Concepts and Models of Parallel and Data-centric Programming

MapReduce – Programming Model

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Outline

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2. Shared Memory
3. GPU Programming
4. Bulk-Synchronous Parallelism
5. Message Passing
6. Distributed Shared Memory
7. Parallel Algorithms
8. Parallel I/O
9. **MapReduce**
10. Apache Spark

a. MapReduce Programming Model
b. Parallelizing MapReduce
c. Hadoop Ecosystem
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e. Yet Another Resource Negotiator
f. Comparison to Other Approaches
g. MapReduce Design Patterns

Word Count (1)

- **Given:** Multiple huge text files
- **Task:** Compute number of times each distinct word appears
- **Application scenarios:**
  - Word statistics (e.g., for tag clouds out of blog posts, user comments)
  - Find popular URLs in web server access log

file1:
this is some text file with some content

file2:
here is some other text file with some further words

Result:

content	1	some	4
file	2	text	2
further	1	this	1
here	1	with	2
is	2	words	1
other	1		

Word Count (2)

file1:
this is some text
file with some
content

file2:
here is some other
text file with some
further words

Result:

content	1	some	4
file	2	text	2
further	1	this	1
here	1	with	2
is	2	words	1
other	1		

- How to solve this task?
- Shell solution:

```
cat file* | tr ' ' '\n' | sort | uniq -c > result
```

- Does this solution scale (for datasets larger than a few GBs)?
  - No, we are just working on a single core of a single machine.

Achieving Scalability (1)

- Parallelize the program: Work on different files in different processes
- **Problem 1:** Splitting work into equal-sized pieces
  - Assigning one file per process leads to load imbalances (different file sizes)
  - Need to assign a file part or several files to a process
- **Problem 2:** Combining the results from the different processes
  - Aggregate count values of words from different processes
- **Problem 3:** Using multiple machines
  - Which machine starts and runs the computation?
  - What if a machine or a process fails?

Achieving Scalability (2)

- Simple problem gets complex when thinking about parallelization and scalability
- How to manage the complexity of parallelization?

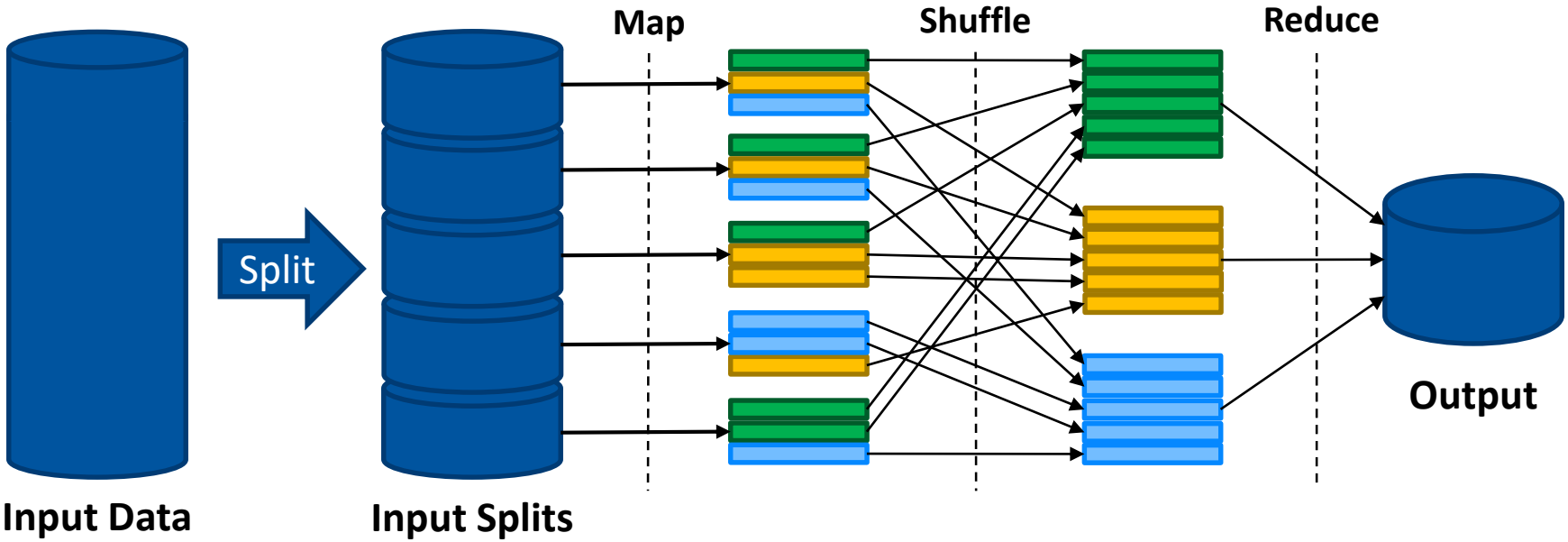
"We can solve any problem by introducing an extra level of indirection."

