

# **Combiners in MapReduce**

# MapReduce Job Components

- Input path (set of directories and files)
- Output path (output directory)
- `map()` function
- `reduce()` function
- `combine()` [OPTIONAL]

# MapReduce Job Components

- **map()** function
  - accept a (key, value)
  - convert (key, value) to a set of (key2, value2) pairs
- **reduce()** function
  - accept (key2, [V\_1, V\_2, ..., V\_n])
  - convert (key2, [V\_1, V\_2, ..., V\_n])  
to a set of (key3, value3) pairs

# Typical MapReduce Job

A typical MapReduce job has two functions:

- `map ()`
- `reduce ()`

But you can further optimize the output of mappers by adding a combiner function (works very similar to the `reduce ()` function):

- `combine ()`

# What is a Combiner?

- `combine()` [OPTIONAL]
- **Combiner** is also known as “**Mini-Reducer**” that summarizes the mappers output with the same key before passing to the Reducer.
- The primary job of Combiner is to process the output data from the mappers, before passing it to reducer.
- The `combine()` function runs after the mapper and before the reducer

# Informal Example

- **Mappers output:**

Partition-1: (K, v1), (K, v2), (K, v3)

Partition-2: (K, t1), (K, t2), (K, t3), (K, t4)

Rather than sending (K, [v1, v2, v3, t1, t2, t3, t4])  
to a reduce() function, we can send (K, [V, T])

Where:

V = combine([v1, v2, v3])

T = combine([t1, t2, t3, t4])

# Informal Example

- Mappers output:

Partition-1: (K, v1), (K, v2), (K, v3)

Partition-2: (K, t1), (K, t2), (K, t3), (K, t4)

Rather than sending (K, [v1, v2, v3, t1, t2, t3, t4]) to a reduce() function,  
we can send (K, [V, T])

where

$V = \text{combine}([v1, v2, v3])$

$T = \text{combine}([t1, t2, t3, t4])$

Note that you have to guarantee 4 properties:

1.  $\text{Type}(V) = \text{Type}(v1) = \text{Type}(v2) = \text{Type}(v3)$
2.  $\text{Type}(T) = \text{Type}(t1) = \text{Type}(t2) = \text{Type}(t3) = \text{Type}(t4)$
3. **combine()** MUST be a **commutative** function.
4. **combine()** MUST be an **associative** function.

# Combiner Example: find sum of values per key

- **Mappers output:**

Partition-1: (K, 2), (K, 3), (K, 4)

Partition-2: (K, 5), (K, 6), (K, 7), (K, 8)

Rather than sending (K, [2, 3, 4, 5, 6, 7, 8]) to a reduce() function, we can send (K, [9, 26]), where

9 = combine([2, 3, 4])

26 = combine([5, 6, 7, 8])

Note the the addition (+) is a commutative and an associative function.



# What about Combiners?

**Combiner** is also known as “**Mini-Reducer**” that summarizes the mapper output record with the **same Key** before passing to the Reducer.

