Introduction to MapReduce

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Adopted from Jimmy Lin's slides (at UMD)

Typical Large-Data Problem

Map

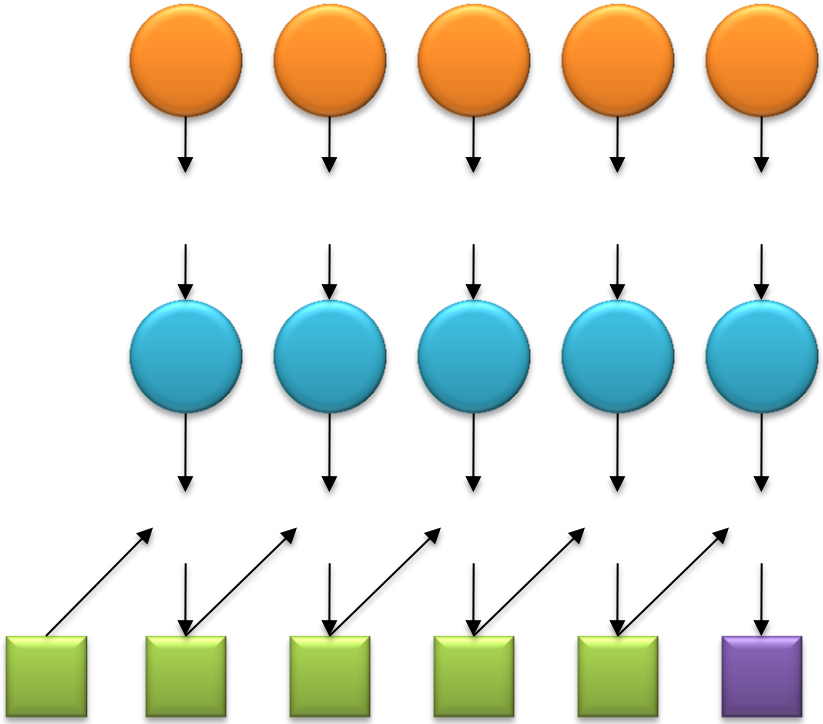
- Iterate over a large number of records
- Extract something of interest from each
- Shuffle and sort intermediate results

Reduce

- Aggregate intermediate results
- Generate final output

Key idea: provide a functional abstraction for these two operations

Roots in Functional Programming



MapReduce

- Programmers specify two functions:

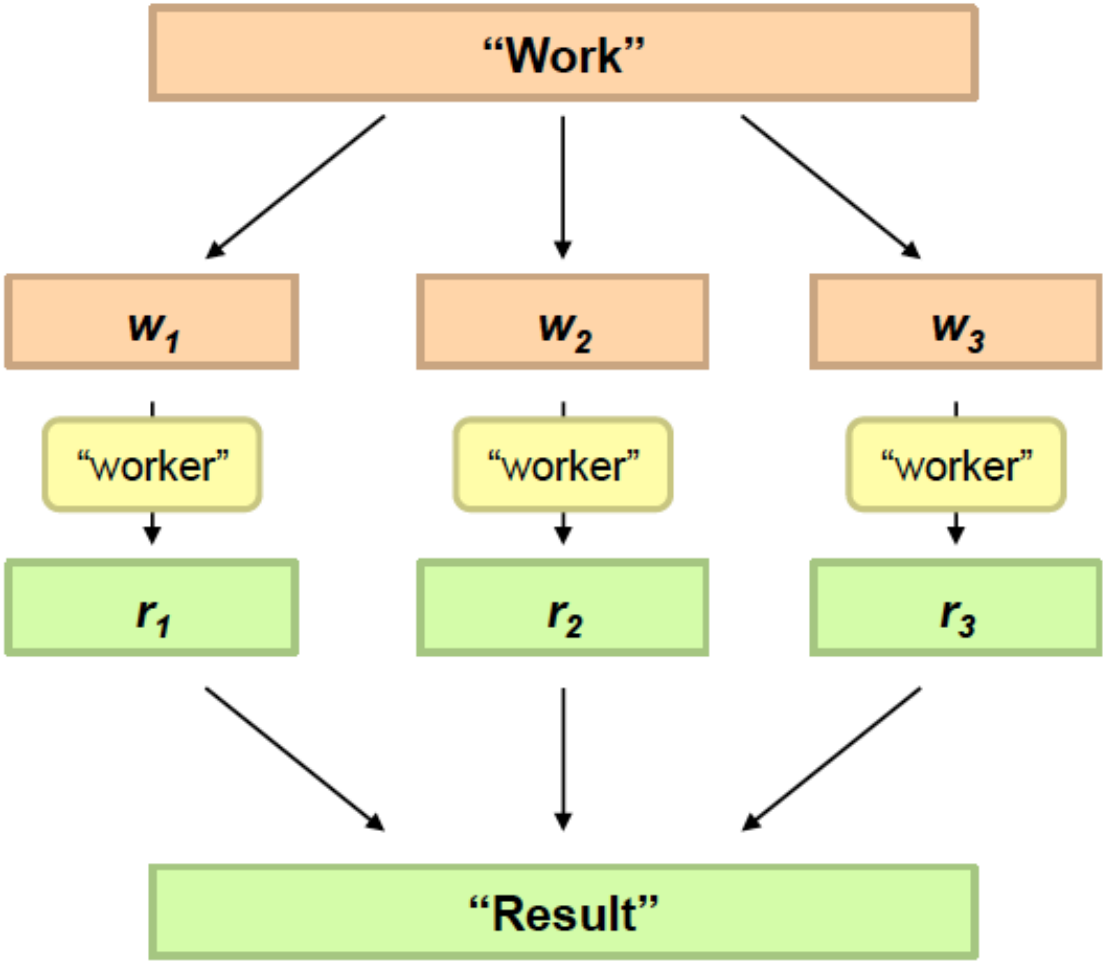
  map (k, v) → [(k', v')]

  reduce (k', [v']) → [(k', v')]