– David J. Wheeler

- **Indirection:** MapReduce programming model and framework
  - Problems defined in this model are implicitly parallelizable
  - Apache Hadoop framework provides practical implementation

MapReduce in a Nutshell

- Two essential functions *Map* and *Reduce* are defined by developer
- Work on data as key-value (KV) pairs, types chosen by developer
- Rest implicitly provided by framework
- Three execution steps: Map, Shuffle, Reduce

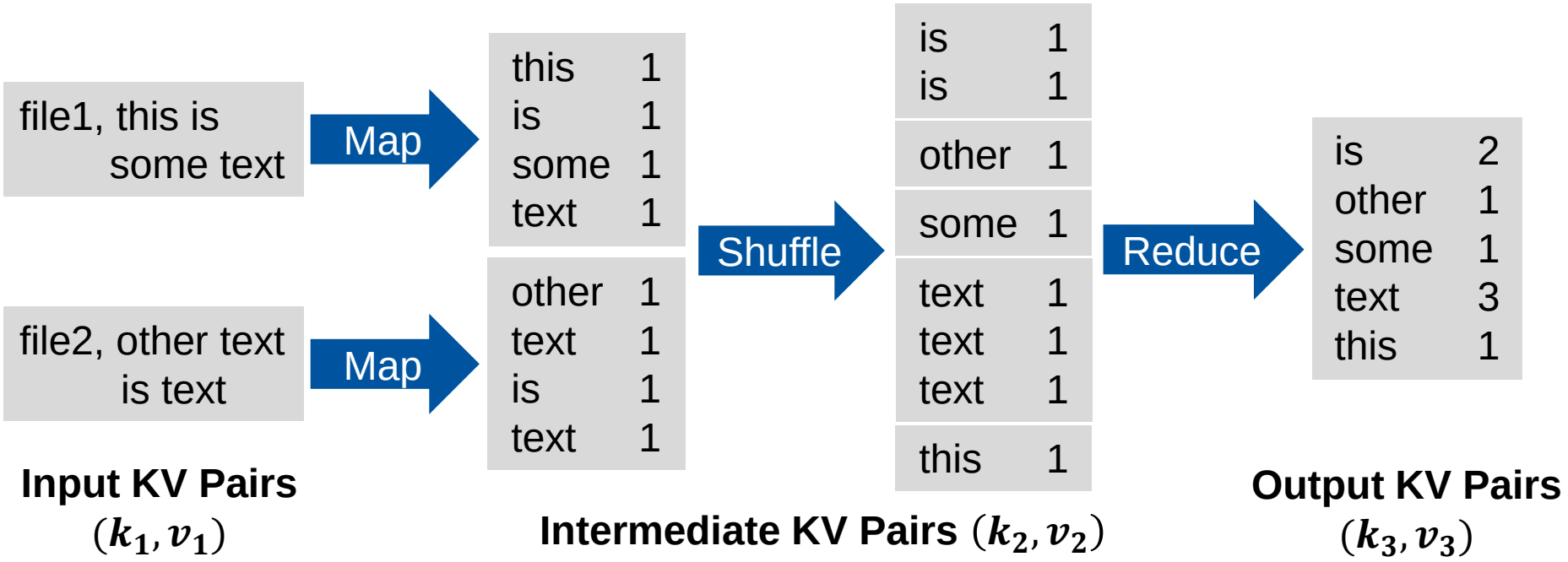


Map and Reduce Functions

- Map and Reduce functions are fundamentals of programming model
- Input for both functions are key-value (KV) pairs
- Map function
