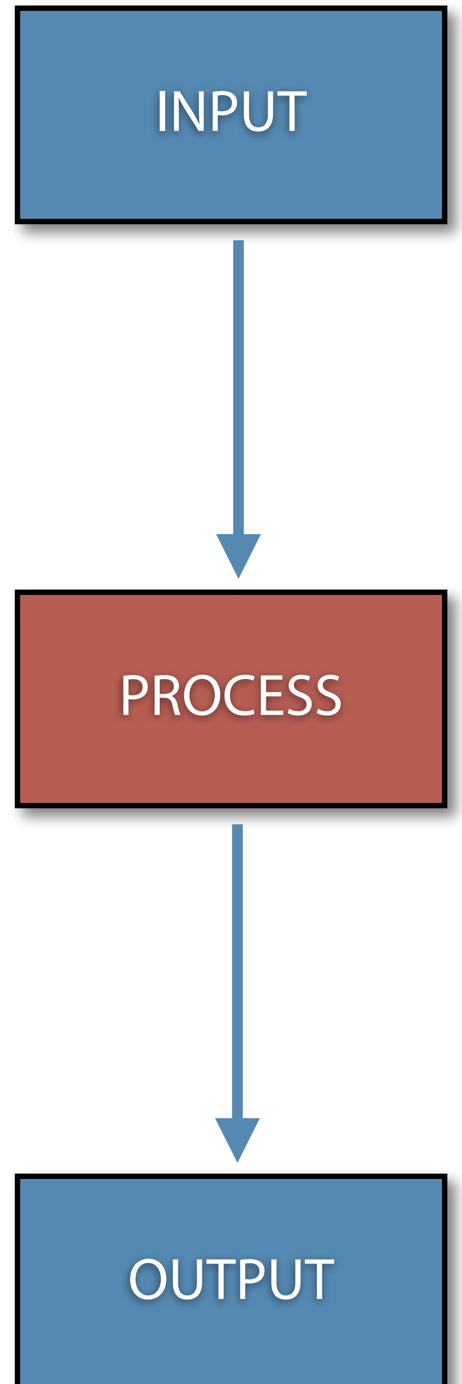
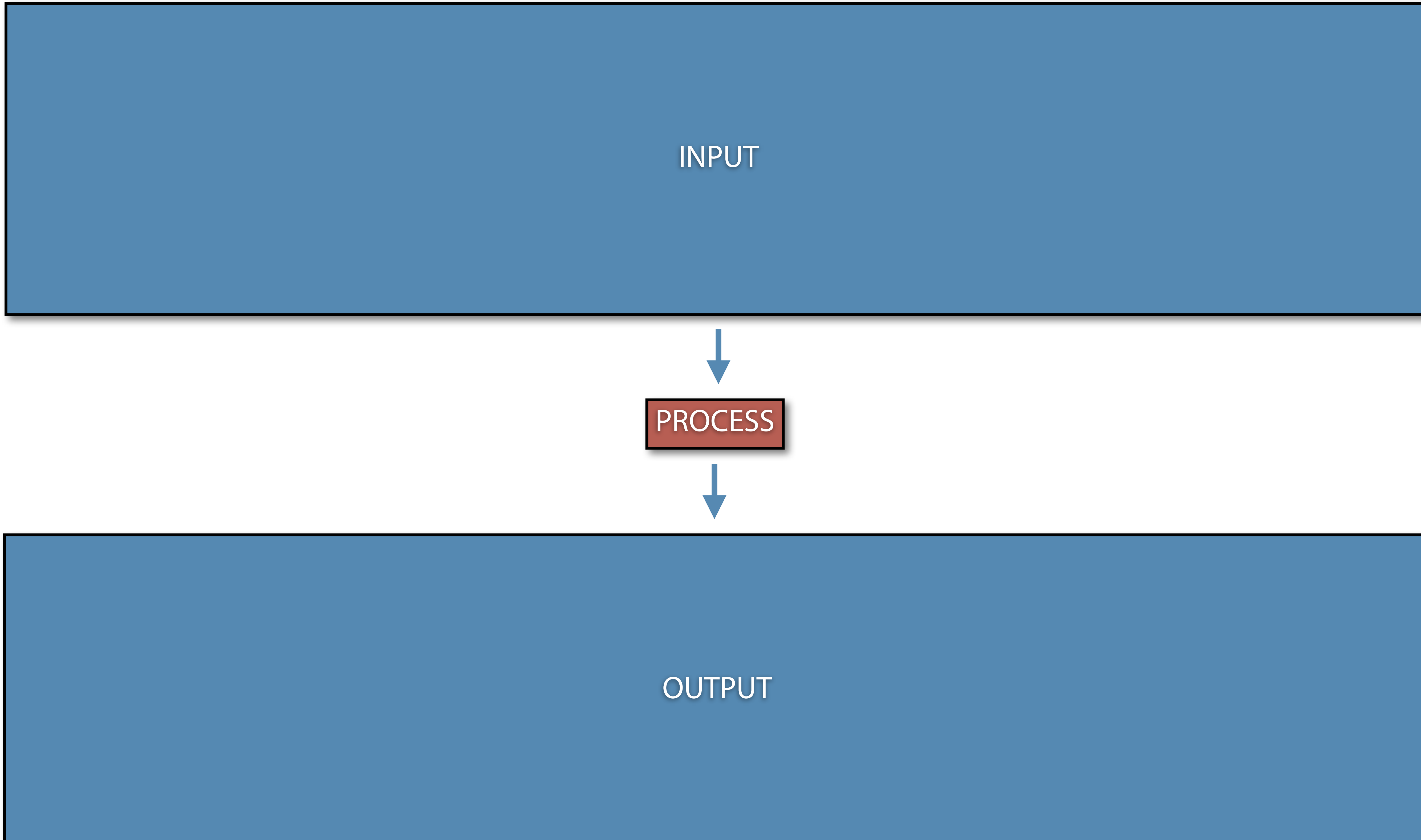
Map Reduce

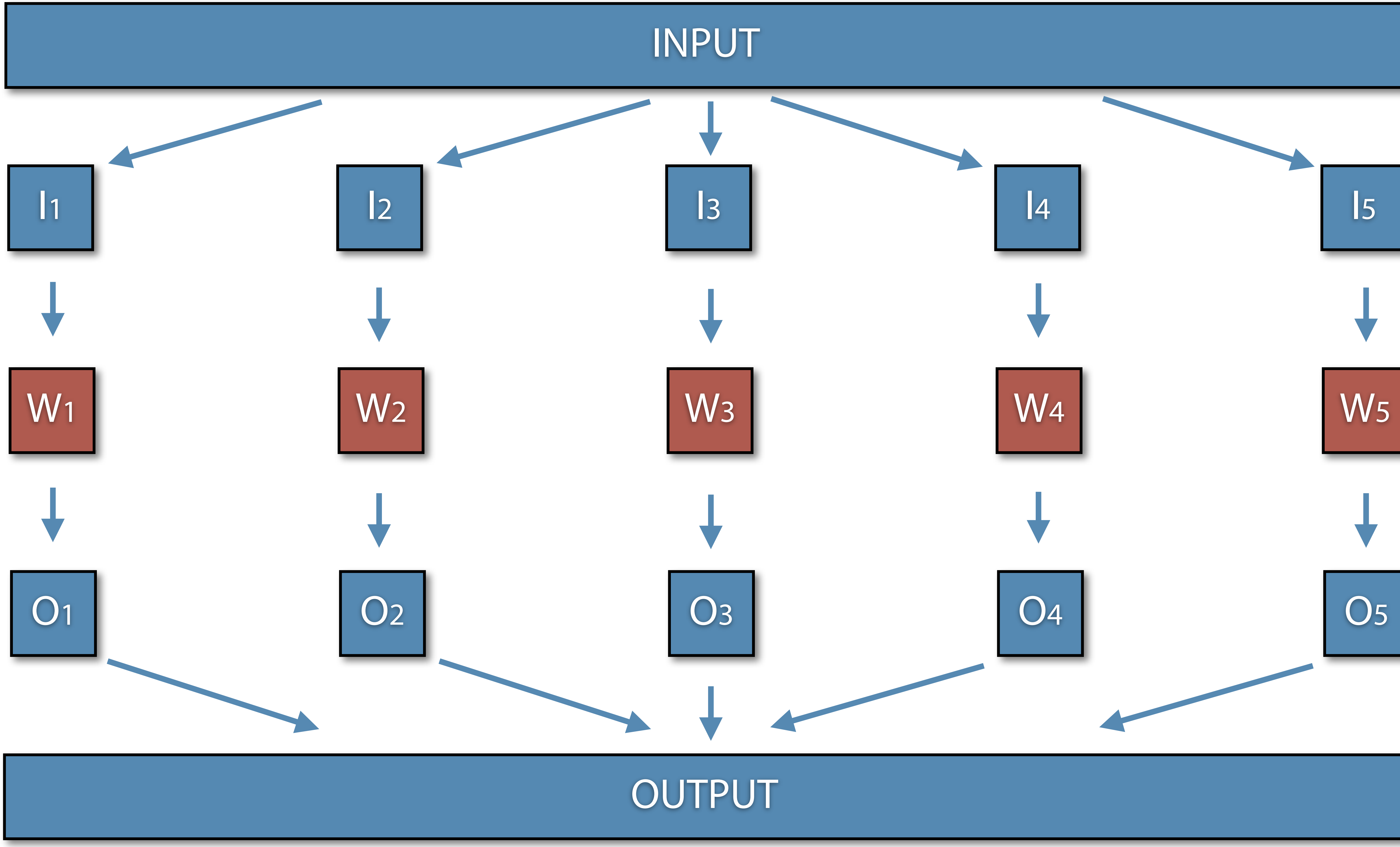
Typical Application



What if...



Divide and Conquer



Questions

- How do we split the input?
- How do we distribute the input splits?
- How do we collect the output splits?
- How do we aggregate the output?
- How do we coordinate the work?
- What if input splits > num workers?
- What if workers need to share input/output splits?
- What if a worker dies?
- What if we have a new input?

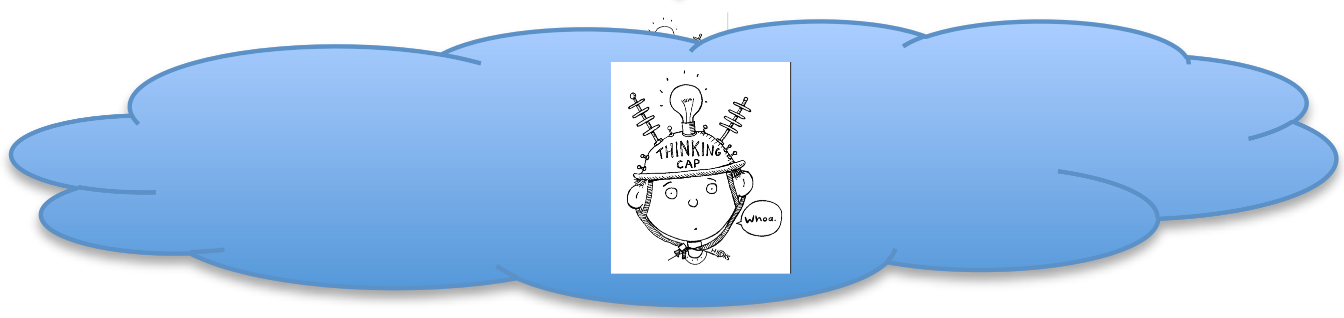

http://www.duiops.net/seresvivos

Design Ideas

- **Scale "out", not "up"**
  - Low end machines
- **Move processing to the data**
  - Network bandwidth bottleneck
- **Process data sequentially, avoid random access**
  - Huge data files
  - Write once, read many
- **Seamless scalability**
  - Strive for the unobtainable
- **Right level of abstraction**
  - Hide implementation details from applications development

Typical Large-Data Problem

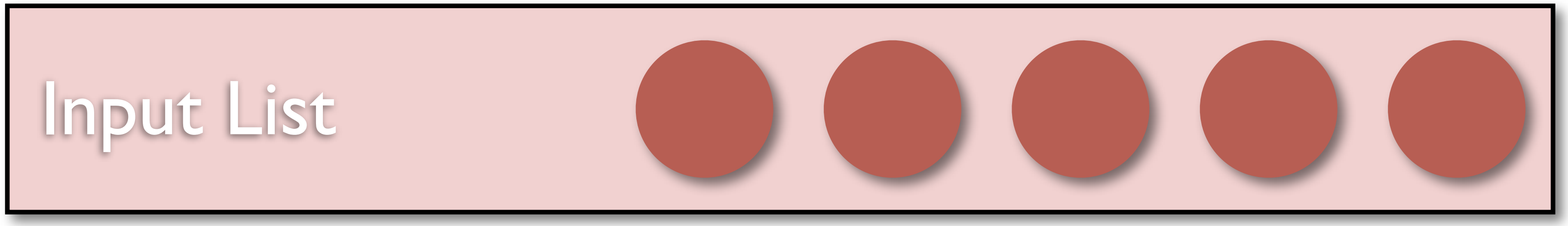
- Iterate over a large number of records
- Extract something of interest from each
- Shuffle and sort intermediate results
- Aggregate intermediate results
- Generate final output



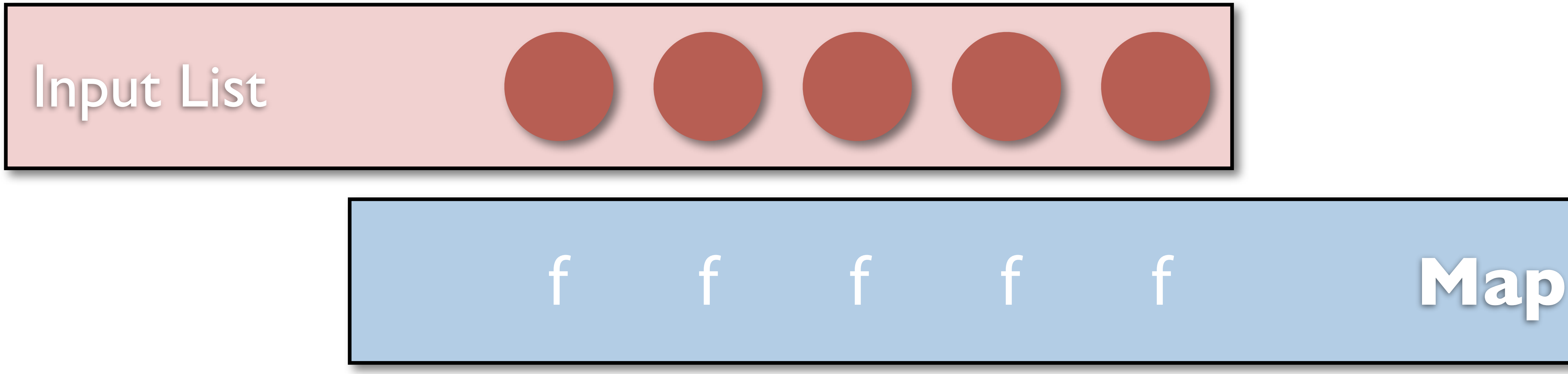
MapReduce
Programming Model

From functional programming...

