MapReduce

MIH-CPP

Learning Objectives

Understand the concepts behind MapReduce program model

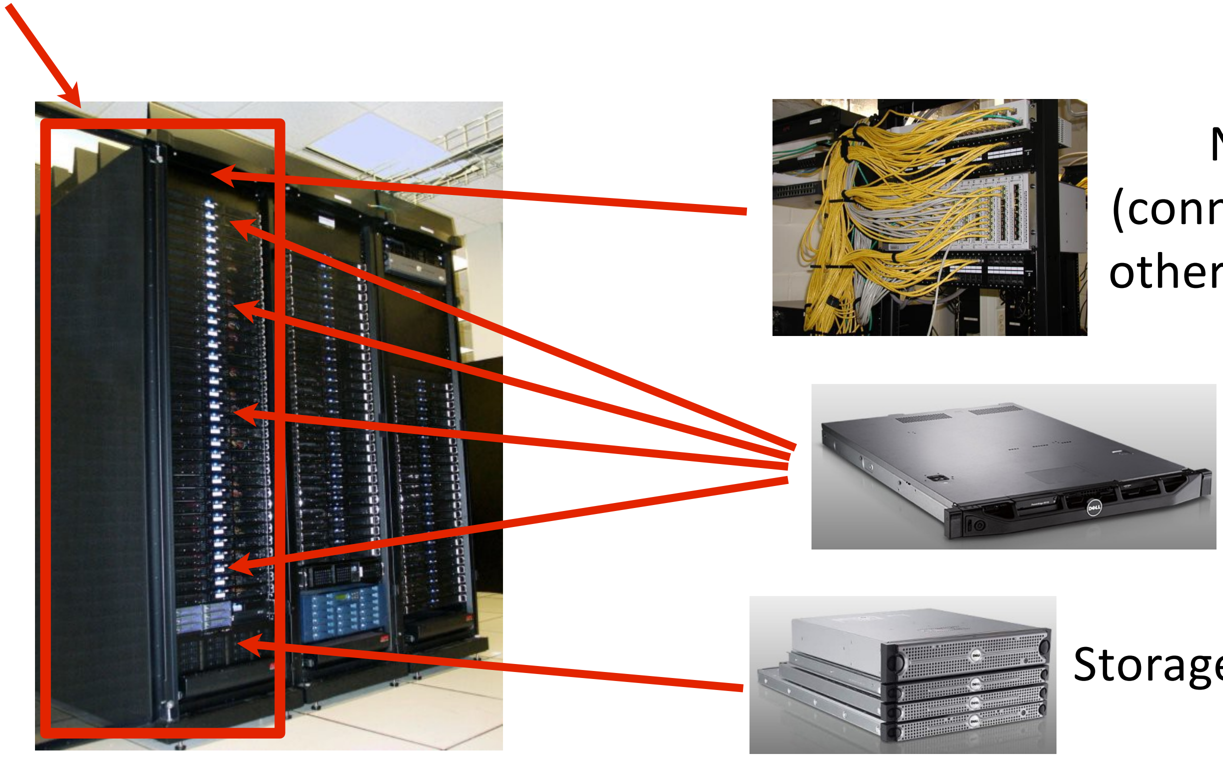
Explore the implementation of MapReduce architecture

Analyze a simple problem in MapReduce program model

Analyze a practical problem in MapReduce program model

Recall this diagram?

Rack



Network switches
(connects nodes with each other and with other racks)

Many nodes/blades
(often identical)

Storage device(s)

Processing and Analyzing Big Data

- A toy problem: The word count
  - We have 10 billion documents
  - Average document's size is 20KB => 10 billion docs = 200TB

- Cute solution:

```
for each document d
{ for each word w in d {word_count[w]++;}
```

Time elapsed..

Background

- Traditional programming is serial
- Parallel programming
  - Break processing into parts that can be executed concurrently on multiple processors
- Challenge
  - Identify tasks that can run concurrently
    - and/or groups of data that can be processed concurrently
  - Not all problems can be parallelized

MapReduce in Big Data Context

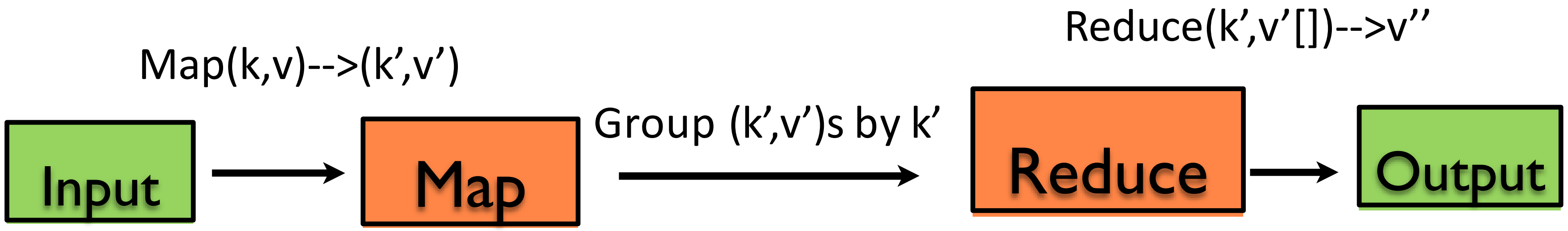
- Created by Google in 2004
  - Jeffrey Dean and Sanjay Ghemawat
- Inspired by LISP
  - `Map(function, set of values)`
    - Applies function to each value in the set
    - `(map ‘length ‘(() (a) (a b) (a b c)))` ⇒ `(0 1 2 3)`
  - `Reduce(function, set of values)`
    - Combines all the values using a binary function (e.g., +)
    - `(reduce #'+ ‘(1 2 3 4 5))` ⇒ `15`

MapReduce in Big Data Context

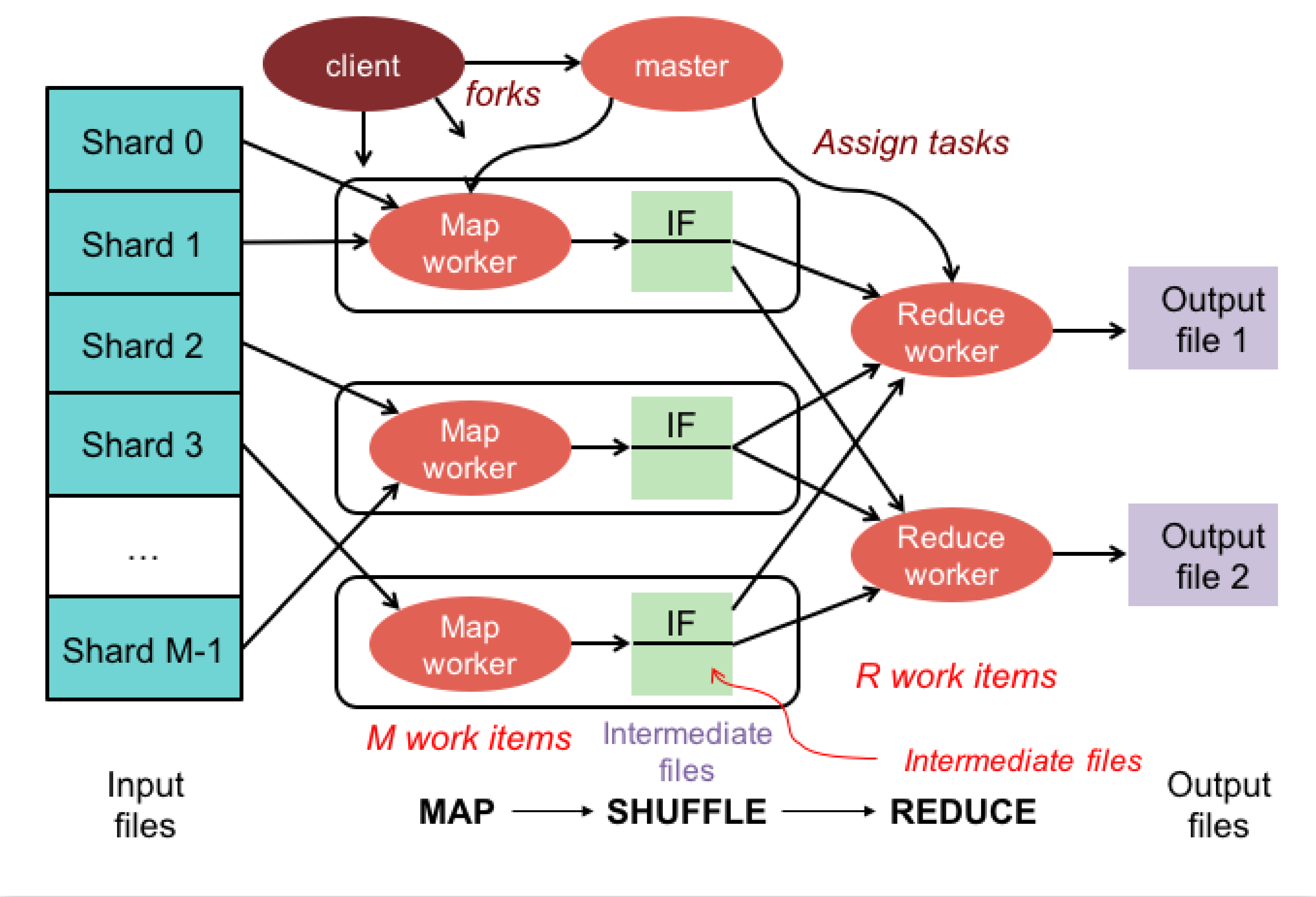
- Framework for parallel computing
- Programmers get simple API
- Don’t have to worry about handling
  - parallelization
  - data distribution
  - load balancing
  - fault tolerance

- *Allows one to process huge amounts of data (terabytes and petabytes) on thousands of processors*

MapReduce Functionality



- Users implement interface of two primary methods:
  - 1. Map: <key1, value1> → <key2, value 2>
  - 2. Reduce: <key2, value2[ ]> → <value3>
- After map phase, all the intermediate values for a given output key are combined together into a list and given to a reducer for aggregating/merging the result.