  - Extracts data out of (un)structured datasets, filtering data
- Reduce function
  - Works on grouped data values (by some key) of Map function
  - Aggregating data values in one group (sum, minimum, maximum, …)

Word Count using MapReduce

- Files available as KV pairs (*name, content*)
  - (“file1”, “this is some text”), (“file2”, “other text is text ”)
- Map function: Emit for each word *w* a KV pair (*w*, 1)
- Reduce function: Sum up the number of KV pairs (*w*, 1) for each word *w*

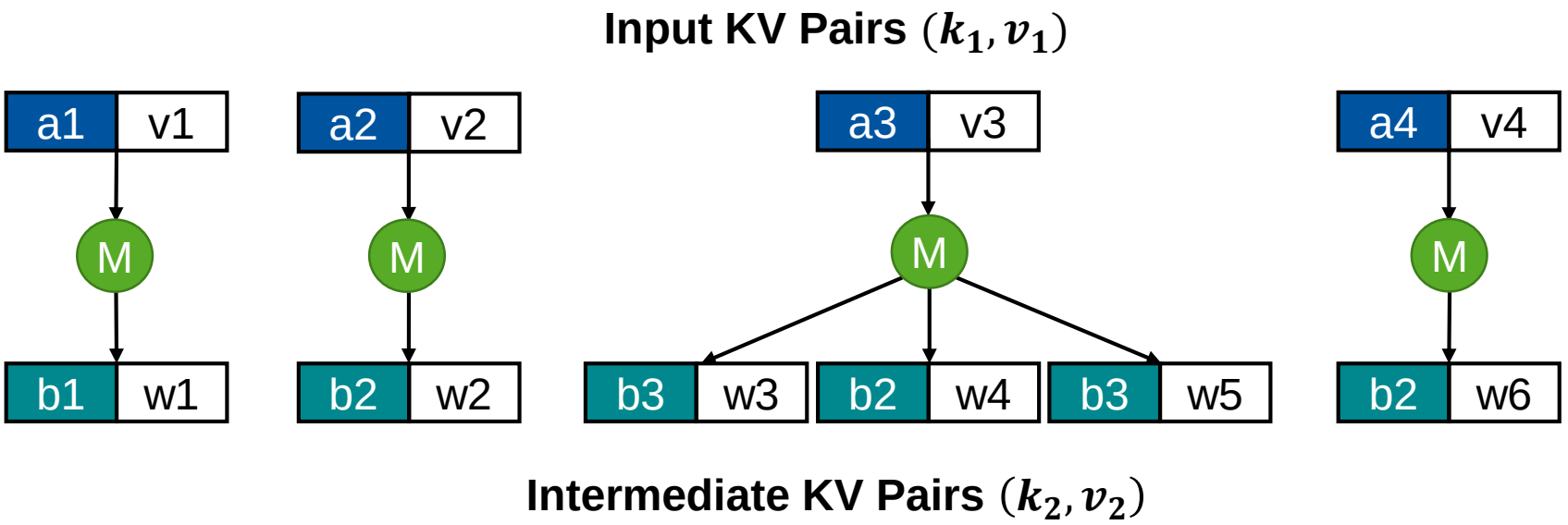


Map Function

- **Given:** Input data as KV pairs, denoted as (k_1, v_1)
- **Map:** Takes input pair and produces a list of intermediate KV pairs (k_2, v_2)