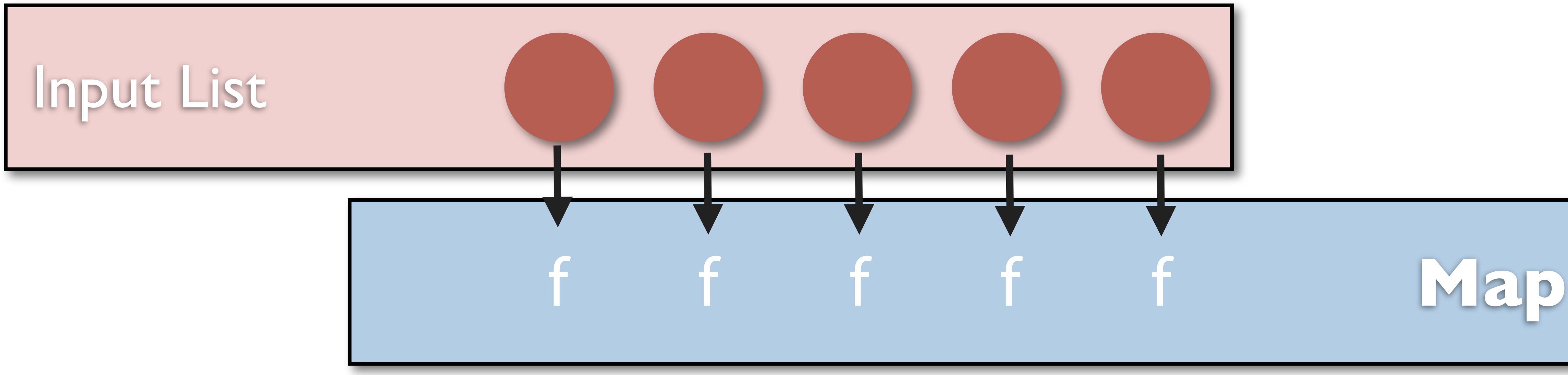
From functional programming...



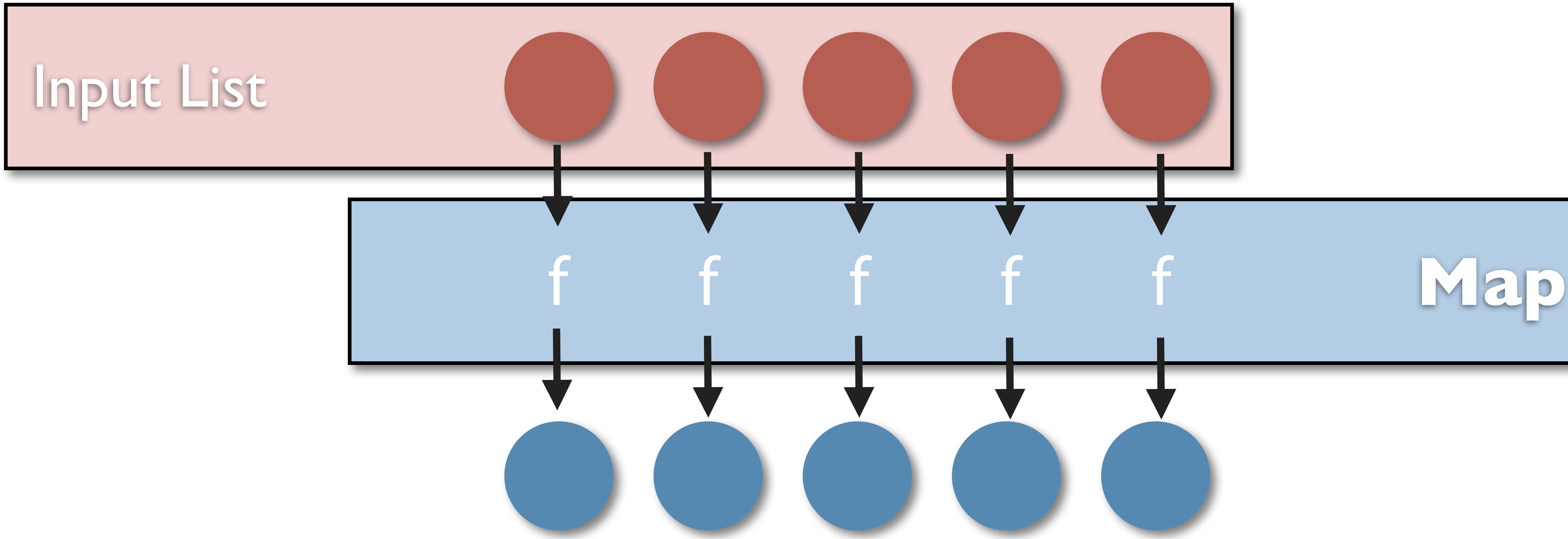
From functional programming...



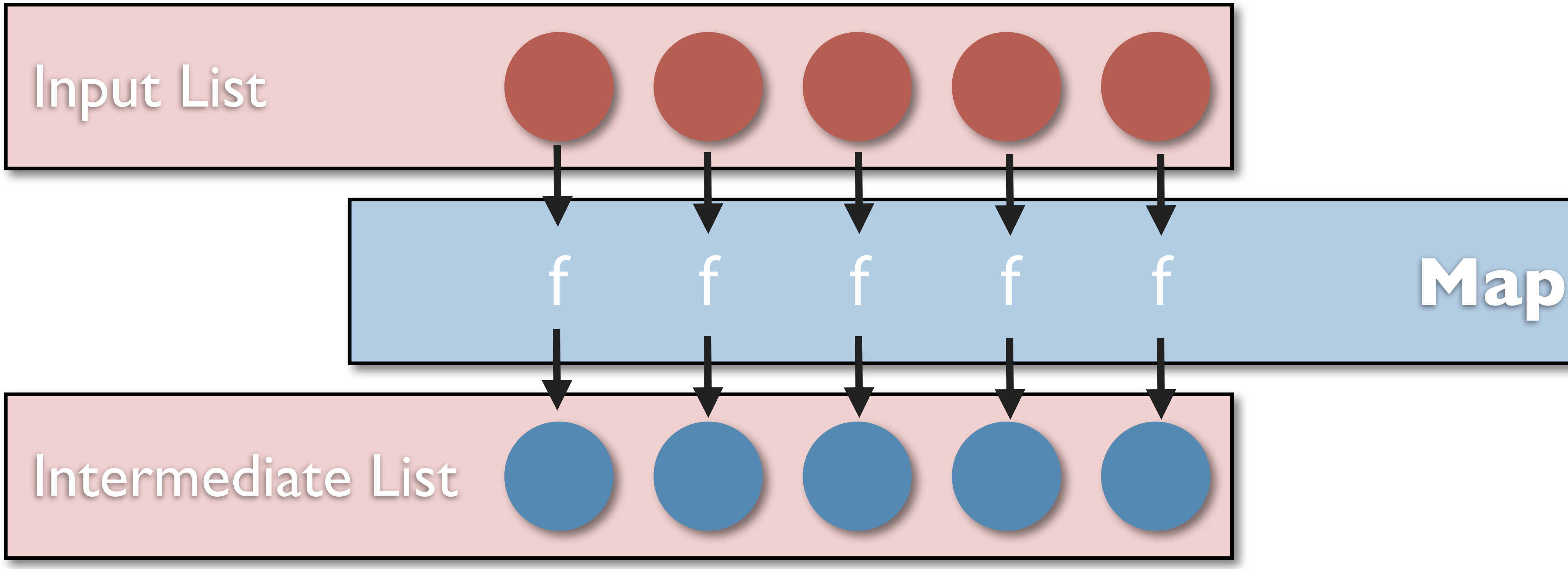
From functional programming...



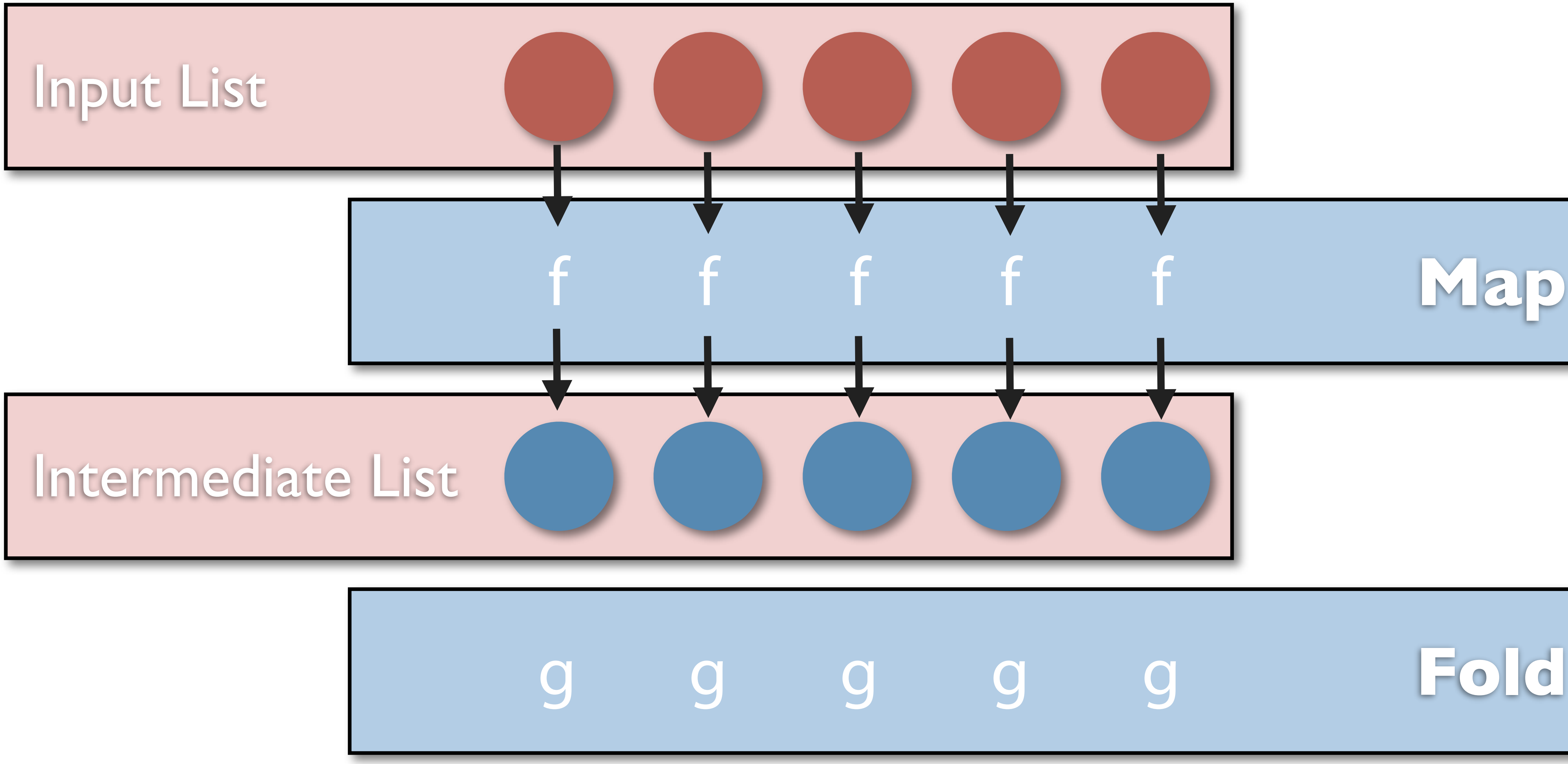
From functional programming...



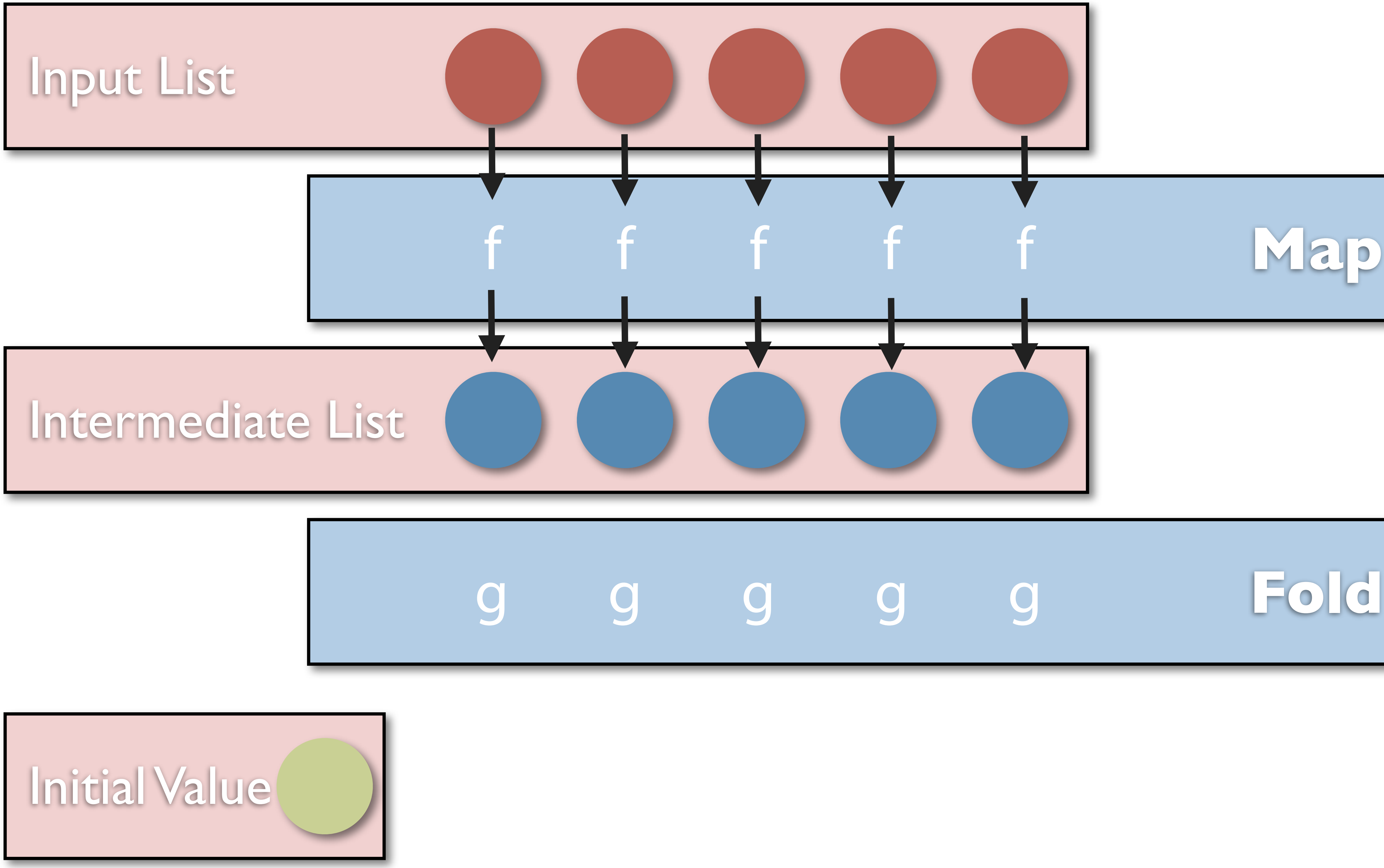
From functional programming...



From functional programming...



From functional programming...