MapReduce Process Level Overview

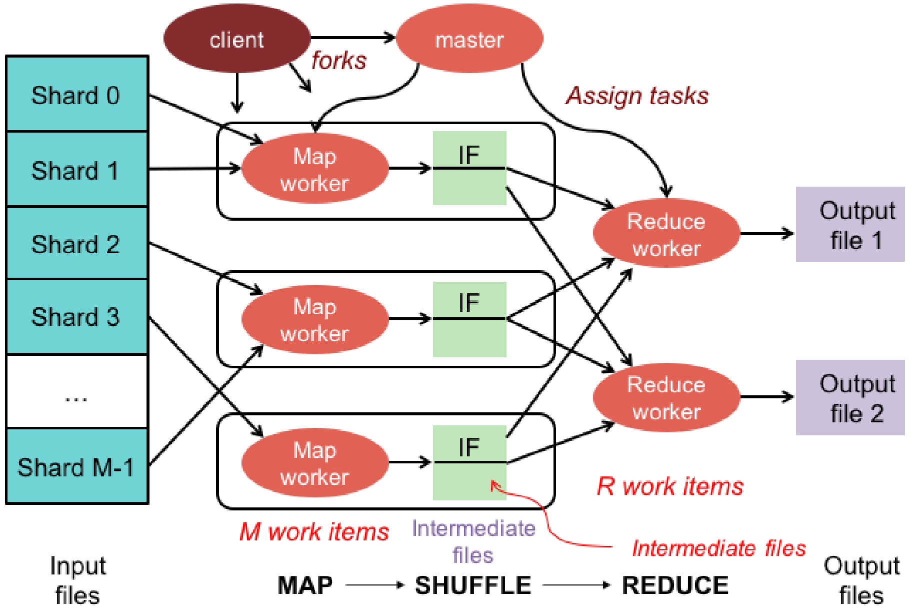
Step 1: Split input files into chunks (shards)

Break up the input data into *M* pieces (typically 64 MB)

Shard 0	Shard 1	Shard 2	Shard 3	…	Shard M-1

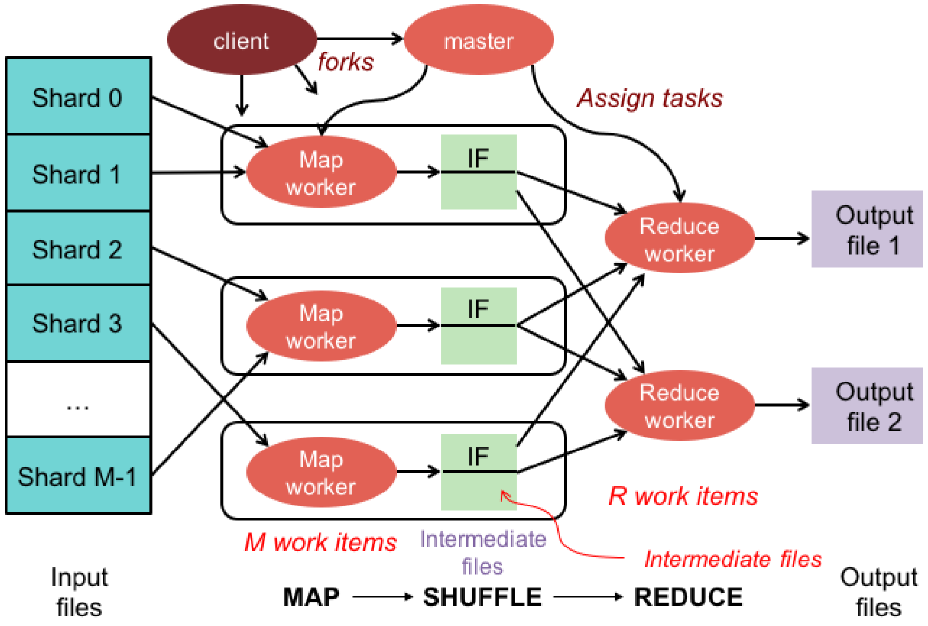
Input files

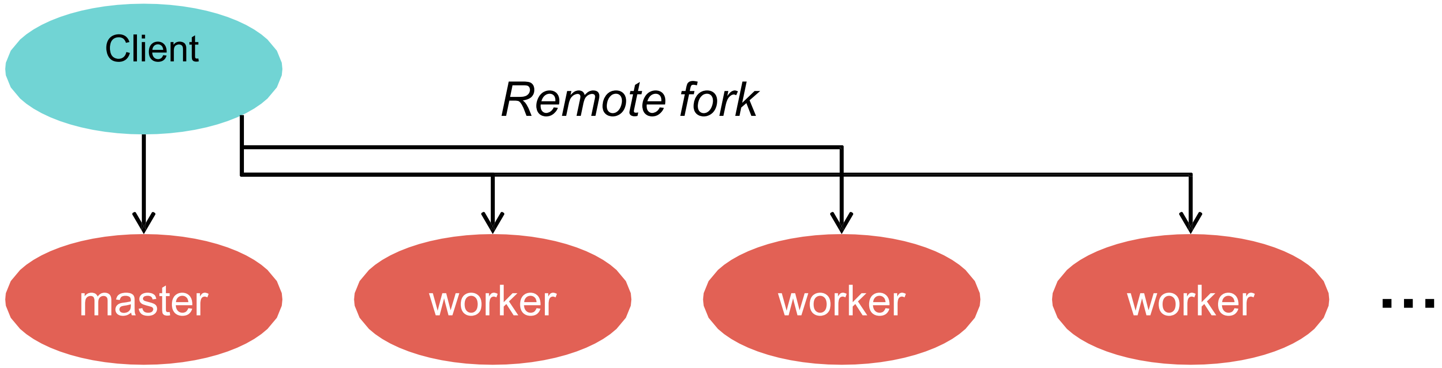
Divided into *M chunks*/shards



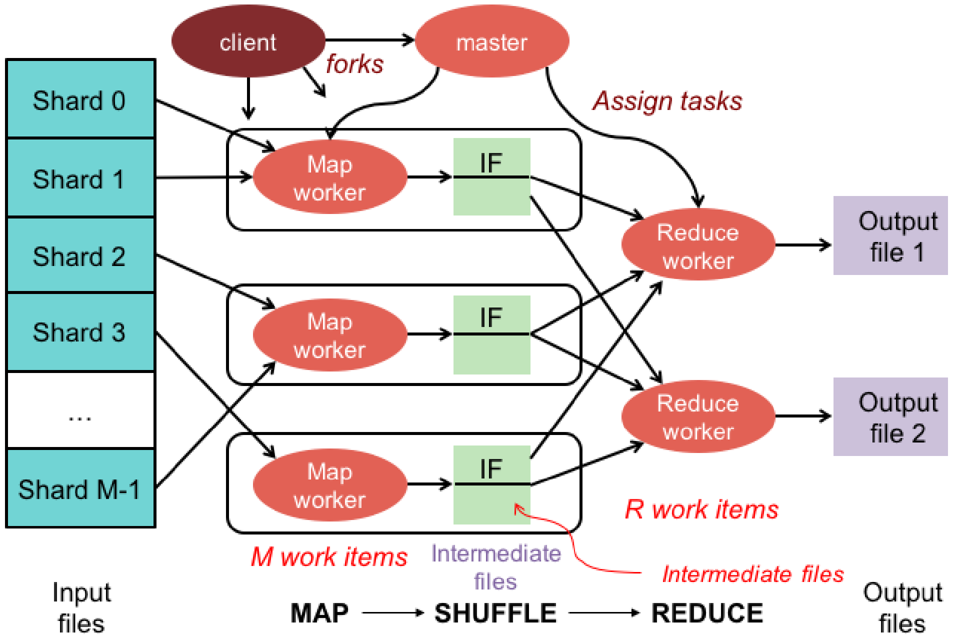
Step 2: Fork processes

- Start up many copies of the program on a cluster of machines
  - **One master**: scheduler & coordinator
  - Lots of workers
- Idle workers are assigned either:
  - map tasks (each works on a shard) – there are *M* map tasks
  - reduce tasks (each works on intermediate files) – there are *R* tasks
    - *R* = # partitions, defined by the user

