Map Reduce

Data at Scale

History

- A *simple* paradigm that popped up several times as paradigm
- Observed by google as a software pattern:
  - Data gets filtered locally and filtered data is then reassembled elsewhere
  - Software pattern: Many engineers are re-engineering the same steps
- Map-reduce:
  - Engineer the common steps efficiently
  - Individual problems only need to be engineered for what makes them different

History

- Open source project (in part sponsored by Yahoo!)
  - Java-based Hadoop
  - Eventually a first tier Apache Foundation project

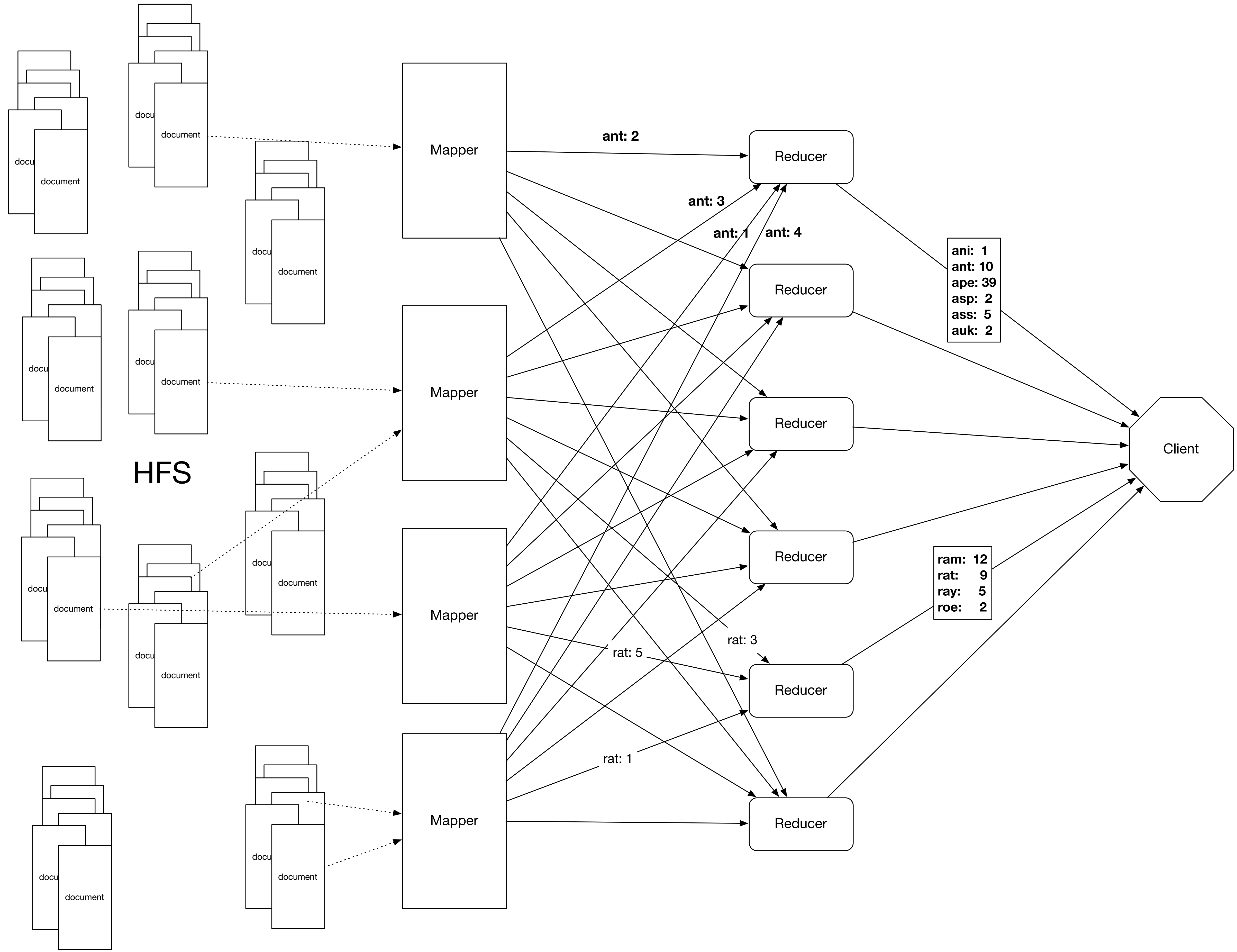
- Other projects at higher level: Pig, Hive, HBase, Mahout, Zookeeper
  - Use Hadoop as foundation
  - Hadoop is becoming a distributed OS

Map Reduce Paradigm

- Input: Large amount of data spread over many different nodes
- Output: A single file of results
- Two important phases:
  - **Mapper**: Records are processed into key-value pairs. Mapper sends key-value pairs to reducers
  - **Reducer:** Create final answer from mapper

Simple Example

- Hadoop Word Count
  - Given different documents on many different sites
    - Mapper:
      - Extract words from record
      - Combines words and generates key-value pairs of type word: key
      - Sends to the reducers based on hash of key
    - Reducer:
      - Receives key-value pairs
      - Adds values for each key
      - Sends accumulated results to aggregator - client



HFS
docu
document
Mapper
Mapper
Mapper
Mapper
ant: 2
ant: 3
ant: 1
ant: 4
rat: 5
rat: 3
rat: 1
Reducer
Reducer
Reducer
Reducer
Reducer
Reducer
ani: 1
ant: 10
ape: 39
asp: 2
ass: 5
auk: 2
ram: 12
rat: 9
ray: 5
roe: 2
Client

Map-reduce paradigm in detail

- The simple mapper -reducer paradigm can be expanded into several, typical components

Map Reduce in Detail

- **Mapper:**
  - Record Reader
    - Parses the data into records
    - Example: Stackoverflow comments.
      - <row Id="5" PostId="5" Score="2" Text="Programming in Portland, cooking in Chippewa ; it makes sense that these would be unlocalized. But does bicycling.se need to follow only that path? I agree that route a to b in city x is not a good use of this site; but general resources would be." CreationDate="2010-08-25T21:21:03.233" UserId="21" />
    - Record reader extract the “Text=” string
    - Passes record into a key-value format to rest of mapper

Map Reduce in Detail

- **Mapper**
  - map
    - Produces “intermediate” key-value pairs from the record
    - Example:
      - **`"Programming in Portland, cooking in Chippewa ; it makes sense that these would be unlocalized. But does bicycling.se need to follow only that path? I agree that route a to b in city x is not a good use of this site; but general resources would be.”`**
      - Map produces: <programming: 1> <in: 1> <Portland: 1> <cooking: 1> <in: 1> …

Map Reduce in Detail

- **Mapper**
  - Combiner — a local reducer
    - Takes key-value pairs and processes them
    - Example:
      - Map produces: <programming: 1> <in: 1> <Portland: 1> <cooking: 1> <in: 1> …
      - Combiner combines words: <programming: 1> <in: 4> <Portland: 3> …

Map Reduce in Detail

- Combiners allow us to reduce network traffic
  - By compacting the same infomrmation

Map Reduce in Detail

- **Mapper**
  - Partitioner
    - Partitioner creates shards of the key-value pairs produced
    - One for each reducer
    - Often uses a hash function or a range
    - Example:
      - md5(key) mod (#reducers)

Map Reduce in Detail

- **Reducer**
  - Shuffle and Sort
  - **Part of the map-reduce framework**
    - Incoming key-value pairs are sorted by key into one large data list
    - Groups keys together for easy agglomeration
    - Programmer can specify the comparator, but nothing else

Map Reduce in Detail

- **Reducer**
  - reduce
    - Written by programmer
    - Works on each key group
    - Data can be combined, filtered, aggregated
    - Output is prepared

