BATCH PROCESSING WITH MAP REDUCE

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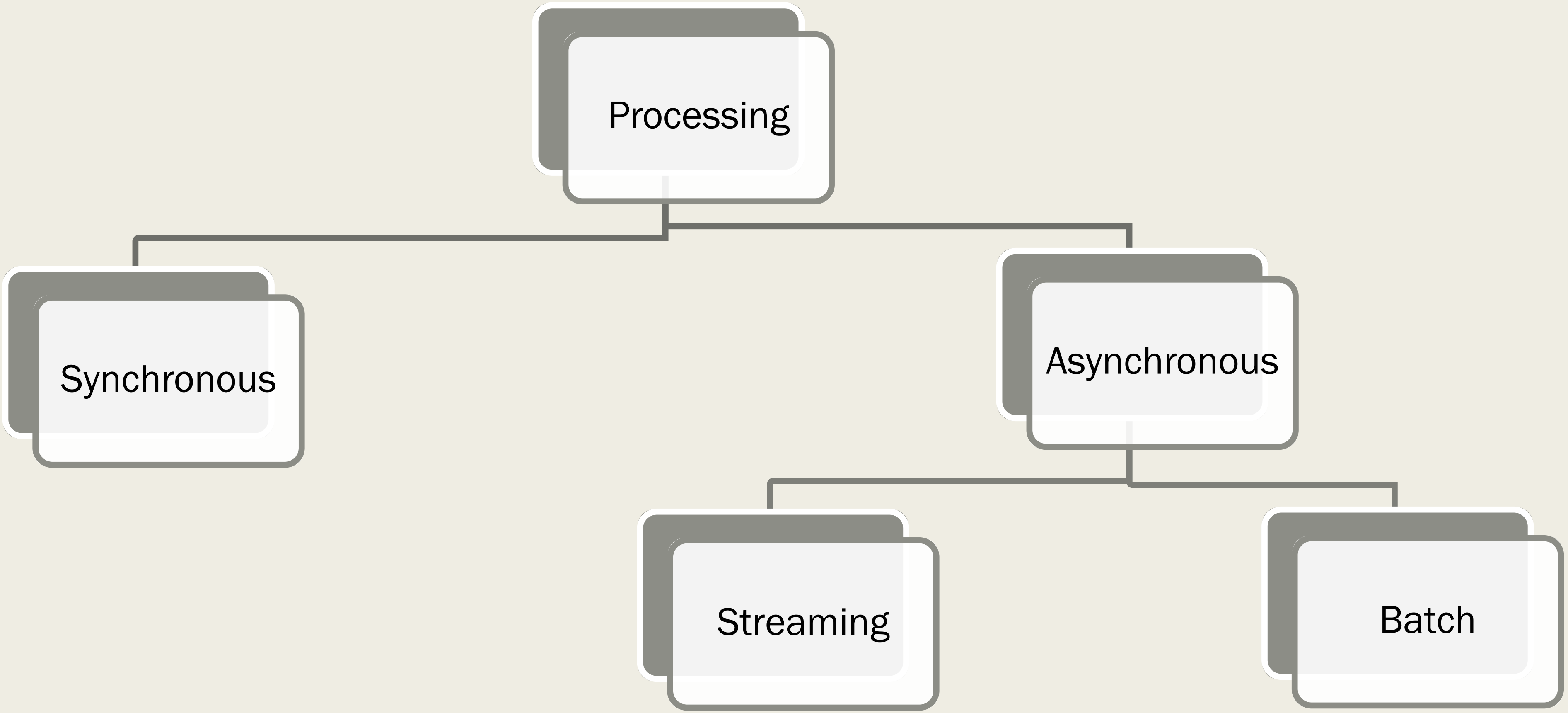
Patterns in processing



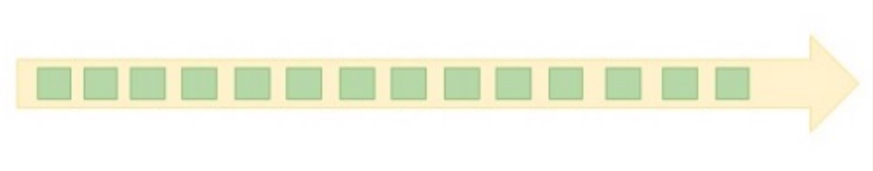
Synchronous vs Asynchronous

- Synchronous
  - *Request is processed and response sent back immediately*
  - *Client blocks for a response*

- Asynchronous
  - *Request is sent as an event/message*
  - *Client does not block*
  - *Event is put in a queue/file and processed later*
  - *Response is generated as another event*
  - *Consumer of response event can be a different service*

Data at rest Vs Data in motion

- At rest:
  - Dataset is fixed (file)
  - bounded
  - can go back and forth on the data
- In motion:
  - continuously incoming data (queue)
  - unbounded
  - too large to store and then process
  - need to process in one pass



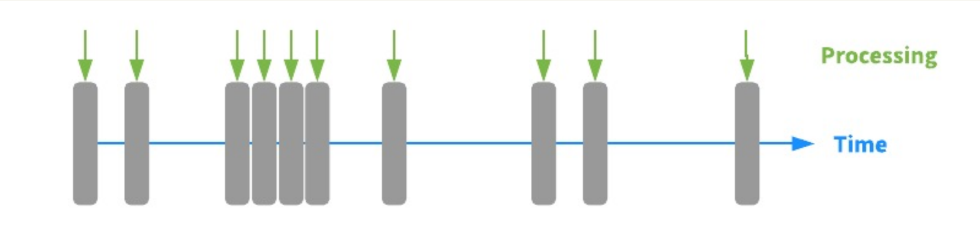
Batch processing

- Problem statement :
  - Process this entire data
  - give answer for X at the end

- Characteristics
  - Access to entire data
  - Split decided at the launch time.
  - Capable of doing complex analysis (e.g. Model training)
  - Optimize for Throughput (data processed per sec)
- Example frameworks : Map Reduce, Apache Spark

Stream processing

- Problem statement :
  - Process incoming stream of data
  - to give answer for X at this moment.



- Characteristics
  - Results for X are based on the current data
  - Computes function on one record or smaller window.
  - Optimizations for latency (avg. time taken for a record)
- Example frameworks: Apache Storm, Apache Flink, Amazon Kinesis, Kafka, Pulsar

Batch vs Streaming

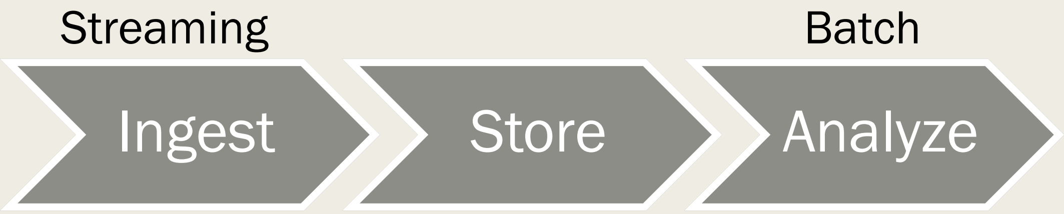
- Find stats about group in a closed room
- Analyze sales data for last month to make strategic decisions

- Finding stats about group in a marathon
- Monitoring the health of a data center

When to use Batch vs Streaming

- Batch processing is designed for ‘data at rest’. ‘data in motion’ becomes stale; if processed in batch mode.
- Real-time processing is designed for ‘data in motion’. But, can be used for ‘data at rest’ as well (in many cases).