$$Map(k_1, v_1) \rightarrow list(k_2, v_2)$$

- Types k_1, v_1, k_2, v_2 can be chosen arbitrarily



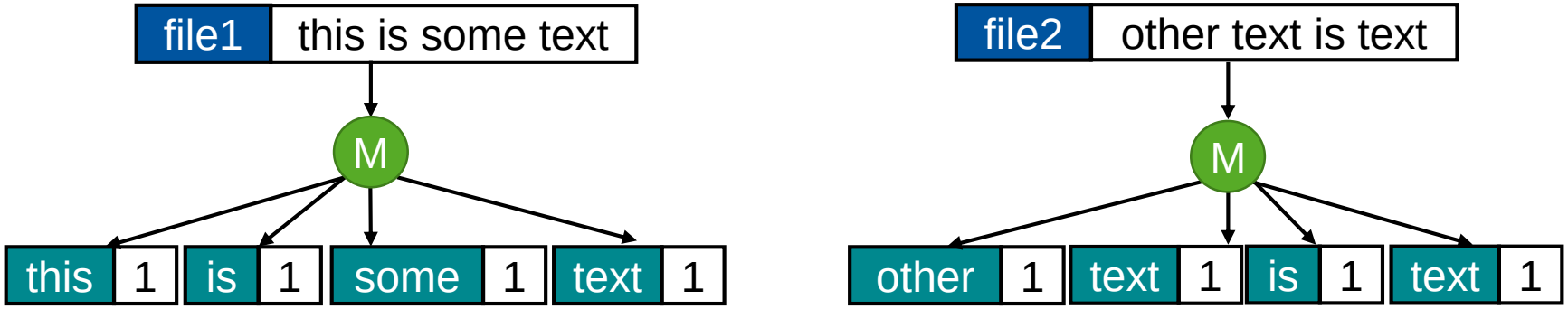
Map Function – Word Count

- Map function general form: $Map(k_1, v_1) \rightarrow list(k_2, v_2)$
- Signature for Word Count: $Map(\text{String}, \text{String}) \rightarrow list(\text{String}, \text{int})$
- Pseudocode:

```
Map(String key, String value):
    // key: document name
    // value: (part of) document contents
    for each word w in value:
        Emit(w, 1)
```

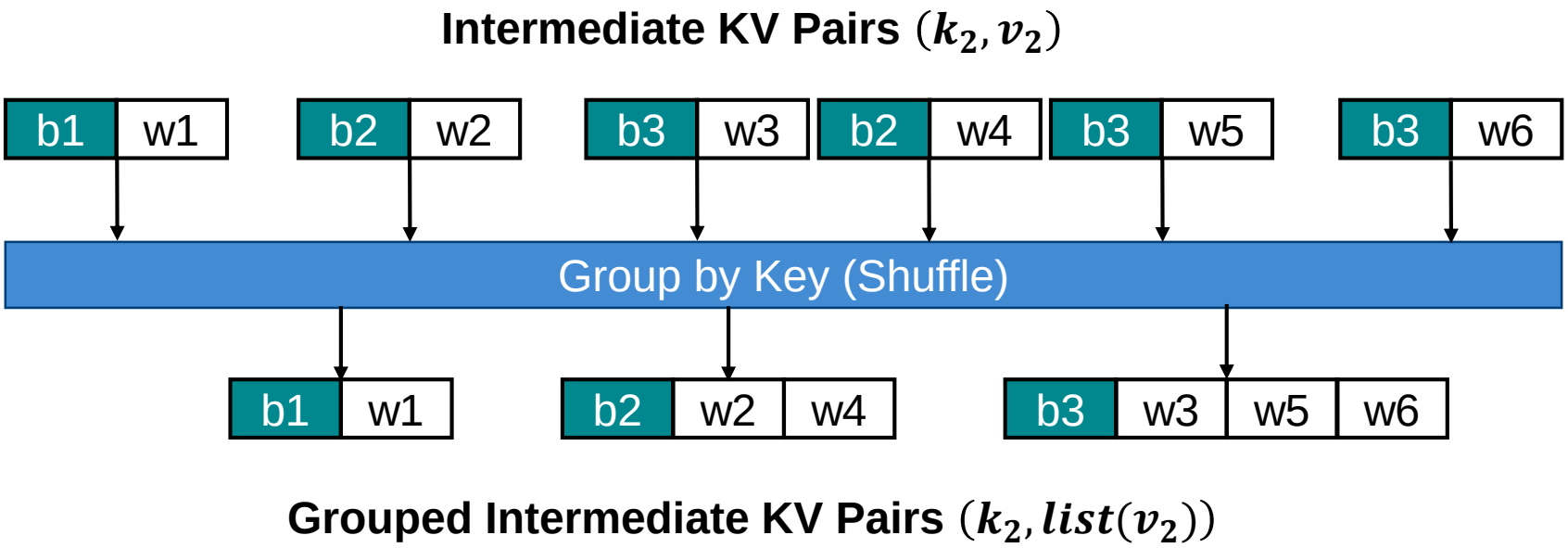
- Examples:
  - Map("file1","this is some text") = [("this",1), ("is",1), ("some",1), ("text",1)]
  - Map("file2","other text is text") = [("other",1), ("text",1), ("is",1), ("text",1)]