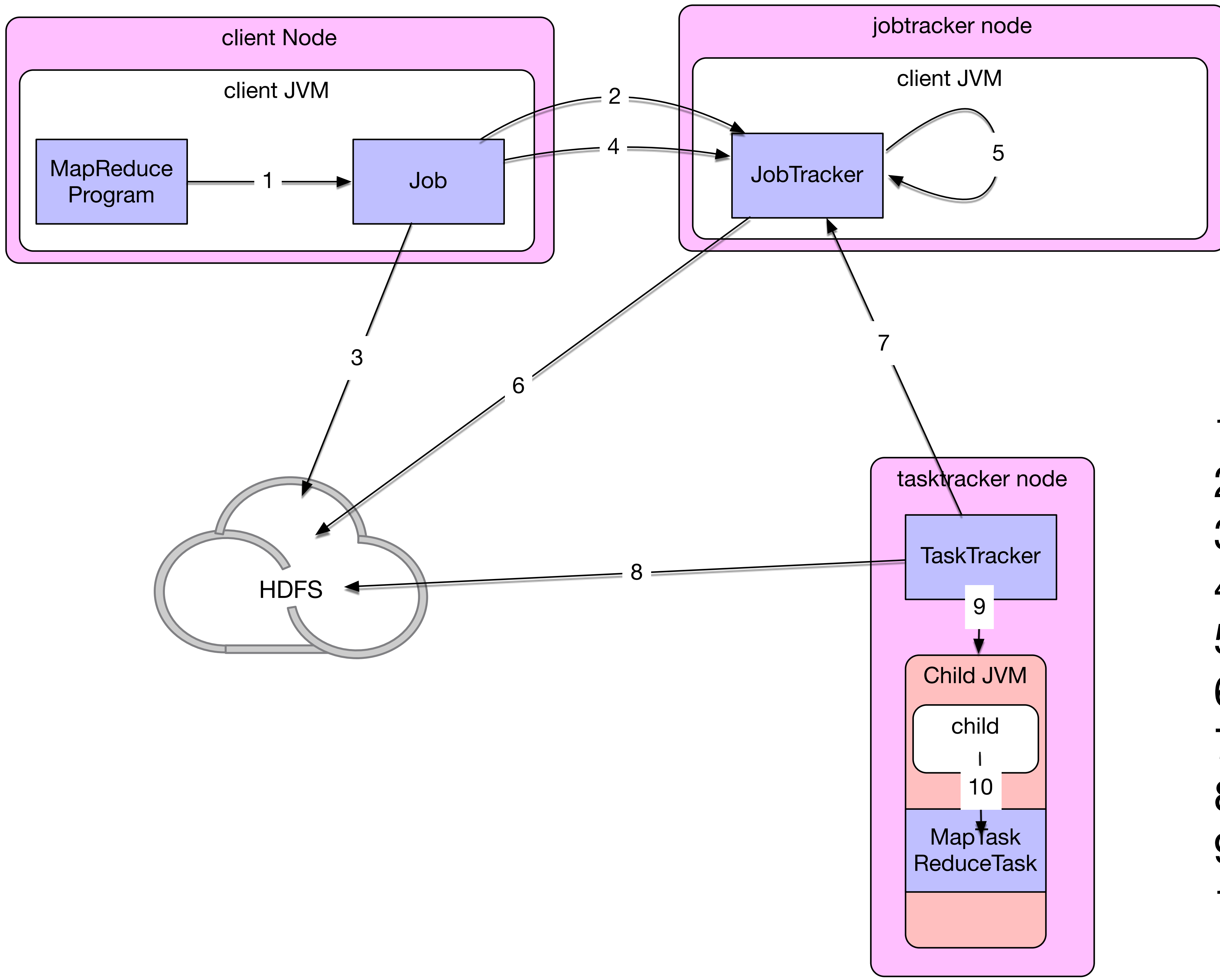
Map Reduce in Detail

- **Reducer**
  - Output format
    - Formats final key-value pair

Hadoop

- Classic Map-Reduce
  - Client that submits the map-reduce job
  - Job trackers which coordinate the job run
  - Task trackers that run the tasks that the job has been split into
  - Distributed file system (HDFS — Hadoop file system) for file sharing between entities

Hadoop Classic

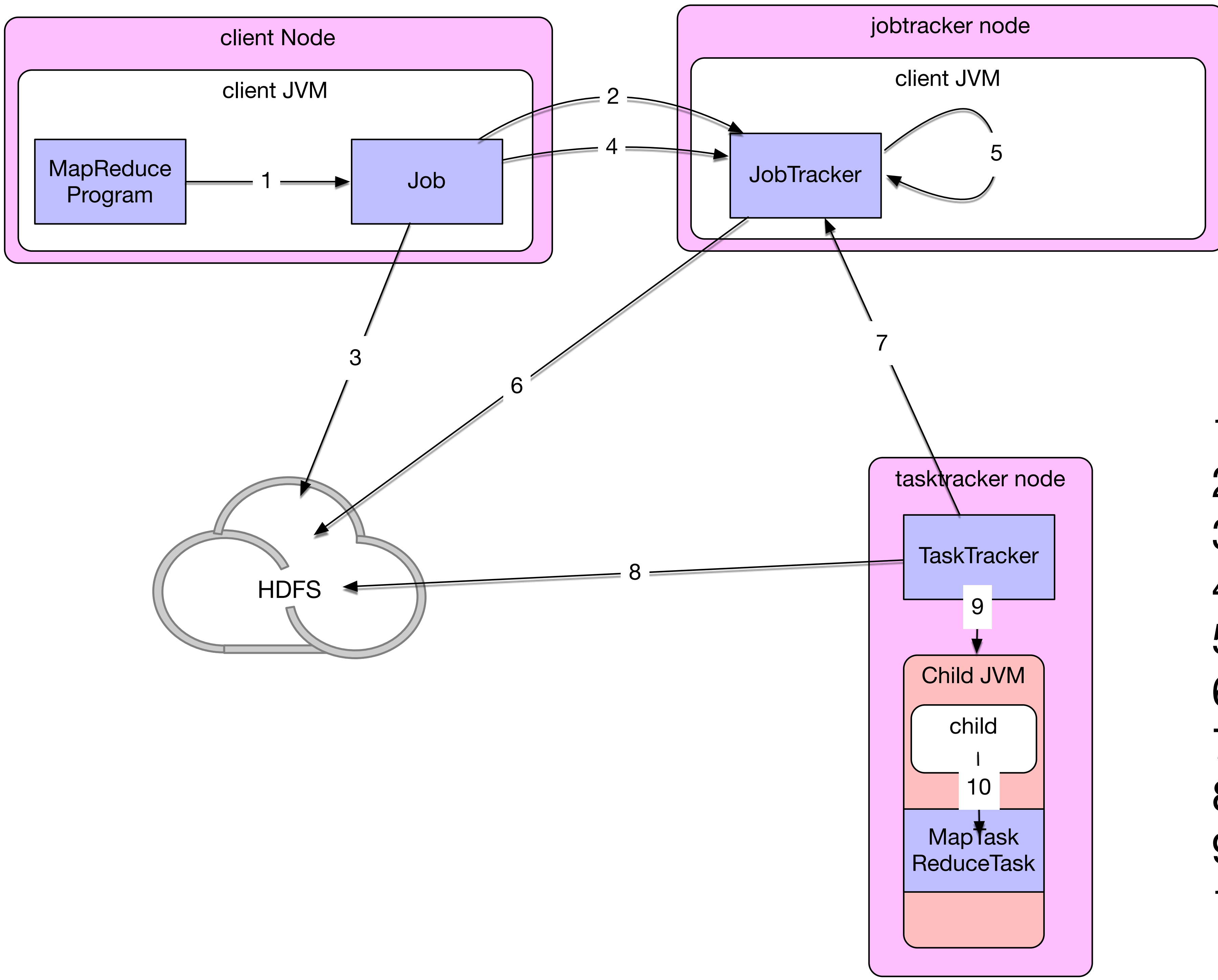


1: run job
2: get new job id
3: copy job resources
4: submit job
5: initialize job
6: retrieve input splits
7: heartbeat
8: retrieve job resources
9: launch
10: run