	Simple	**Complex Iterative**
Real time	Stream	Stream/ Batch
Non real time	Stream/ Batch	Batch



Big data flow

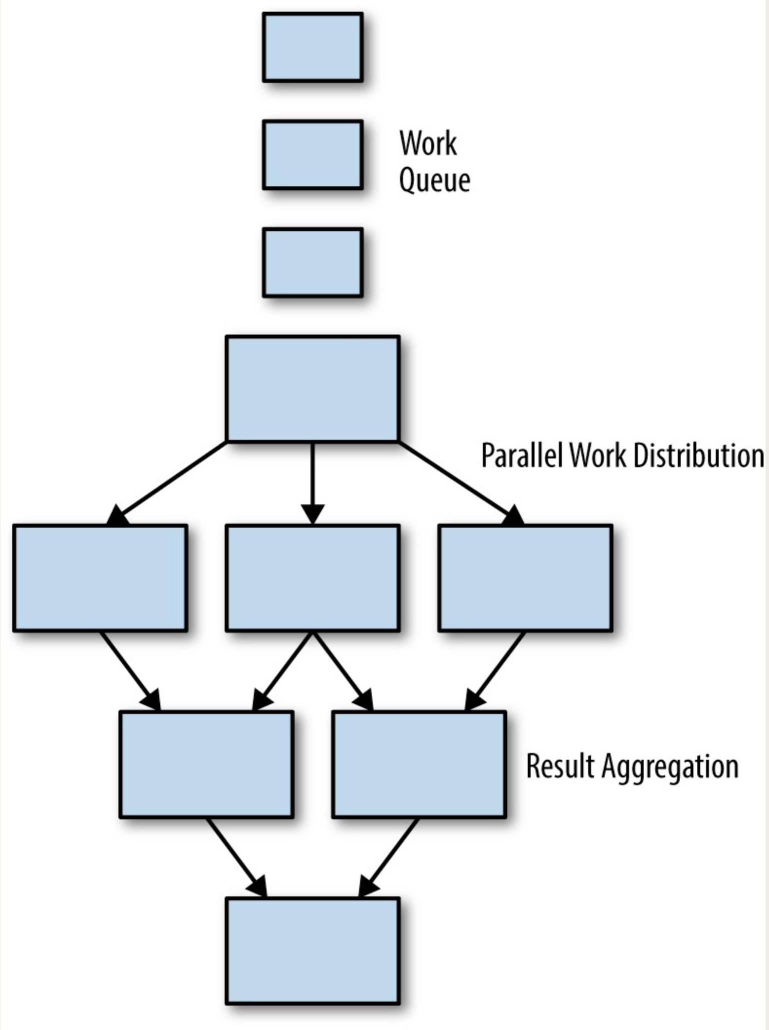
Design goals of batch processing systems

- Fast processing
  - *Data ought to be in primary storage, or even better, RAM*
- Scalable
  - *Should be able to handle growing data volumes*
- Reliable
  - *Should be able to handle failures gracefully*
- Ease of programming
  - *Right level of abstractions to help build applications*
- Low cost

➢ Need a whole ecosystem

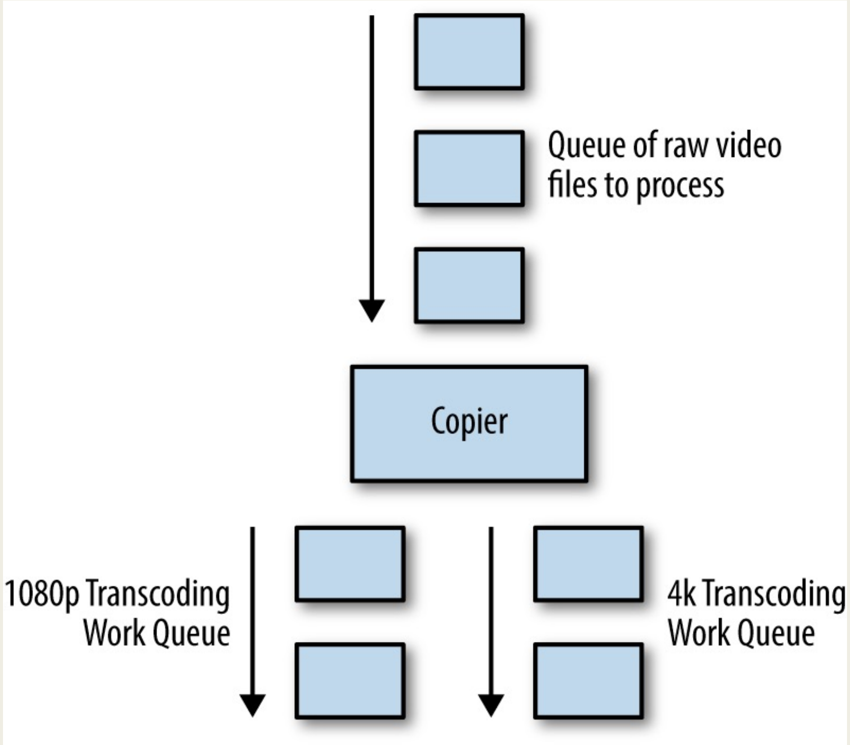
Batch processing flows

- flow of work through a directed, acyclic graph
- different operators for coordinating the flow
- Lets look at some common patterns



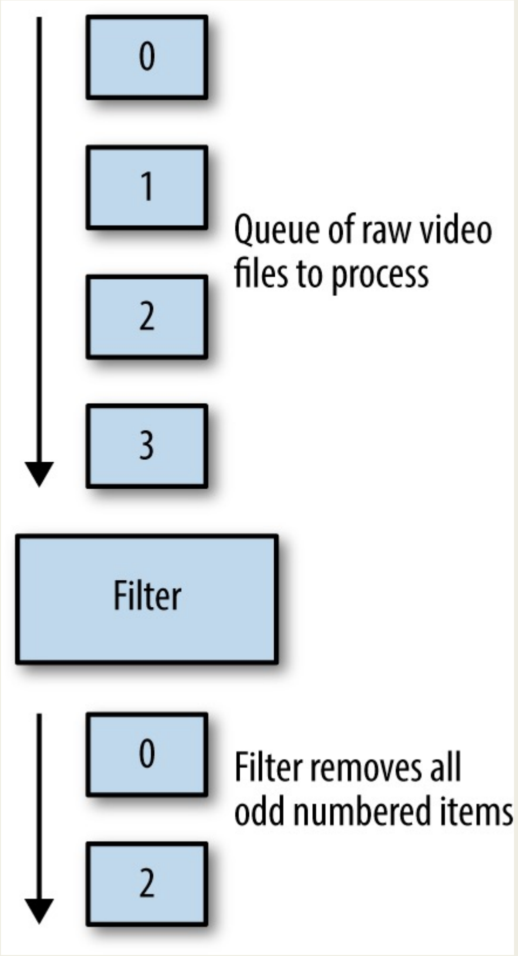
Copier

- Duplicate input to multiple outputs
- Useful when different independent processing steps need to be done on same input



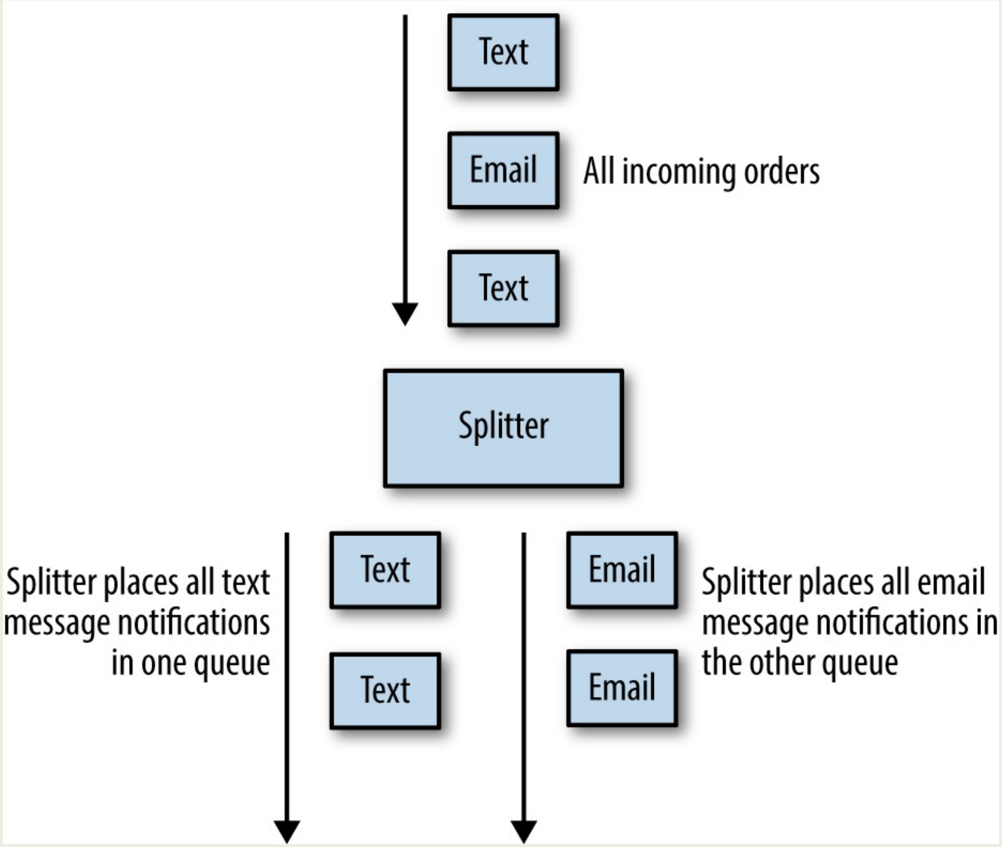
Filter

- Select a subset of the input items
- Usually based on a predicate on the input attribute values