  – All values with the same key are sent to the same reducer

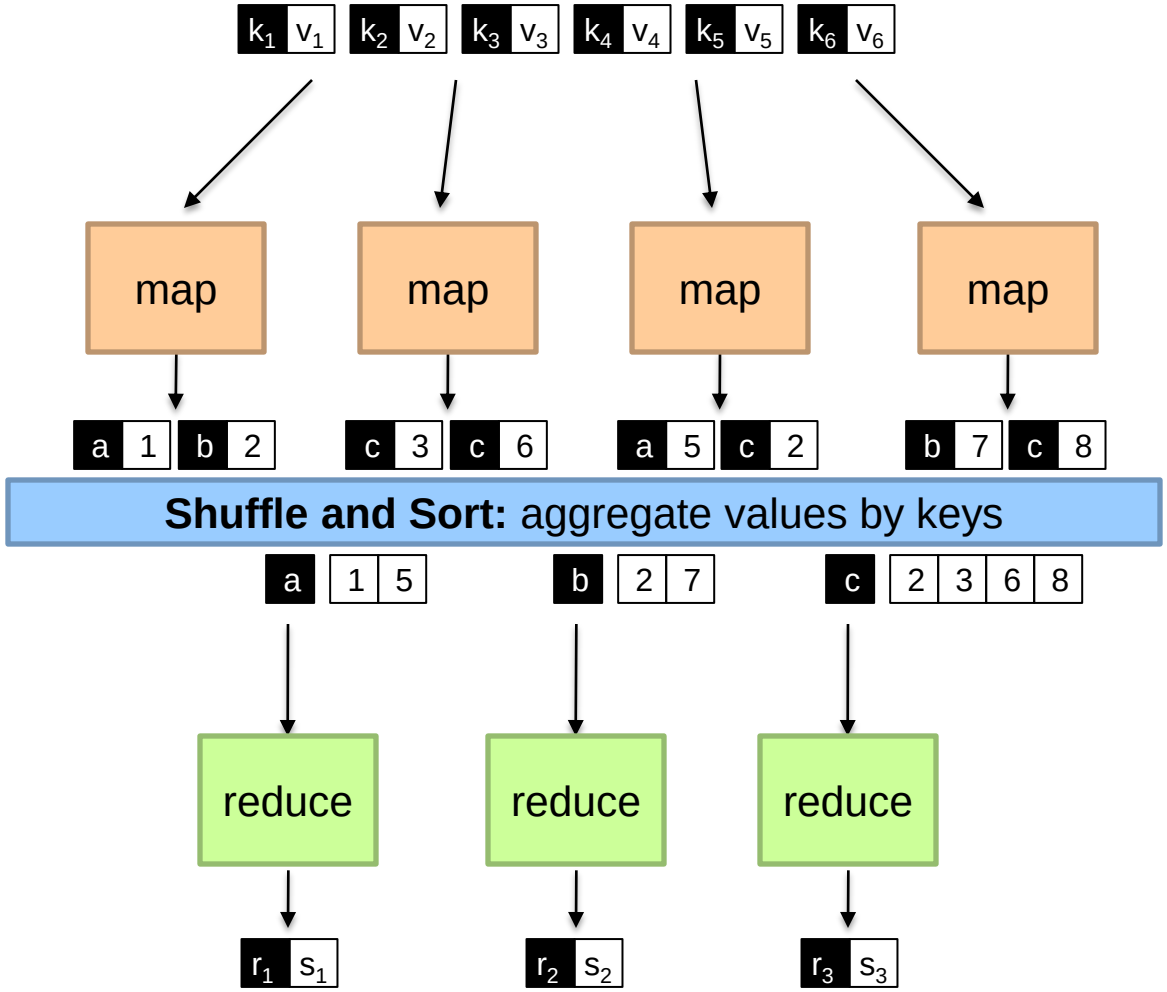
- The execution framework handles everything else…

Divide and Conquer



Divide Work

Combine Results


k1 v1
k2 v2
k3 v3
k4 v4
k5 v5
k6 v6
map
map
map
map
a 1
b 2
c 3
c 6
a 5
c 2
b 7
c 8
Shuffle and Sort: aggregate values by keys
a 1 5
b 2 7
c 2 3 6 8
reduce
reduce
reduce
r1 s1
r2 s2
r3 s3