Map Function – Word Count

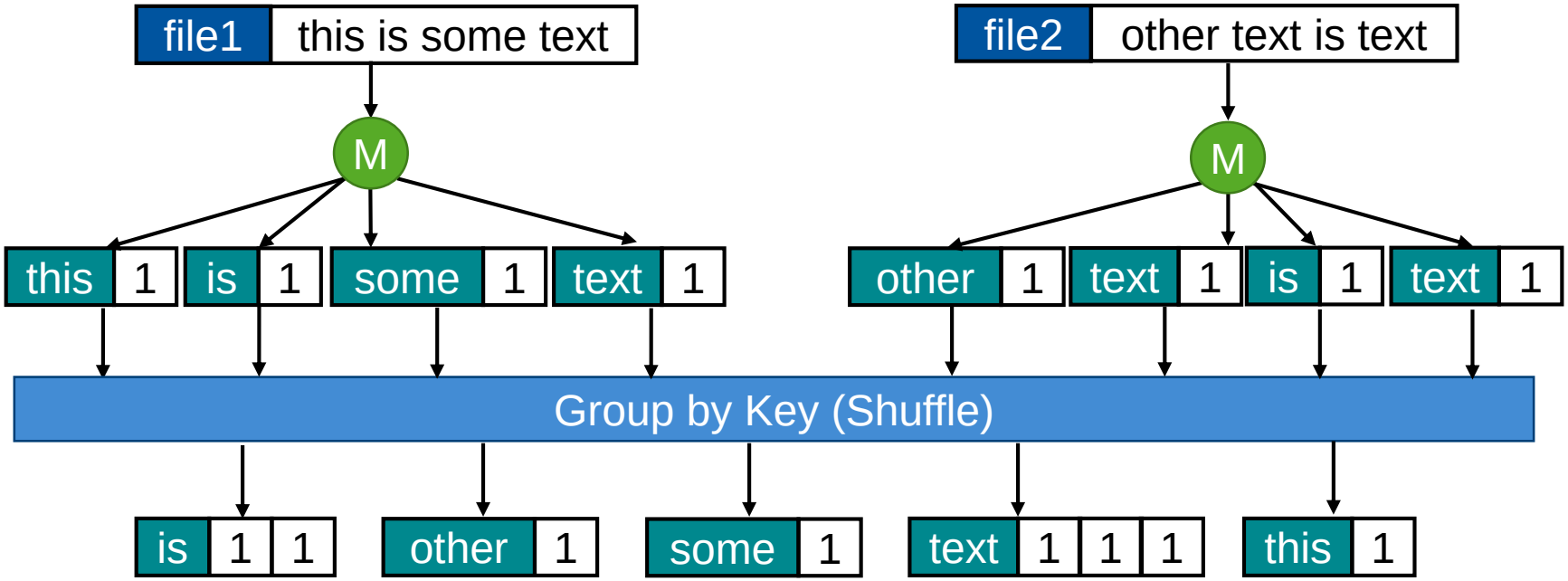


Group by Key (Shuffle)