Hadoop

- Job submission
  - Creates an internal JobSummitter instance
    - JobSubmitter
      - asks jobtracker for a new jobid
      - check the output specifications of the job
      - computes the input split for the job
      - copies the resources needed for the job
      - tells the jobtracker that the job is ready for submission

Hadoop Classic



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10: run

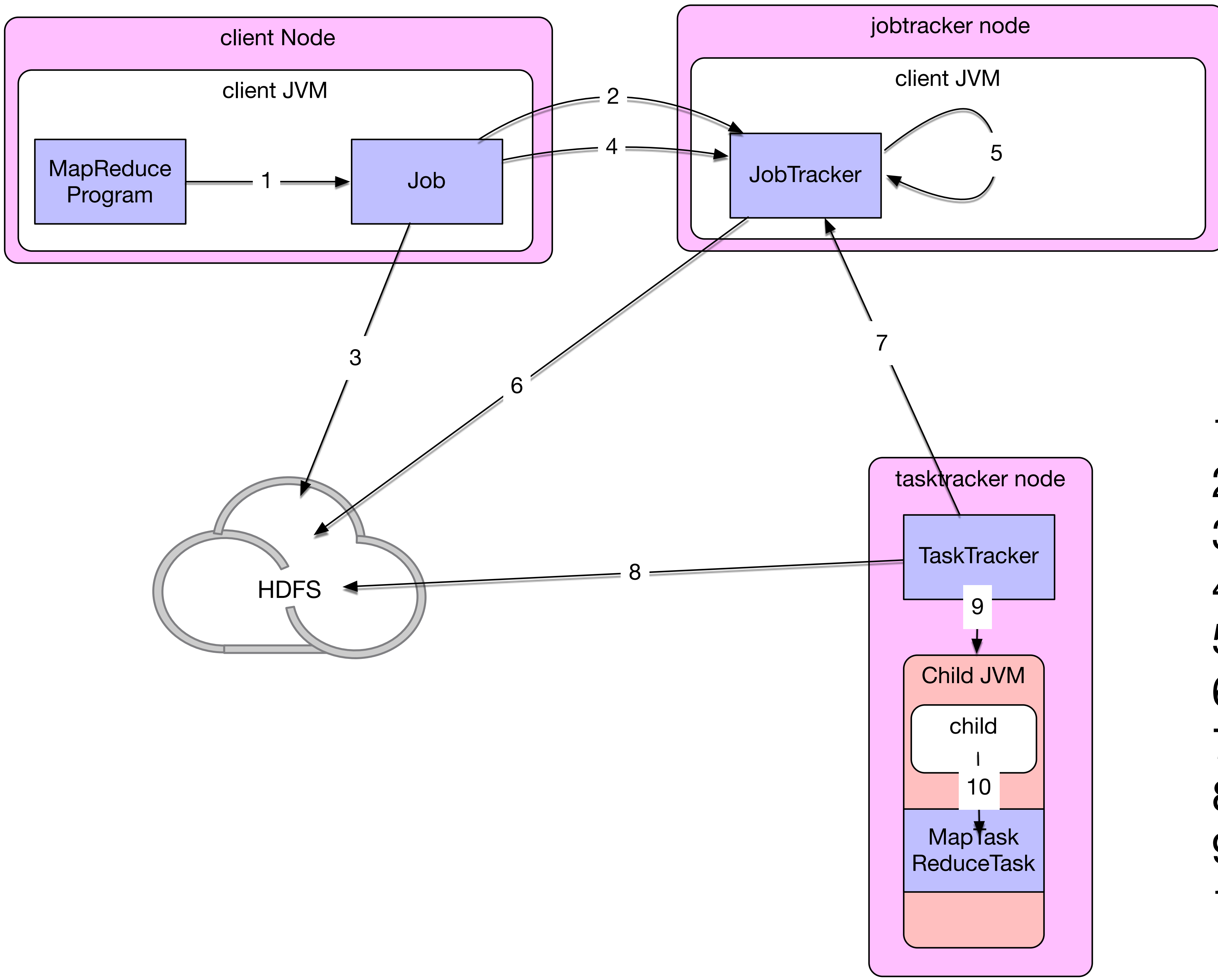
Hadoop

- Jobtracker receives call from submitJob( )
  - places it in internal queue
  - retrieves the input splits computed by the client
  - creates a map task for each split
    - number of mappers is set by the mapred.reduce.tasks
  - runs job setup task
  - runs job cleanup task

Hadoop

- Task assignment
  - Tasktrackers periodically send heartbeat to jobtracker
    - Includes message if task is done so that node can get a new job
  - Tasktrackers have a set number of map and reduce jobs that they can handle
  - To create a reduce task, the jobtracker simply goes through the list of reduce tasks and assigns one
  - Preference is given to data-local (reduce on the same node) or rack-local

Hadoop Classic



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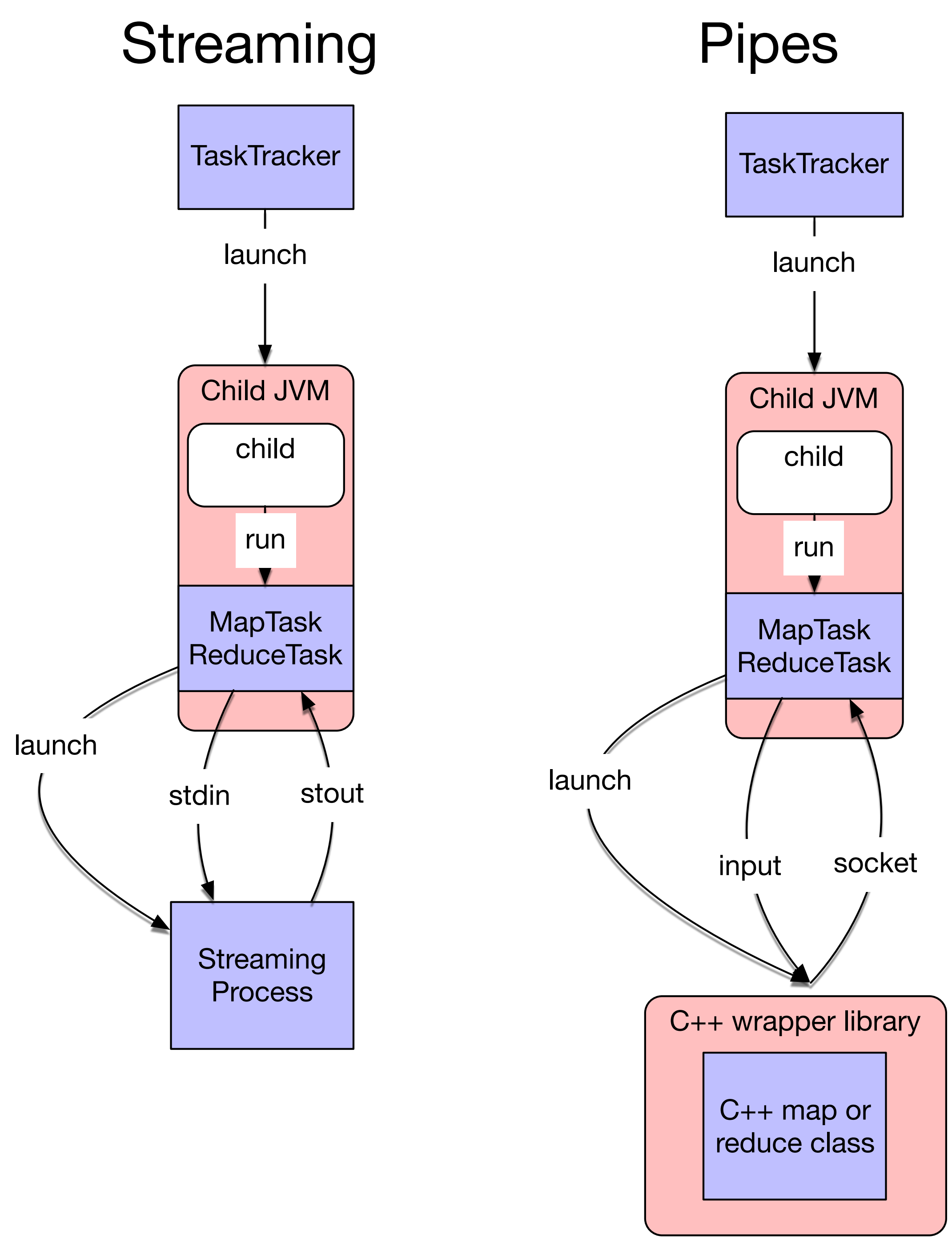
Classical Hadoop