MapReduce

- Programmers specify two functions:

  map (k, v) → <k', v'>*

  reduce (k', v') → <k', v'>*

  – All values with the same key are sent to the same reducer

- The execution framework handles everything else…

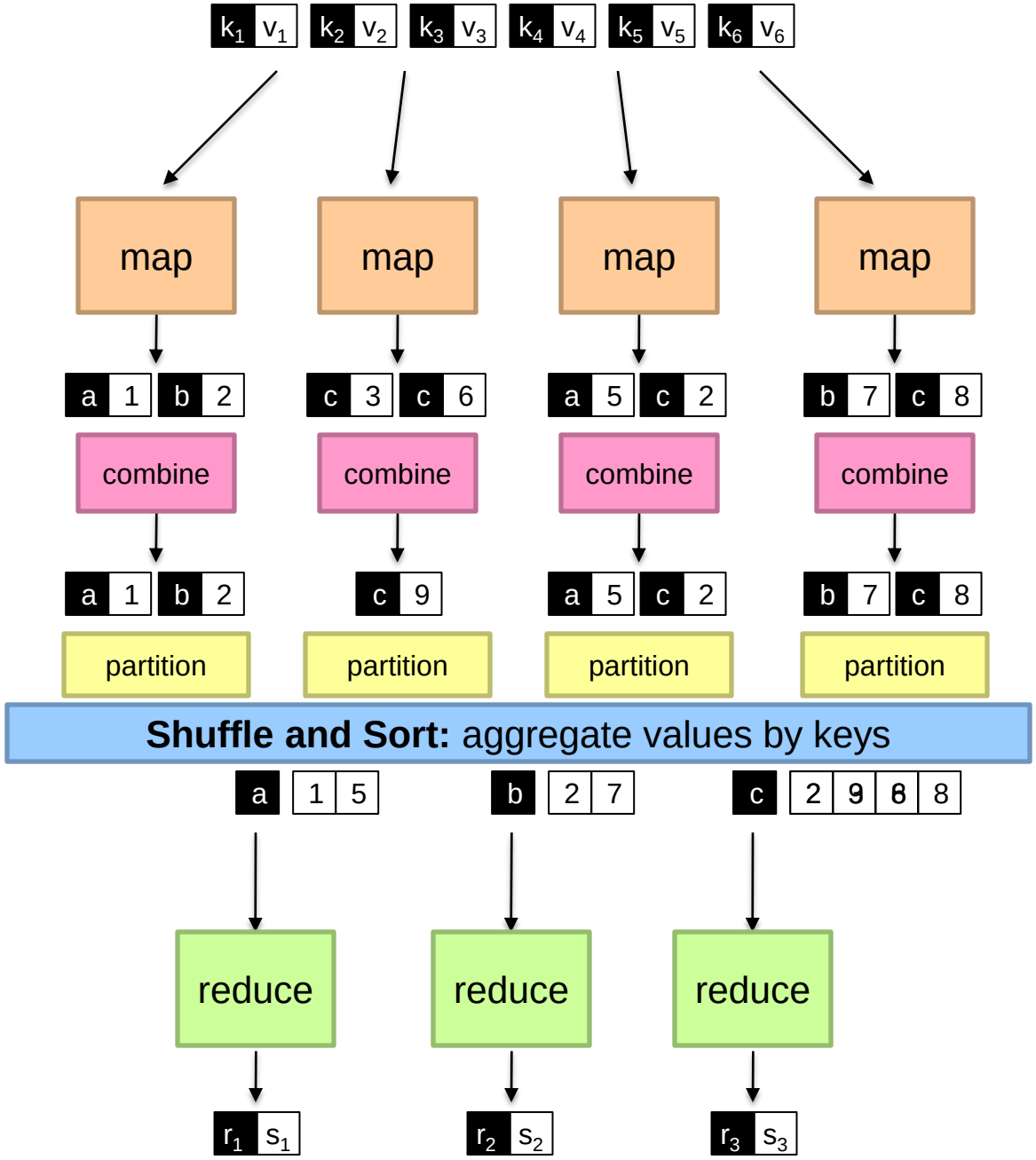
What's "everything else"?

MapReduce “Runtime”

- Handles scheduling
  - Assigns workers to map and reduce tasks
- Handles “data distribution”
  - Moves processes to data
- Handles synchronization
  - Gathers, sorts, and shuffles intermediate data
- Handles errors and faults
  - Detects worker failures and restarts
- Everything happens on top of a distributed FS (later)

MapReduce

- Programmers specify two functions:
  map (k, v) → [(k', v')]
  reduce (k', [v']) → [(k', v')]
  – All values with the same key are reduced together
- The execution framework handles everything else…
- Not quite…usually, programmers also specify:
  partition (k', number of partitions) → partition for k'
  – Often a simple hash of the key, e.g., hash(k') mod n
  – Divides up key space for parallel reduce operations
  combine (k', [v']) → [(k', v'')]
  – Mini-reducers that run in memory after the map phase
  – Used as an optimization to reduce network traffic


k1 v1
k2 v2
k3 v3
k4 v4
k5 v5
k6 v6
map
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a 1
b 2
c 3
c 6
a 5
c 2
b 7
c 8
combine
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Shuffle and Sort: aggregate values by keys
a 1 5
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reduce
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r1 s1
r2 s2
r3 s3

Two more details…

- Barrier between map and reduce phases
  - But we can begin copying intermediate data earlier
- Keys arrive at each reducer in sorted order
  - No enforced ordering *across* reducers

MapReduce can refer to…

- The programming model
- The execution framework (aka “runtime”)
- The specific implementation

Usage is usually clear from context!