Splitter

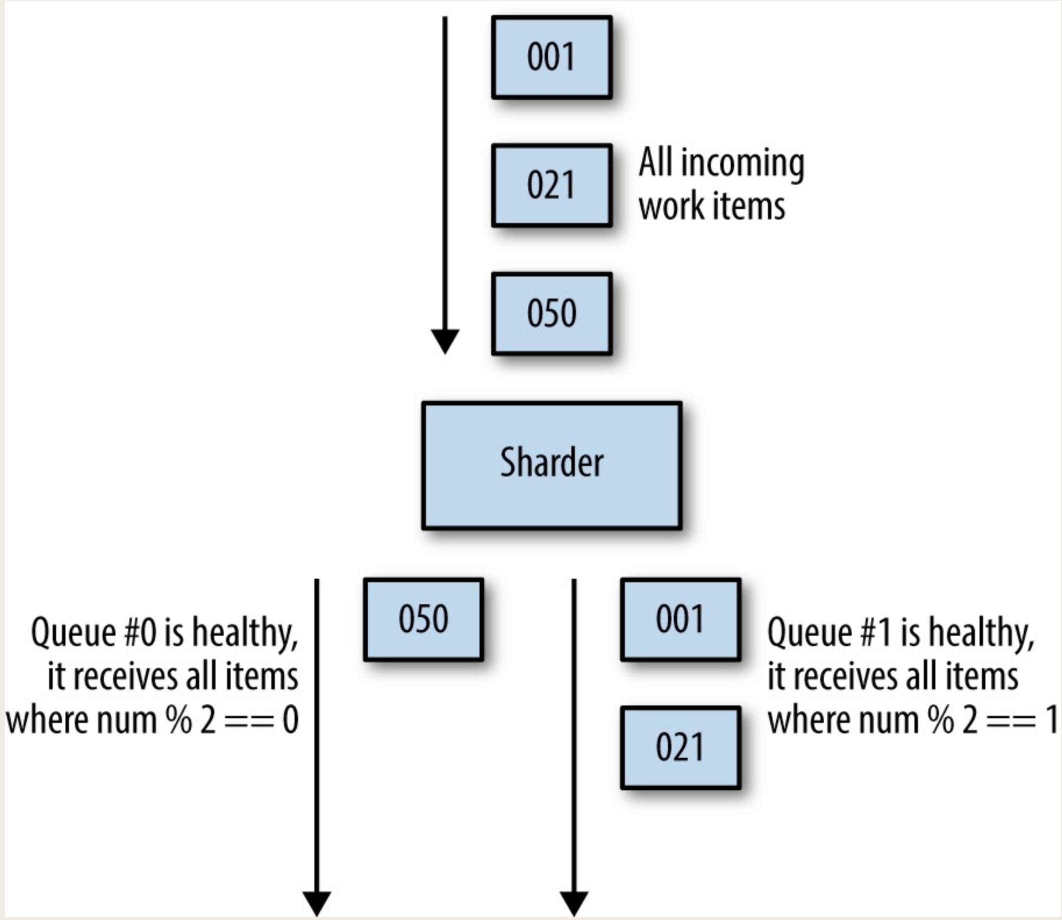
- Split input set into two or more different output sets
- Partitioning vs copy
- Usually based on some predicate – different processing to be done for each partition



Sharding

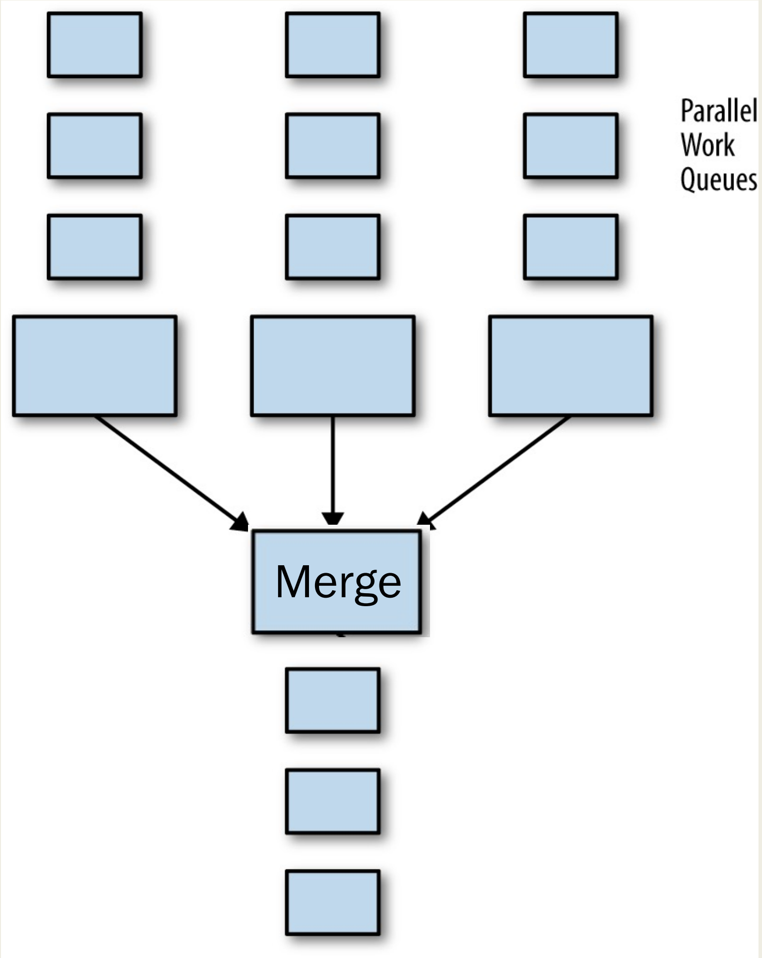
- Split based on some sharding function
- Same processing for all parit

itions
- Reasons for sharding
  - *To distribute load among multiple processors*
  - *Resilience to failures*