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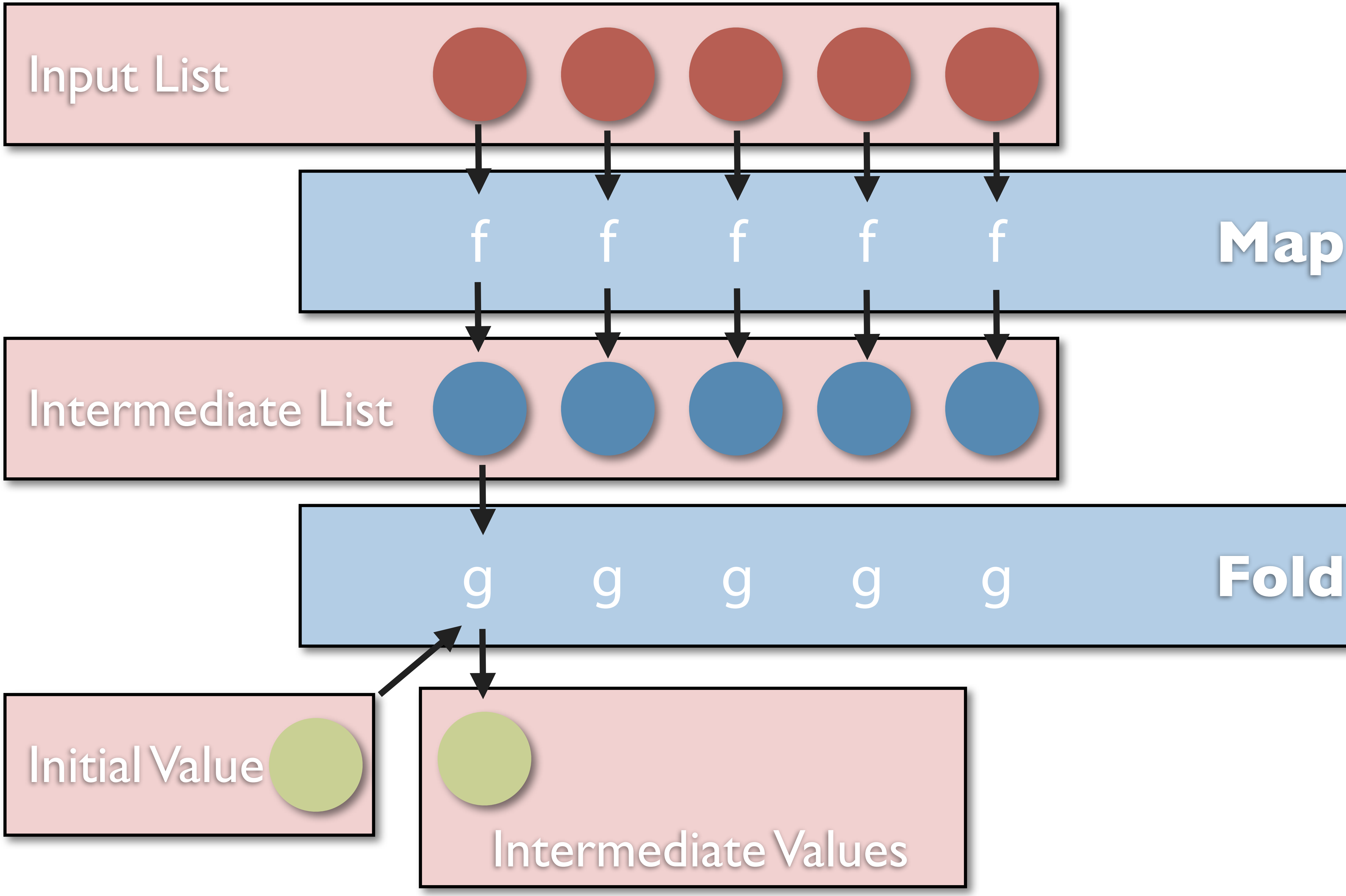

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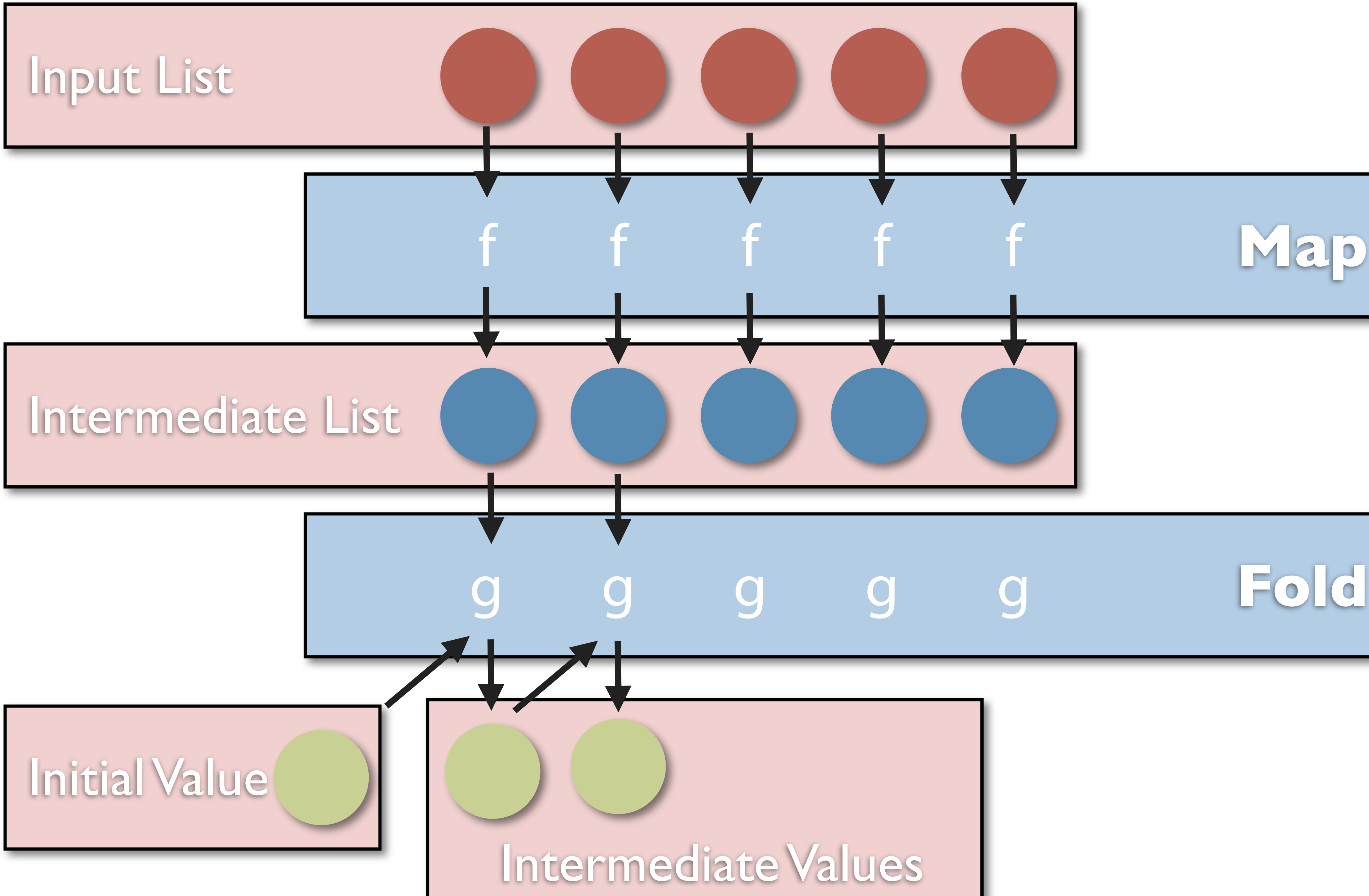

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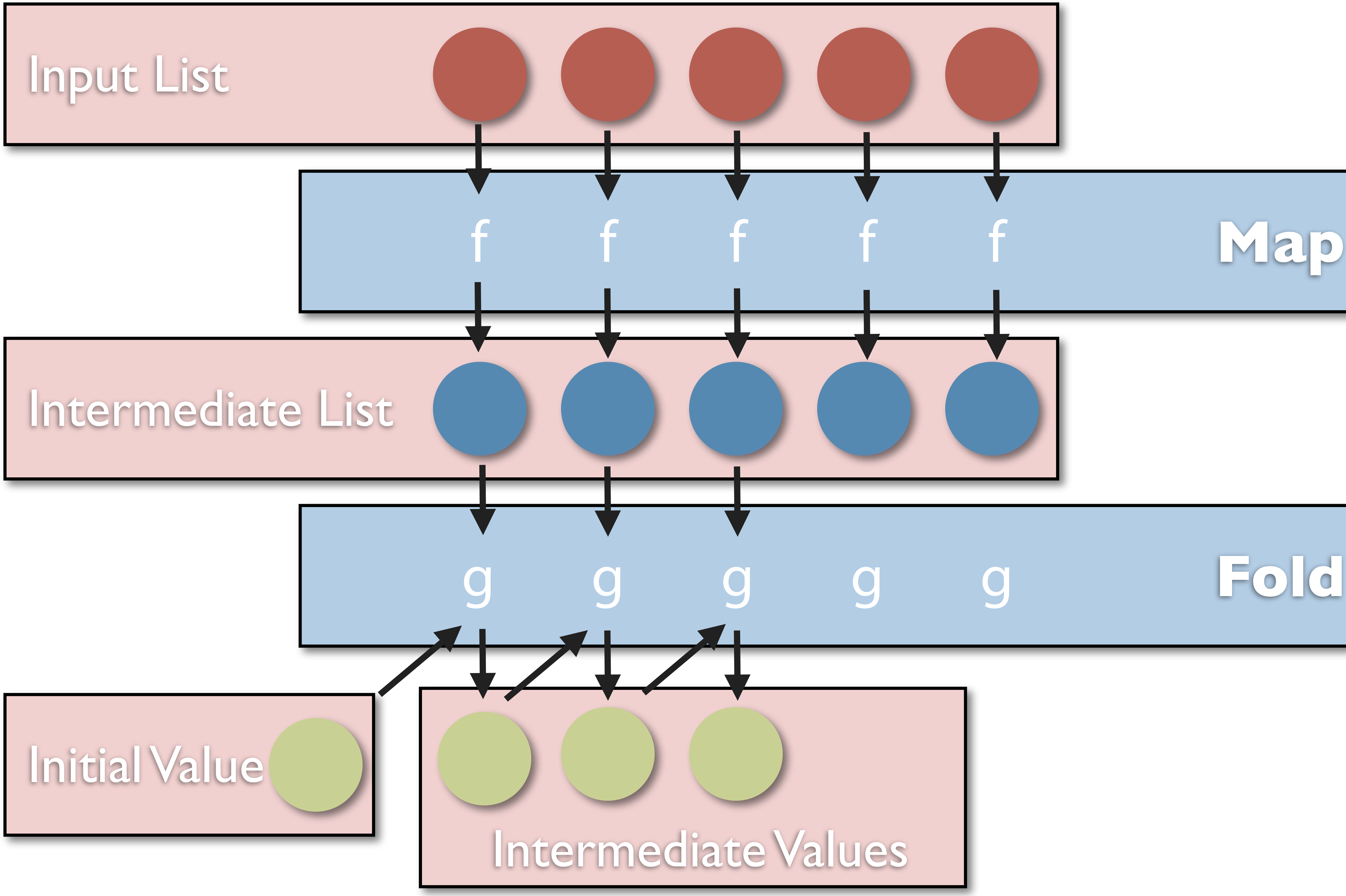
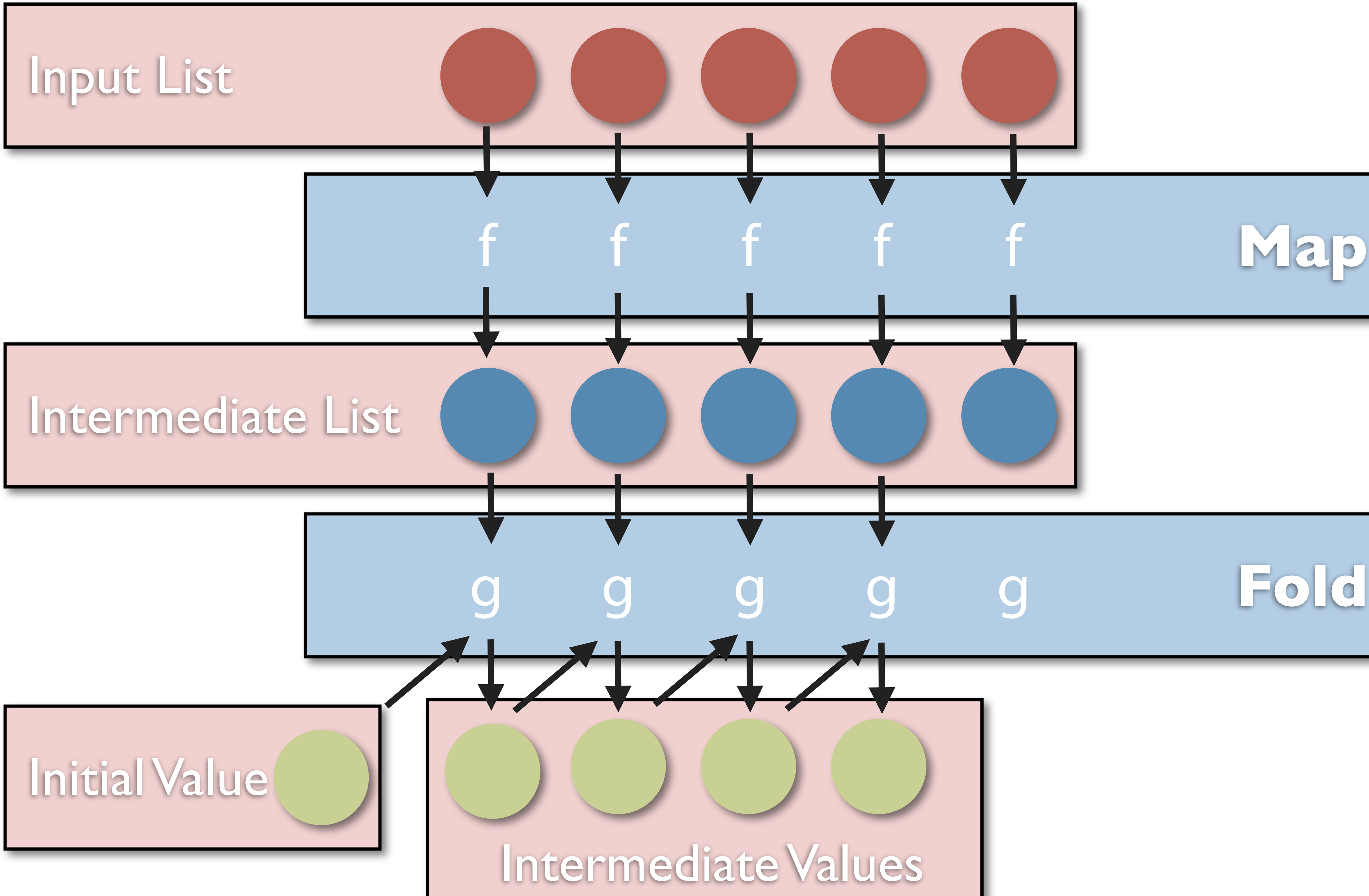
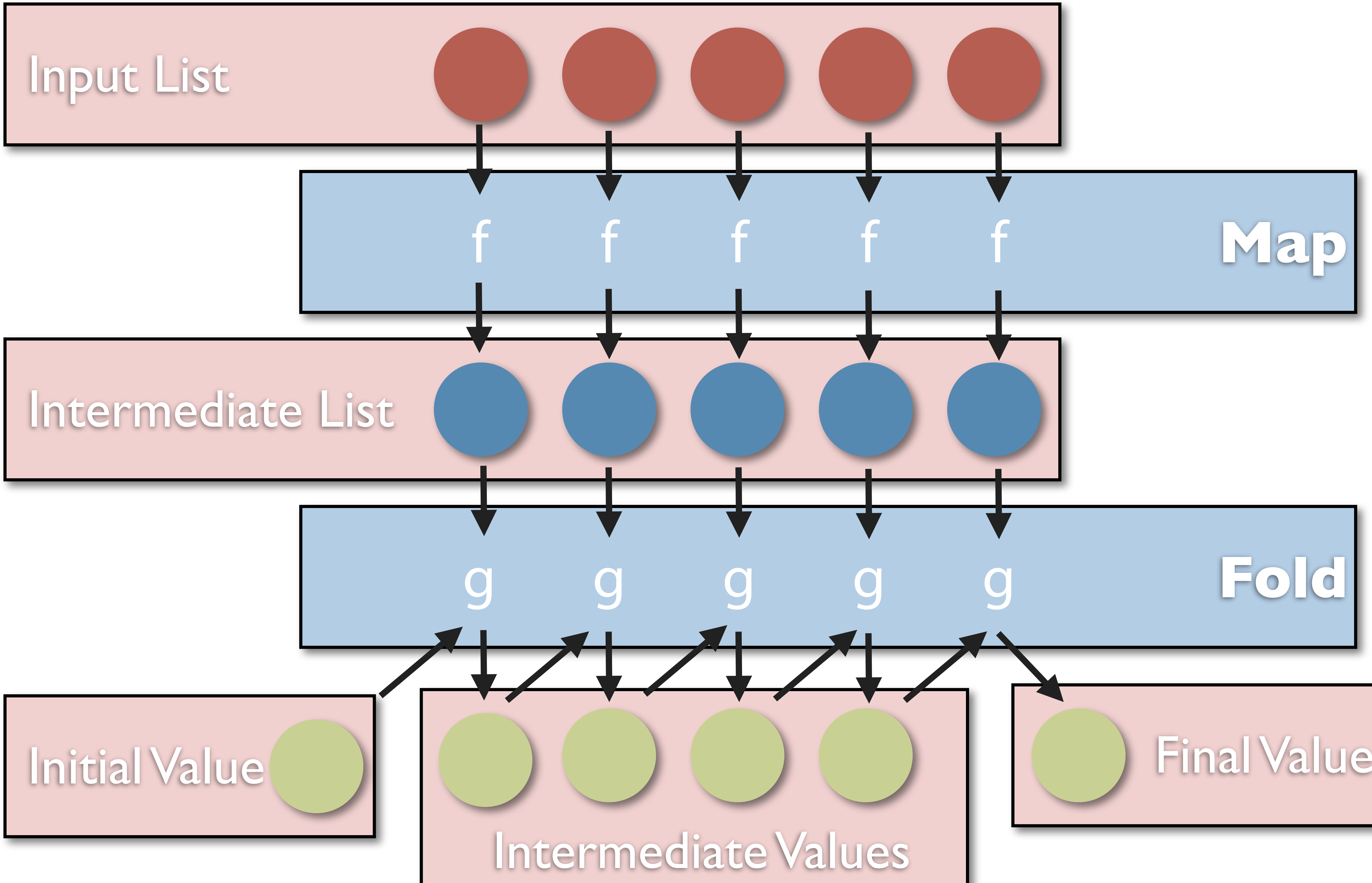


From functional programming...