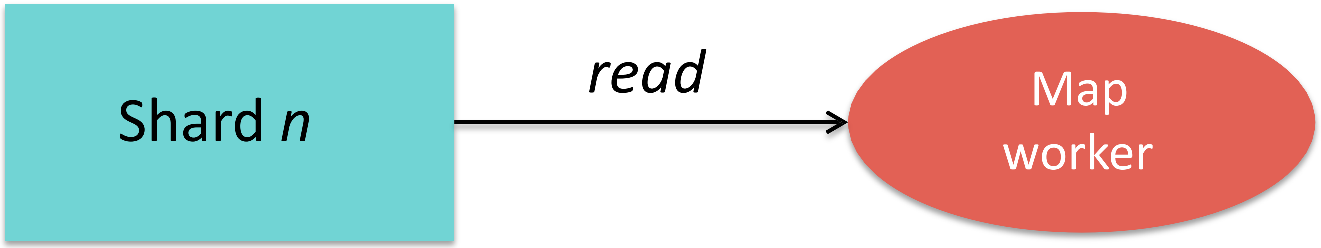




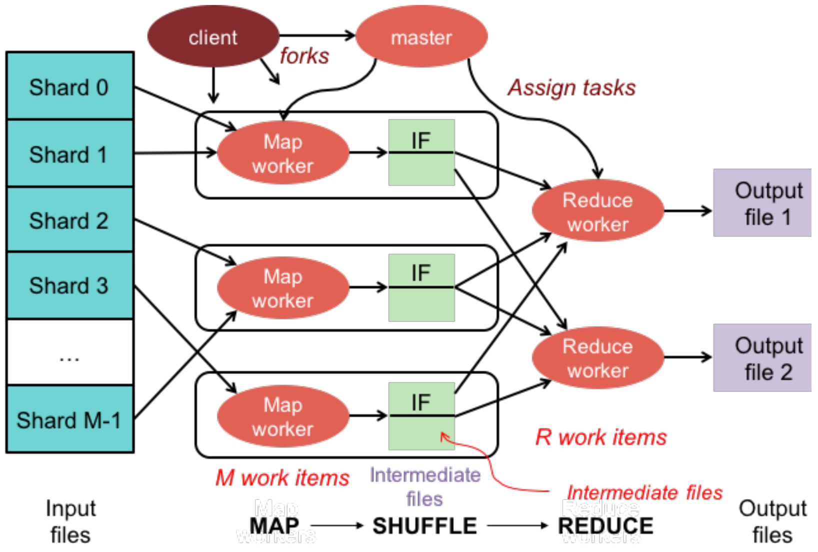
Step 3: Run Map Tasks



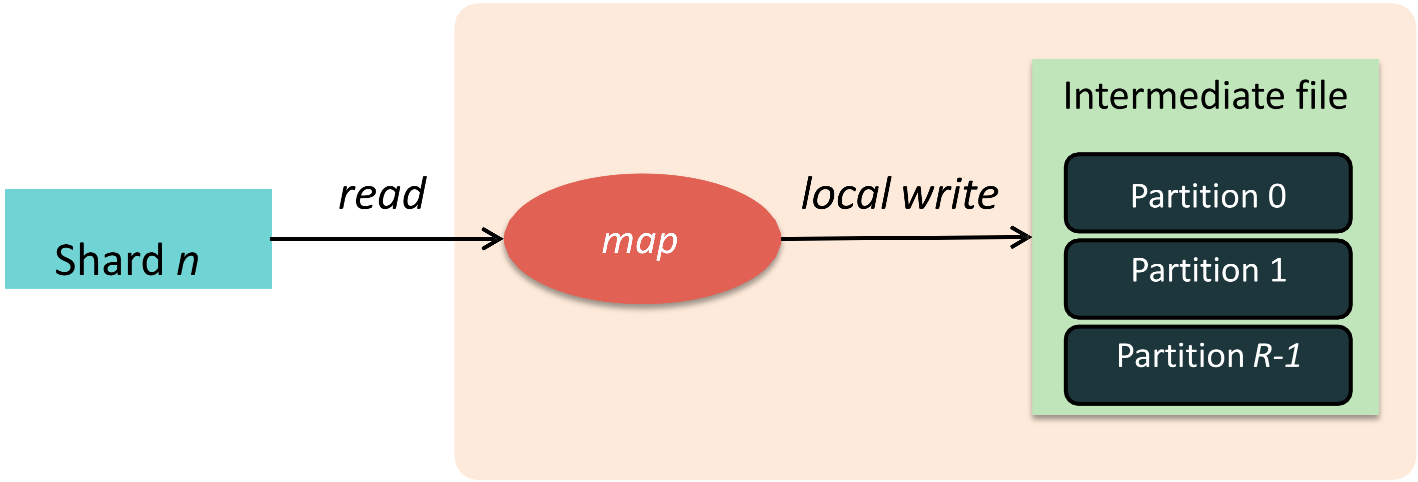
- Reads contents of the input shard assigned to it
- Parses key/value pairs out of the input data
- Passes each pair to a user-defined *map* function
  - Produces intermediate key/value pairs
  - These are buffered in memory



Step 4: Create intermediate files



- Intermediate key/value pairs produced by the user's *map* function buffered in memory and are periodically written to the local disk
  - Partitioned into *R* regions by a partitioning function
- Notifies master when complete
  - Passes locations of intermediate data to the master
  - Master forwards these locations to the reduce worker



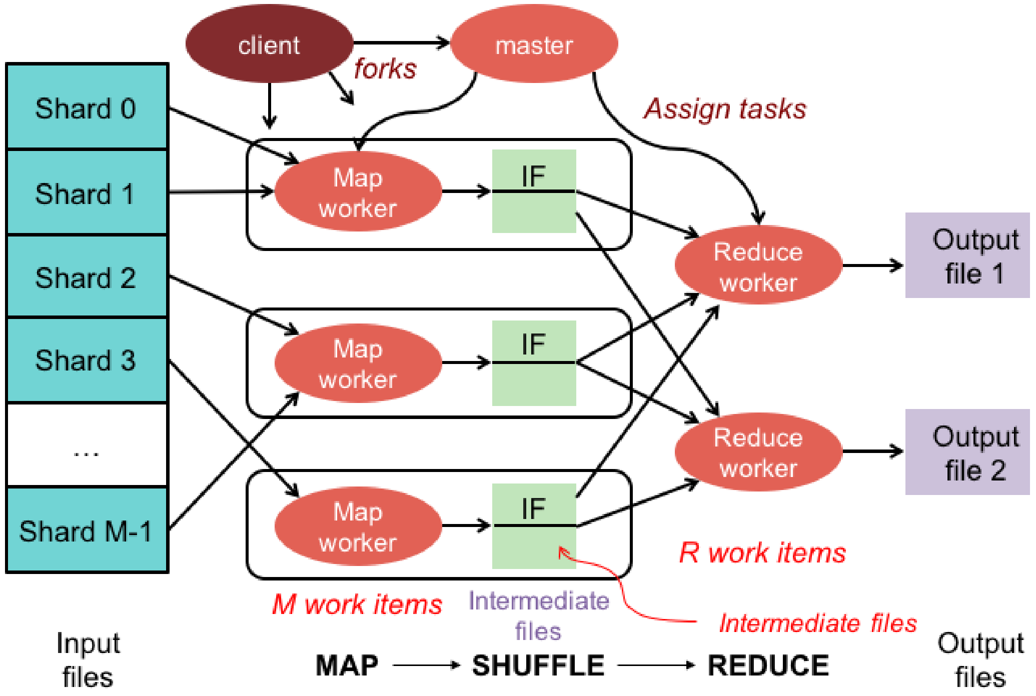
Step 4a. Partitioning

- Map data will be processed by Reduce workers
  - User's *Reduce* function will be called once per unique key generated by *Map*.

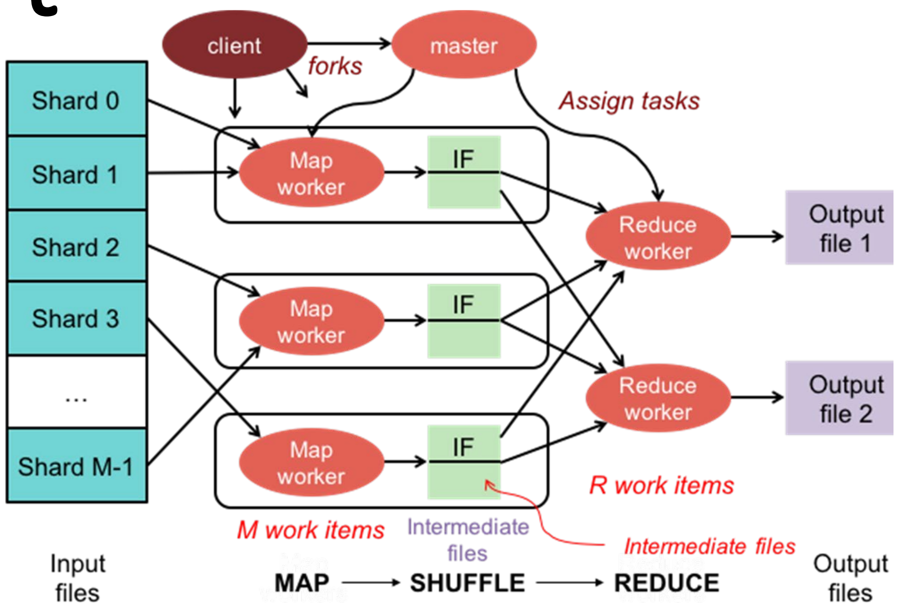
- We first need to group all the (*key, value*) data by keys and decide which Reduce worker processes which keys
  - The Reduce worker will later sort the values within the keys

- **Partition function**
  Decides which of *R* reduce workers will work on which key
  - Default function: *hash(key) mod R*
  - Map worker partitions the data by keys