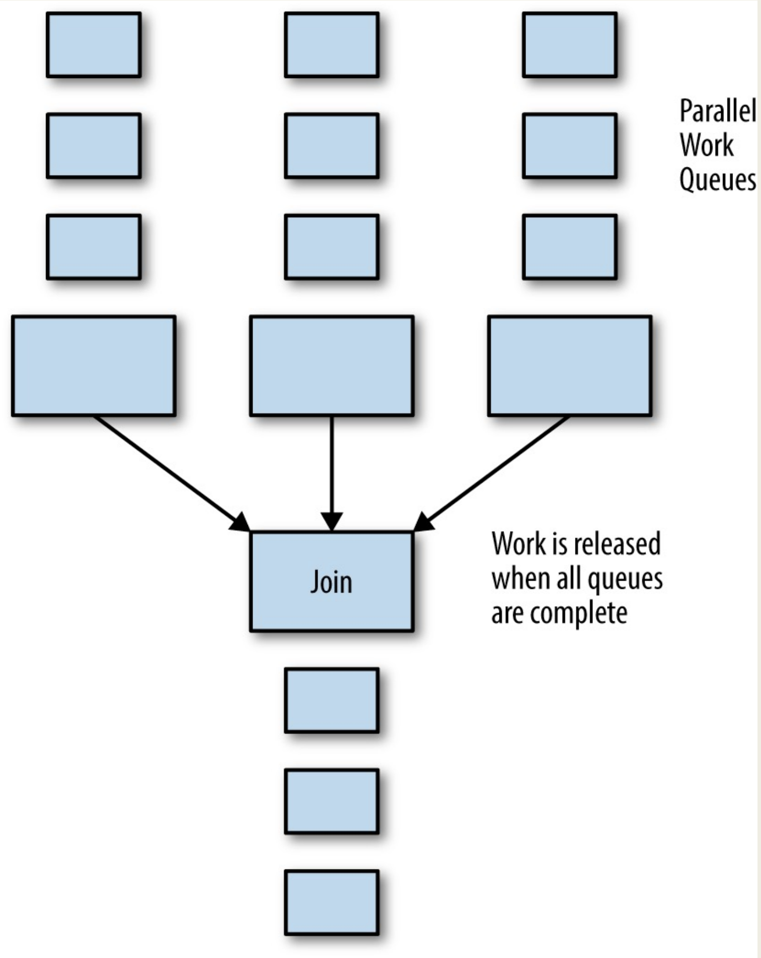
Merge

- Combine multiple input sets into a single output set
- A simple union



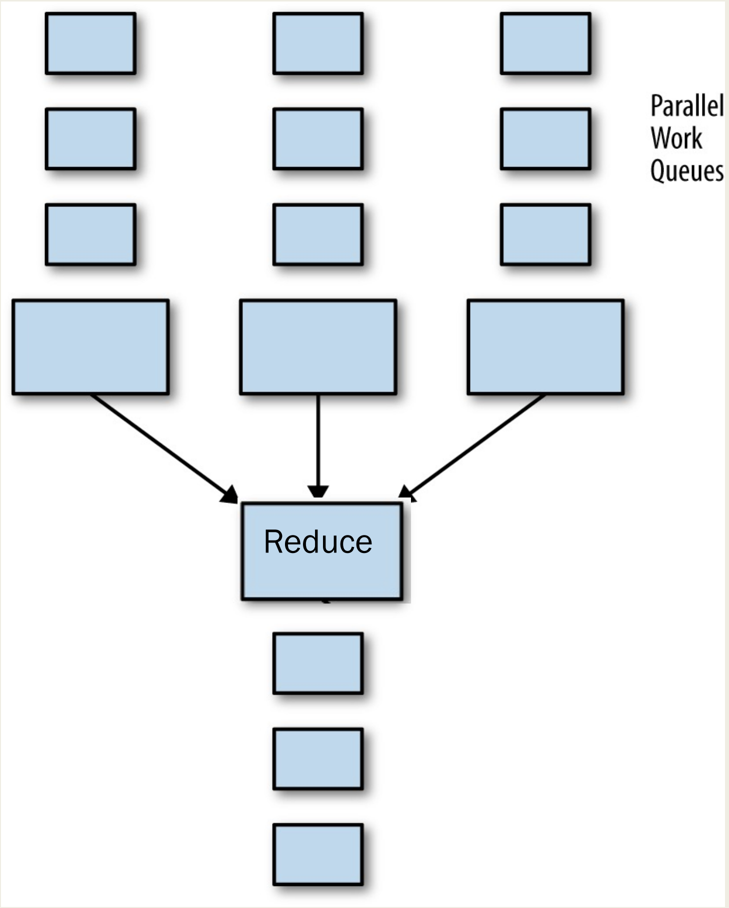
Join

- Barrier synchronization
- Ensures that previous step is complete before starting the next step
- Reduces parallelism



Reduce

- Group and merge multiple input items into a single output item
- Usually, some form of aggregation
- Need not wait for all input to be ready



A simple problem

- Find transactions with sale >= 10
- Which patterns will you use?
- How will you parallelize?

Product	Sale
P1	10
P2	15
P1	5
P2	40
P5	15
P1	55
P2	10
P5	30
P3	25
P3	15

Copy, Filter, Split, Shard, Merge, Join, Reduce

Copy, **Filter**, Split, **Shard**, **Merge**, Join, Reduce

A simple problem - extended

- Find total sales by category for transactions with sale >= 10
- Which patterns will you use?
- How to parallelize?

e.g.: PC1, 105

Category	Product
PC1	P1, P3
PC2	P2, P4, P5

Product	Sale
P1	10
P2	15
P1	~~5~~
P2	40
P5	15
P1	55
P2	10
P5	30
P3	25
P3	15

Copy, Filter, Split, Shard, Merge, Join, Reduce

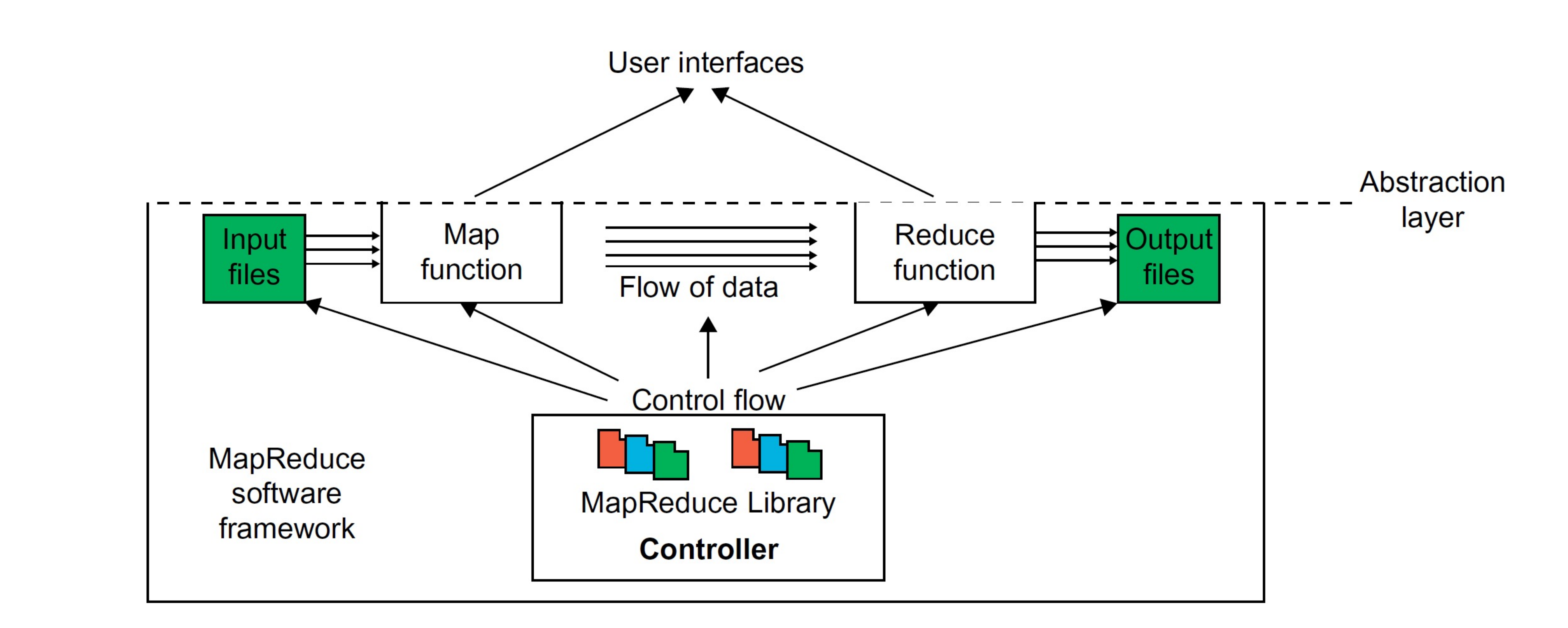
Copy, **Filter**, Split, **Shard**, Merge, Join, **Reduce**

Challenges in parallelization

- How to break a large problem into smaller tasks?
- How to assign tasks to workers distributed across machines?
- How to ensure that workers get the data they need?
- How to coordinate synchronization across workers?
- How to share partial results from one worker to another?
- How to handle software errors and hardware faults?