Mappers → Combiners → Reducers

# Combiner Example

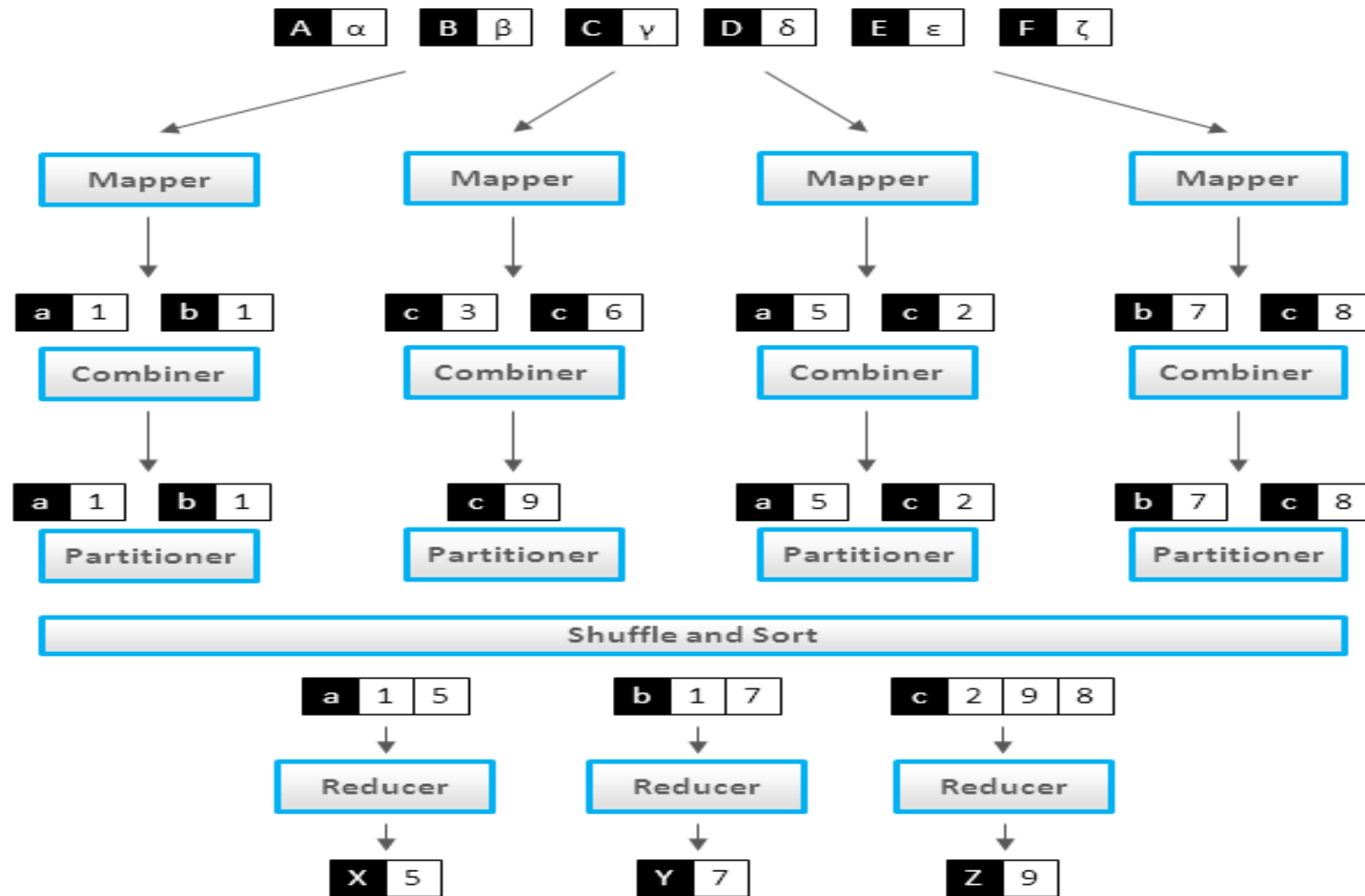
In the following figure (next slide), for the 2<sup>nd</sup> partition, mappers have created:

$(c, 3)$

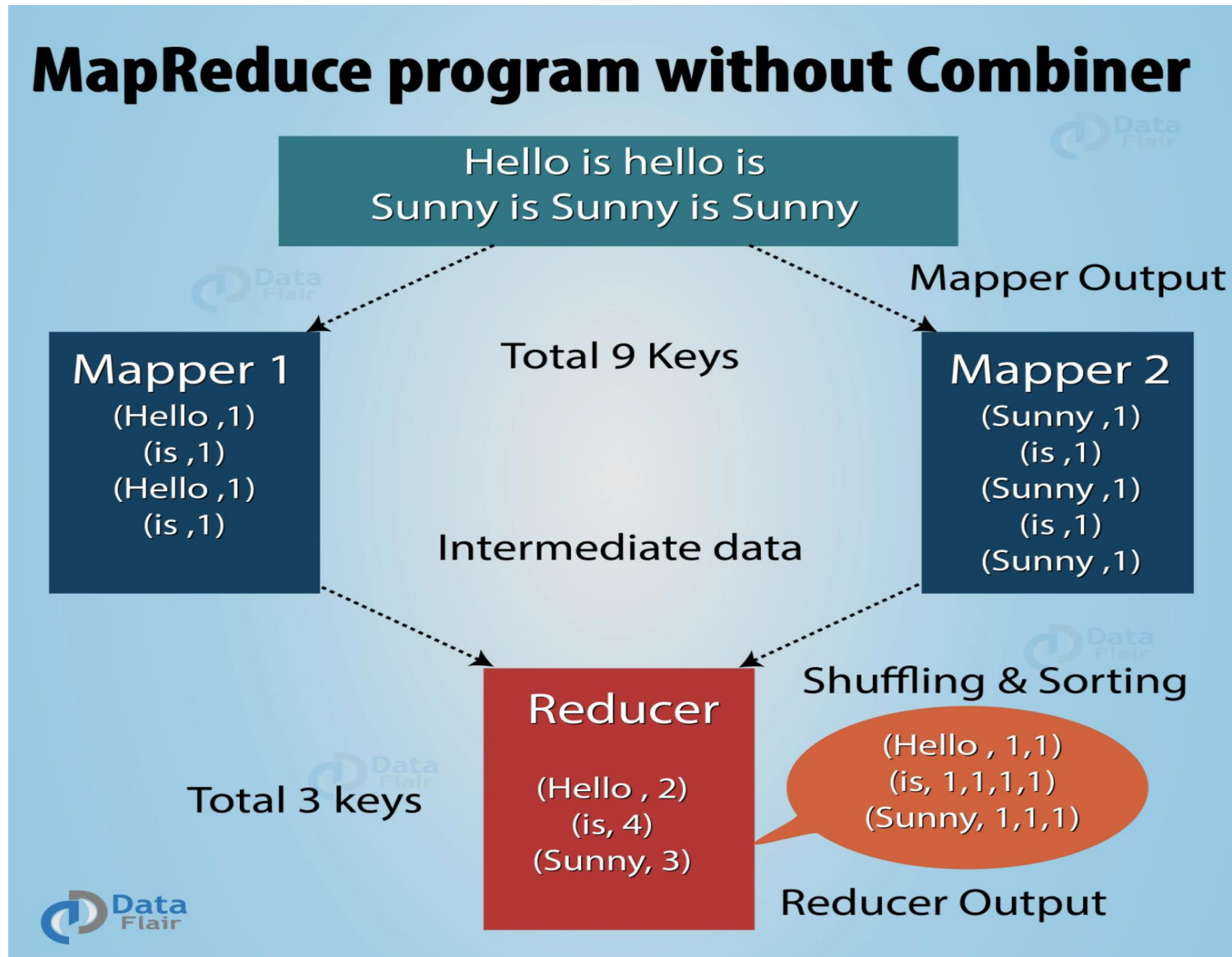
$(c, 6)$

The combiner function combines these two (with the SAME key as “c”) into  $(c, 9)$ , where  $9 = 3 + 6$

# What about Combiners?



# MapReduce without Combiners



# Combiner Example

In the following figure (next slide),

Mapper 1

(Hello, 1)

(Hello, 1)

Mapper 2

(Sunny, 1)

(Sunny, 1)

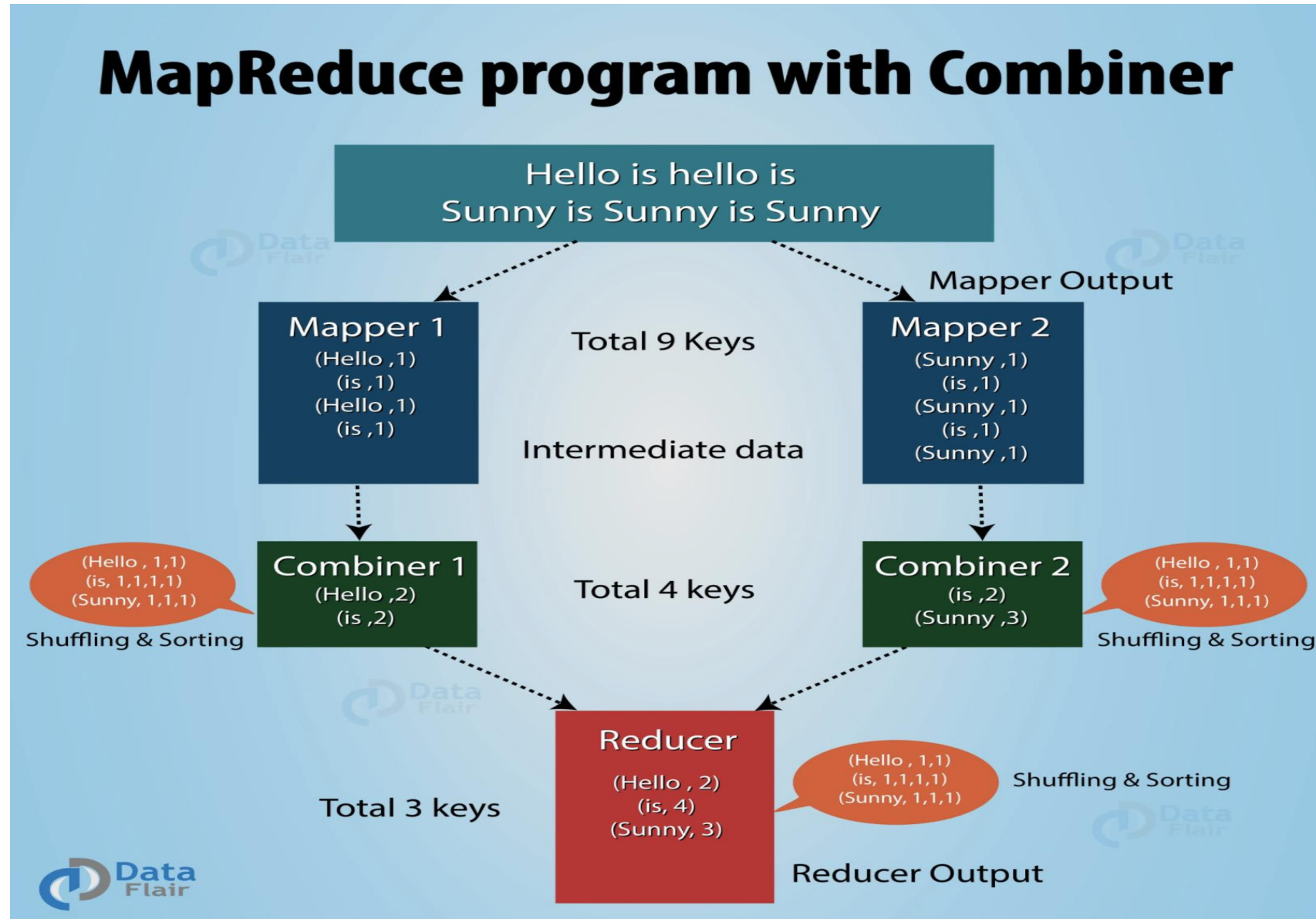
(Sunny, 1)