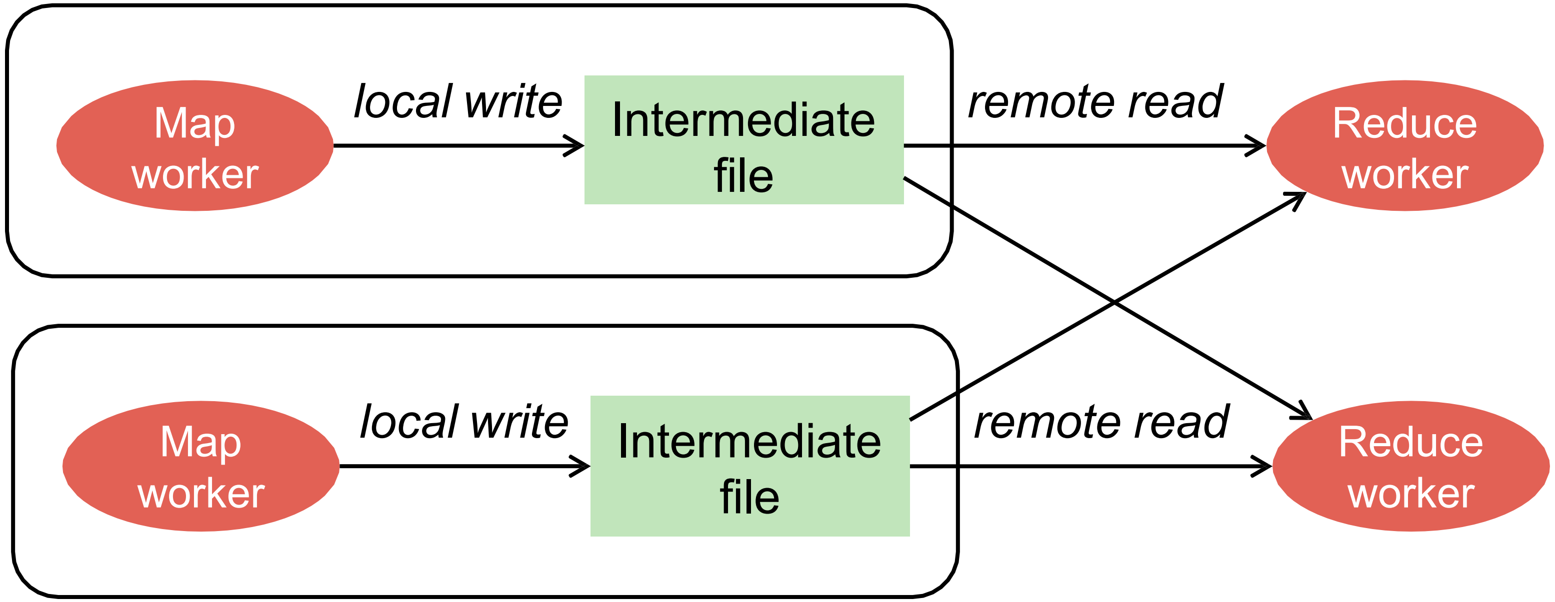
- Each Reduce worker will later read their partition from every Map worker



Step 5: Reduce Task: Shuffle & Sort



- Reduce worker gets notified by the master about the location of intermediate files for its partition
- Shuffle: Uses RPCs to read the data from the local disks of the map workers
- Sort: When the *reduce* worker gets all the (*key, value*) data for its partition from all workers
  - It sorts the data by the intermediate keys
  - All occurrences of the same key are grouped together

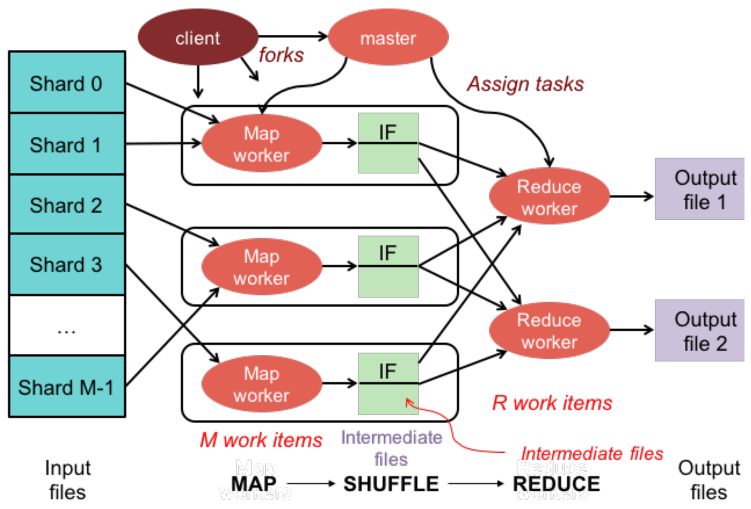


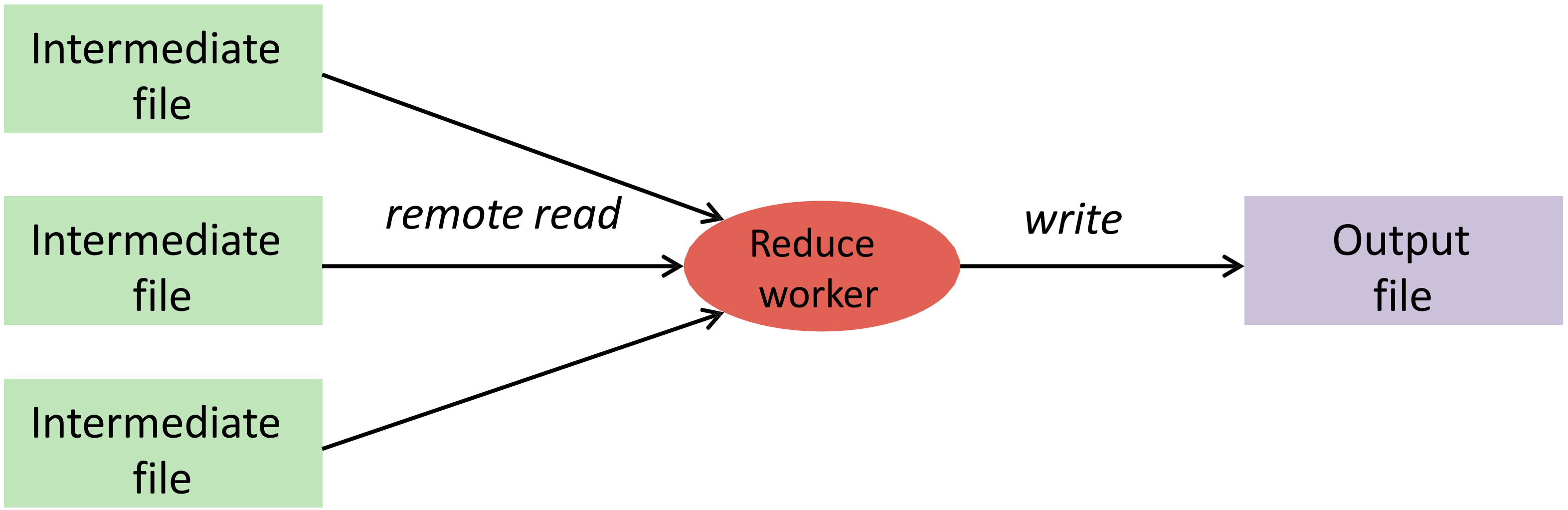
Step 6: Reduce Task

- The sort phase grouped data by keys
- User's ***Reduce*** function is given the key and the set of intermediate values for that key

  < key, (value1, value2, value3, value4, …) >

- The output of the *Reduce* function is appended to an output file

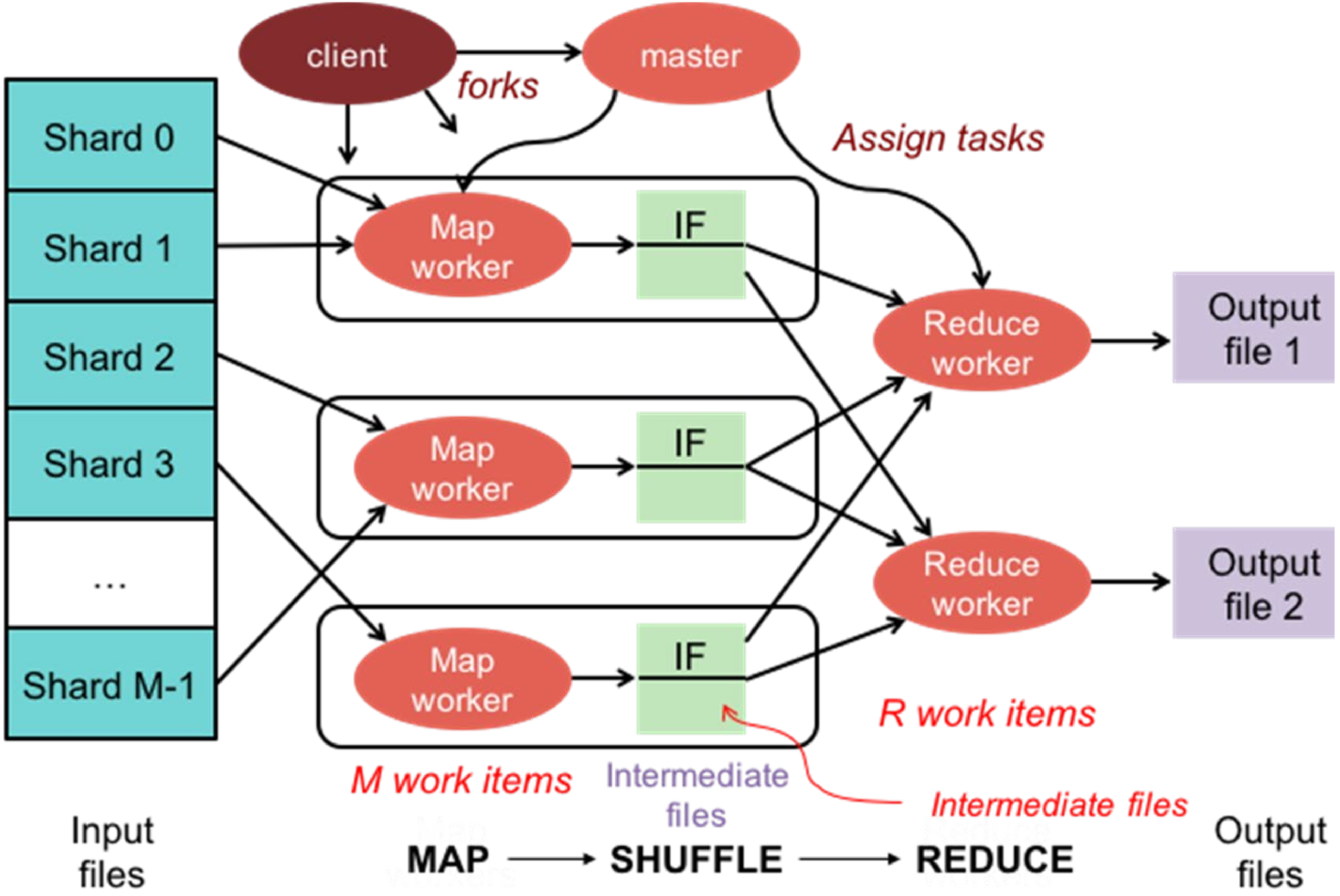




Step 7: Return to user

- When all *map* and *reduce* tasks have completed, the master wakes up the user program