Programmer should not be burdened with all these details => need an abstraction

Map-reduce


User interfaces
Abstraction layer
Input files
Map function
Flow of data
Reduce function
Output files
Control flow
MapReduce software framework
MapReduce Library
Controller

Abstraction

Two processing layers/stages

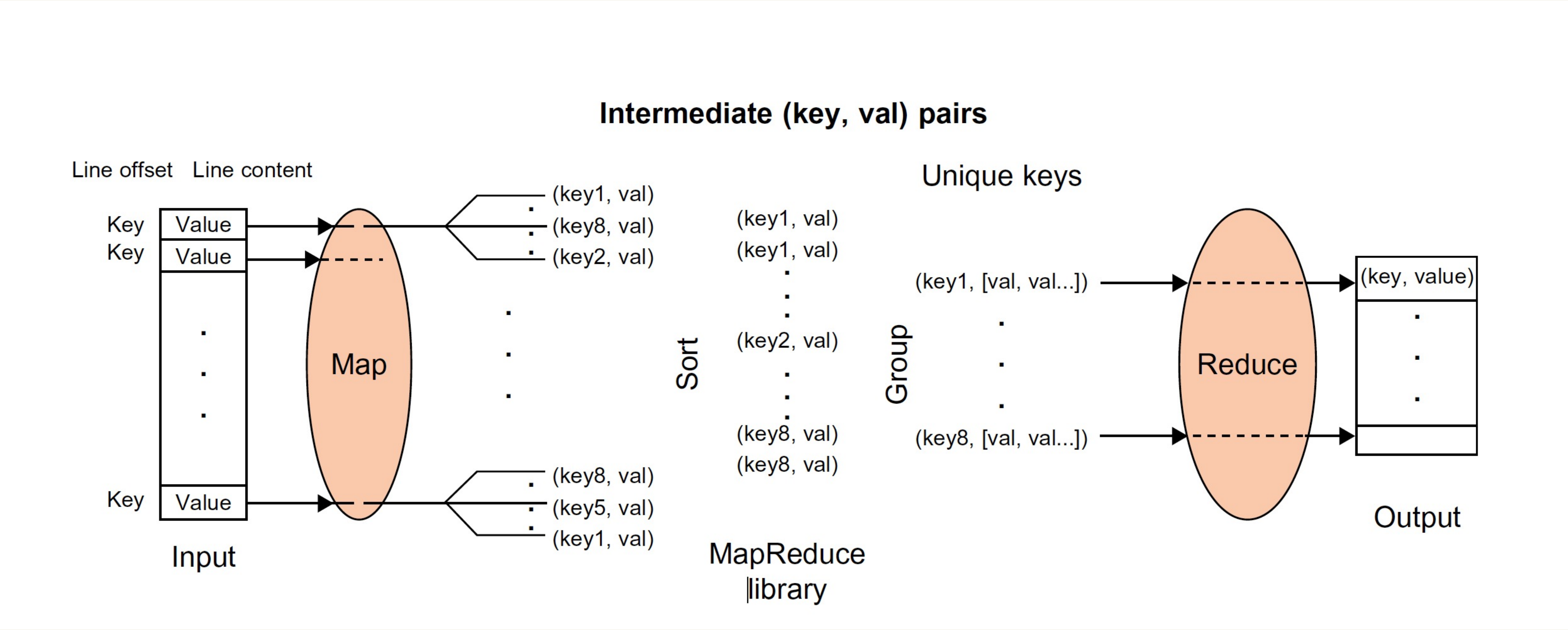
- map: (k1, v1) → [(k2, v2)]
- reduce: (k2, [v2]) → [(k3, v3)]

Revisiting the problem

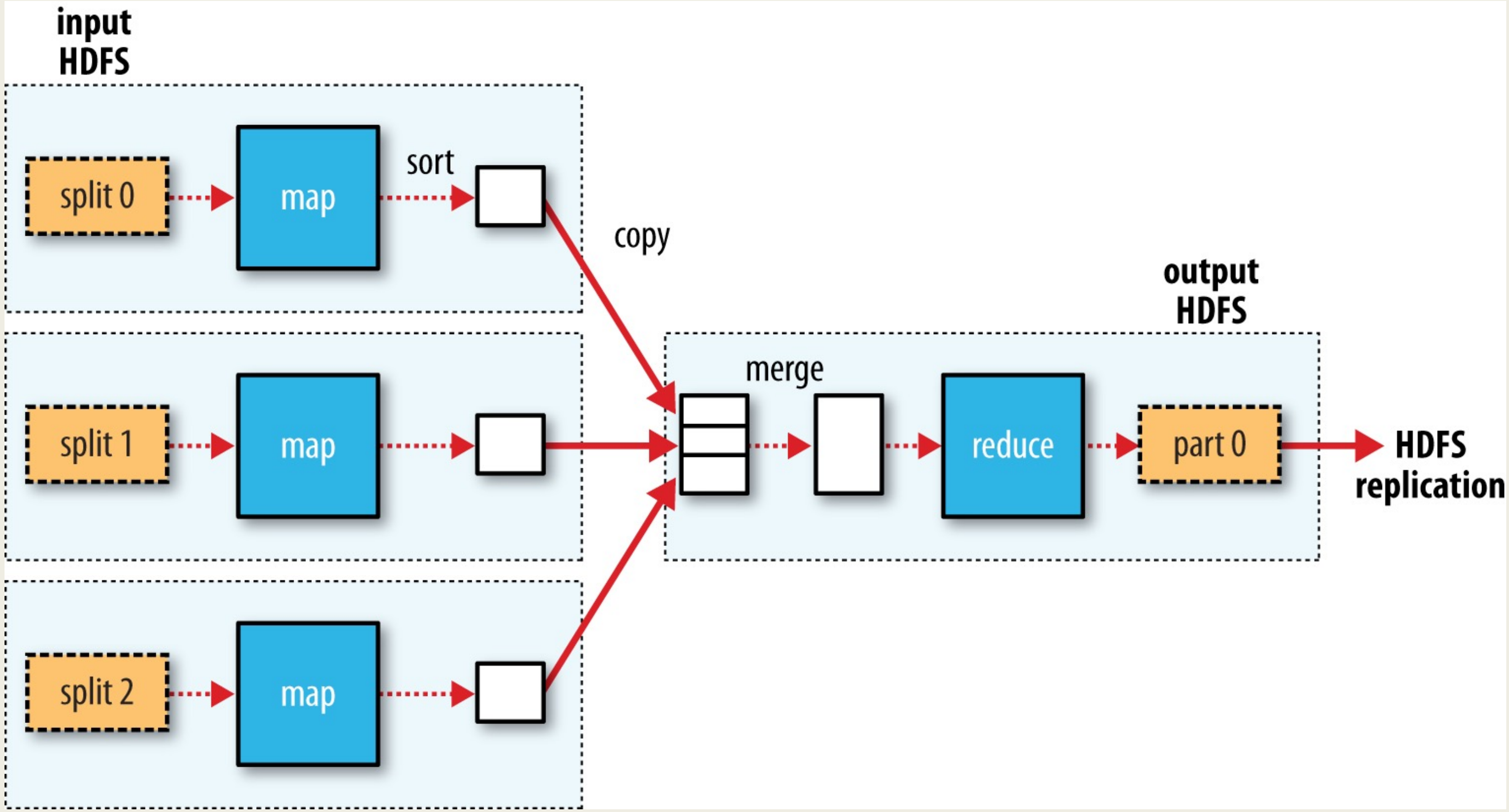
```
public class ProductMapper extends
Mapper<LongWritable, Text, Text, IntWritable> {

   @Override
   public void map(LongWritable key, Text value,
Context context)
         throws IOException, InterruptedException {
      String line = value.toString();
      String parts[] = line.split(",");

      String product = parts[0];
      Integer sale = Integer.valueOf(parts[1]);

      if (sale >= 10) {
         String category = getCategory(product);
         context.write(new Text(category), new
IntWritable(sale));
      }
   }
}
```

```
public class ProductReducer extends
ReducerReducer<Text, IntWritable, Text, IntWritable> {

   @Override
   public void reduce(Text key, Iterable<IntWritable>
values, Context context)
         throws IOException, InterruptedException {
      int total = 0;
      for (IntWritable val : values) {
         total += val;
      }
      context.write(key, new IntWritable(total));
   }

}
```