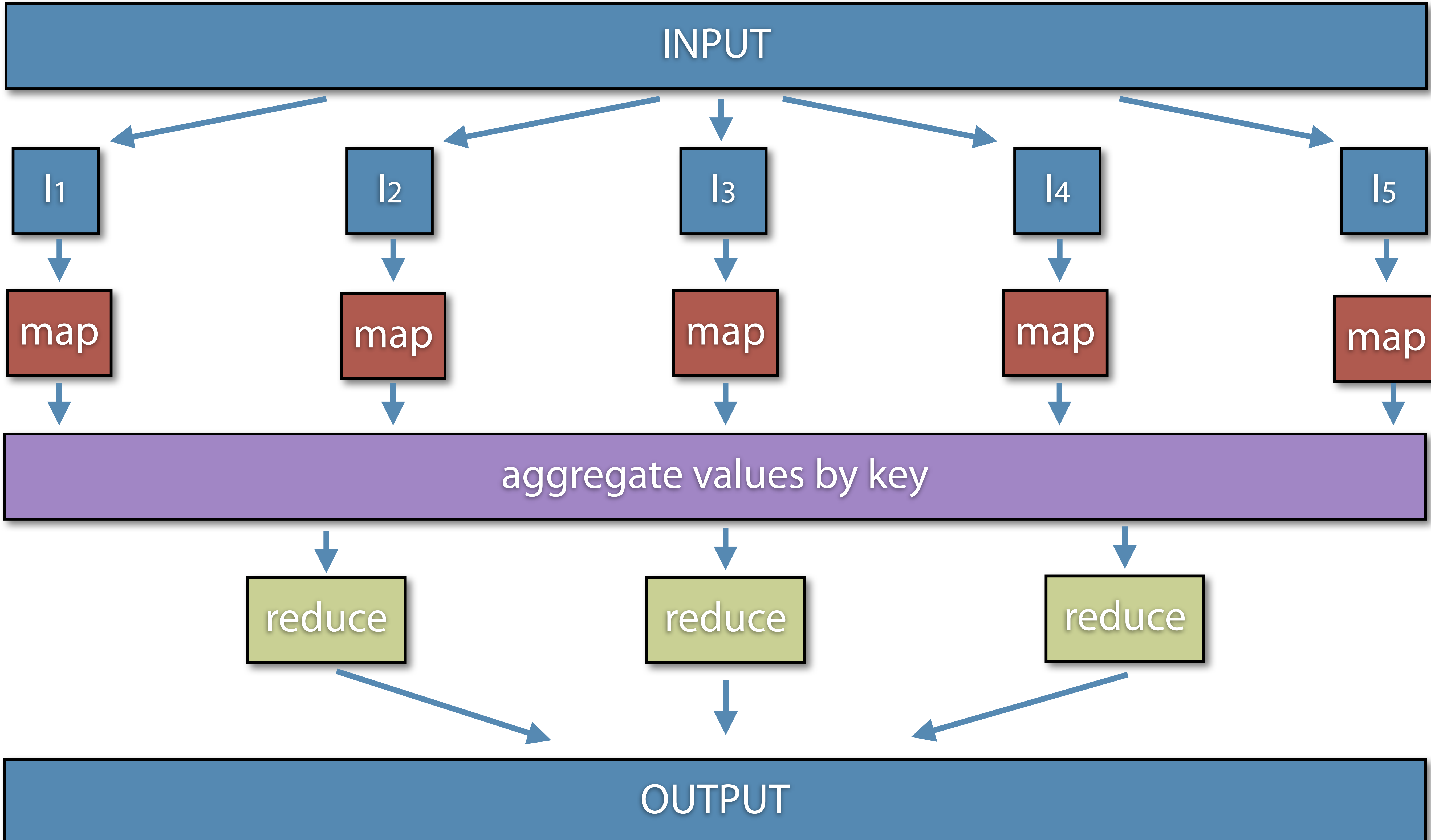
From functional programming...



...to Map Reduce

- **Programmers specify two functions**
  - **map** $(k_1,v_1) \dashrightarrow [(k_2,v_2)]$
  - **reduce** $(k_2,[v_2]) \dashrightarrow [(k_3,v_3)]$
- **Map**
  - Receives as input a key-value pair
  - Produces as output a list of key-value pairs
- **Reduce**
  - Receives as input a key-list of values pair
  - Produces as output a list of key-value pairs (typically just one)
- **The runtime support handles everything else...**

Programming Model (simple)



Example (I)

```
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)
```

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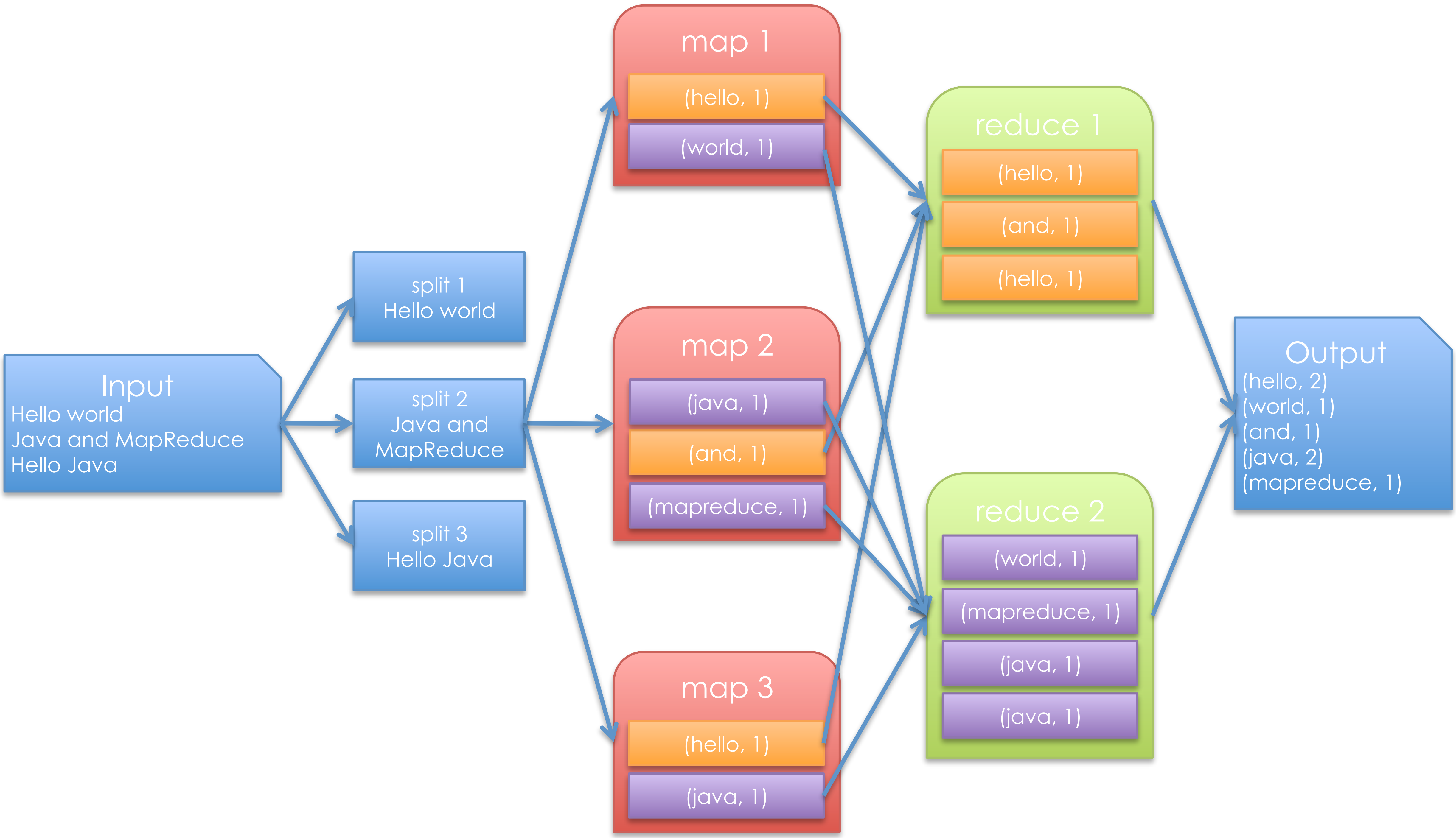
Example (II)

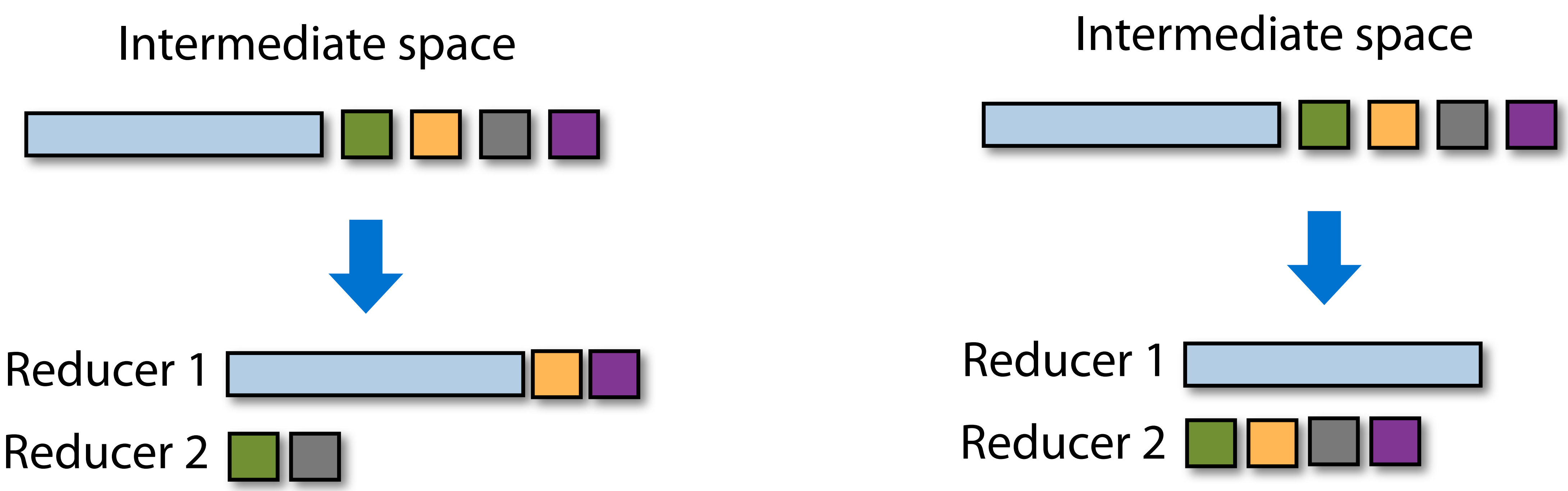

Input
Hello world
Java and MapReduce
Hello Java
split 1
Hello world
split 2
Java and
MapReduce
split 3
Hello Java
map 1
(hello, 1)
(world, 1)
map 2
(java, 1)
(and, 1)
(mapreduce, 1)
map 3
(hello, 1)
(java, 1)
reduce 1
(hello, 1)
(and, 1)
(hello, 1)
reduce 2
(world, 1)
(mapreduce, 1)
(java, 1)
(java, 1)
Output
(hello, 2)
(world, 1)
(and, 1)
(java, 2)
(mapreduce, 1)

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**

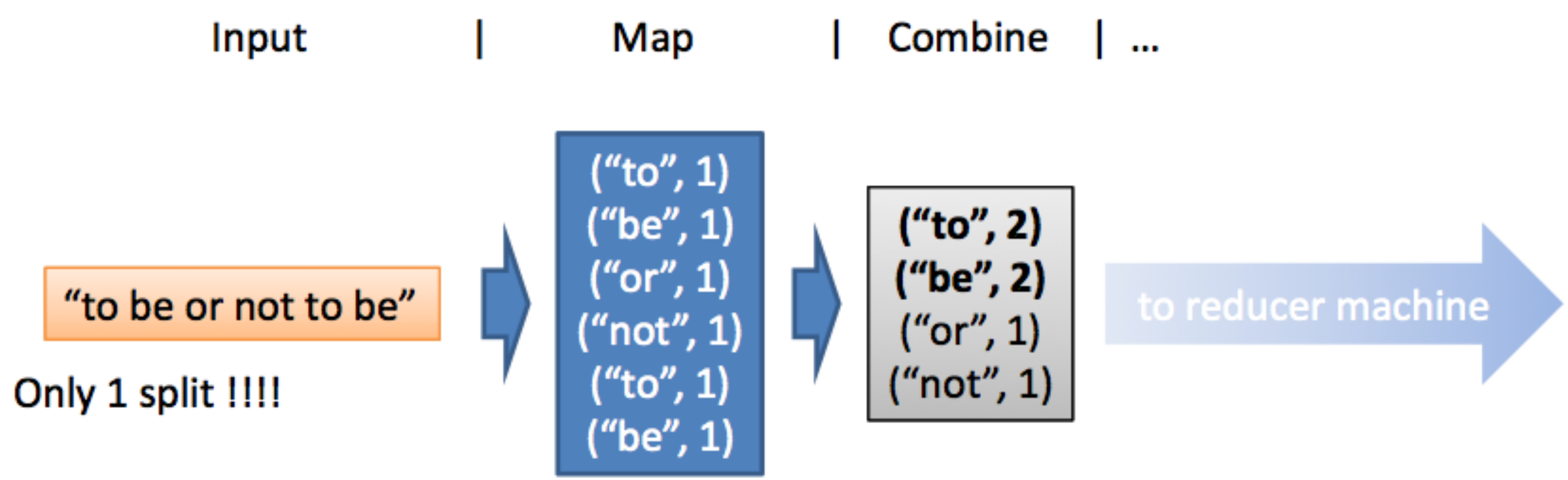
Partitioners

- **Balance the key assignments to reducers**
  - By default, intermediate keys are hashed to reducers
  - Partitioner specifies the node to which an intermediate key-value pair must be copied
  - Divides up key space for parallel reduce operations
  - Partitioner only considers the key and ignores the value