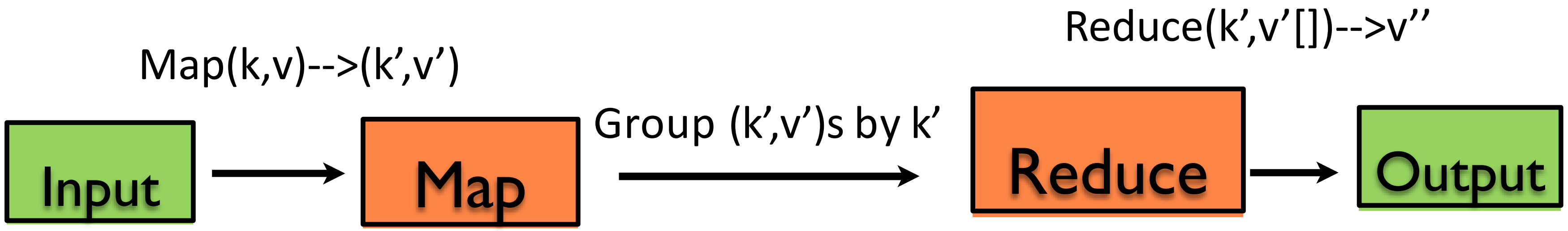
- The *MapReduce* call in the user program returns and the program can resume execution.
- Output of *MapReduce* is available in *R* output files


client
master
forks
Assign tasks
Shard 0
Shard 1
Shard 2
Shard 3
...
Shard M-1
Map worker
Map worker
Map worker
IF
IF
IF
Reduce worker
Reduce worker
Output file 1
Output file 2
R work items
M work items
Intermediate files
Intermediate files
Input files
MAP → SHUFFLE → REDUCE
Output files

A Simple

- Word count is challenging over massive amounts of data
- Fundamentals of statistics often are aggregate functions
- Most aggregation functions have distributive nature
- MapReduce breaks complex tasks into smaller pieces which can be executed in parallel

MapReduce Programming Model



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- After map phase, all the intermediate values for a given output key are combined together into a list and given to a reducer for aggregating/merging the result.

Map Phase

- Input to the Mapper

```
(3414, 'the cat sat on the mat')
(3437, 'the aardvark sat on the sofa')
```

Count the # of occurrences of each word in a large amount of input data

```
Map(input_key, input_value) {
  foreach word w in input_value:
    emit(w, 1);
}
```

- Output from the Mapper

```
('the', 1), ('cat', 1), ('sat', 1), ('on', 1),
('the', 1), ('mat', 1), ('the', 1), ('aardvark', 1),
('sat', 1), ('on', 1), ('the', 1), ('sofa', 1)
```

Shuffling/Sorting

- After the Map, all the intermediate values for a given intermediate key are combined together into a list

Mapper Output

```
('the', 1),
('cat', 1),
('sat', 1),
('on', 1),
('the', 1),
('mat', 1),
('the', 1),
('aardvark', 1),
('sat', 1),
('on', 1),
('the', 1),
('sofa', 1)
```

Reducer Input

```
aardvark, 1
cat, 1
mat, 1
on [1, 1]
sat [1, 1]
sofa, 1
the [1, 1, 1, 1]
```

Reducer

- Input of the shuffling/sorting

```
('the', 1), ('cat', 1), ('sat', 1), ('on', 1),
('the', 1), ('mat', 1), ('the', 1), ('aardvark', 1),
('sat', 1), ('on', 1), ('the', 1), ('sofa', 1)
```

Reducer Input

```
aardvark, 1
cat, 1
mat, 1
on [1, 1]
sat [1, 1]
sofa, 1
the [1, 1, 1, 1]
```

Add up all the values associated with each intermediate key:

```
Reduce(output_key, intermediate_vals) {
  set count = 0;
  foreach v in intermediate_vals:
    count += v;
  emit(output_key, count);
}
```

- Output from the Reducer

```
('the', 4), ('sat', 2), ('on', 2), ('sofa', 1),
('mat', 1), ('cat', 1), ('aardvark', 1)
```

Map+ Reduce At a glance

Mapper Input

```
the cat sat on the mat
the aardvark sat on the sofa
```

Mapping

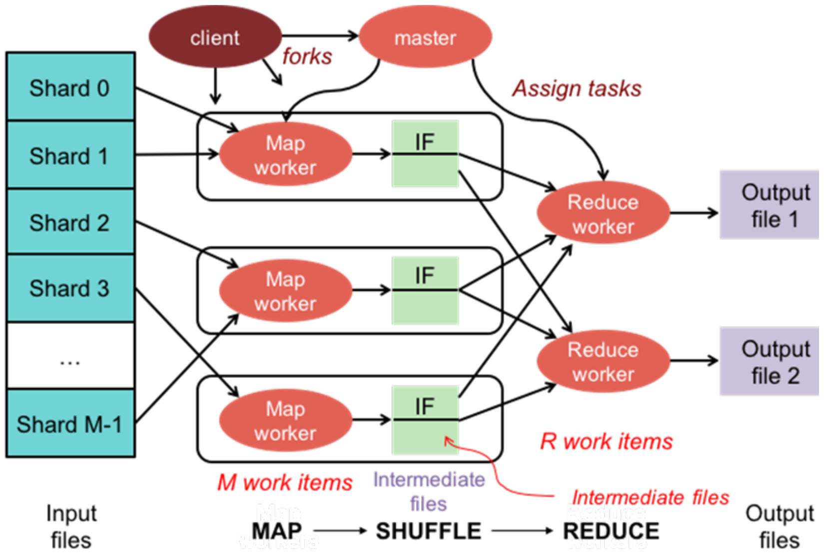
```
('the', 1),
('cat', 1),
('sat', 1),
('on', 1),
('the', 1),
('mat', 1),
('the', 1),
('aardvark', 1),
('sat', 1),
('on', 1),
('the', 1),
('sofa', 1)
```

Shuffle/ Sorting

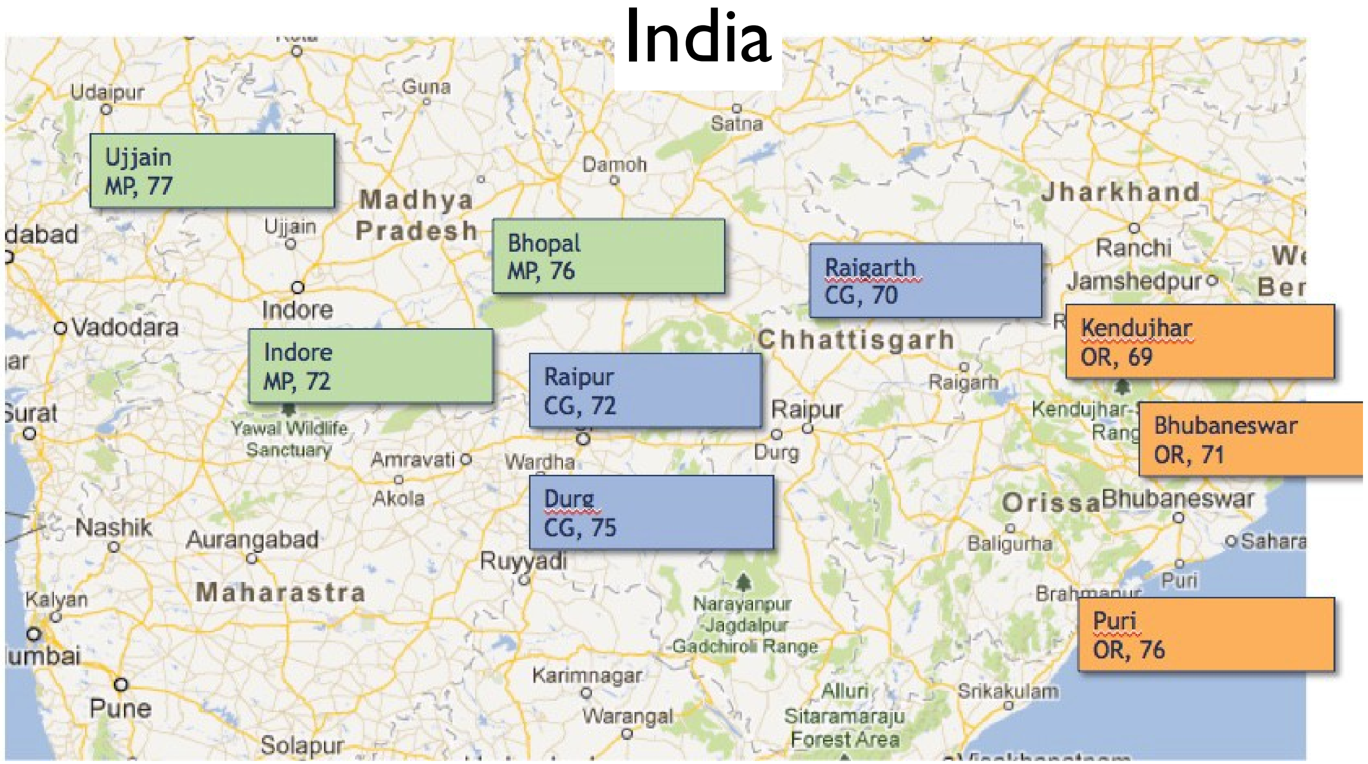
```
aardvark, 1
cat, 1
mat, 1
on [1, 1]
sat [1, 1]
sofa, 1
the [1, 1, 1, 1]
```