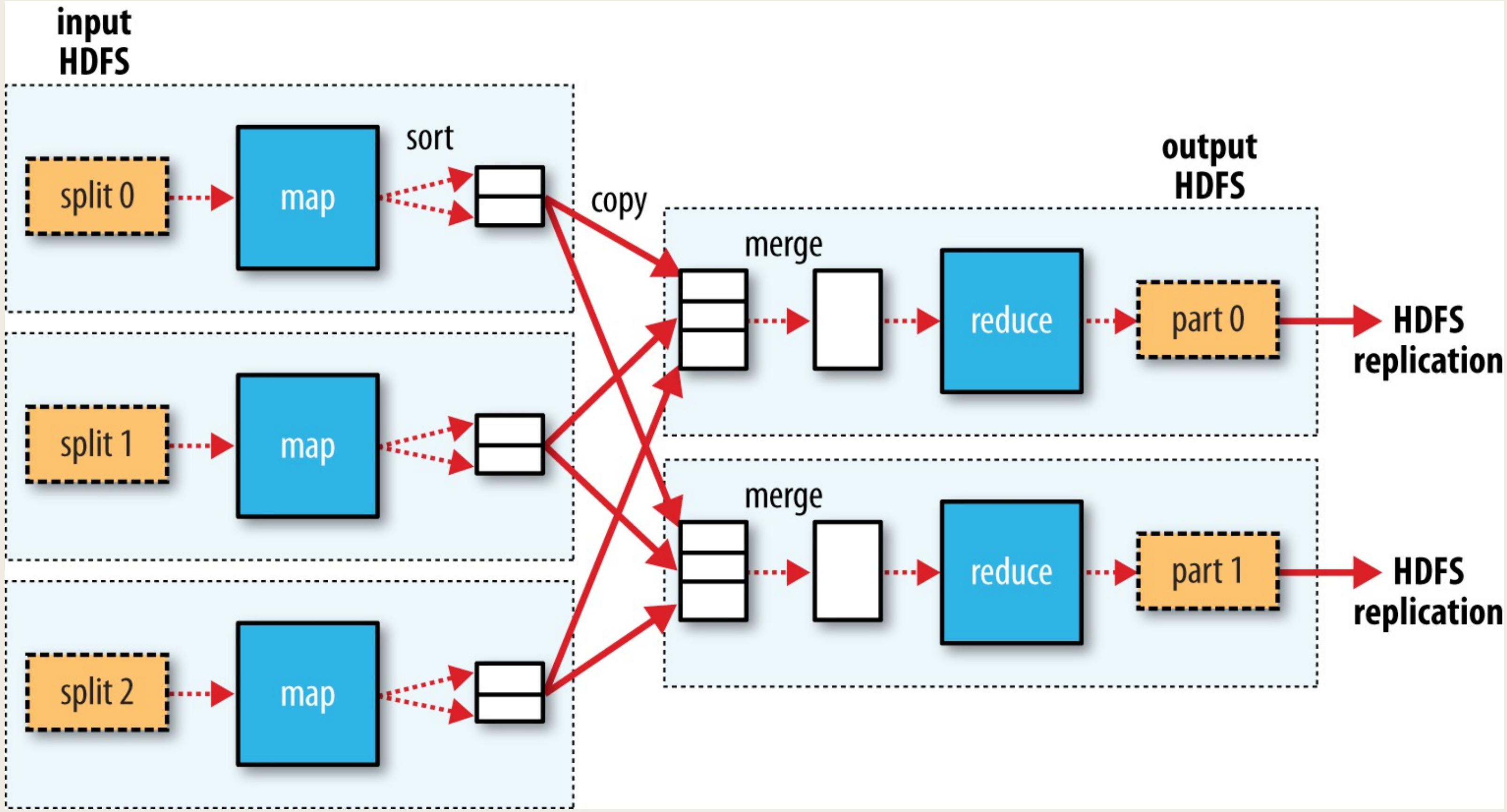
Processing stages



Scaling out


input
HDFS
split 0
map
sort
split 1
map
split 2
map
copy
output
HDFS
merge
reduce
part 0
HDFS
replication

Multiple reduce tasks



Our example

- Map Tasks ➔
  - *Mapper task 1 : P1 [key], 10[sale value]; P2, 15; P1, 5*
  - *Output: PC1, 10; PC2, 15; ~~PC1, 5~~*

  - *Mapper task 2 : P2, 40; P5, 15; P1, 55; P2, 10*
  - *Output: PC2, 40; PC2, 15; PC1, 55; PC2, 10*

  - *Mapper task 3 : P5, 30; P3, 25; P3, 15*
  - *Output: PC2, 30; PC1, 25; PC1, 15*

Category	Product
PC1	P1, P3
PC2	P2, P4, P5

- Partitions [reducers] ➔by product category

Shuffle, sort and partition

<u>Data from Mappers:</u>

- PC1, 10; *PC2, 15;*
- *PC2, 40*; PC2, 15; PC1, 55; PC2, 10
- PC2, 30; PC1, 25; PC1, 15

- PC1, 10
- PC1, 55
- PC1, 25
- PC1, 15

Partition [reducer] 1 ➔ PC1, 105

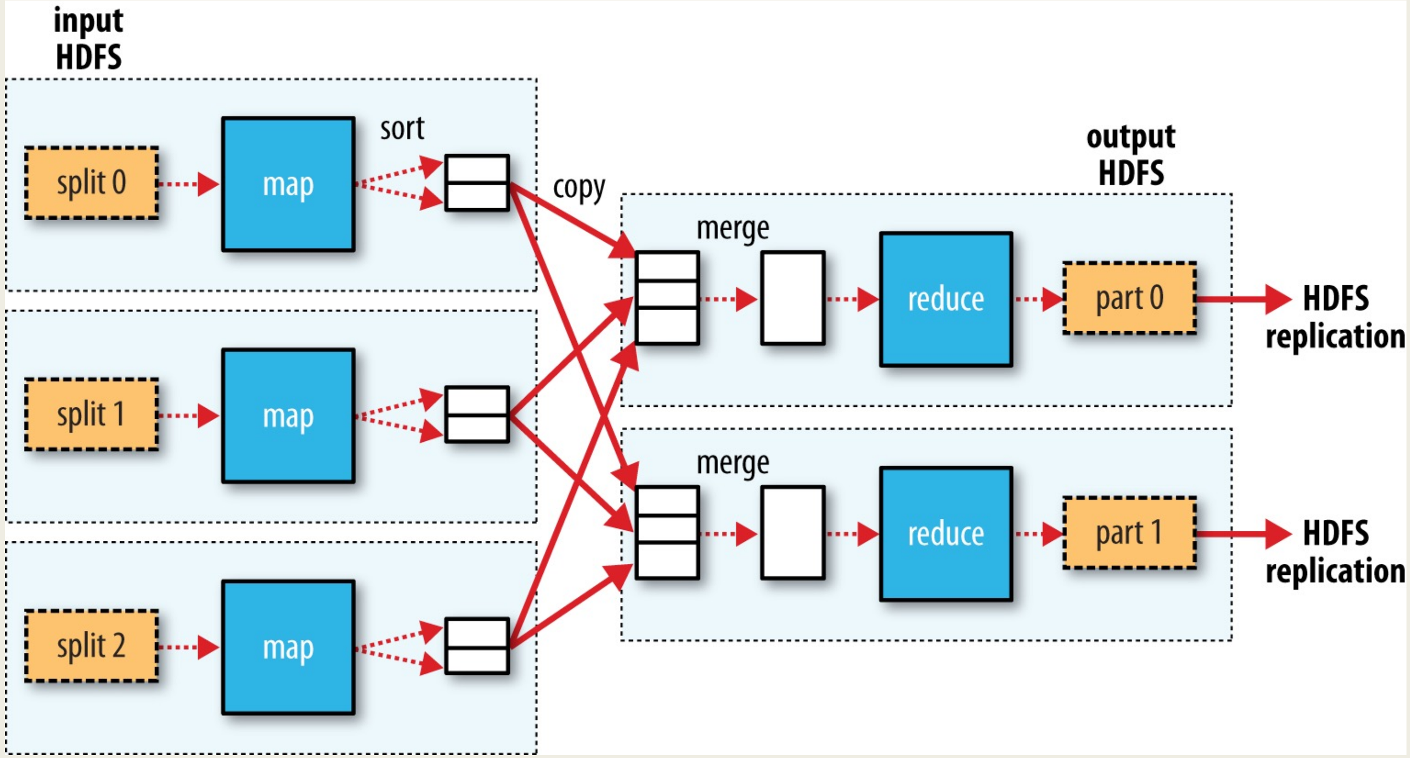
- PC2, 15
- PC2, 40
- PC2, 15
- PC2, 10
- PC2, 30;

Partition [reducer] 2➔ ???