Map--Reduce Code

- `main()` method
- `Job` object –Collects up all the specs for the job
  - Where is the JAR file to distribute?
  - Type of the output pair
  - `Mapper` and `Reducer` classes
  - Input and output file formats
  - Input file(s), output directory

- Configuration object – forwarded to `map()`, `reduce()`
  - Job level parameters communicated via this object

Map--Reduce Code

- MapClass
  - Extends `Mapper`, declaring the input and output pair types for the `map()` method

- `map()` method
  - Arguments: input pair, and the `Context`
  - Output done via the context object

Map--Reduce Code

- ReduceClass
  - Extends `Reducer`, declaring the input and output pair types for the `reduce()` method

- `reduce()` method
  - Arguments: input pair, and the `Context`
  - Output done via the context object

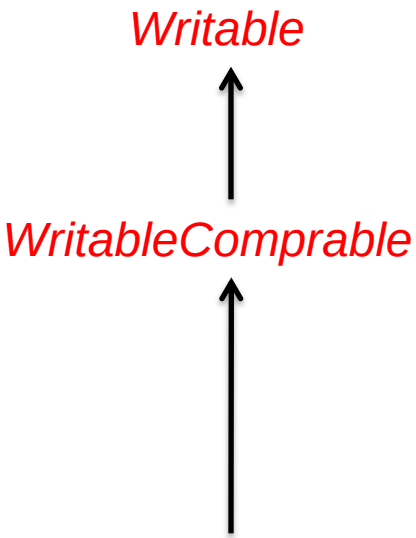
Map--Reduce Code

- `map()` and `reduce()` input pair and output pair types
- Derived from `Writable`
  - `readFields(DataInput in)`
  - `write(DataOutput out)`

- `Text`, `IntWritable`, `LongWritable` all implement `Writable`
  - As do many other types, some of which we will use

- Possible to design your own class that implements `Writable`

Data Types in Hadoop: Keys and Values



Defines a de/serialization protocol. Every data type in Hadoop is a Writable.

Defines a sort order. All keys must be of this type (but not values).

Concrete classes for different data types.

Binary encoded of a sequence of key/value pairs

“Hello World”: Word Count

```
Map(String docid, String text):
    for each word w in text:
        Emit(w, 1);

Reduce(String term, Iterator<Int> values):
    int sum = 0;
    for each v in values:
        sum += v;
        Emit(term, value);
```

Example Word Count (Map)

```
public static class TokenizerMapper
     extends Mapper<Object, Text, Text, IntWritable>{

  private final static IntWritable one = new IntWritable(1);
  private Text word = new Text();

  public void map(Object key, Text value, Context context
                  ) throws IOException, InterruptedException {
    StringTokenizer itr = new StringTokenizer(value.toString());
    while (itr.hasMoreTokens()) {
      word.set(itr.nextToken());
      context.write(word, one);
    }
  }
}
```

Example Word Count (Reduce)

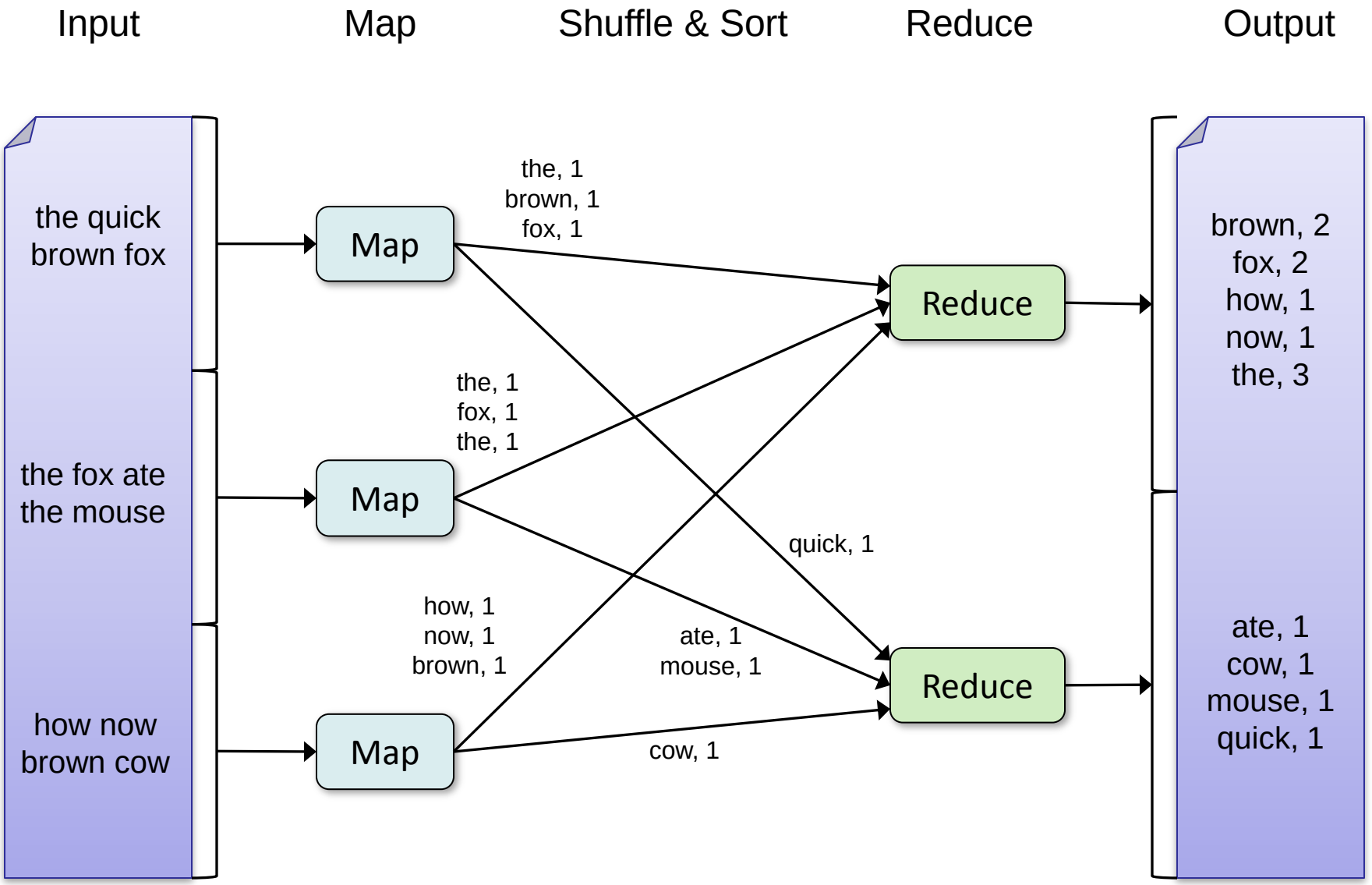
```
public static class IntSumReducer
     extends Reducer<Text,IntWritable,Text,IntWritable> {
  private IntWritable result = new IntWritable();

  public void reduce(Text key, Iterable<IntWritable> values,  Context context )
                              throws IOException, InterruptedException {
    int sum = 0;
    for (IntWritable val : values) {
      sum += val.get();
    }
    result.set(sum);
    context.write(key, result);
  }
}
```