Reducing

```
aardvark, 1
cat, 1
mat, 1
on, 2
sat, 2
sofa, 1
the, 4
```

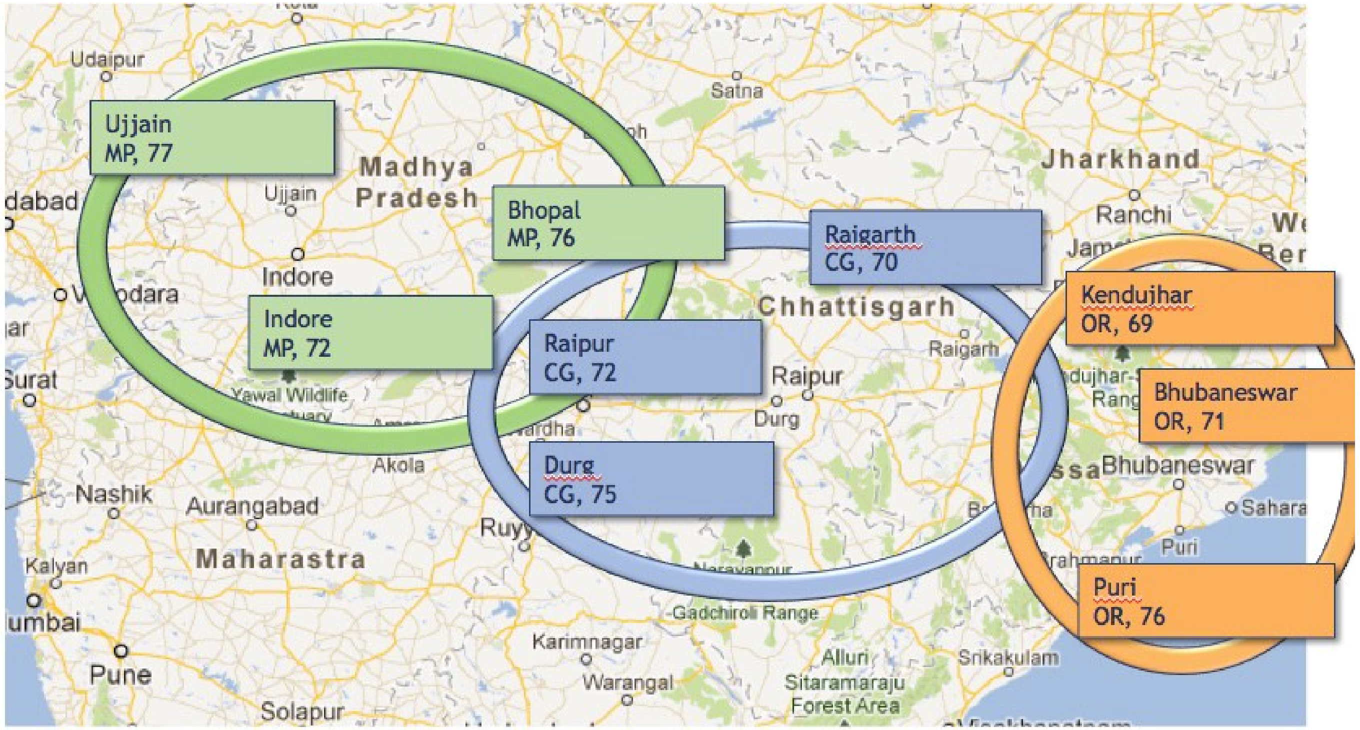


Let’s use MapReduce to help Google Map



We want to compute the average temperature for each state

Let's use MapReduce to help Google Map



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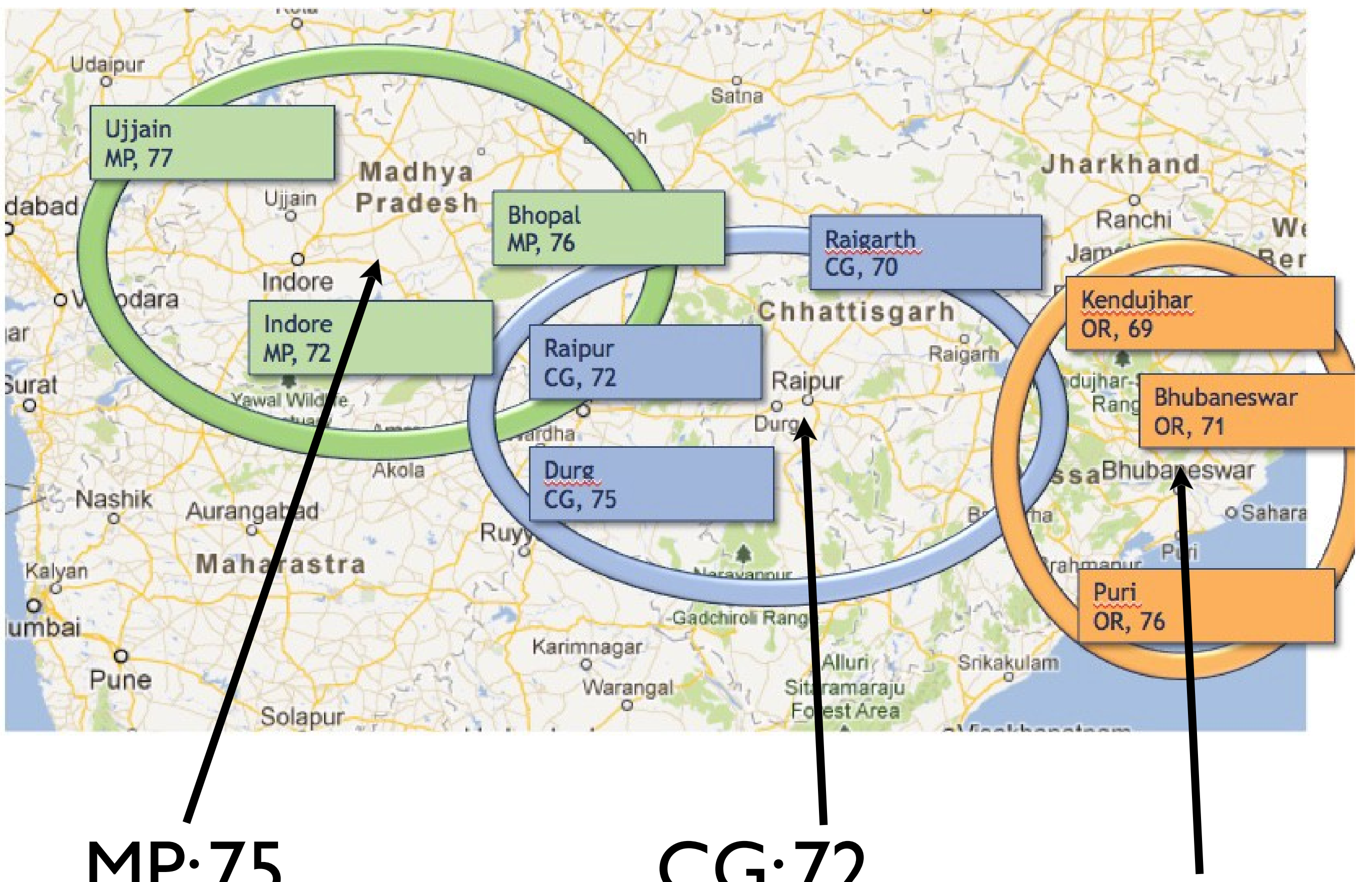
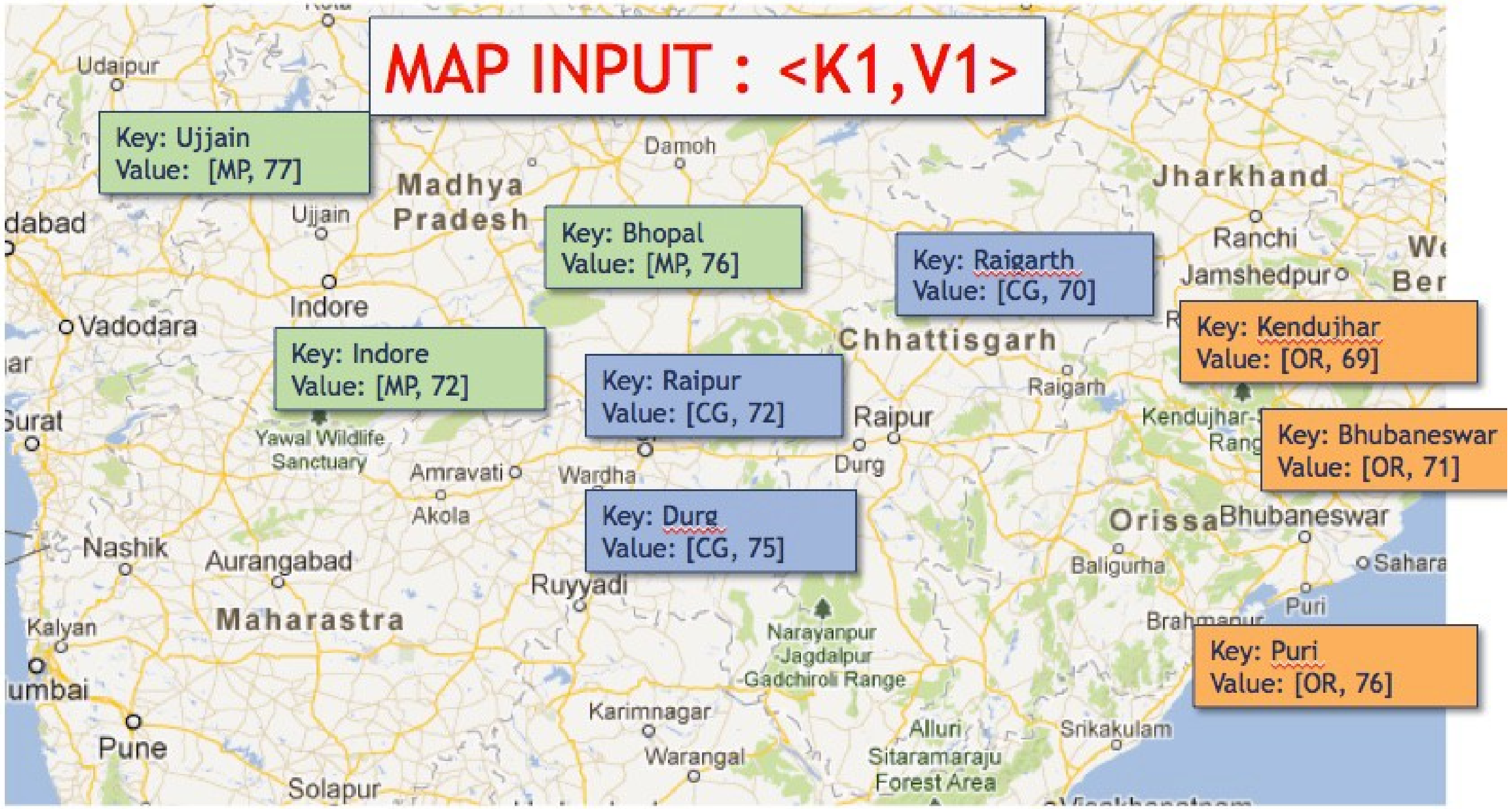