- Group the output of *Map* tasks by k_2
- Generate KV pairs $(k_2, list(v_2))$ where $list(v_2)$ contains all elements with key k_2 from the Map outputs



Group by Key – Word Count

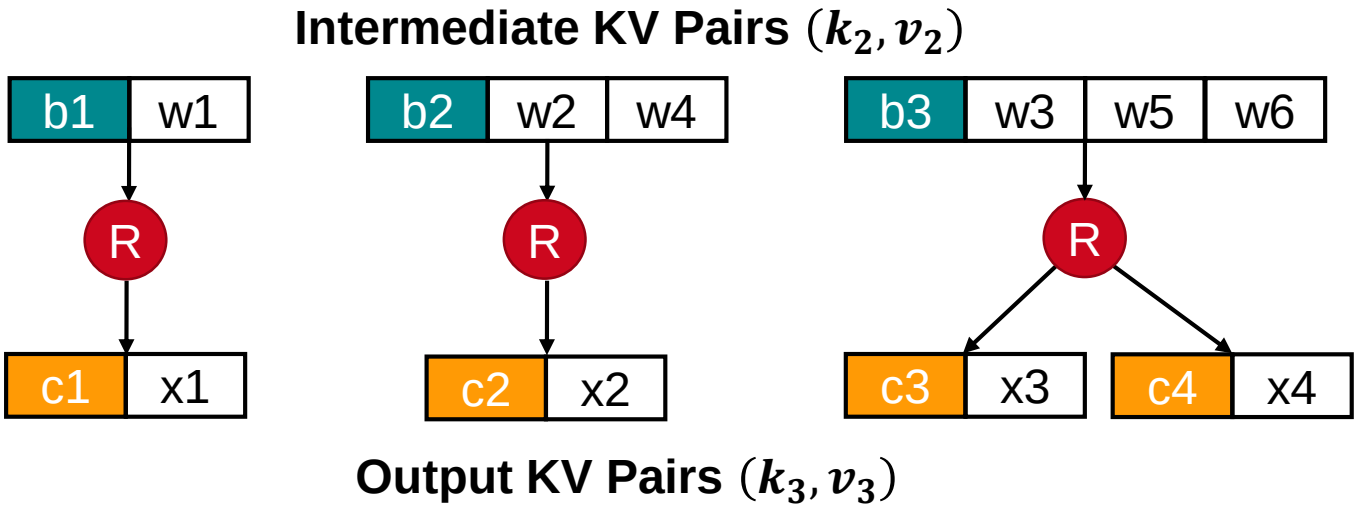


Reduce Function

- **Given:** Intermediate KV pairs grouped by k_2: $(k_2, list(v_2))$
- **Reduce:** Gets intermediate key k_2 with list of values v_2 associated with k_2 and produces a list of reduced output KV pairs (k_3, v_3)

$$Reduce\big(k_2, list(v_2)\big) \rightarrow list(k_3, v_3)$$

- Often: $k_2 = k_3$ (i.e., types are the same) and output list size is 1
- Typical Reduce functions: sum, maximum, minimum of values



Reduce Function – Word Count

- Reduce function general form: $Reduce\big(k_2, list(v_2)\big) \rightarrow list(k_3, v_3)$
- Signature for Word Count: $Reduce(\text{String}, list(\text{int})) \rightarrow list(\text{String}, \text{int})$
- Pseudocode:

```
Reduce(String key, Iterator values):
    // key: a word
    // values: list of counts
    int sum = 0
    for each v in values:
        sum += v
    Emit(key, sum)
```

- Examples:
  - $Reduce$("text", [1, 1, 1]) = [("text", 3)]
  - $Reduce$("this", [1]) = [("this", 1)]

Reduce Function – Word Count