Example Word Count (Driver)

```
public static void main(String[] args) throws Exception {
  Configuration conf = new Configuration();
  String[] otherArgs = new GenericOptionsParser(conf,
    args).getRemainingArgs();
   if (otherArgs.length != 2) {
    System.err.println("Usage: wordcount <in> <out>");
    System.exit(2);
     }
  Job job = new Job(conf, "word count");
  job.setJarByClass(WordCount.class);
  job.setMapperClass(TokenizerMapper.class);
  job.setCombinerClass(IntSumReducer.class);
  job.setReducerClass(IntSumReducer.class);
  job.setOutputKeyClass(Text.class);
  job.setOutputValueClass(IntWritable.class);
  FileInputFormat.addInputPath(job, new Path(otherArgs[0]));
  FileOutputFormat.setOutputPath(job, new Path(otherArgs[1]));
  System.exit(job.waitForCompletion(true) ? 0 : 1);
 }
```

Word Count Execution



An Optimization: The Combiner

- A combiner is a local aggregation function for repeated keys produced by same map
- Combines multiple outputs from a Mapper before shuffle
- For associative ops. like sum, count, max
- Decreases size of intermediate data

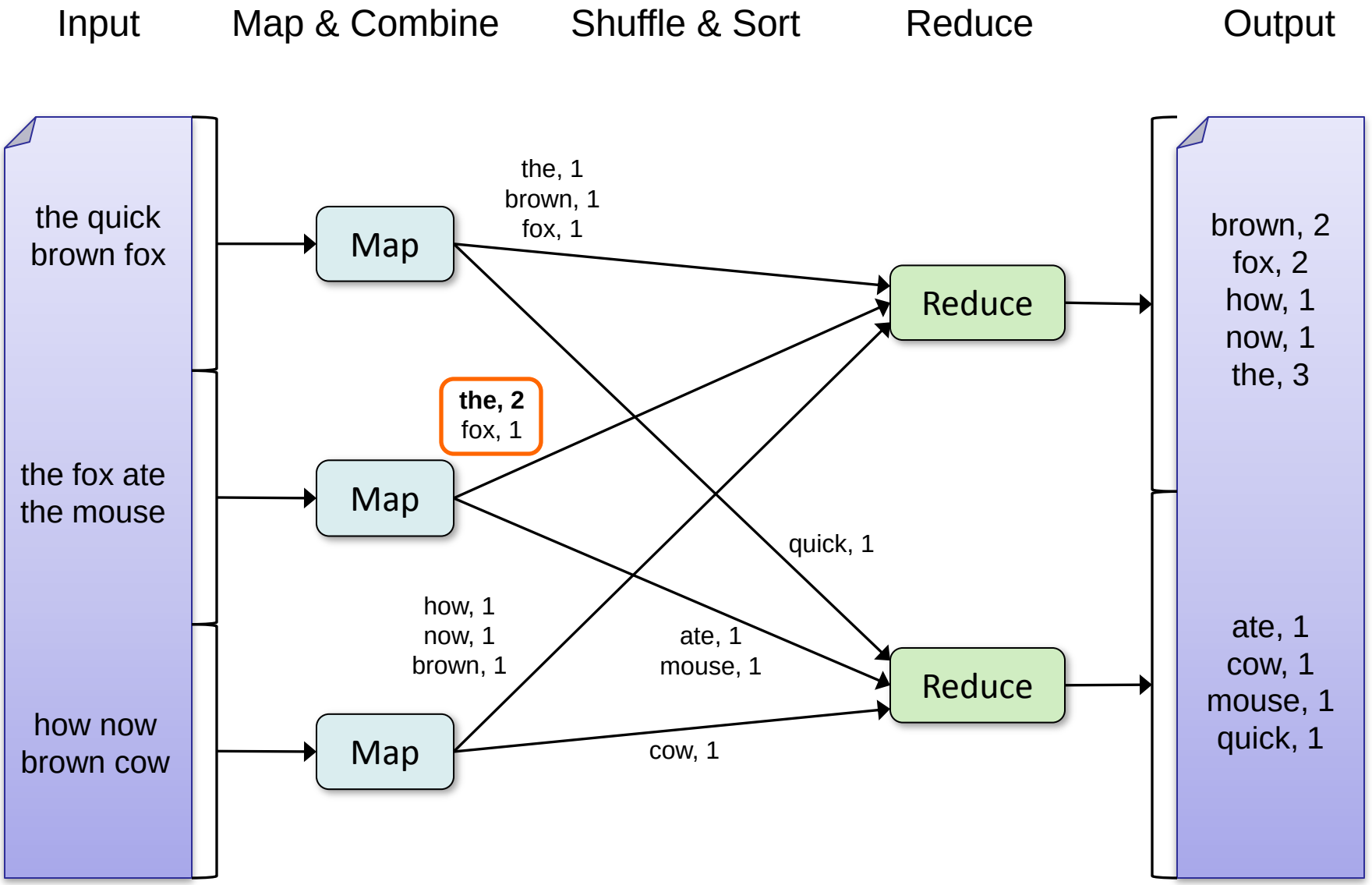
- Example: local counting for Word Count:

```
def combiner(key, values):
  output(key, sum(values))
```