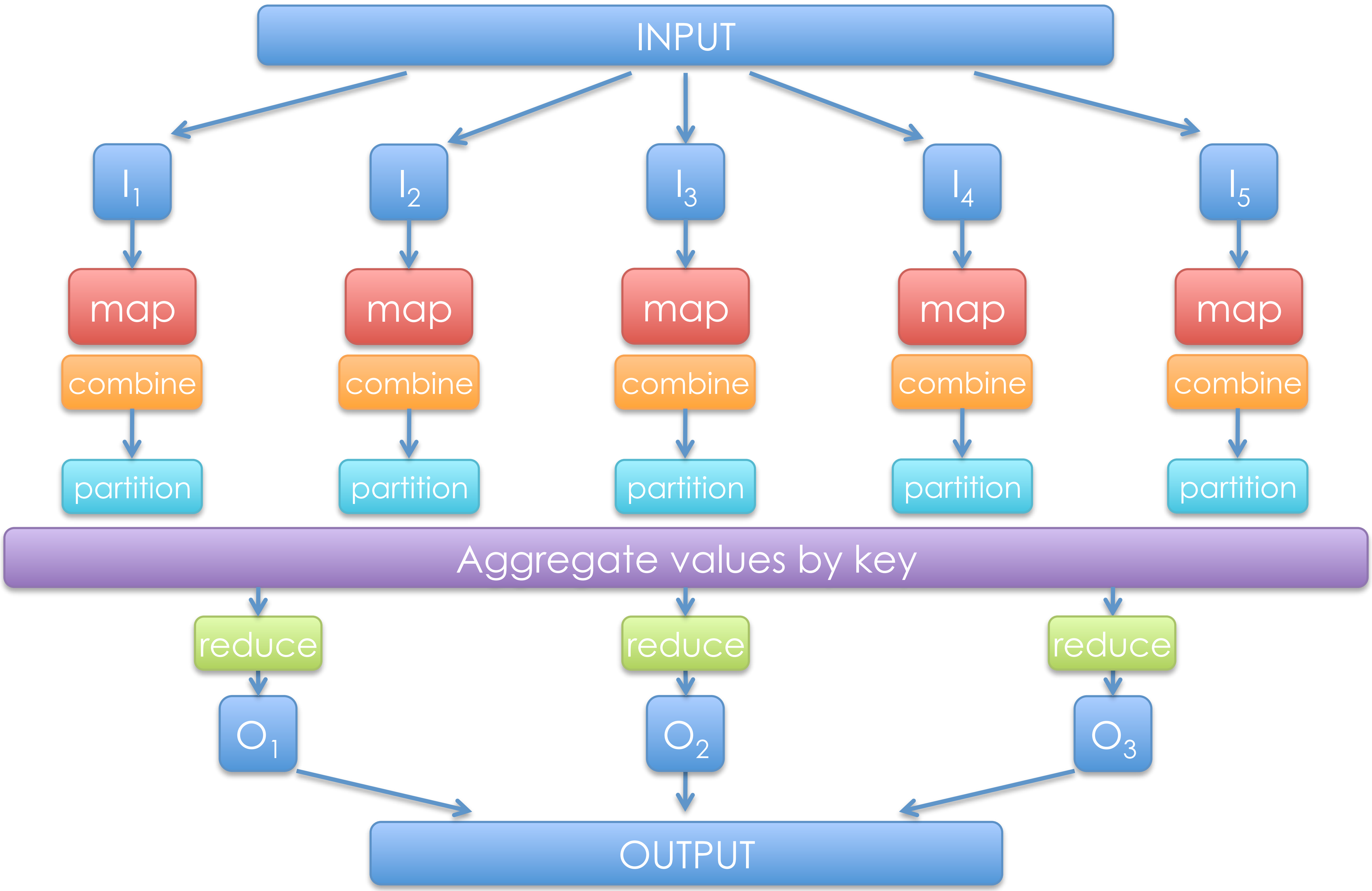


Combiners

- **Local aggregation before the shuffle**
  - All the key-value pairs from mappers need to be copied across the network
  - The amount of intermediate data may be larger than the input collection itself
  - Perform local aggregation on the output of each mapper (same machine)
  - Typically, a combiner is a (local) copy of the reducer



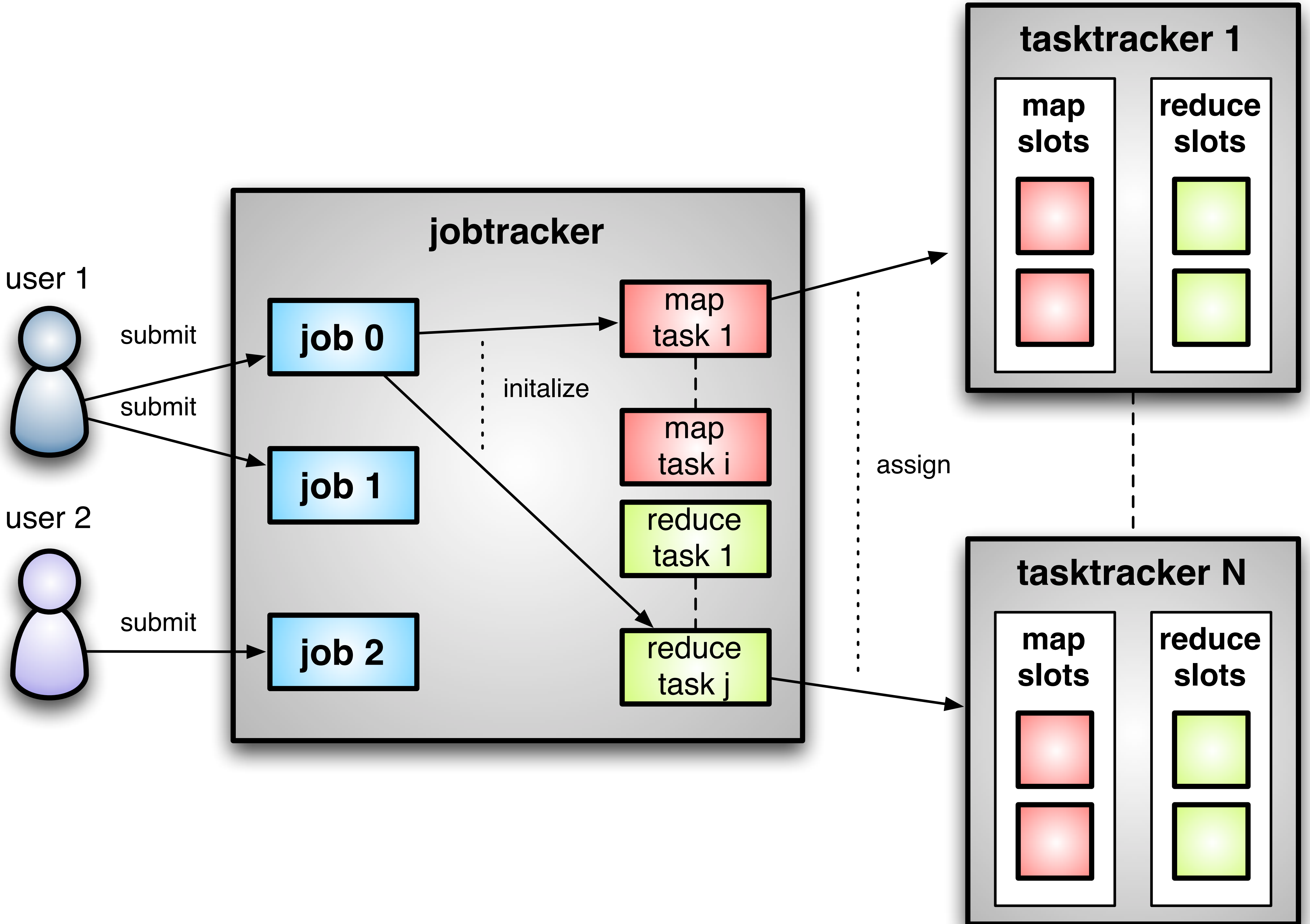
Programming Model (complete)



Terminology

- **Job**
- **Task**
- **Slot**
- **JobTracker**
  - Accepts Map/Reduce jobs submitted by users
  - Assigns Map and Reduce tasks to Task Trackers
  - Monitors task and Task Tracker status, re-executes tasks upon failure
- **TaskTracker**
  - Run Map and Reduce tasks upon instruction from the Job Tracker
  - Manage storage and transmission of intermediate output
- **Splits**
  - Data locality optimization

Runtime



tasktracker 1
map slots
reduce slots
jobtracker
user 1
submit
submit
job 0
map task 1
initalize
map task i
assign
job 1
reduce task 1
user 2
tasktracker N
submit
job 2
reduce task j
map slots
reduce slots

Scheduling

- **One master, many workers**
  - Input data split into M map tasks (typically 64 MB in size)
  - Reduce phase partitioned into R reduce tasks (hash(k) mod R)
  - Tasks are assigned to workers dynamically
  - Often: M=200,000; R=4000; workers=2000
- **Master assigns each map task to a free worker**
  - Considers locality of data to worker when assigning a task
  - Worker reads task input (often from local disk)
  - Worker produces R local files containing intermediate k/v pairs
- **Master assigns each reduce task to a free worker**
  - Worker reads intermediate k/v pairs from map workers
  - Worker sorts & applies user's reduce operation to produce the output

Parallelism

- **Map functions run in parallel, create intermediate values from each input data set**
  - The programmer must specify a proper input split (chunk) between mappers to enable parallelism
- **Reduce functions also run in parallel, each will work on different output keys**
  - Number of reducers is a key parameter which determines map-reduce performance

Speculative Execution

- **Problem: Stragglers (i.e., slow workers) significantly lengthen the completion time**
  - Other jobs may be consuming resources on machine
  - Bad disks with soft (i.e., correctable) errors transfer data very slowly
  - Other weird things: processor caches disabled at machine init
- **Solution: Close to completion, spawn backup copies of the remaining in-progress tasks.**
  - Whichever one finishes first, "wins"
- **Additional cost: a few percent more resource usage**
- **Example: A sort program without backup = 44% longer.**

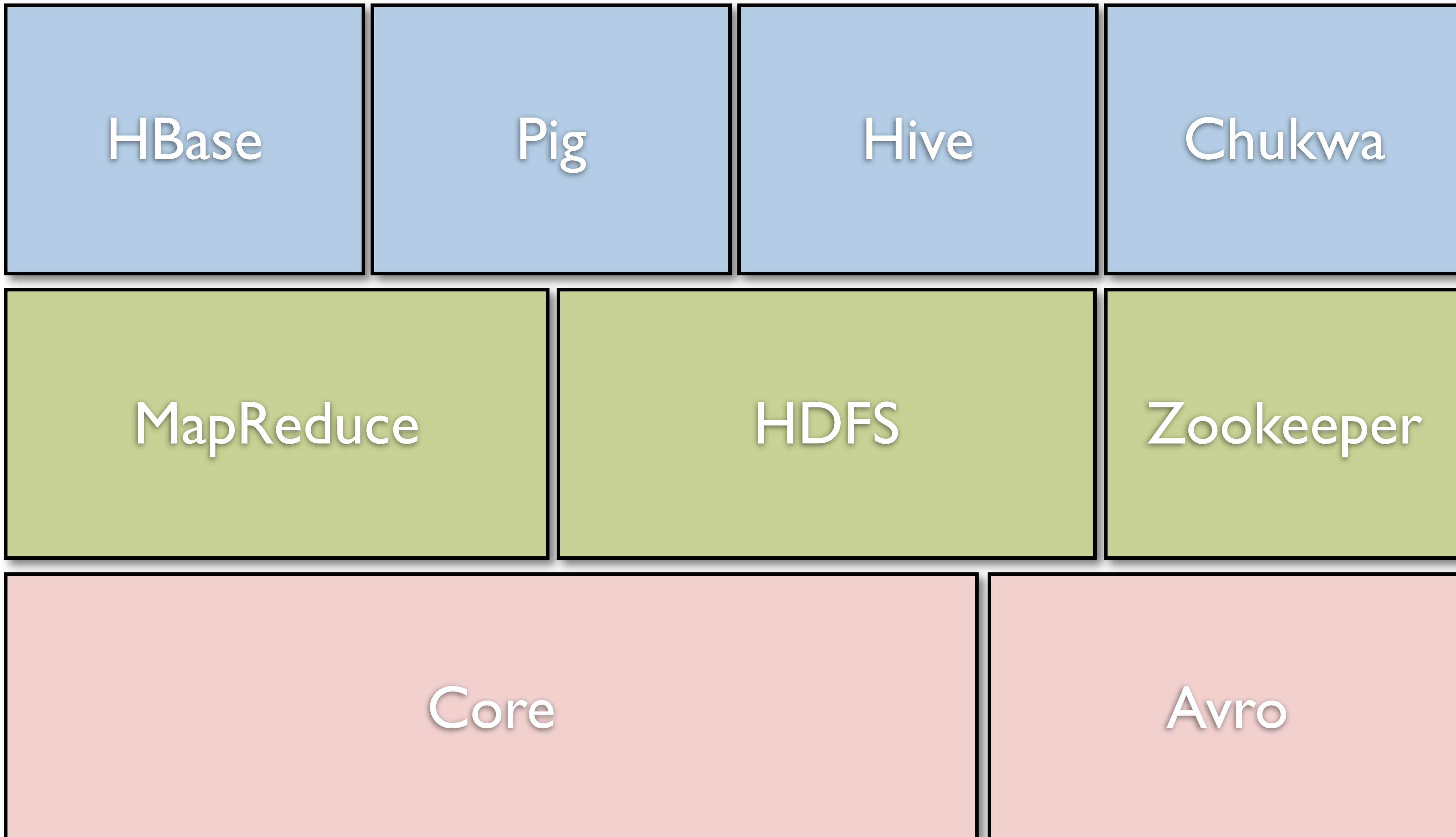
Fault Tolerance

- **Master keeps track of progress of each task and worker nodes**
  - If a node fails, it re-executes the completed as well as in-progress map tasks on other nodes that are alive
  - It also executes in-progress reduce tasks.
- **If particular input key/value pairs keep crashing**
  - Master blacklists them and skips them from re-execution
- **Tolerate small failures, allow the job to run in best-effort basis**
  - For large datasets containing potentially millions of records, we don't want to stop computation for a few records not processing correctly
  - User can set the failure tolerance level

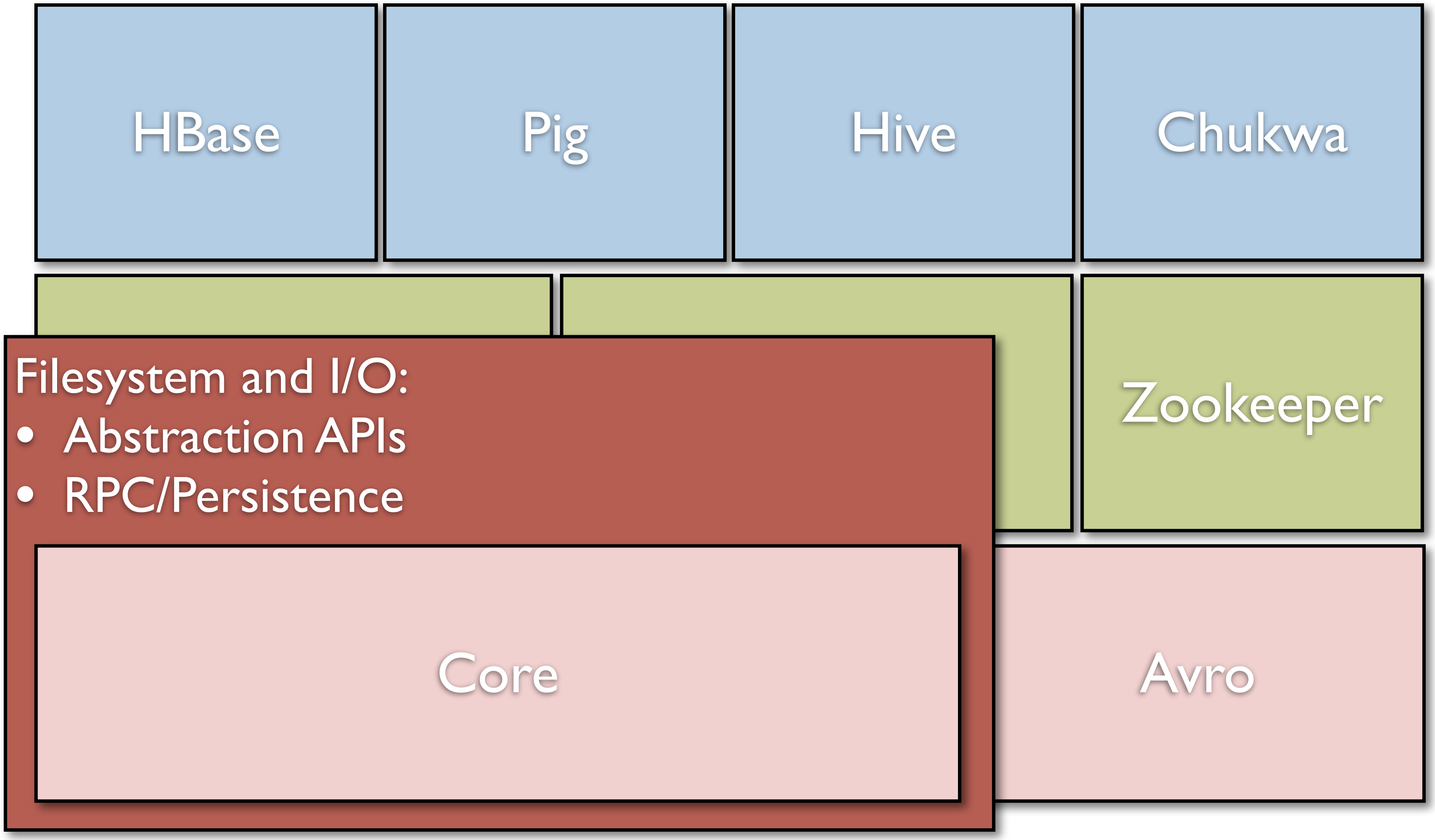
Performance

- **Maximizing Map input transfer rate**
  - Input Locality
  - Minimal deserialization overhead
- **Small intermediate output**
  - M x R transfers over the network
  - Minimize/compress transfers
  - Avoid shuffling/sorting if possible (e.g. map-only computations)
  - Use combiners and/or partitioners!!!
  - Compress everything (automatic)
- **Opportunity to Load Balance**
- **Changing algorithm to suit architecture yields best implementation**