- Task execution
  - Tasktracker localizes the job JAR from the file system
  - It copies any files needed from the distributed cache
  - Creates instances of TaskRunner to run the task
    - TaskRunners launch a new Java Virtual Machine
    - Child informs parent of progress

Classical Hadoop

- Streaming and pipes run special map and reduce tasks
  - Streaming:
    - communicates with process using standard input and output streams
  - Pipes:
    - Pipes task listens on socket
    - passes C++ process a port number
  - In both cases
    - Java process passes input key-value pairs to the external process

Classic Hadoop Streaming and Piping



Classical Hadoop

- Progress and status updates
  - Map-Reduce jobs can take hours
  - Each job has a status
  - System estimates progress for each task
    - Mappers: per cent input dealt with
    - Reducers: More complicated, but estimates are possible
  - Tasks use set of counters for various events
    - Can be user defined — see below

Classical Hadoop

- Job completion
  - If job tracker receives notification that last task has completed
    - Job status changes to “successful”
    - Job statistics are sent to console

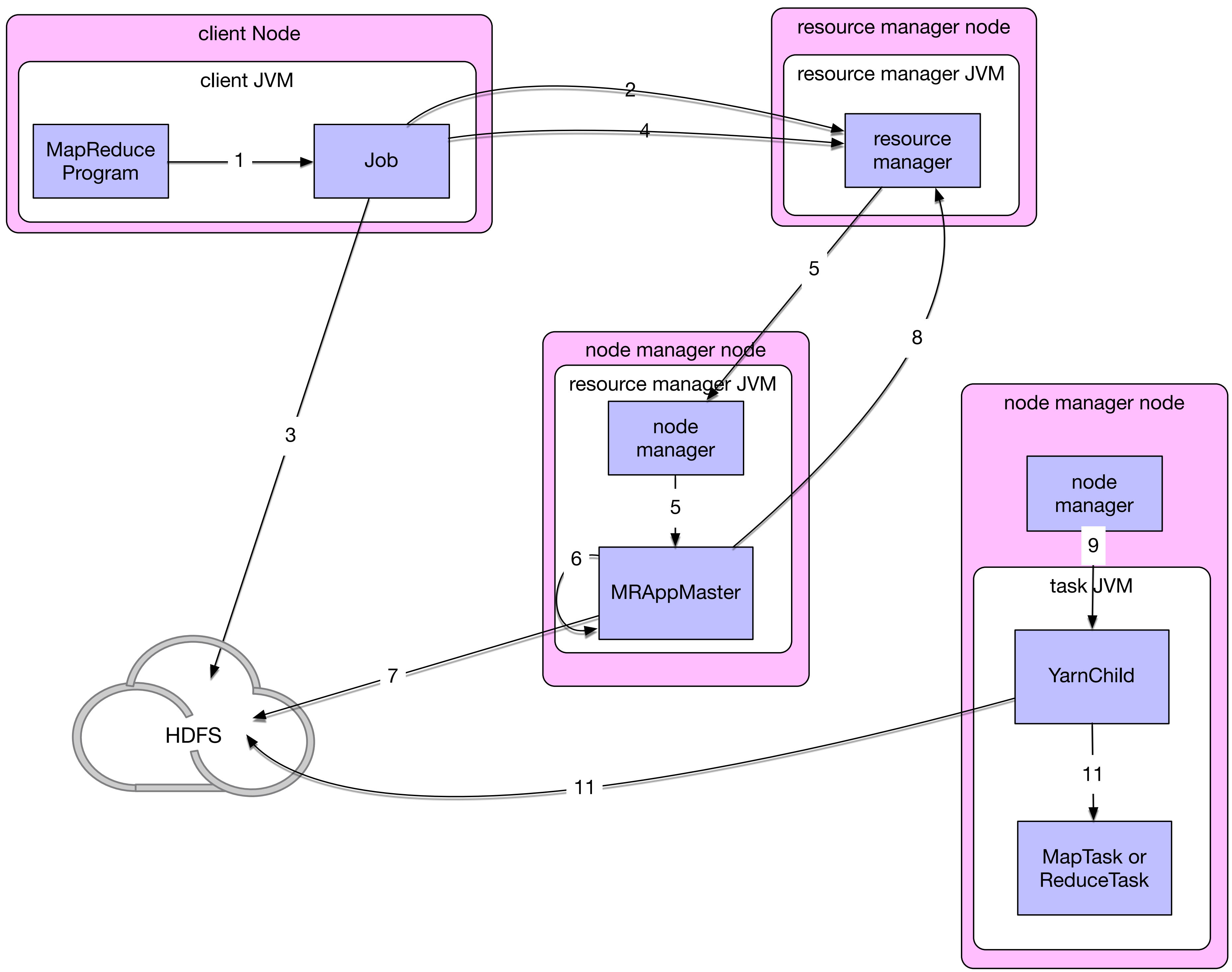
Yarn: Hadoop 2

- Classic structure runs into bottlenecks at about 4000 nodes
- YARN: Yet Another Resource Negotiator
  - YARN splits jobtrackers into various entities:
    - Resource manager daemon
    - Application master