Can it be optimized further?

<u>Data from Mappers:</u>

- PC1, 10; *PC2, 15;*
- *PC2, 40*; PC2, 15; PC1, 55; PC2, 10
- PC2, 30; PC1, 25; PC1, 15



Combiner

- Runs on the output of mapper
- No guarantee on how many times it will be called by the framework
- Calling the combiner function zero, one, or many times should produce the same output from the reducer.
- Contract for combiner – same as reducer
  - *(k2, [v2]) → [(k3, v3)]*
- Reduces the amount of data shuffled between the mappers and reducers

Combiner example

Data from Mappers:

- PC1, 10; *PC2, 15;*
- *PC2, 40*; PC2, 15; PC1, 55; PC2, 10
- PC2, 30; PC1, 25; PC1, 15

After combining:

- PC1, 10; *PC2, 15;*
- *PC2, 65*; PC1, 55
- PC2, 30; PC1, 40

Framework design

- So where should execution of mapper happen ?
- And how many map tasks ?

“Where to execute?” : Data Locality

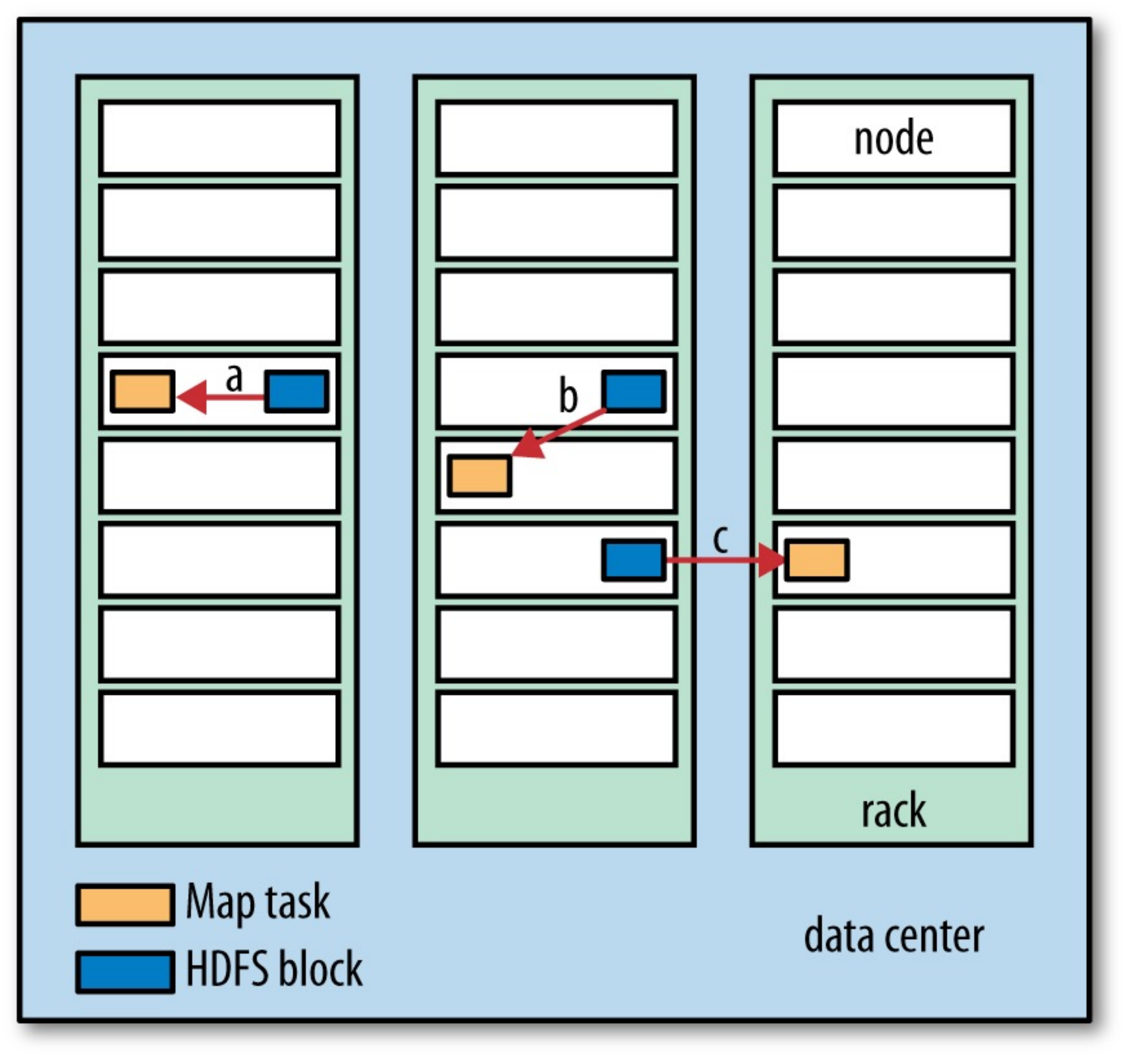
- *Move computation close to the data rather than data to computation*”.

- A computation requested by an application is much more efficient if it is executed near the data it operates on when the size of the data is very huge.

- Minimizes network congestion and increases the throughput of the system

- Hadoop will try to execute the mapper on the nodes where the block resides.
  - *In case the nodes [think of replicas] are not available, Hadoop will try to pick a node that is closest to the node that hosts the data block.*
  - *It could pick another node in the same rack, for example.*

Data locality



Data-local (a), rack-local (b), and off-rack (c) map tasks

How many mapper tasks?

Number of mappers set to run are completely dependent on :

1) File Size and

2) Block [split] Size

Internals

- **Mapper** writes the output to the local disk of the machine it is working.
  - *This is the temporary data. Also called intermediate output.*

- As mapper finishes, data (output of the mapper) travels from mapper node to reducer node. Hence, this movement of output from mapper node to reducer node is called **shuffle.**