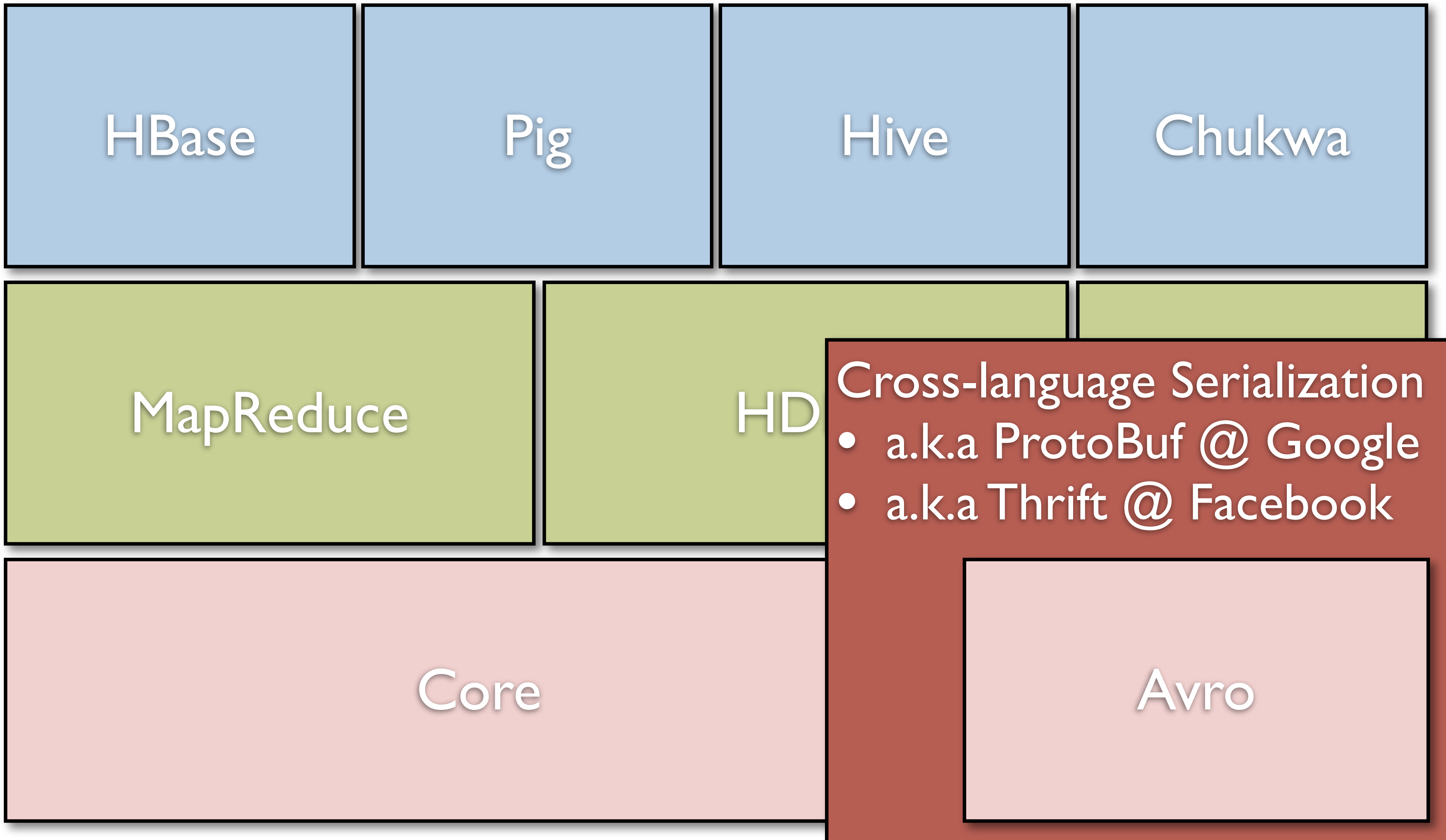
HADOOP



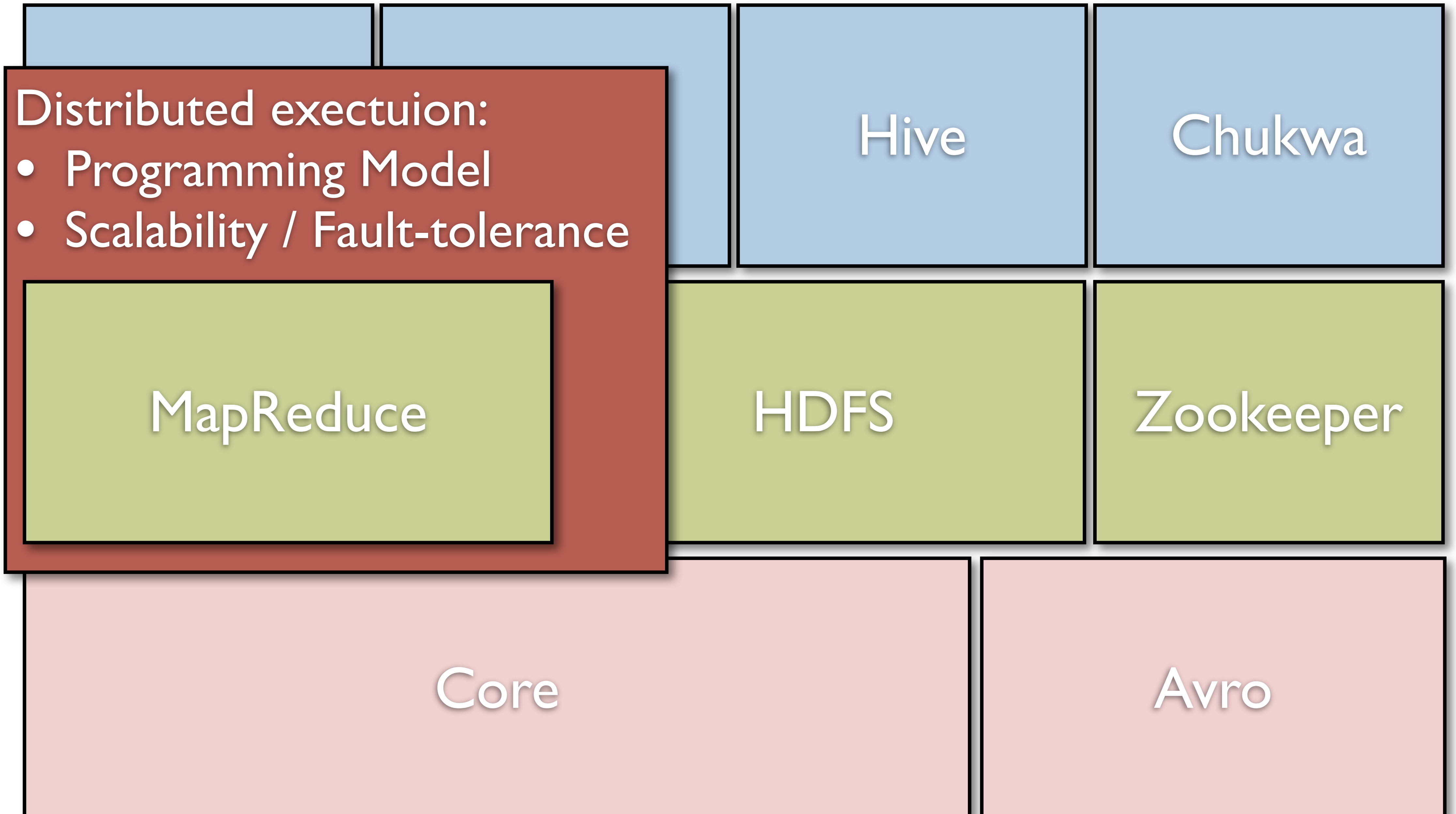
HADOOP


HBase
Pig
Hive
Chukwa
Zookeeper
Filesystem and I/O:
• Abstraction APIs
• RPC/Persistence
Core
Avro

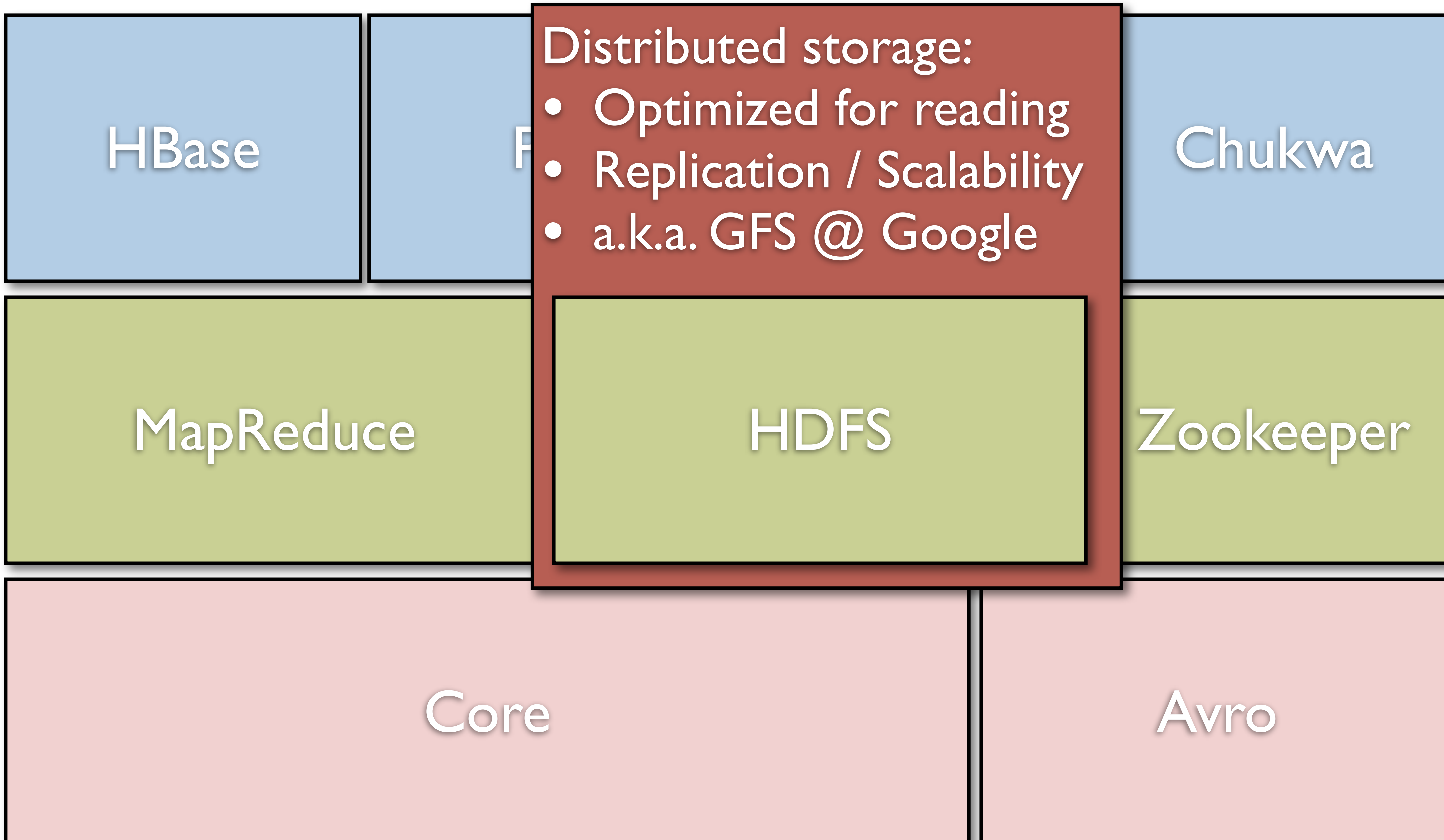
HADOOP


HBase
Pig
Hive
Chukwa
MapReduce
HD
Cross-language Serialization
• a.k.a ProtoBuf @ Google
• a.k.a Thrift @ Facebook
Core
Avro

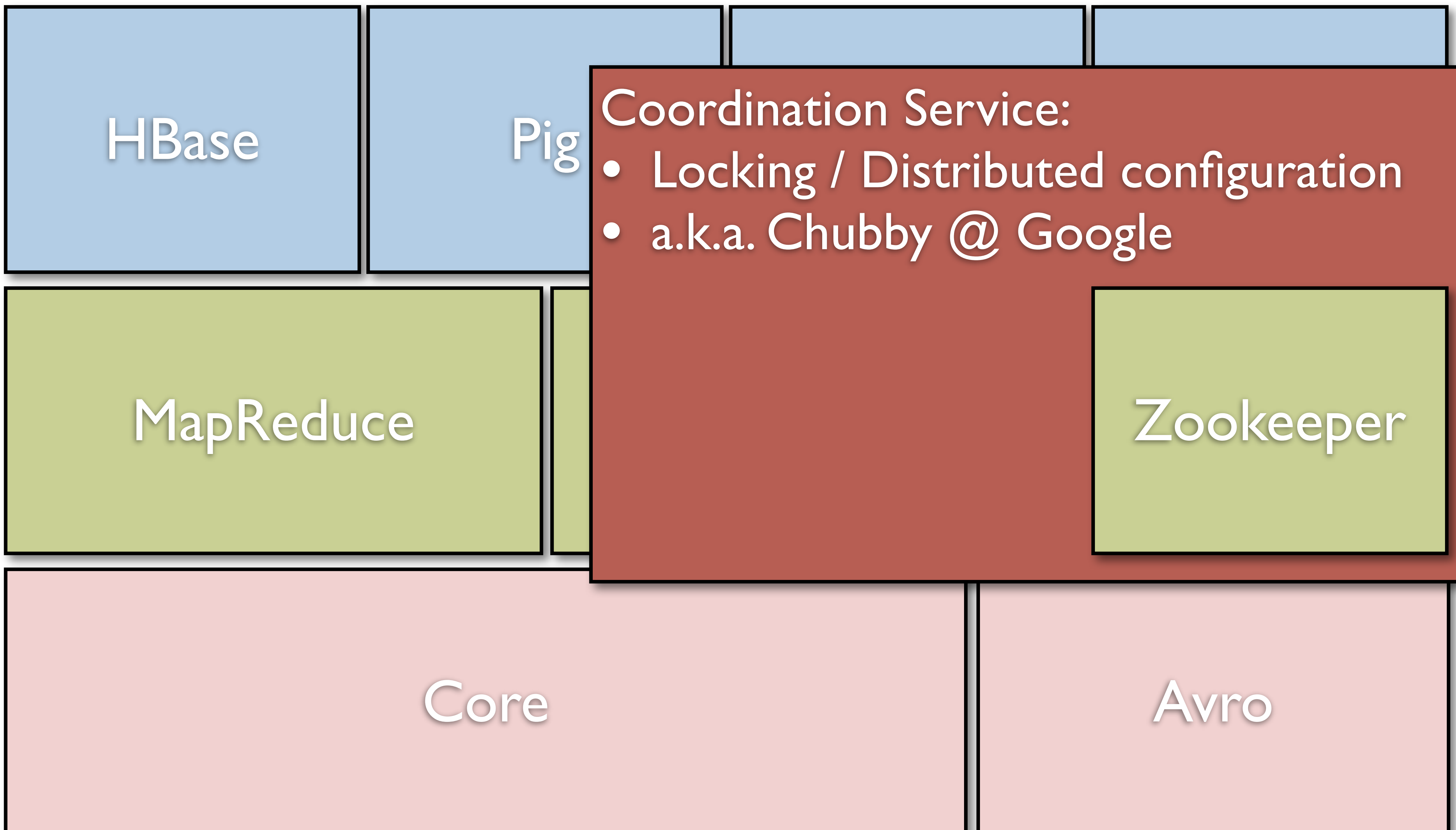
HADOOP


Distributed exectuion:
• Programming Model
• Scalability / Fault-tolerance
Hive
Chukwa
MapReduce
HDFS
Zookeeper
Core
Avro