Yarn: Hadoop 2

- Each application instance has a dedicated application master
-

Yarn: Hadoop 2



1: run job
2: get new application
3: copy job resources
4: submit application
5: start container and launch
6: initialize job
7: retrieve input splits
8: allocate resources
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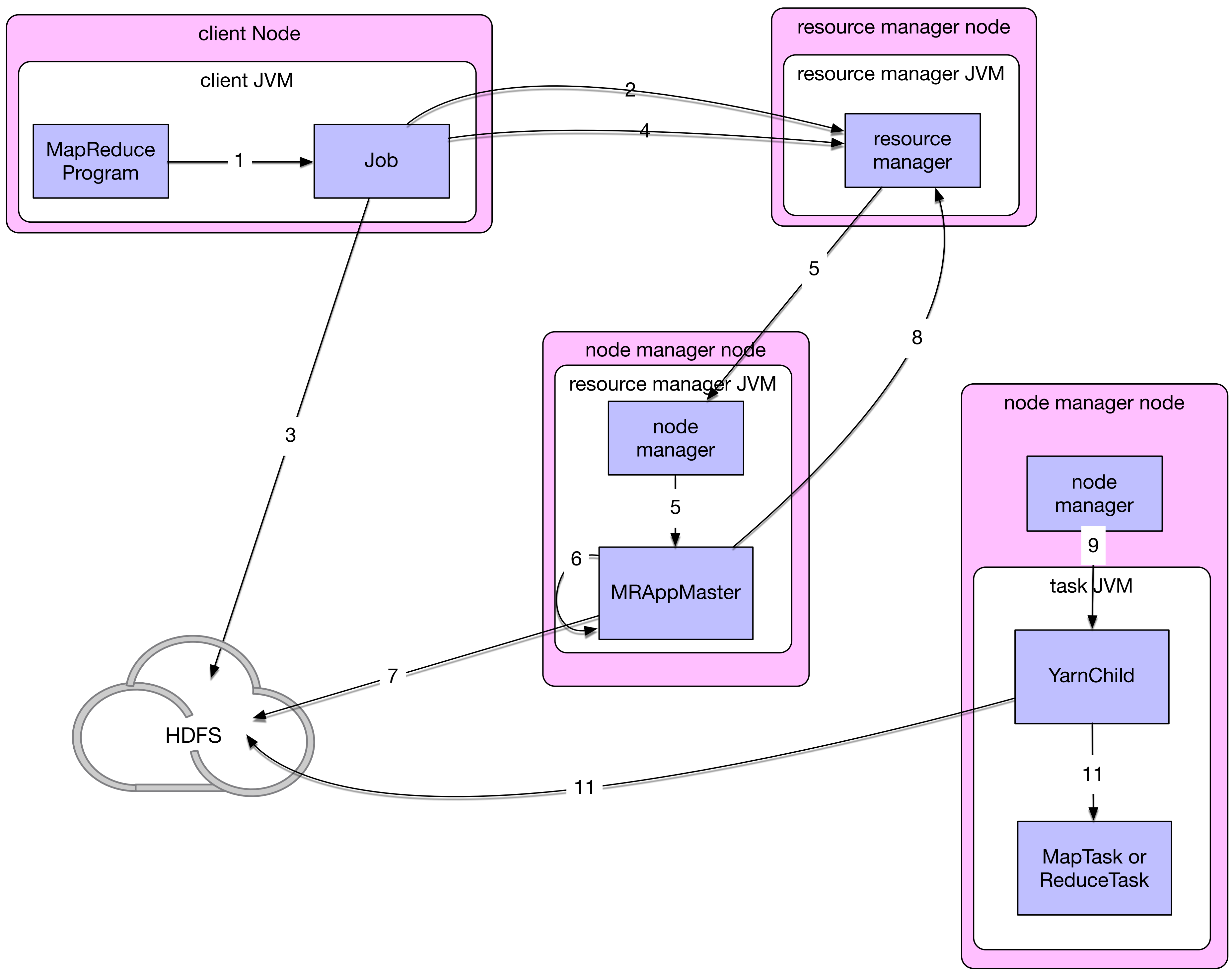
10: retrieve job resources
11: run

Yarn: Hadoop 2

- Job submission as before
- When resource manager receives a call to submitApplication() hands off to scheduler
- Scheduler allocates a container
- Resource manager launches application master process there (5)
-

Yarn: Hadoop 2



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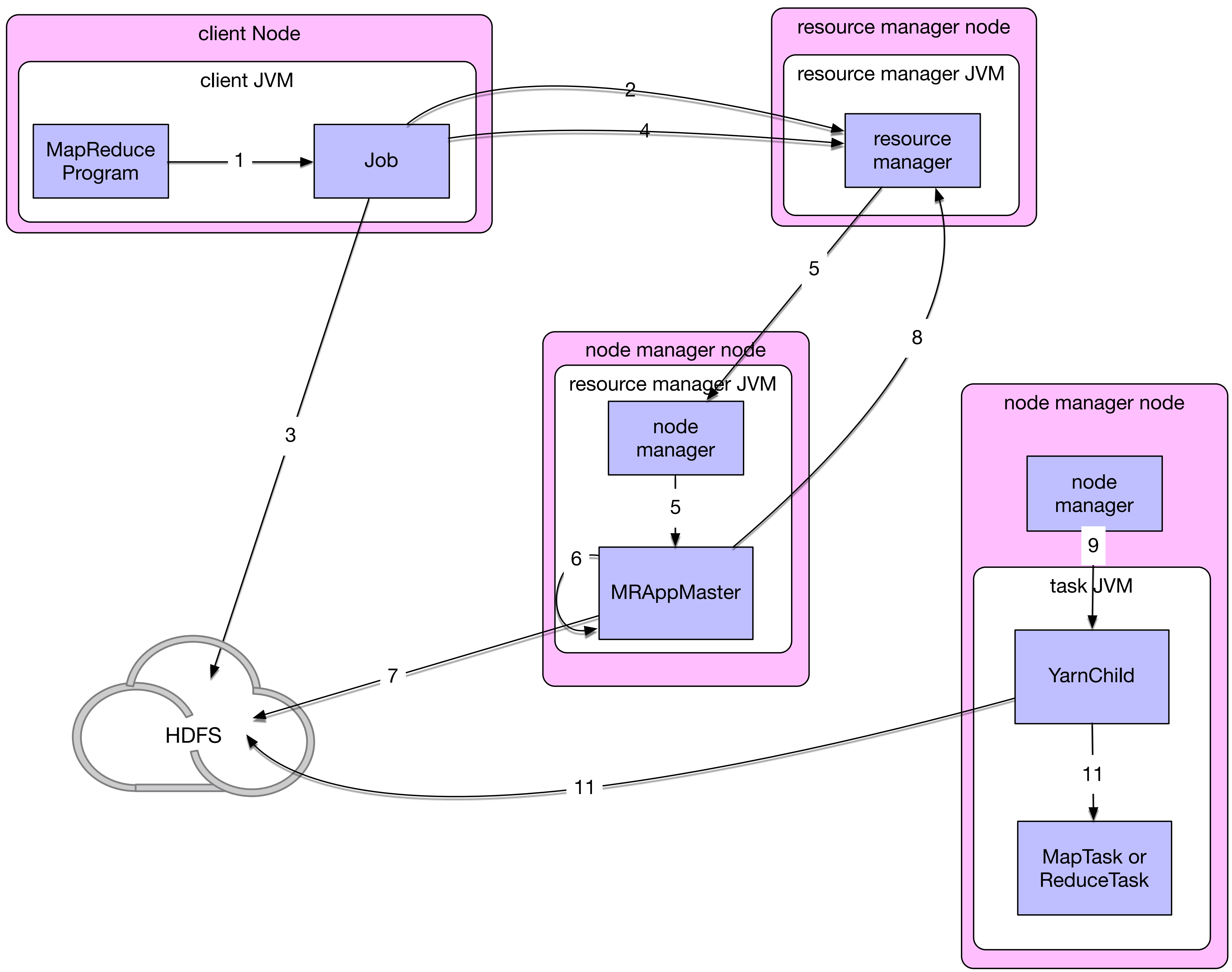
Yarn: Hadoop 2

- Application master
  - initializes the job by creating book-keeping objects
    - to receive and report on progress by individual tasks
  - Retrieves input splits
  - Creates a map task object for each split
  - Creates a number of reduce tasks (mapreduce.job.reduces)
  - Decides how to run job
    - Small jobs might be run in the same node
    - *Uber* tasks

Yarn: Hadoop 2

- Application master requests containers for all map and reduce tasks from resource manager
  - Scheduler gets enough information to make smart decisions
  - One of the selling points of Yarn: Resource allocation is much smarter

