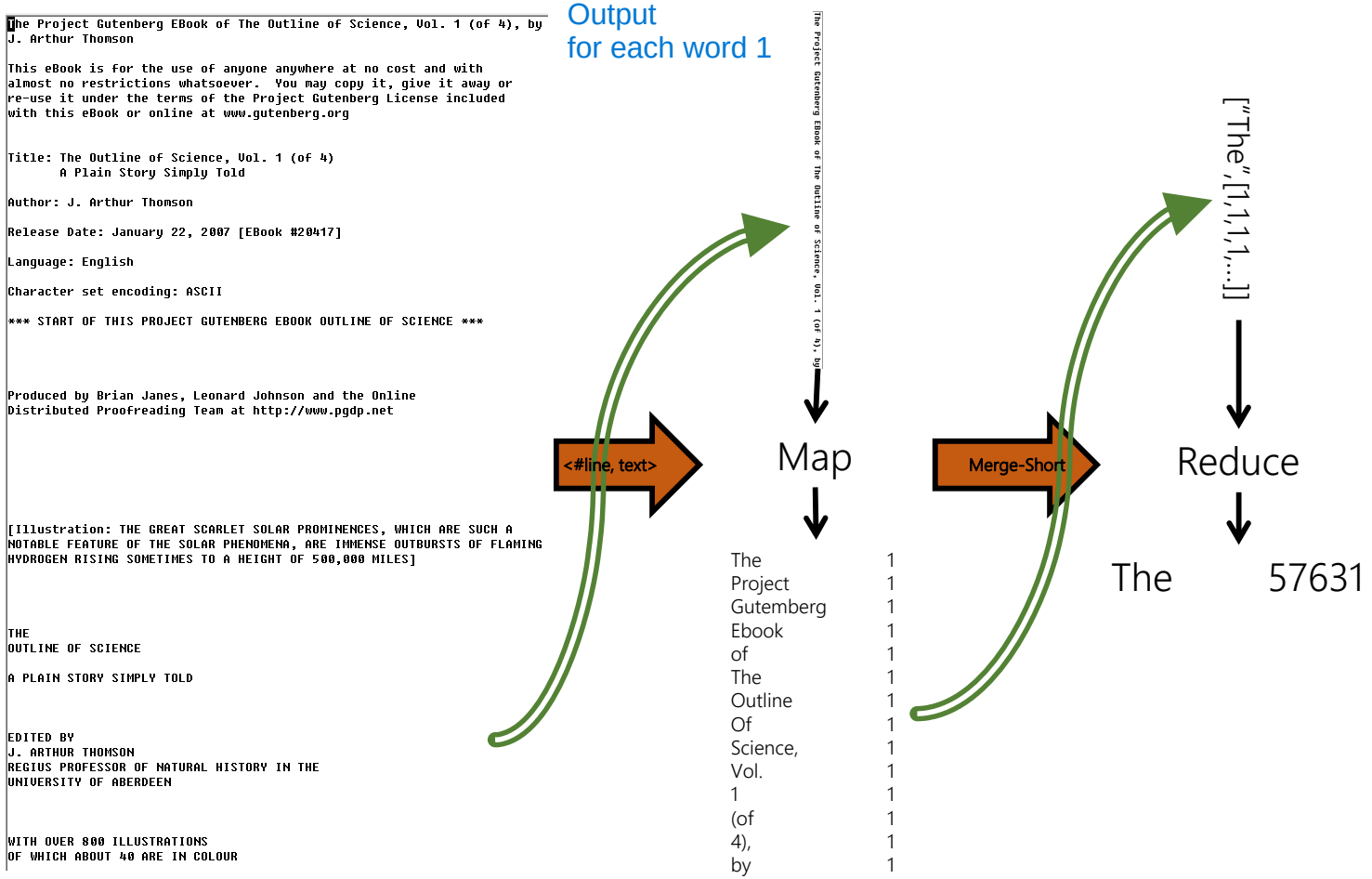
Word count

Word count example

Map
Key - file path
Value - content

Output
for each word 1

Reduce
by word aggregate

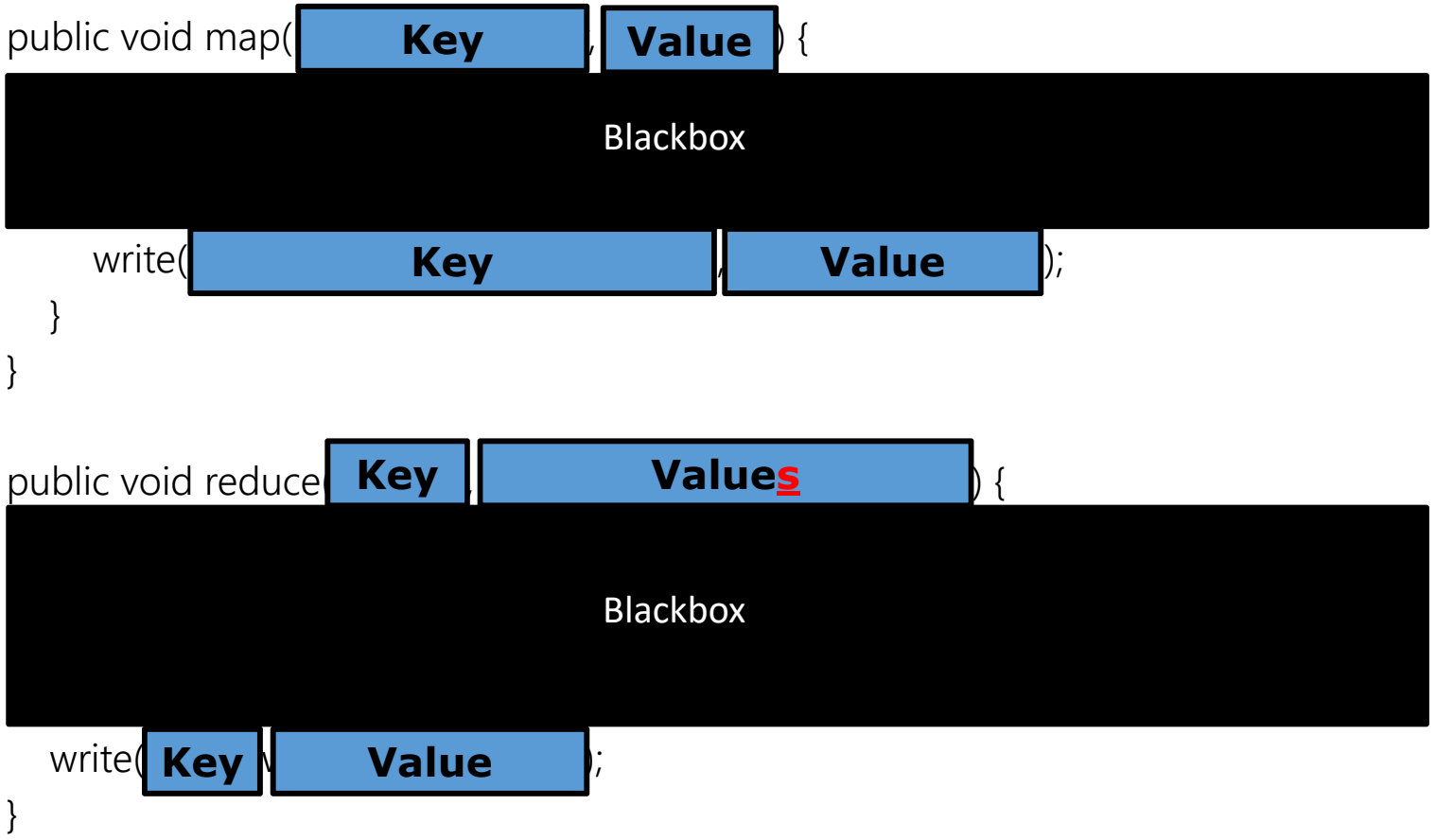


WordCount Code Example

```
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



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 in alphabetical order
  - 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)

It is not declared language but is a procedural library.

Relational operations: Projection

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

Relational operations: Cross Product

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

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