The combiner function combines these two into

(Hello, 2)

(Sunny, 3)

# MapReduce with Combiners



# EXAMPLE-1: Find Sum of Values per Key

## Solution-1: Without Combiners

- `map()`
- `reduce()`

## Solution-2: With Combiners

- `map()`
- `combine()`
- `reduce()`

## EXAMPLE-1: Find Sum of Values (ratings) per Key (movie\_id)

### Solution-1: Without Combiners

```
# K: record number: ignored
# V: record as "<movie_id><,><rating>"
map(K, V) {
    tokens = V.split(",")
    movie_id = tokens[0]
    rating = int(tokens[1])
    emit (movie_id, rating)
}
```



## EXAMPLE-1: Find Sum of Values (ratings) per Key (movie\_id)

### Solution-1: Without Combiners

Sort & Shuffle phase will produce:

(movie\_id\_1, [2, 4, 5, 1, 1, 3])

(movie\_id\_2, [1, 1, 3, 5])

(movie\_id\_3, [1, 1, 1, 1, 2, 2])

...

## EXAMPLE-1: Find Sum of Values (ratings) per Key (movie\_id)

### Solution-1: Without Combiners

```
# K: a unique movie_id
# V: [v_1, v_2, ..., v_n] (all ratings for K)
# V denotes all ratings for K (a unique
movie_id)
reduce(K, V) {
    sum_of_ratings = sum(V)
    emit (K, sum_of_ratings)
}
```

# EXAMPLE-1: Find Sum of Values per Key

## Solution-2: With Combiners

- `map()`
- `combine()`
- `reduce()`

## EXAMPLE-1: Find Sum of Values (ratings) per Key (movie\_id)

### Solution-2: With Combiners

```
# K: record number: ignored
# V: record as "<movie_id><,><rating>"
map(K, V) {
    tokens = V.split(",")
    movie_id = tokens[0]
    rating = int(tokens[1])
    emit (movie_id, rating)
}
```

## EXAMPLE-1: Find Sum of Values (ratings) per Key (movie\_id)

### Solution-2: With Combiners

combine() function combines output of mappers per worker node for the same key:

```
# K: a unique movie_id
# V: [v_1, v_2, ..., v_n]
# V denotes all ratings for K
combine(K, V) {
    sum_of_ratings = sum(V)
    emit (K, sum_of_ratings)
}
```

## EXAMPLE-1: Find Sum of Values (ratings) per Key (movie\_id)

### Solution-2: With Combiners

`reduce():` reducer function

```
# K: a unique movie_id
# V: [v_1, v_2, ..., v_n]
# V denotes all ratings for K
reduce(K, V) {
    sum_of_ratings = sum(V)
    emit (K, sum_of_ratings)
}
```

# How do we write Combiners? For Averages?

We need to write 3 functions:

- `map()`
- `combine()`
- `reduce()`
- **BUT Note that**
  - “average of an average is not an average”
- What does this mean?