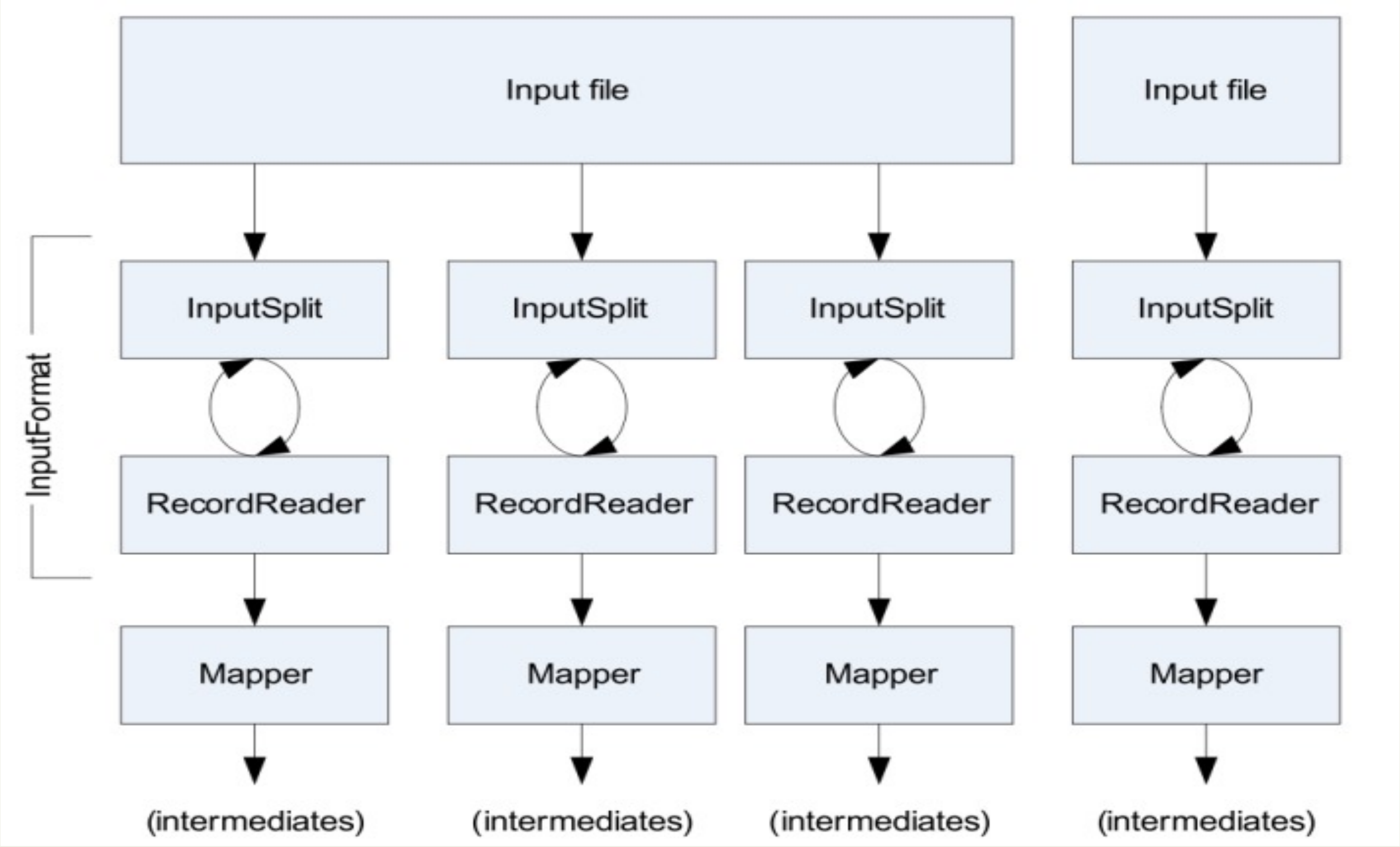
- An output from mapper is partitioned into many partitions;
  - *Each of this partition goes to a reducer based on some conditions*

Map Internals

InputSplits are created by InputFormat. Example formats – FileInputFormat, DBInputFormat

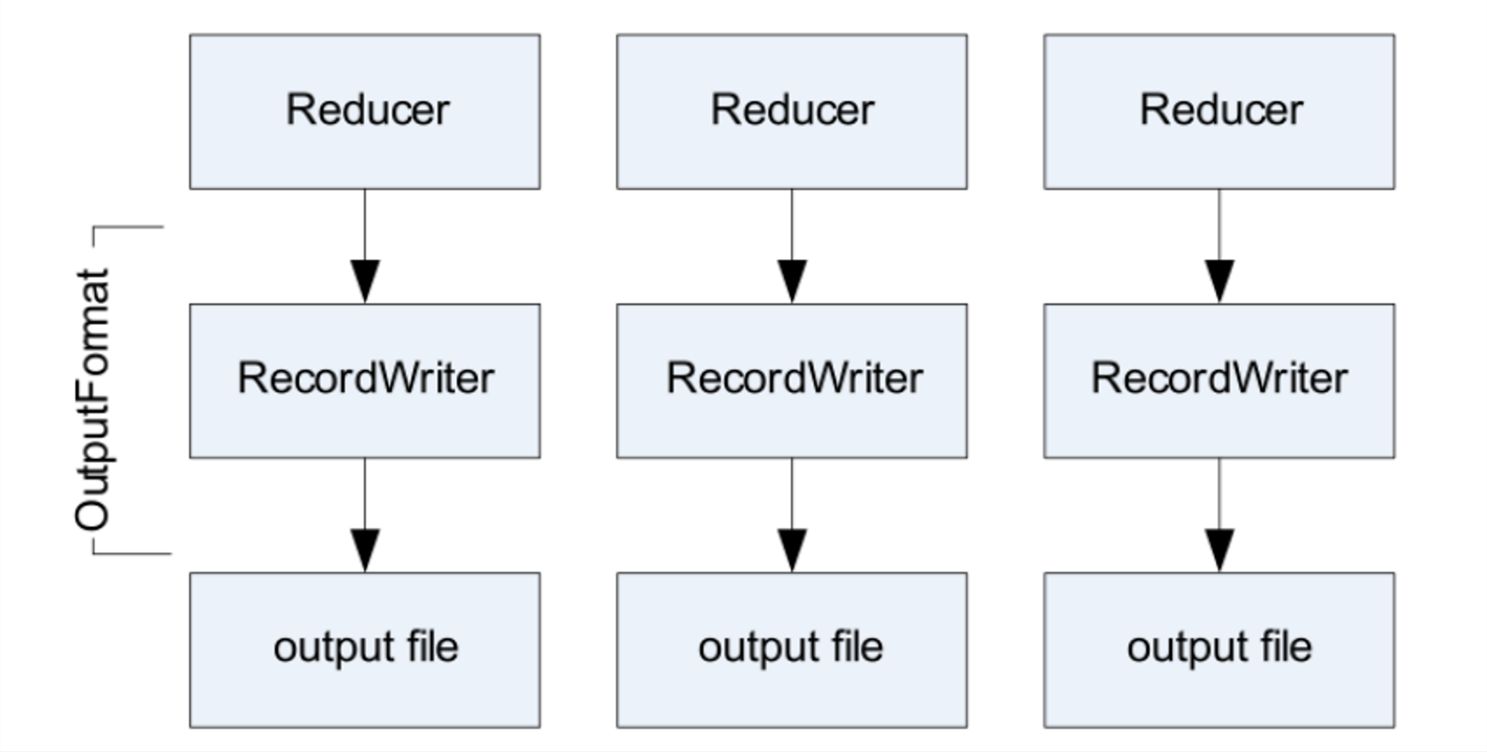
<u>RecordReader</u>'s responsibility is to keep reading/converting data into key-value pairs until the end; which is sent to the mapper.

Number of map tasks will be equal to the number of InputSplits
Mapper on any node should be able to access the split → need a distributed file system (HDFS)



Intermediate output is written to local disks

Same with Output Formats and Record Writers



MR Algorithm design

```
class Mapper
    method Map(docid a, doc d)
        for all term t ∈ doc d do
            Emit(term t, count 1)

class Reducer
    method Reduce(term t, counts [c1, c2, . . .])
        sum ← 0
        for all count c ∈ counts [c1, c2, . . .] do
            sum ← sum + c
        Emit(term t, count sum)
```

Pseudo-code for a basic word count algorithm

Improvement – local within document aggregation

```
class Mapper
    method Map(docid a, doc d)
        H ← new AssociativeArray
        for all term t ∈ doc d do
            H{t} ← H{t} + 1                    ▷ Tally counts for entire documen
        for all term t ∈ H do
            Emit(term t, count H{t})
```

Local across document aggregation

```
class Mapper
    method Initialize
        H ← new AssociativeArray
    method Map(docid a, doc d)
        for all term t ∈ doc d do
            H{t} ← H{t} + 1                ▷ Tally counts across documents
    method Close
        for all term t ∈ H do
            Emit(term t, count H{t})
```

No longer pure functional programming – state maintained across function calls!

Do we still need combiners?

- Limitations of in-mapper combining
  - *State needs to be maintained*
  - *Scalability – size of the state can grow without bounds*
- Keep bounded state
  - *Write intermediate results*
  - *Use combiners*

Summary

- MR – powerful abstraction for parallel computation
- Framework handles the complexity of distribution, data transfer, coordination, failure recovery

Reading list

- Designing Distributed Systems, Brendan Burns
  - *Chapters 11 and 12, except Hands on sections*
- Distributed and cloud computing, Kai Hwang, Geoffrey C Fox, Jack J Dongarra
  - *Sections 6.2.2 except 6.2.2.7*

- Optional reading
  - *Data-Intensive Text Processing with MapReduce*
    - Sections 2.1 to 2.4