HADOOP

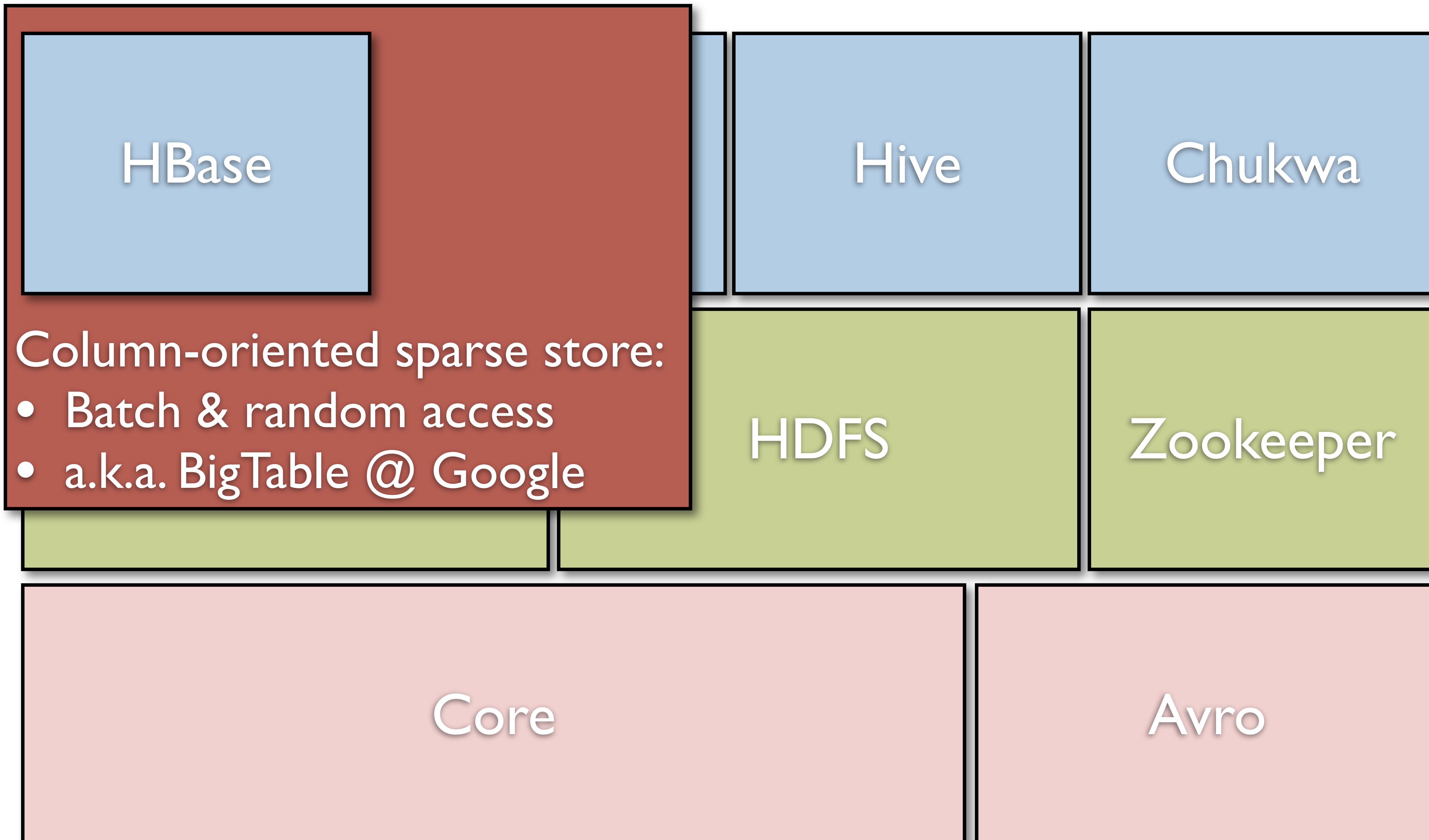

HBase
Distributed storage:
• Optimized for reading
• Replication / Scalability
• a.k.a. GFS @ Google
Chukwa
MapReduce
HDFS
Zookeeper
Core
Avro

HADOOP

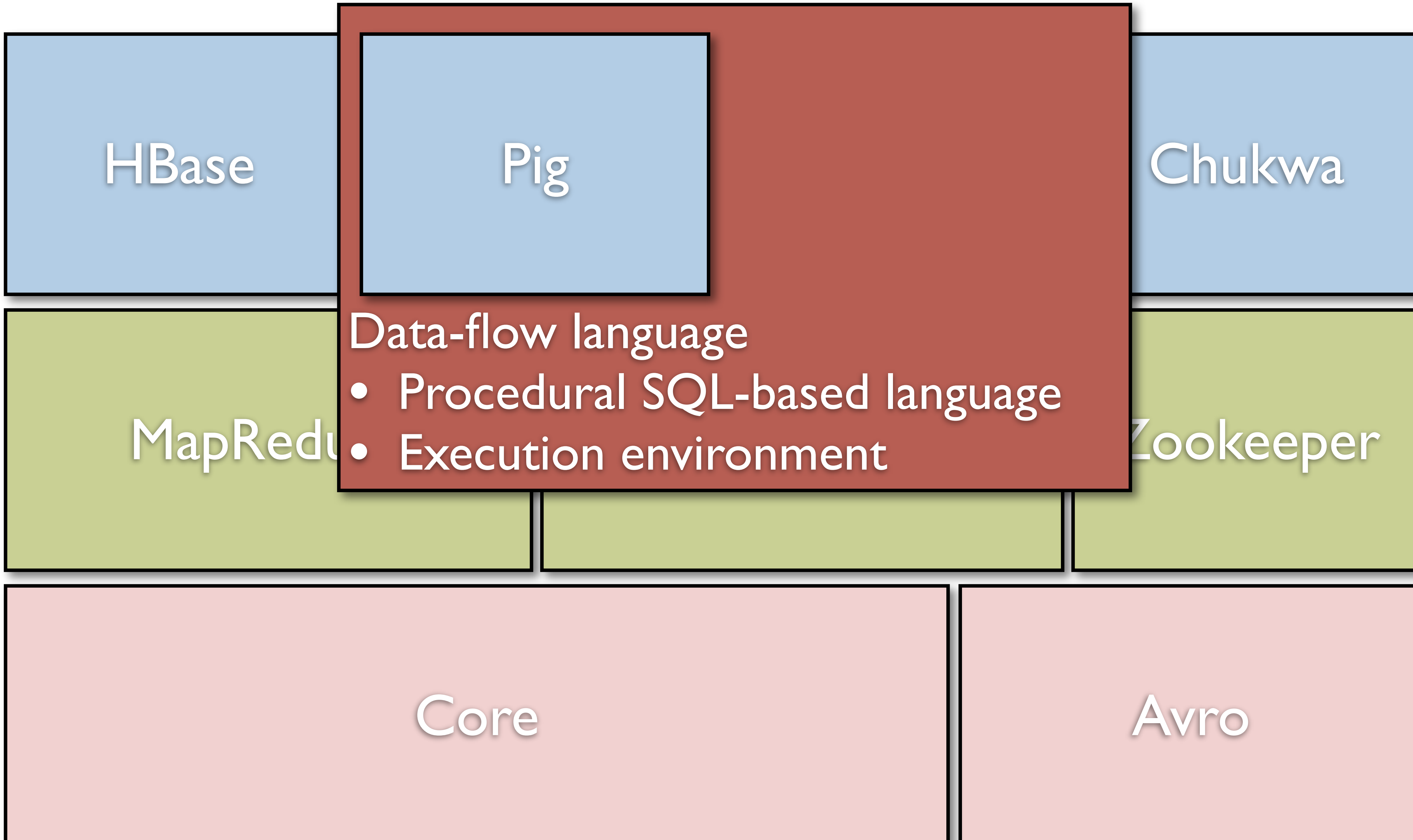


HBase
Pig
Coordination Service:
• Locking / Distributed configuration
• a.k.a. Chubby @ Google
MapReduce
Zookeeper
Core
Avro

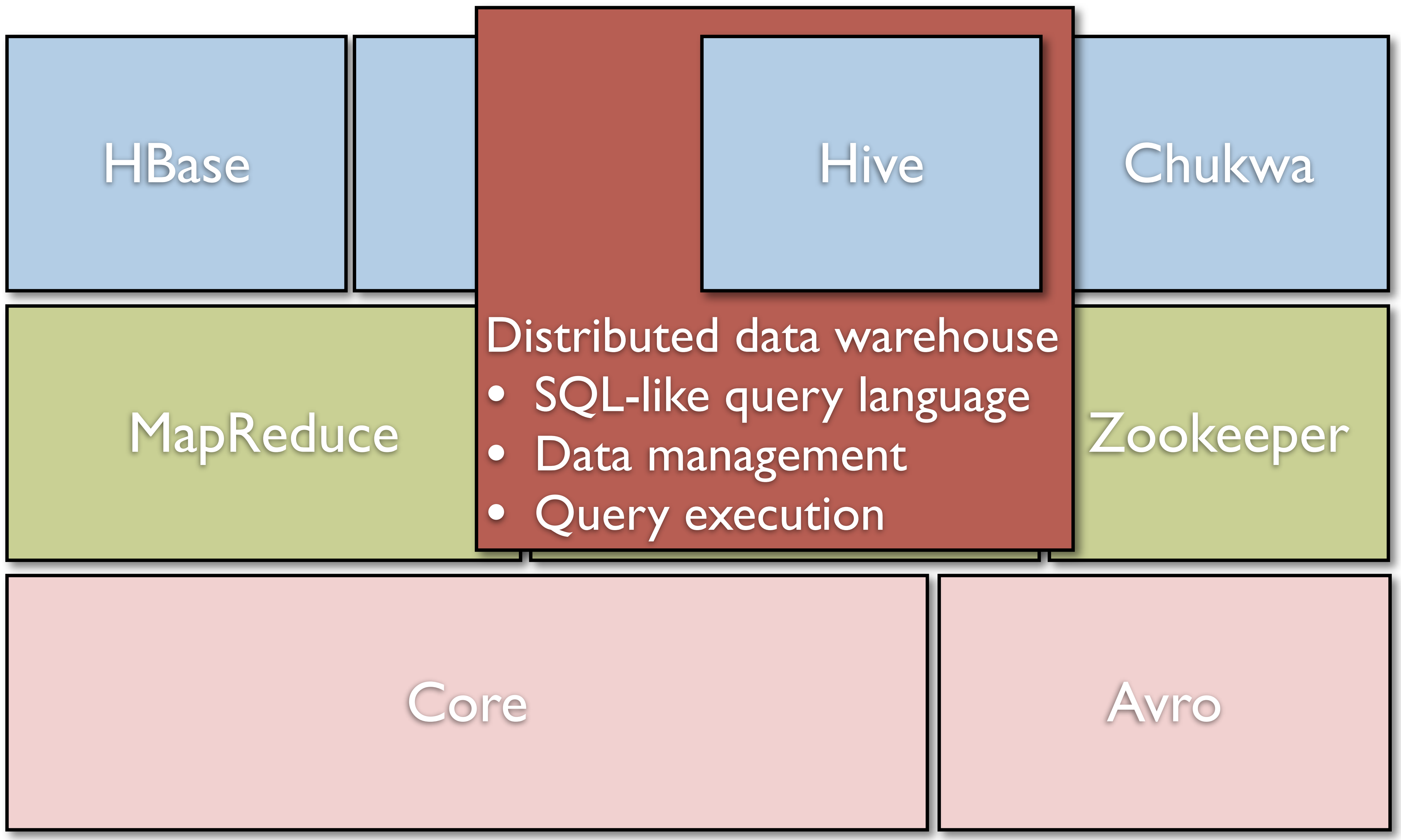
HADOOP


HBase
Hive
Chukwa
Column-oriented sparse store:
• Batch & random access
• a.k.a. BigTable @ Google
HDFS
Zookeeper
Core
Avro

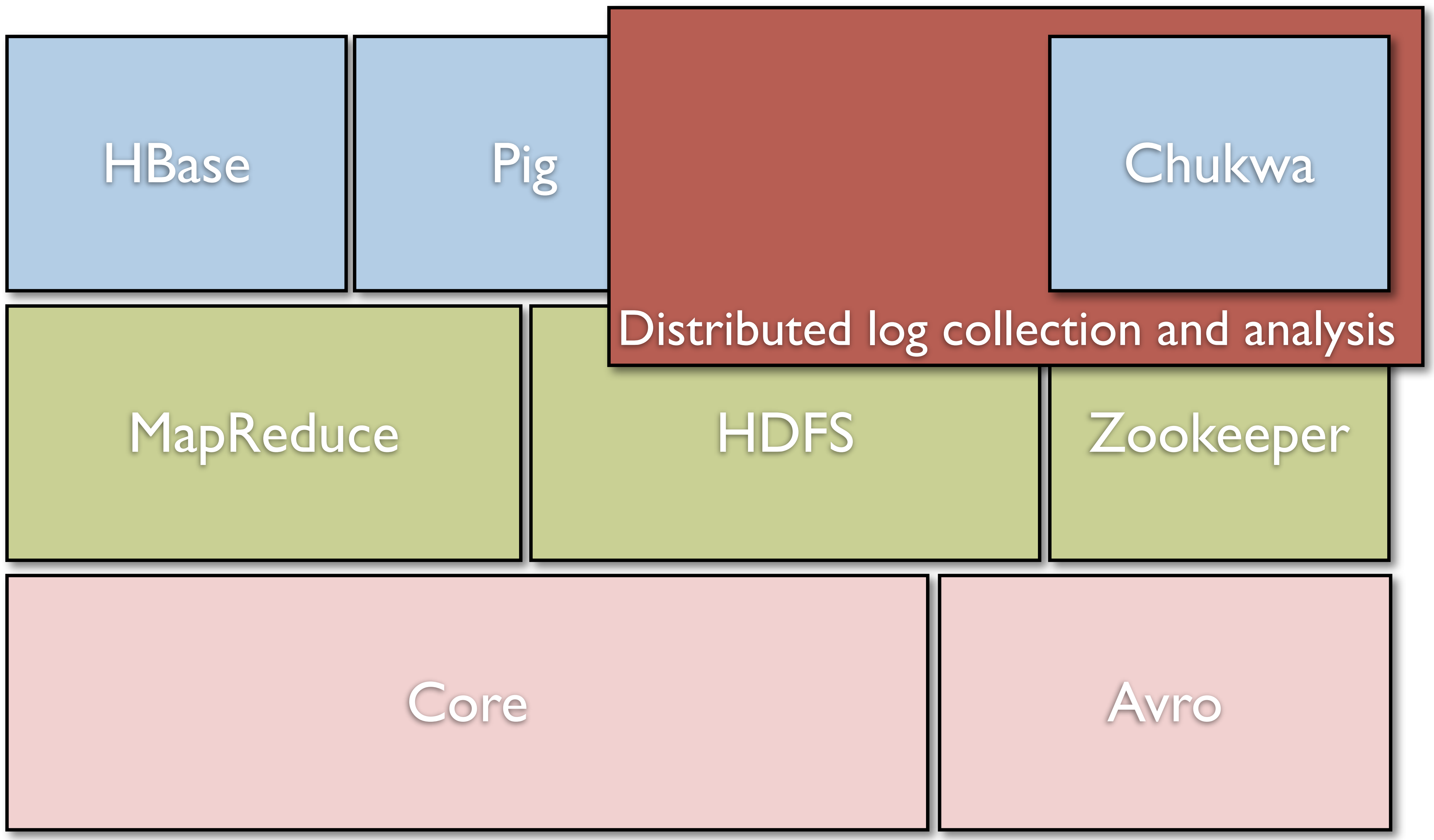
HADOOP


HBase
Pig
Chukwa
Data-flow language
• Procedural SQL-based language
• Execution environment
MapRedu
Zookeeper
Core
Avro