# Average of an Average is not an Average

- Let say we have 2 partitions
- Partition-1: (K, 6), (K, 7)
  - Average of Partition-1:  $(6+7)/2 = 6.5$
- Partition-2: (K, 8)
  - Average of Partition-2:  $(8)/1 = 8.0$
- Average of Partition-1 and Partition-2:
  - $(6.5 + 8.0)/2 = 7.25 \Rightarrow$  NOT CORRECT

$$\text{Average}(6, 7, 8) = (6+7+8)/3 = 21/3 = 7.0$$

Hmmmmmm? How to solve this?



## Make Average of an Average as an Average By Changing Output of Mappers

- Let say we have 2 partitions
- Partition-1: (K, 6), (K, 7)
- Partition-2: (K, 8)
- $(K, V) \rightarrow (K, (V, 1))$
- Change map() to create (K, (sum, count))
- (K, 6) --> (K, (6, 1))
- (K, 7) --> (K, (7, 1))
- (K, 8) --> (K, (8, 1))

# Make Average of an Average as an Average

- Let say we have 2 partitions:
- Partition-1:  $(K, (6, 1)), (K, (7, 1))$
- Partition-2:  $(K, (8, 1))$
- Average(Partition-1):  $(K, (6+7, 1+1)) = (K, (13, 2))$
- Average(Partition-2):  $(K, (8, 1))$
- **Average(Partition-1, Partition-2) =**  
 $(K, (13+8, 2+1)) =$   
 $(K, (21, 3)) =$   
 $(K, (\text{sum}, \text{count}))$   
 $\Rightarrow (K, 21/3) = (K, 7)$

# Sample output of Mappers

- Let say we have 2 partitions:
  - Partition-1: (K, (6, 1)), (K, (7, 1))
  - Partition-2: (K, (8, 1))
- combine(Partition-1): (K, (6+7, 1+1)) = (K, (13, 2))
- combine(Partition-2): (K, (8, 1))

# Combine must be Associative & Commutative

## Commutative:

$$(a + b) = (b + a)$$

$$F(a, b) = F(b, a)$$

$$(sum1, count1) + (sum2, count2) = (sum2, count2) + (sum1, count1)$$

$$\begin{aligned}(sum1+sum2, count1+count2) &= (sum2+sum1, count2+count1) \\ &= (sum1+sum2, count1+count2)\end{aligned}$$

## Associative:

$$(a + (b + c)) = ((a + b) + c)$$

$$F(a, F(b, c)) = F(F(a, b), c)$$

$$\begin{aligned}(sum1, count1) + ((sum2, count2) + (sum3, count3)) &= \\ ((sum1, count1) + (sum2, count2)) + (sum3, count3)\end{aligned}$$

# What to consider for combiners & reducers

- Make their functions to be **associative** and **commutative**:
- Let + be a binary function

- **Commutative Laws**

$$a + b = b + a$$

- **Associative Laws**

$$(a + b) + c = a + (b + c)$$

# Commutative Example

- Addition is commutative
  - $2 + 3 = 3 + 2 = 5$
  - $100 + 200 = 200 + 100 = 300$
- Multiplication is commutative
  - $2 * 5 = 5 * 2 = 10$
  - $20 * 30 = 30 * 20$

# Subtraction and Division is NOT Commutative

## Subtraction

- $F(a, b) \neq F(b, a)$
- $5 - 3 = 2$
- $3 - 5 = -2$
- 2 NOT EQUAL to -2

## Division

- $10 / 2 = 5$
- $2 / 10 = 0.2$
- 5 NOT EQUAL to 0.2

# Average function is not Associative

- $\text{Avg}(1, 2, 3) = 2.0$
- $\text{Avg}(1, \text{Avg}(2, 3)) = \text{Avg}(1, 2.5) = 1.75$
- 2.0 NOT EQUAL to 1.75



# References

1. Monoidify! Monoids as a Design Principle for Efficient MapReduce Algorithms by Jimmy Lin
2. Data Algorithms (book) by Mahmoud Parsian
3. Data Algorithms with Spark (book) by Mahmoud Parsian