Combiner

- Input and output pair types must be the same.
  - Why?
- When can a combiner be used?
  - Map output can be processed (“combined”) even through we do not see all values associated with the key
  - Combiner output can be interpreted by reducer
  - Word count, and many other counting applications can use a combiner.

Word Count with Combiner

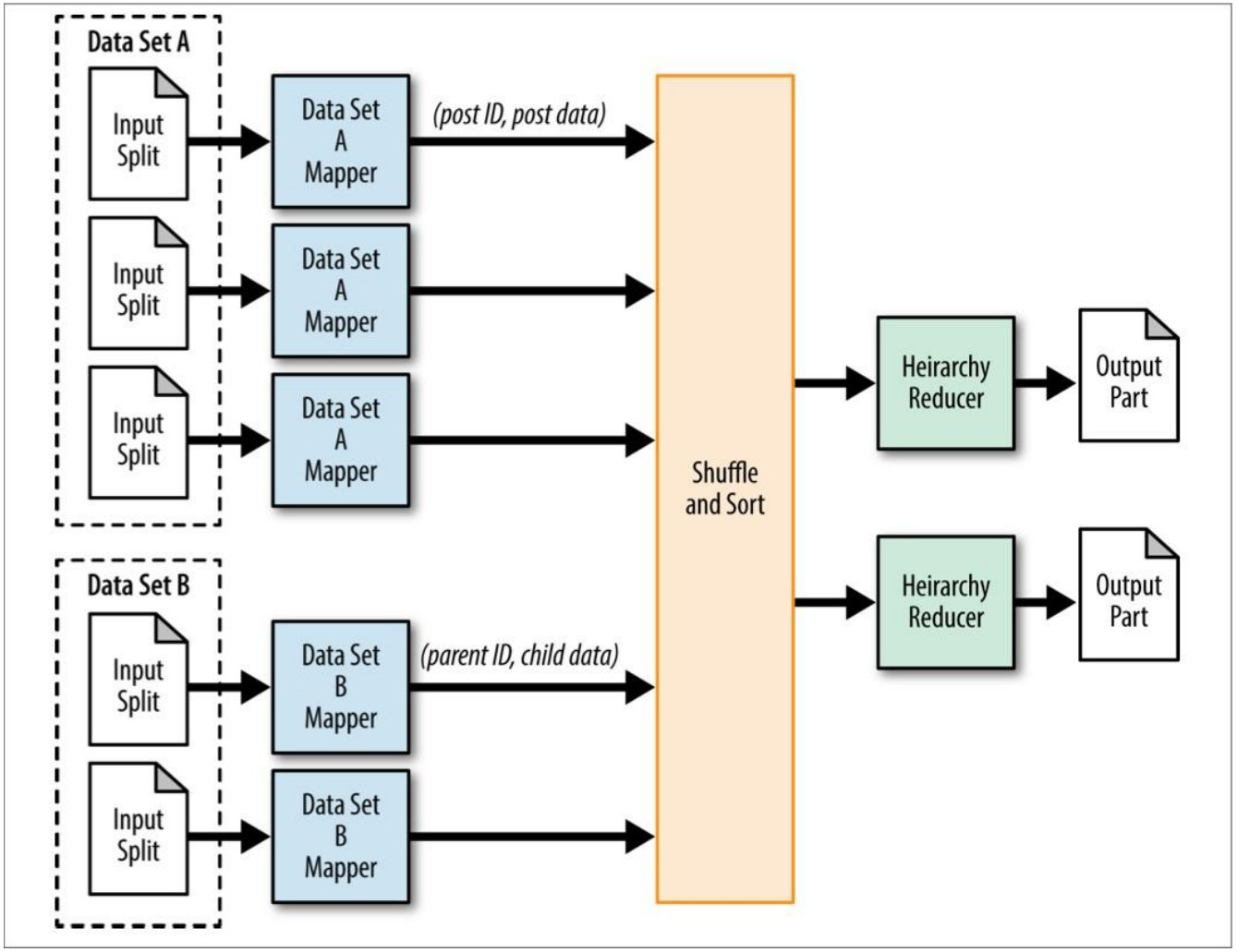


Multiple Inputs

- It is possible to define multiple mappers
- Each mapper can read a different input format
- Each mapper transforms the input data to a common format for output
  - Extracts the key
  - Puts the data into a common data structure