Yarn: Hadoop 2



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Yarn: Hadoop 2

- Task execution:
    - Application master starts container by contacting the node manager
    - Streaming and pipes work in the same way as Classical MapReduce

Yarn: Hadoop 2

- Progress and Status reports
  - tasks report progress and status to application masters
  - (Classical: reports move from child through tasktracker to jobtracker for aggregation)
  - client polls application master every second

Failures in Classic Hadoop

- Child task is failing:
    - Throwing a runtime exception
        - JVM through task master informs client
        - Taskmaster can take on another task
        - Streaming tasks are marked as failed
    - Sudden exit of child JVM
        - Taskmaster notes exit and marks attempt as failed

Failures in Classic Hadoop

- Child task is failing
    - Hanging tasks
        - Tasktracker notices lack of progress updates and marks task as failed
            - Normal timeout period is 10 minutes

Failures in Classic Hadoop

- When jobtracker is notified that a task attempt has failedL
  - jobtracker reschedules task elsewhere
  - jobtracker does try a maximum of four times
  - Client can specify the percentage of tasks that are allowed to fail

Failures in Classic Hadoop

- Users, jobtrackers can kill task attempts
  - E.g. speculative execution can kill duplicates
  - E.g. Tasktracker has failed

Failures in Classic Hadoop

- Tasktracker failure
  - Tasktracker then no longer sends heartbeats
  - Jobtracker removes tasktracker from its pool
  - Jobtracker arranges for map tasks to restart
    - Because there might be no access to the local results
  - Tasktrackers can be blacklisted if too many tasks there fail

Failures in Classic Hadoop

- Jobtracker failure
    - No mechanism in Hadoop to deal with this type of failure

Failures inYARN

- Task failures like before:
  - Propagated back to application master
  - Application master marks them as failed
  - Hanging tasks are discovered by application master

Failures inYARN

- Application master failure
    - Several attempts for a task to succeed
    - Application master sends heartbeats to Resource manager
    - Resource manager can restart application master elsewhere

Failures inYARN

- Node manager failure
  - Application manager will know due to lack of hearbeats

Failures inYARN

- Resource manager failure
    - Resource manager is hardened by using checkpointing to save state

Job Scheduling

- First implementations just used FIFO
- Later, priorities were introduced
- Fair scheduler: every user gets equal access to the capacity of the cluster
- Capacity scheduler: made up of queues
  - Each queues is run like a fair scheduler
  - Gives administrator more control over how different users are treated

Shuffle and Sort

- Each reduce job gets sorted input
- System part that sorts input and transfers to outputs of mappers to reducers is *shuffle*

Shuffle and Sort

- Map side
  - Output is not simply written to disk
  - For better performance:
    - Output is put into buffers
    - Buffers are partitioned and sorted when flushed to disk as *spill files*
  - When mapper finishes:
    - Spill files are combined
  - Output is made available to reducers using HDFS

Shuffle and Sort

- Reduce side:
  - Reducers start copying mapper output as soon as they are available (*copy phase*)
  - If mapper outputs at reducer reach critical size, they are placed into spill files on disk
  - Spill files are sorted and combined in batches — typically 10 spill files
  - Final combination feeds directly to reducer

Map Reduce Patterns

- Summarizations
  - Input: A large data set that can be grouped according to various criteria
  - Output: A numerical summary
  - Example:
    - Calculate minimum, maximum, total of certain fields in documents in xml format ordered by user-id

Summarization

- Example:
  - Given a database in xml-document format

```
<row Id="193" PostTypeId="1" AcceptedAnswerId="194"
CreationDate="2010-10-23T20:08:39.740" Score="3" ViewCount="30"
Body="&lt;p&gt;Do you lose one point of reputation when you
down vote community wiki?  Meta? &lt;/p&gt;&#xA;&#xA;&lt;p&gt;I
know that you do for &quot;regular questions&quot;. &lt;/
p&gt;&#xA;" OwnerUserId="134"
LastActivityDate="2010-10-24T05:41:48.760" Title="Do you lose
one point of reputation when you down vote community wiki?
Meta?" Tags="&lt;discussion&gt;" AnswerCount="1"
CommentCount="0" />
```

  - Determine the earliest, latest, and number of posts for each user

Summarization

- Mapper:
    - Step 1: Preprocess document by extracting the user ID and the date of the post
    - Step 2: map:
        - User ID becomes the key.
        - Value stores the date twice in Java-date format and adds a long value of 1

```
"134":  (2010-10-23T20:08:39.740, 2010-10-23T20:08:39.740, 1)
```

Summarization

- Mapper:
  - Step 3: Combiner
    - Take intermediate User-ID — value pairs
    - Combine the value pairs
      - Combination of two values:
        - first item is minimum of the dates
        - second item is maximum of the dates
        - third item is sum of third items

Summarization

- The map reduce framework is given the number of reducers
  - Autonomously maps combiner results to reducers
  - Each reducer gets key-value parts for a range of user-IDs grouped by user-ID

Summarization

- Reducer:
  - Passes through each group combining key-value pairs
  - End-result:
    - Key-value pair with key = user-id
    - Value is a triple with
      - minimum posting date
      - maximum posting date
      - number of posts

Summarization

- Reducer:
  - Each summary key— value pair is sent to client

Summarization

- Example (cont.)

Mapper 1

UserID 12345	01.02.2010	01.02.2010	1
UserID 12345	02.02.2010	02.02.2010	1
UserID 12345	04.02.2010	04.02.2010	1
UserID 98765	12.02.2010	12.02.2010	1
UserID 98765	02.02.2010	02.02.2010	1
UserID 98765	05.02.2010	05.02.2010	1
UserID 56565	02.02.2010	02.02.2010	1
UserID 56565	03.02.2010	03.02.2010	1

Combiner →

UserID 12345	01.02.2010	04.02.2010	3
UserID 98765	02.02.2010	12.02.2010	3
UserID 56565	02.02.2010	03.02.2010	2

Mapper 2

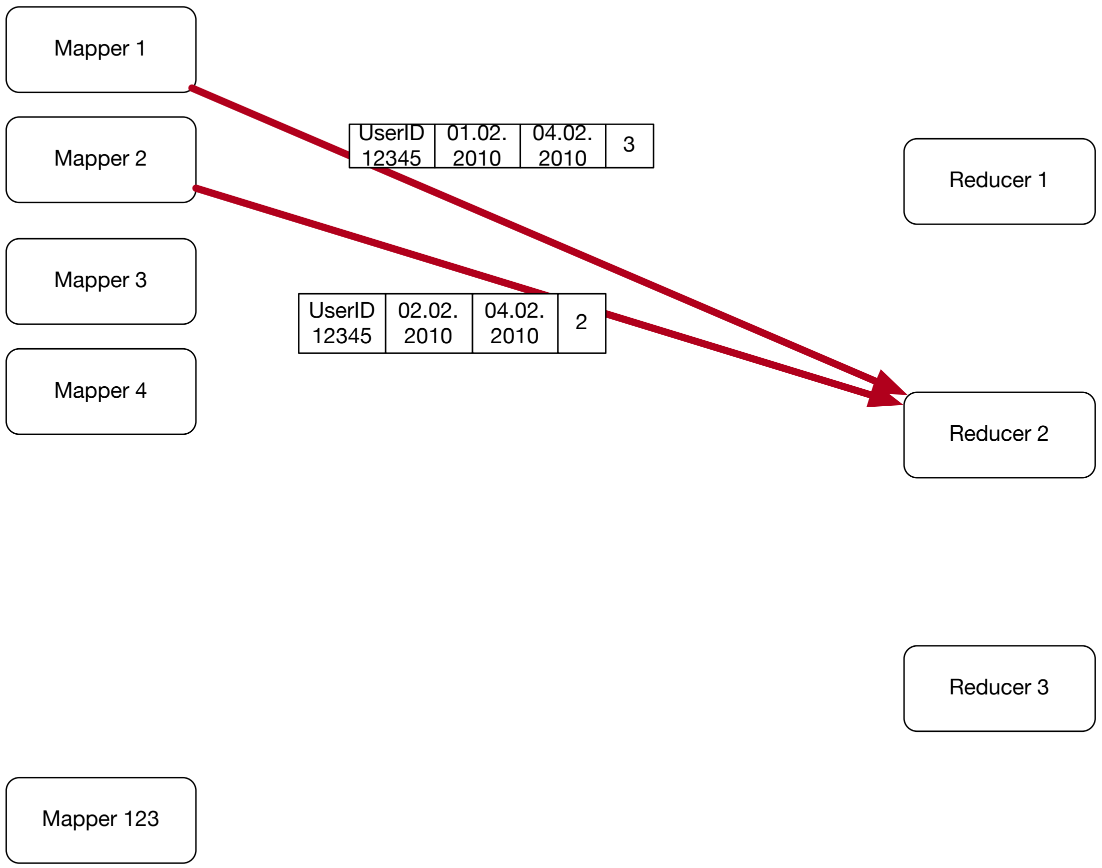
UserID 12345	02.02.2010	02.02.2010	1
UserID 12345	04.02.2010	04.02.2010	1
UserID 77444	12.02.2010	12.02.2010	1
UserID 77444	02.02.2010	02.02.2010	1
UserID 98765	05.02.2010	05.02.2010	1