MP:75

CG:72

OR:72

Let's use MapReduce to help Google Map



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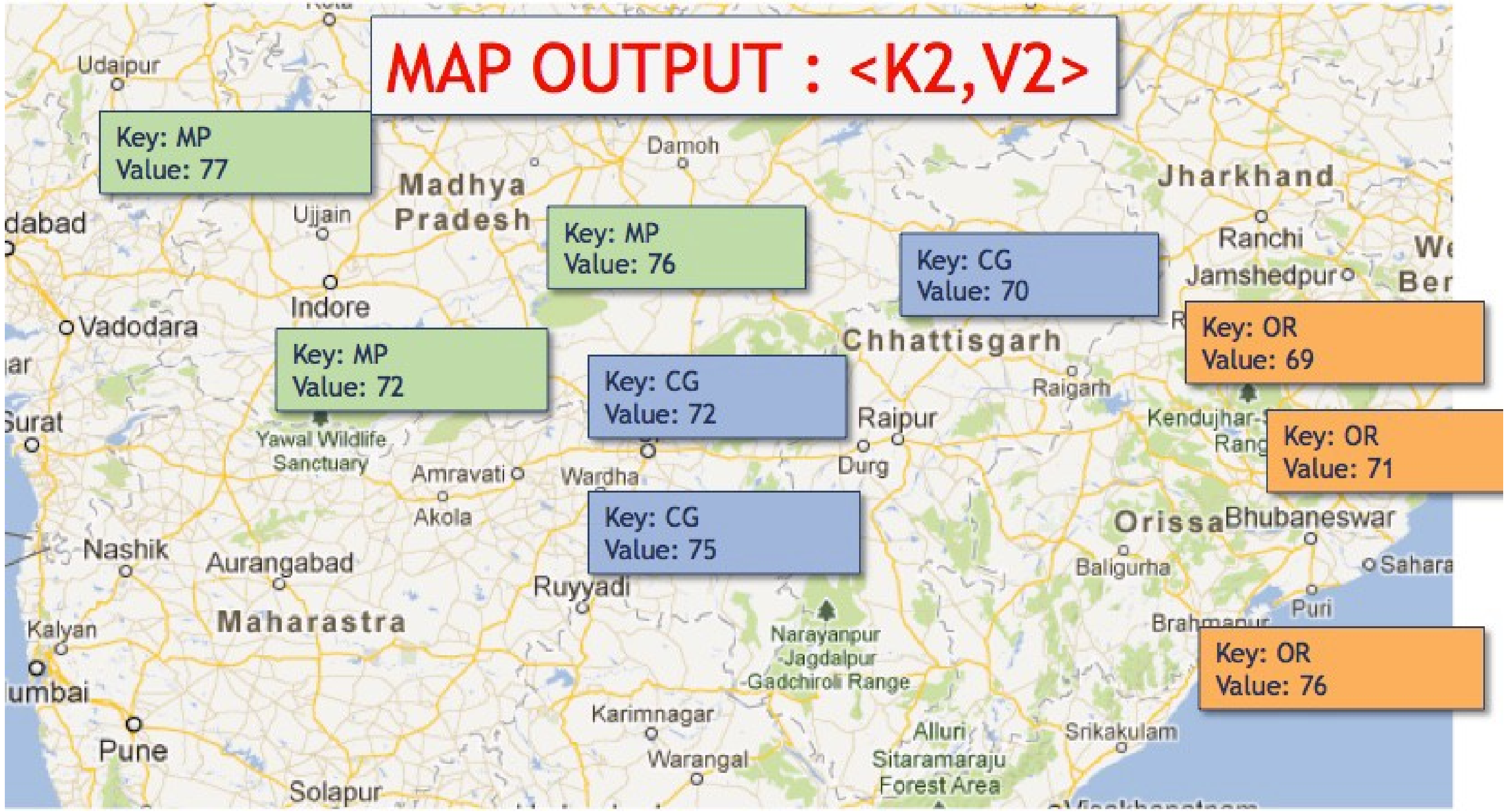

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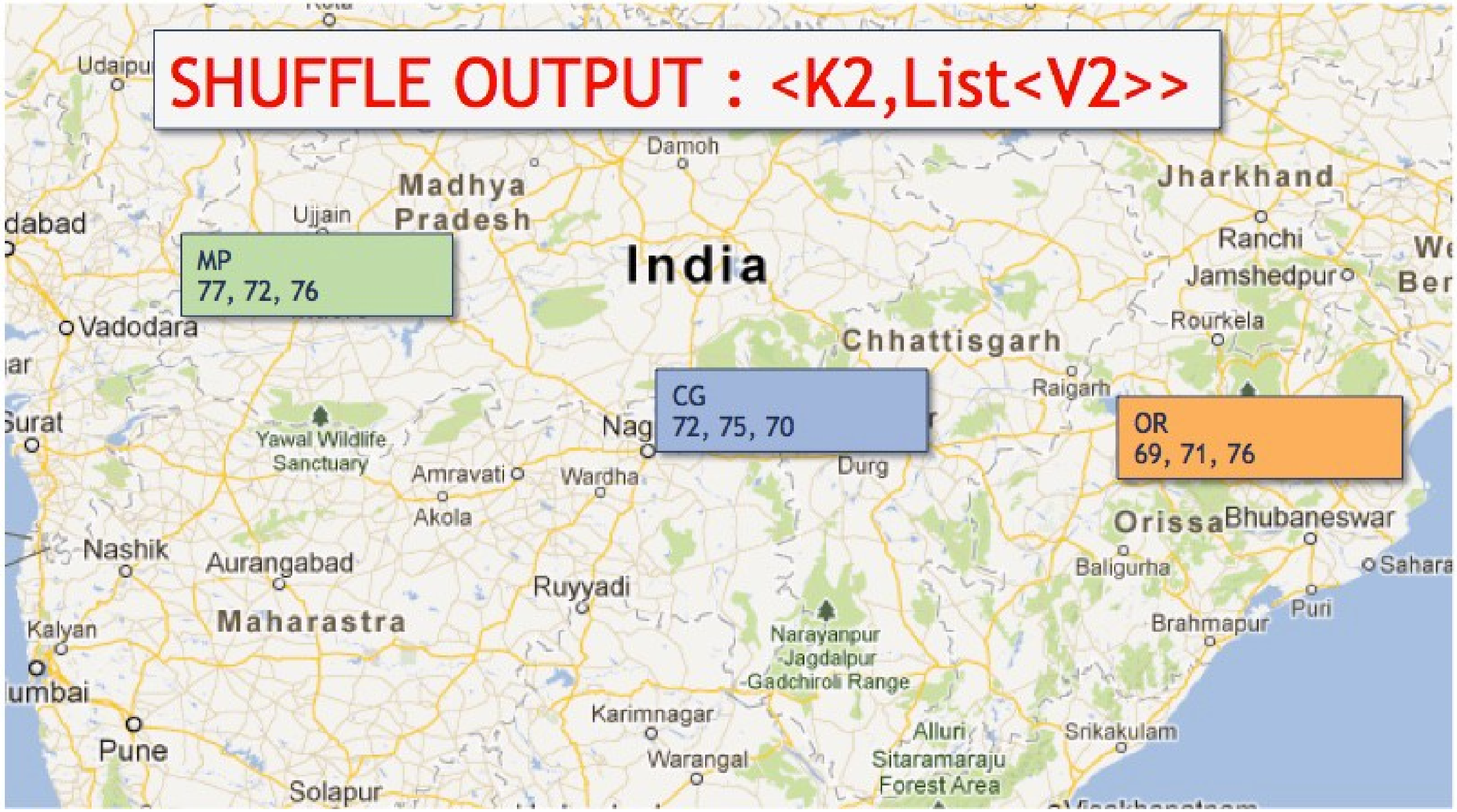