HADOOP


HBase
Hive
Chukwa
Distributed data warehouse
• SQL-like query language
• Data management
• Query execution
MapReduce
Zookeeper
Core
Avro

HADOOP


HBase
Pig
Chukwa
Distributed log collection and analysis
MapReduce
HDFS
Zookeeper
Core
Avro

Basic HADOOP API (0.20.2)

- **Package org.apache.hadoop.mapreduce**
- **Class Mapper<KEYIN, VALUEIN, KEYOUT, VALUEOUT>**
  - void setup(Mapper.Context context)
  - void cleanup(Mapper.Context context)
  - void map(KEYIN key, VALUEIN value, Mapper.Context context)
  - output is generated by invoking context.collect(key, value);
- **Class Reducer<KEYIN, VALUEIN, KEYOUT, VALUEOUT>**
  - void setup(Reducer.Context context)
  - void cleanup(Reducer.Context context)
  - void reduce(KEYIN key, Iterable<VALUEIN> values, Reducer.Context context)
  - output is generated by invoking context.collect(key, value);
- **Class Partitioner<KEY, VALUE>**
  - abstract int getPartition(KEY key, VALUE value, int numPartitions)

Basic HADOOP Data Types (0.20.2)

- **Package org.apache.hadoop.io**

interface
Writable

Defines a de/serialization protocol

Any key or value type in the Hadoop Map-Reduce framework implements this interface

interface
WritableComparable<T>

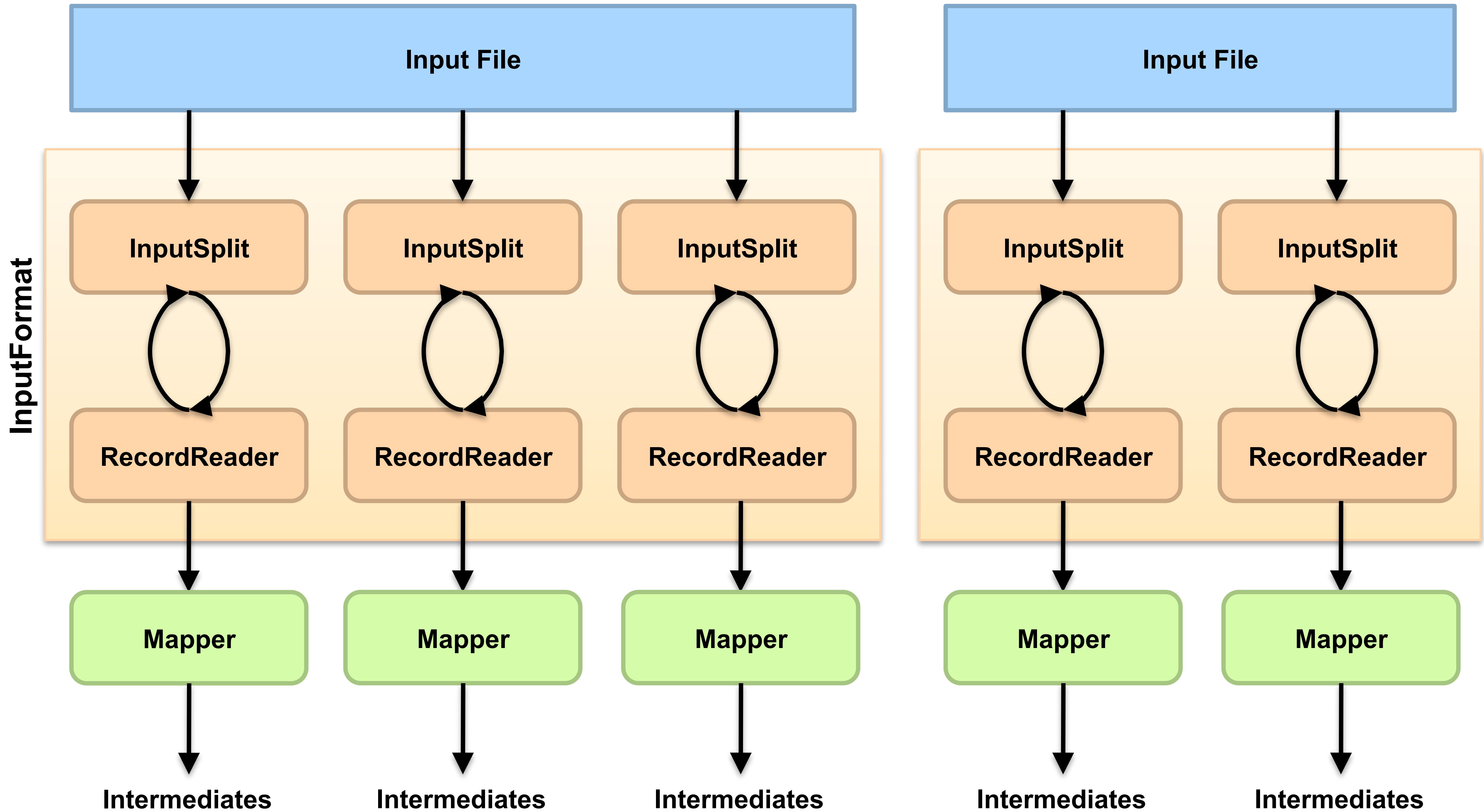
WritableComparables can be compared to each other, typically via Comparators

Any type which is to be used as a key in the Hadoop Map-Reduce framework should implement this interface

IntWritable
LongWritable
Text

Concrete classes for common data types

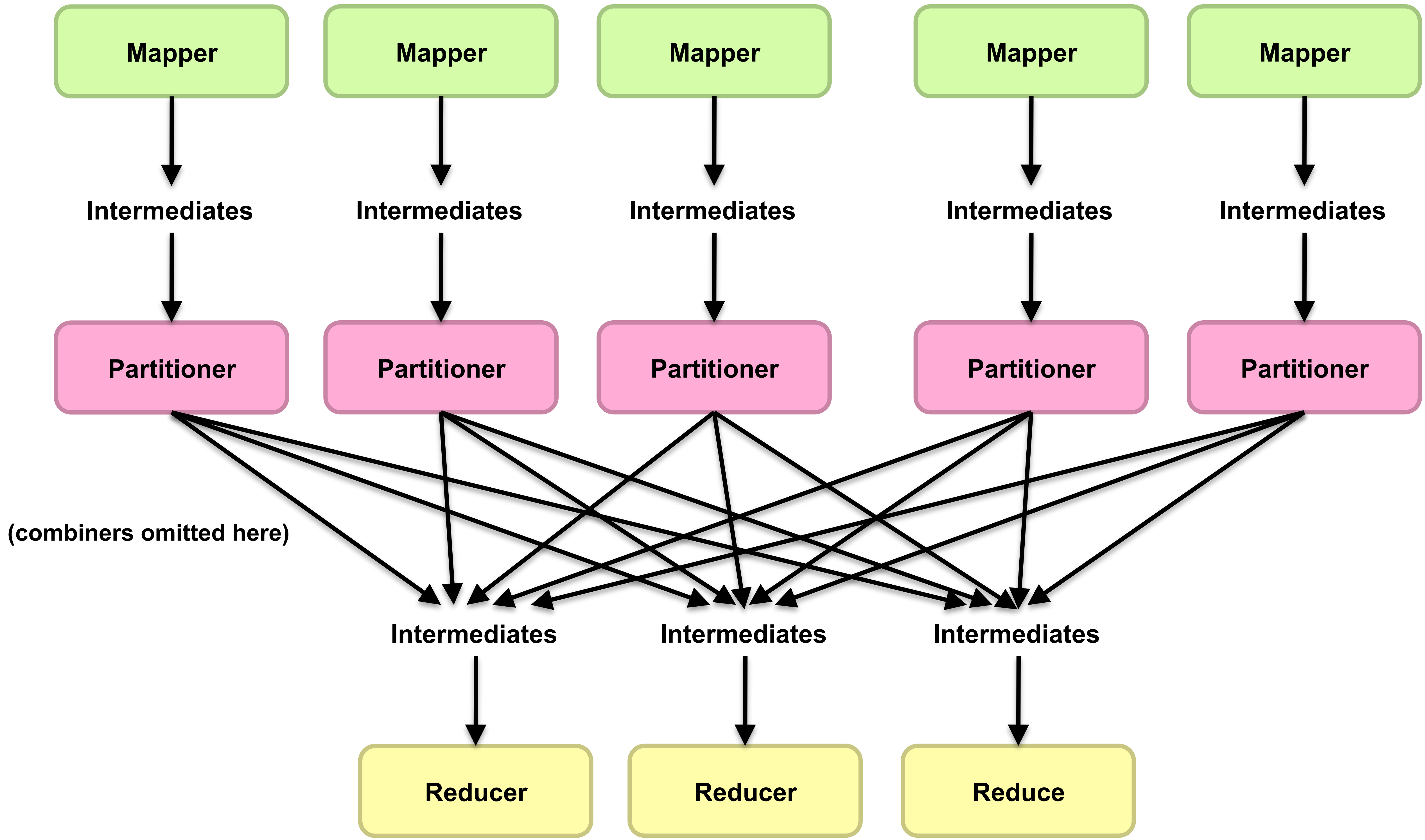
Hadoop Dataflow (I)



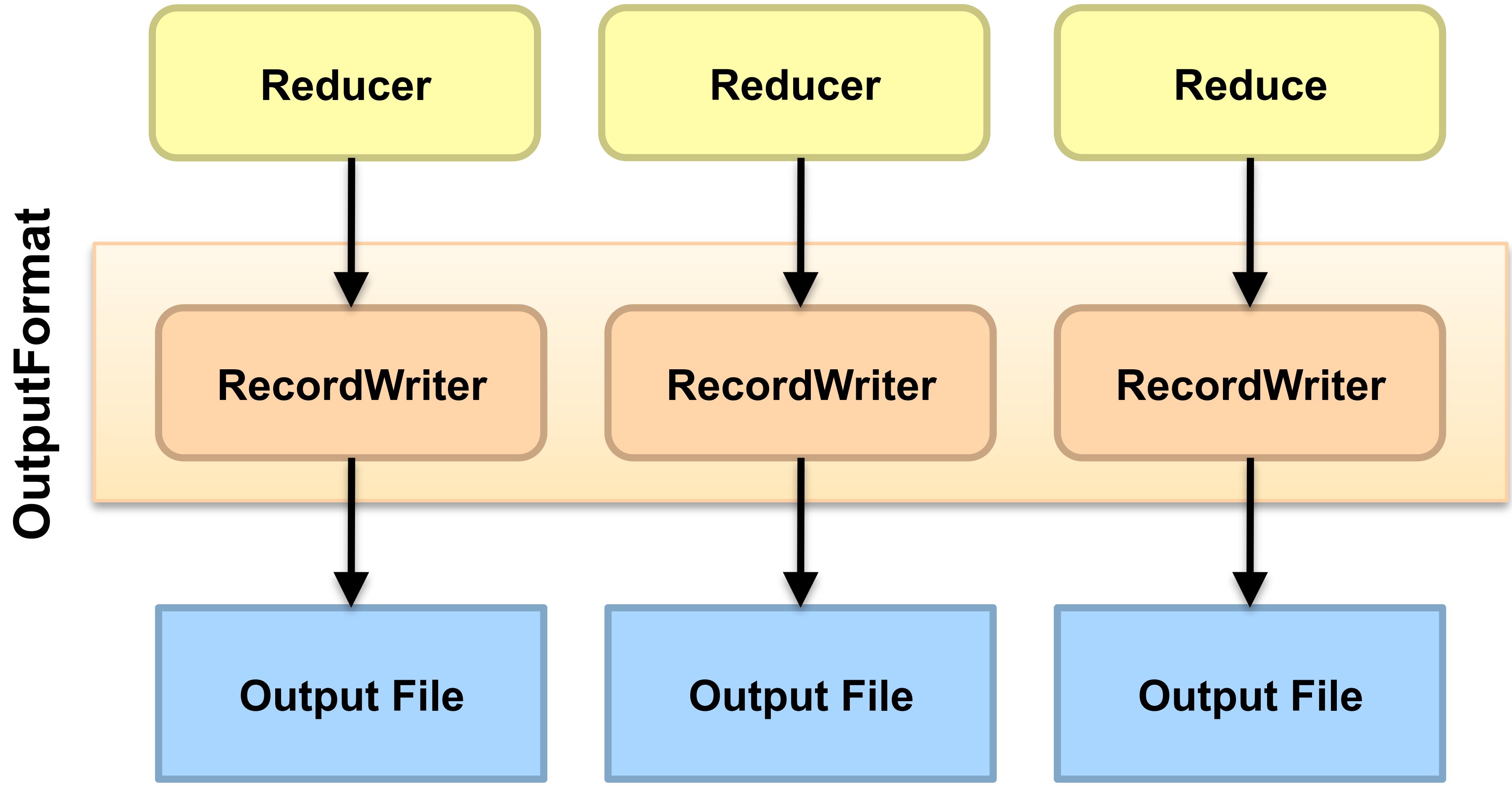
HADOOP Data Reading (0.20.2)

- Data sets are specified by **InputFormats**
  - Defines input data (e.g., a directory)
  - Identifies partitions of the data that form an **InputSplit**, each of which will be assigned to a mapper
  - Provide the **RecordReader** implementation to extract (k, v) records from the input source
- Base class implementation is **FileInputFormat**
  - Will read all files out of a specified directory and send them to the mappers
  - **TextInputFormat** – Treats each '\n'-terminated line of a file as a value
  - **KeyValueTextInputFormat** – Maps '\n'- terminated text lines of "k SEP v"
  - **SequenceFileInputFormat** – Binary file of (k, v) pairs with some add'l metadata
  - **SequenceFileAsTextInputFormat** – Same, but maps (k.toString(), v.toString())

Hadoop Dataflow (II)



Hadoop Dataflow (III)



HADOOP Data Writing (0.20.2)

- Data sets are specified by **OutputFormats**
  - Analogous to InputFormat
- Base class implementation is **FileOutputFormat**
  - TextOutputFormat – Writes "key val\n" strings to output file
  - SequenceFileOutputFormat – Uses a binary format to pack (k, v) pairs
- Other implementation is **NullOutputFormat**
  - Discards output to /dev/null

Hadoop Shuffle & Sort

- **Map Side**
  - Mapper outputs are buffered in memory in a circular buffer
  - When buffer reaches threshold, contents are "spilled" to disk
  - Spills are merged in a single partitioned file (sorted within each partition)
  - Combiners run here
- **Reduce Side**
  - Firstly, mapper outputs are coped over to the reducer machine
  - "Sort" is a multi-pass merge of map outputs (in memory and on disk)
  - Combiners run here
  - Final merge pass goes directly into reducer
- **Probably the most complex aspect of the framework!**