Combiner →

UserID 12345	02.02.2010	04.02.2010	2
UserID 77444	02.02.2010	12.02.2010	2
UserID 98765	05.02.2010	05.02.2010	1

Summarization

- Example (cont.) Automatic Shuffle and Sort
  - Records with the same key are sent to the same reducer



Summarization

- Example (cont.)
  - Reducer receives records already ordered by user-ID
  - Combines records with same key

UserID 12345	01.02.2010	04.02.2010	3
UserID 12345	02.02.2010	04.02.2010	2
UserID 12345	26.03.2010	30.04.2010	5
UserID 12345	19.01.2010	01.04.2010	3
UserID 16542	02.02.2010	04.02.2010	6
UserID 16542	26.03.2010	29.05.2010	5
UserID 16542	19.01.2010	19.01.2010	1

UserID 12345	01.02.2010	30.02.2010	13
UserID 16542	19.01.2010	29.05.2010	12

Summarization

- In (pseudo-)pig:
  - Load data

```
posts = LOAD '/stackexchange/posts.tsv.gz'
USING PigStorage('\t') AS (
post_id : long,
user_id : int,
text : chararray,
…
post : date
)
```

Summarization

- In (pseudo-)pig:
  - Group by user-id

```
post_group = GROUP posts BY user_id;
```

  - Obtain min, max, count:

```
result = FOREACH post_group GENERATE group,
MIN(posts.date), MAX(posts.date),
COUNT_STAR(post_group)
```

Summarization

- In (pseudo-)pig:
  - Load data

```
orders = LOAD '/stackexchange/posts.tsv.gz'
USING PigStorage('\t') AS (
post_id : long,
user_id : int,
text : chararray,
…
post : date
)
```

Summarization

- Your turn:
  - Calculate the average score per user
  - The score is kept in the “score”-field

Summarization

- Solution:
  - Need to aggregate sum of score and number of posts
  - Mapper: for each user-id, create a record with score

    `userid: score, 1`

  - Combiner adds scores and counts

    `userid: sum_score, count`

  - Reducer combines as well
  - Generates output key-value pair and sends it to the user
  - `userid: sum_score/count`

Summarization

- Finding the median of a numerical variable
  - Mapper aggregates all values in a list
  - Reducer aggregates all values in a list
  - Reducer then determines median of the list
- Can easily run into memory problems

Summarization

- Median calculation:
  - Can compress lists by using counts
    - `2, 3, 3, 3, 2, 4, 5, 2, 1, 2` becomes

      `(1,1), (2,4), (3,3), (4,1) (5,1)`
    - Combiner creates compressed lists
    - Reducer code directly calculates median
      - An instance where combiner and reducer use different code

Summarization

- Standard Deviation
  - Square-root of variance
  - Variance — Average square deviation from average
  - $$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$$
    - Leads to a two pass solution, calculate average first

Summarization

- Standard Deviation
  - Numerically dangerous one-path solution
  - $$\begin{aligned}\sigma_x^2 &= \frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2\\ &= \frac{1}{N}\sum_{i=1}^{N}(x_i^2-2\bar{x}x_i+\bar{x}^2)\\ &= \frac{1}{N}\sum_{i=1}^{N}x_i^2-2\bar{x}\frac{1}{N}\sum_{i=1}^{N}x_i+\bar{x}^2\\ &= \frac{1}{N}\sum_{i=1}^{N}x_i^2-2\bar{x}^2+\bar{x}^2=\frac{1}{N}\sum_{i=1}^{N}x_i^2+\bar{x}^2\end{aligned}$$

Summarization

- Chan's adaptation of Welford's online algorithm
  - Using the counts of elements, can calculate the variance in parallel from any number of partitions

```
def parallel_variance(avg_a, count_a, var_a, avg_b, count_b, var_b):
    delta = avg_b - avg_a
    m_a = var_a * (count_a - 1)
    m_b = var_b * (count_b - 1)
    M2 = m_a + m_b + delta ** 2 * count_a * count_b / (count_a + count_b)
    return M2 / (count_a + count_b - 1)
```

  - Unfortunately, can still be numerically instable

Summarization

- Standard Deviation:
  - Schubert & Gertz: Numerically Stable Parallel Computation of (Co)-Variance
    - SSDBM '18 Proceedings of the 30th International Conference on Scientific and Statistical Database Management

Summarization

- Inverted Index
  - Analyze each comment in StackOverflow to find hyperlinks to Wikipedia
  - Create an index of wikipedia pages pointing to StackOverflow comments that link to them

Summarization

- Inverted Index is a group-by problem solved almost entirely in the map-reduce framework