Data Flow

Figure 4–1 from MapReduce Design Patterns



Partitioning

- Organize “similar” records into partitions

- Why?
  - Future jobs will only focus on subsets of the data
- Partitioning schemes:
  - Time: hour, day, week, month, year
  - Geography: ZIP, DMA, state, time zone, country
  - Data source: web site
  - Data type

Partitioning

- No downside, as a mapReduce job can run over all partitions if needed

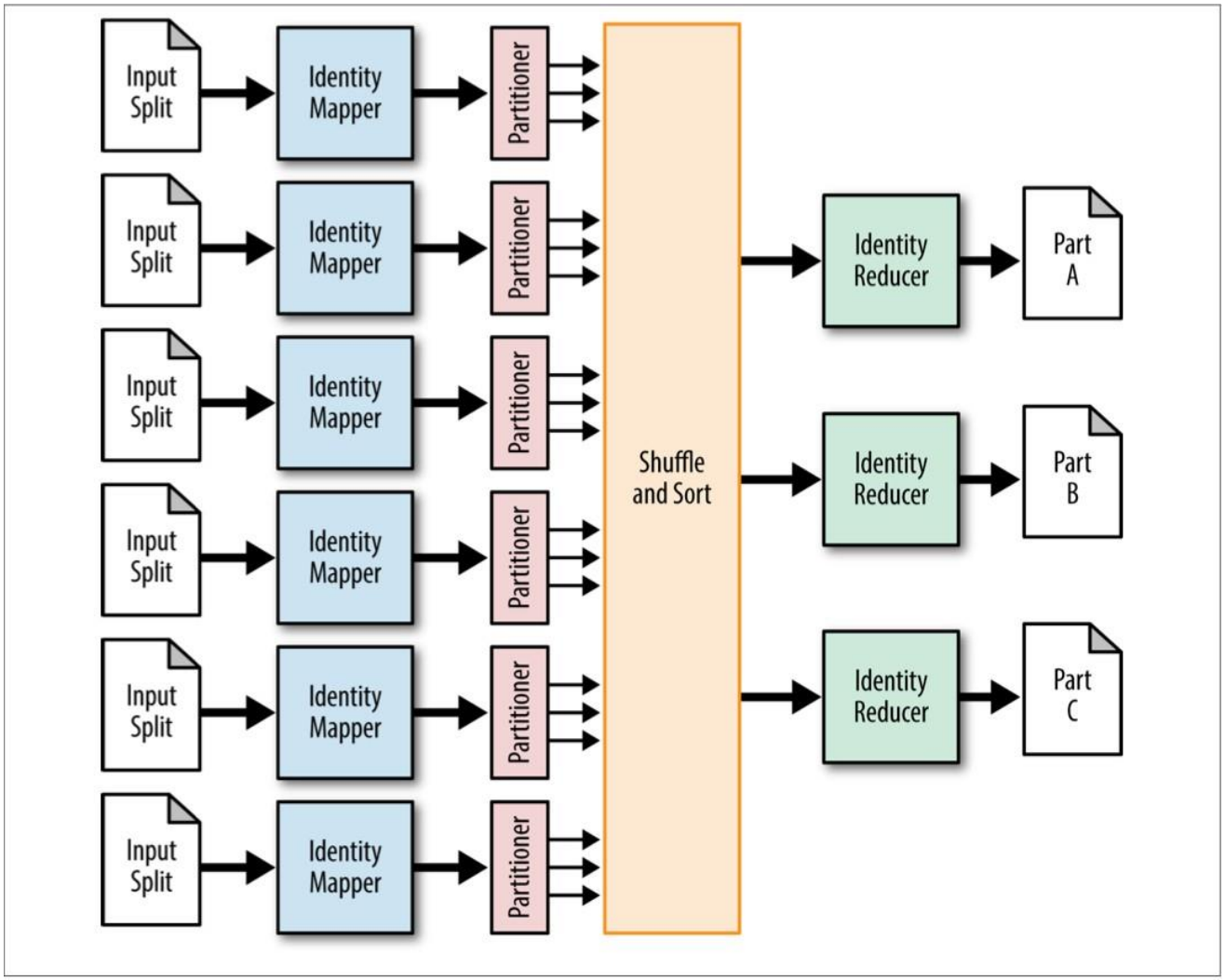
- We do need to know *a priori* how many partitions we want
  - Can run a job that scans and summarizes the data
  - Get possible values, and counts
  - Just like we did for user sessions

Partitioning

- Define a `Partitioner`
- Examines each `map()` output pair
- Computes a `partition` number