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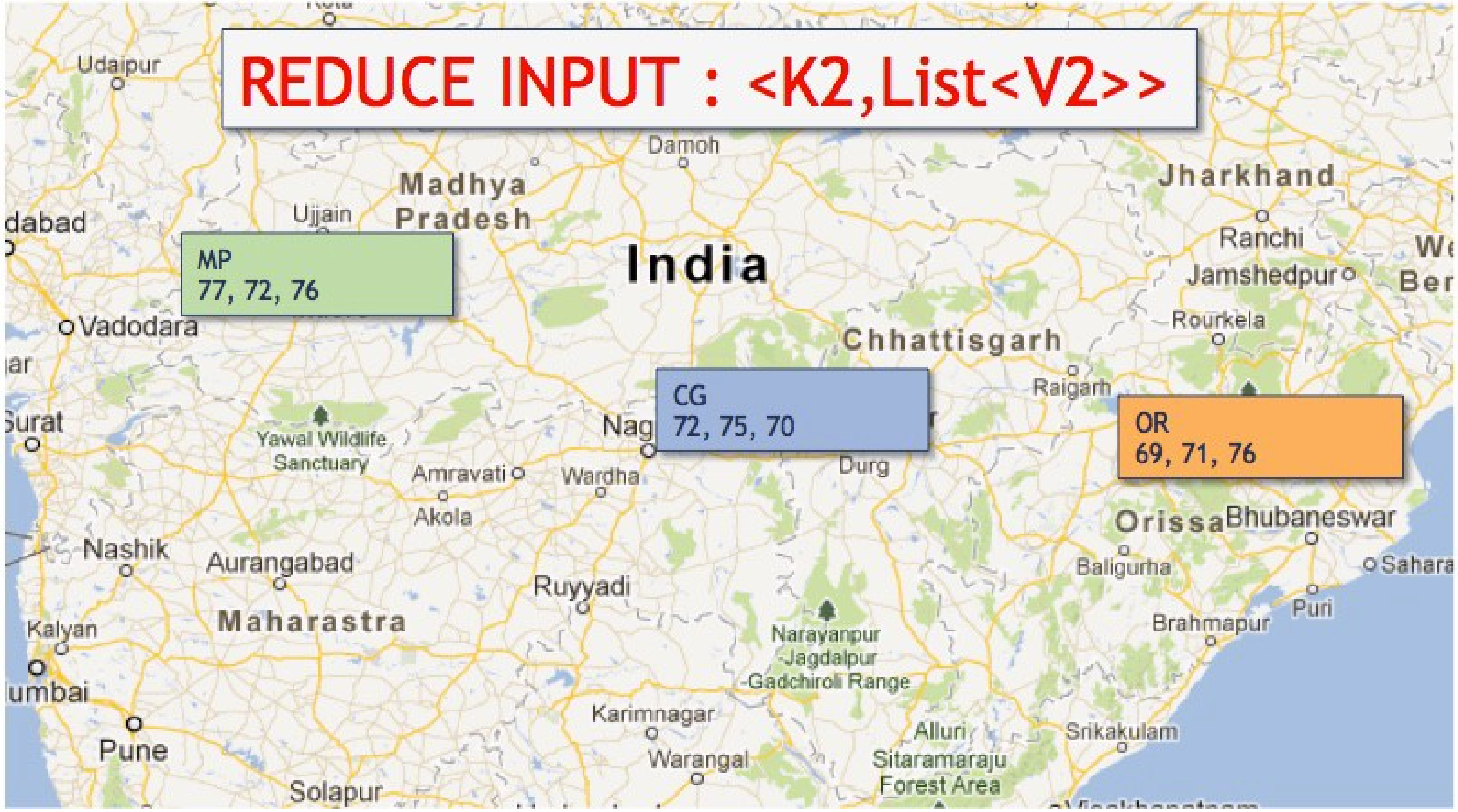

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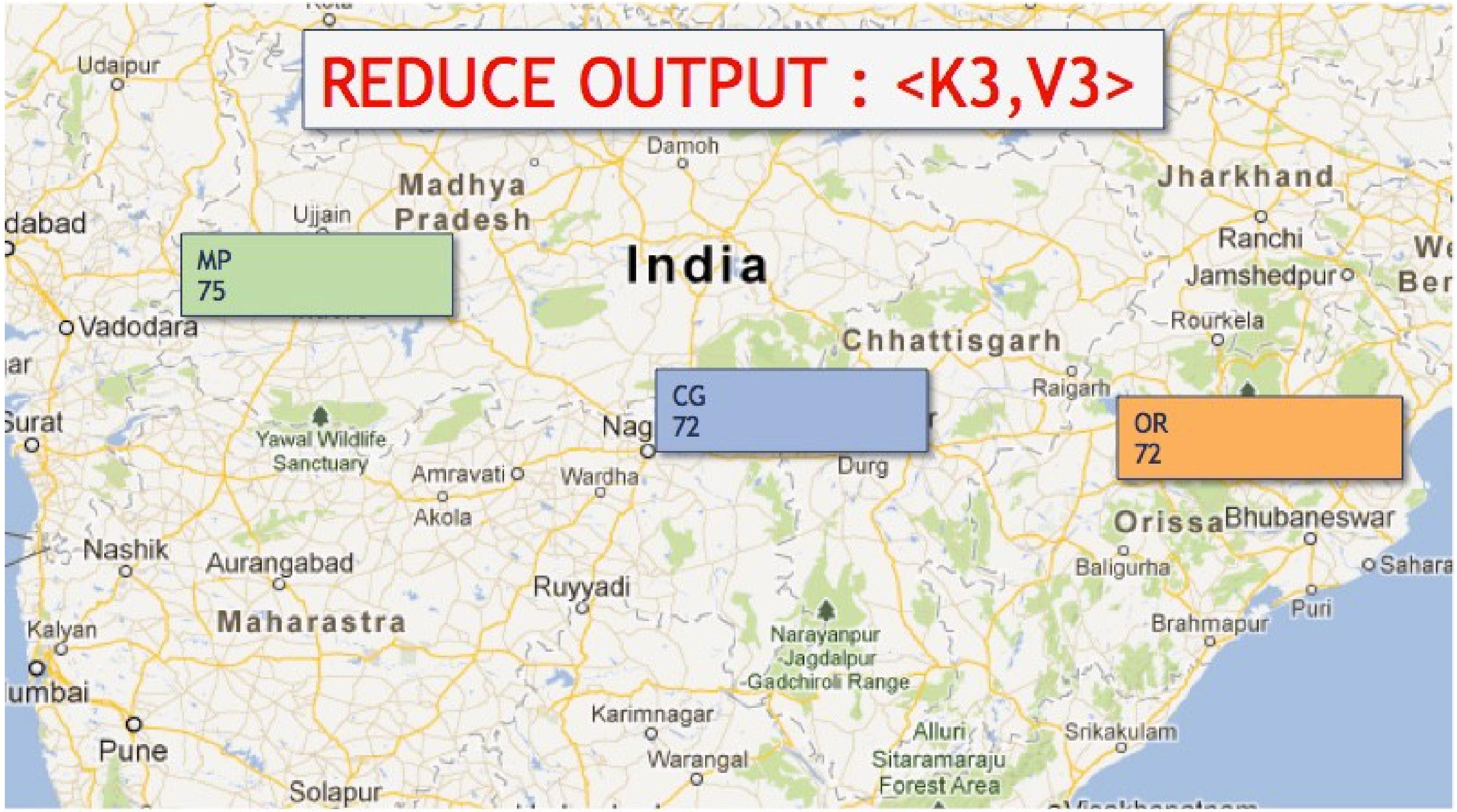
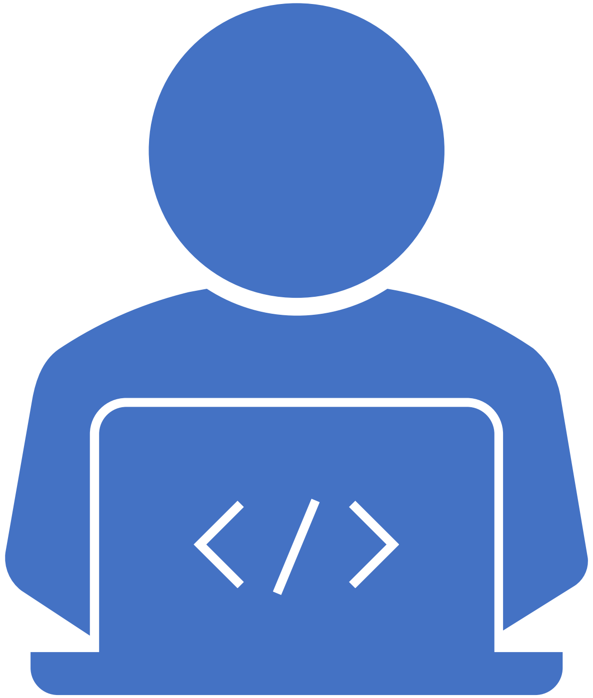


Questions?



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Slides Acknowledgement