Data Flow

Figure 4-2 from MapReduce Design Patterns



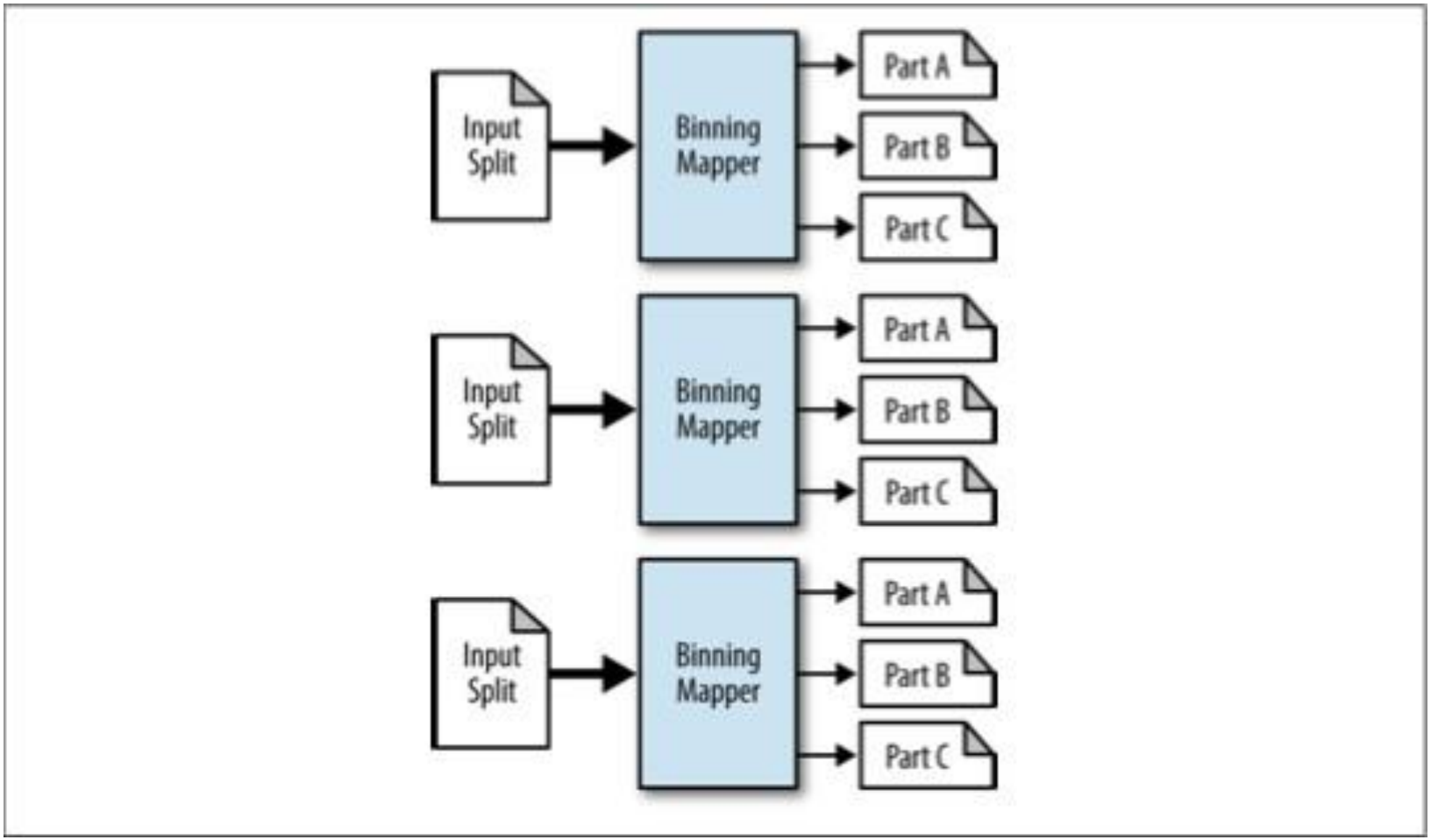
Binning

- Similar to partitioning
  - Want to organize output into categories
  - Map-only pattern (# reduce tasks set to 0)

- Mapper output written to output directories
- Uses `MultipleOutputs` class
  - Call `write()` on `MultipleOutputs`, not `Context`
  - For each category, each mapper writes a file
  - Expensive if many mappers and many categories

Binnig Data Flow

Figure 4–3 from MapReduce Design Patterns



Three Gotchas

- Avoid object creation if possible
  - Reuse Writable objects, change the payload
- Execution framework reuses value object in reducer
- Passing parameters via class statics

Getting Data to Mappers and Reducers

- Configuration parameters
  - Directly in the Job object for parameters
- “Side data”
  - DistributedCache
  - Mappers/reducers read from HDFS in setup method

Complex Data Types in Hadoop

- How do you implement complex data types?
- The easiest way:
  - Encoded it as Text, e.g., (a, b) = “a:b”
  - Use regular expressions to parse and extract data
  - Works, but pretty hack-ish
- The hard way:
  - Define a custom implementation of Writable(Comprable)
  - Must implement: readFields, write, (compareTo)
  - Computationally efficient, but slow for rapid prototyping
  - Implement WritableComparator hook for performance
- Somewhere in the middle:
  - JSON support and lots of useful Hadoop types

Debugging Hadoop

- First, take a deep breath
- Start small, start locally
- Build incrementally

Code Execution Environments

- Different ways to run code:
  - Plain Java
  - Local (standalone) mode
  - Pseudo-distributed mode
  - Fully-distributed mode

Hadoop Debugging Strategies

- Good ol' System.out.println
  - Learn to use the webapp to access logs
  - Logging preferred over System.out.println
  - Be careful how much you log!
- Fail on success
  - Throw RuntimeExceptions and capture state
- Programming is still programming
  - Use Hadoop as the "glue"
  - Implement core functionality outside mappers and reducers
  - Independently test (e.g., unit testing)
  - Compose (tested) components in mappers and reducers