Summarization / Inverted Index

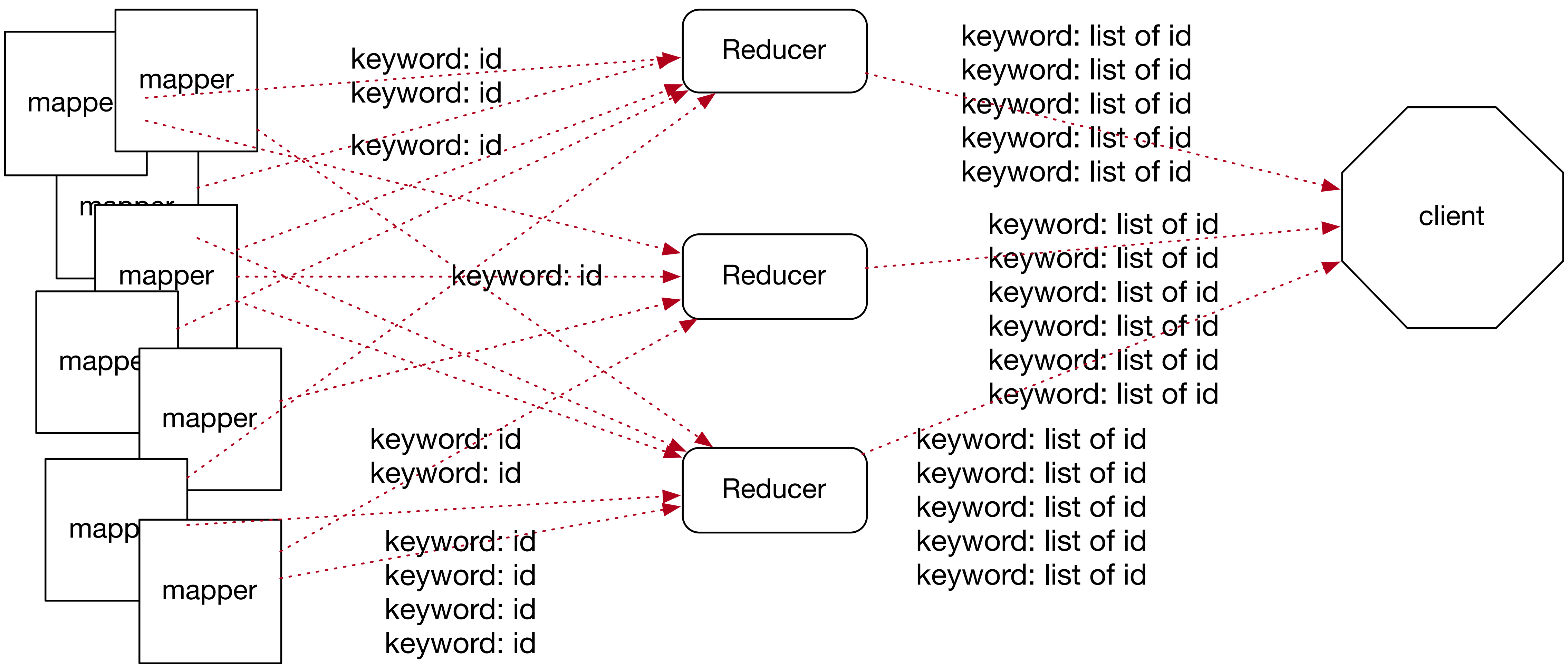
- **Mapper**
  - Parser:
    - Processes posts
    - Checks for right type of post, extracts a list of wikipedia urls (or Null if there are none)
    - Outputs key-value pairs :
      - Keys: wikipedia url
      - Value: row-ID of post
    - Optional combiner:
      - Aggregates values for a wikipedia url in a single list

Summarization / Inverted Index

- **Reducer**
  - Aggregates values belonging to the same key in a list

Summarization / Inverted Index

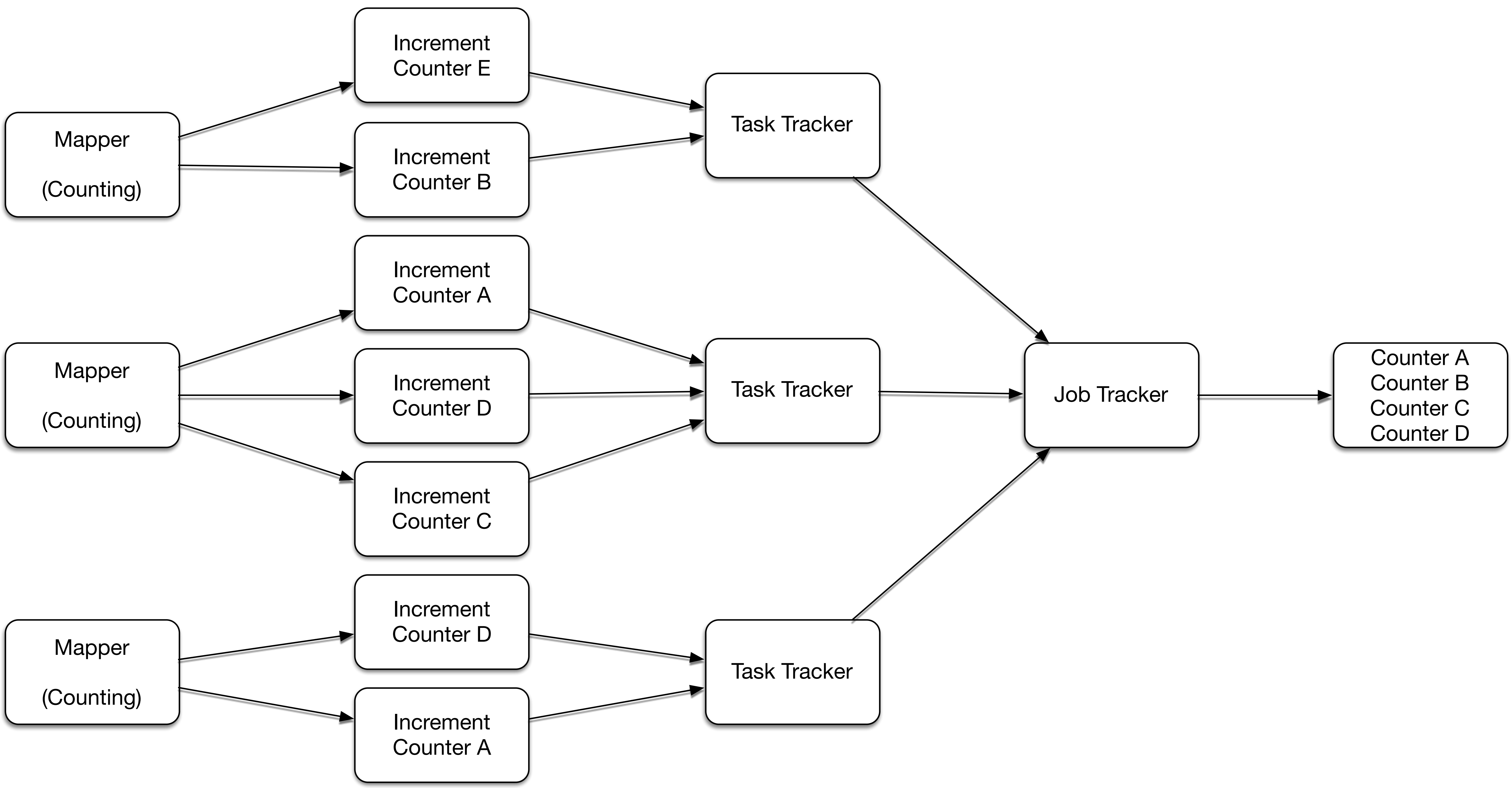
- Generic Inverted Index diagram



Counter Pattern

- Used to gather stats on an Hadoop job
  - Create various counters (but not too many)
  - Counters work exclusively in the Map-Reduce Paradigm

Counter Pattern



Counter Pattern

- Mapper processes each input
  - Increments counter for each record
- Counters are aggregated by Task Trackers
- Task Trackers report counts to Job Tracker
- Job Tracker aggregates counts (unless task tracker failed)

Counter Pattern

```
public static class CountNrUsersByState extends Mapper<Object,
Text, NullWritable, Null Writable> {

public void map(Object key, Text value, Context context)
throws IOException, Interrupted Exception {
Map<String, String> parsed =
MRDPUtils.transformXmlToMap(value.toString())

String location = parsed.get(“Location”);
if location !=null && !location.isEmpty()) {
  if (states.contains(state)) {
     context.getCounter(STATE_COUNTER_GROUP, state).increment(1);
     break;
  }
…
}
```

Counter Pattern

- To get the counts, just

```
int code = job.waitForCompletion(true)? 0 : 1;
if(code == 0){
   for (Counter counter : job.getCounters().getGroup(
        CountNumUsersByStateMapper.STATECOUNTERGROUP)){
       System.out.println(counter.getDisplayName() +
           “t” + counter.getValue());
   }
}
```

Filtering Patterns

- Extract data from records without changing them
  - Sampling:
    - get a few random records
    - get records with very high or low values in a field

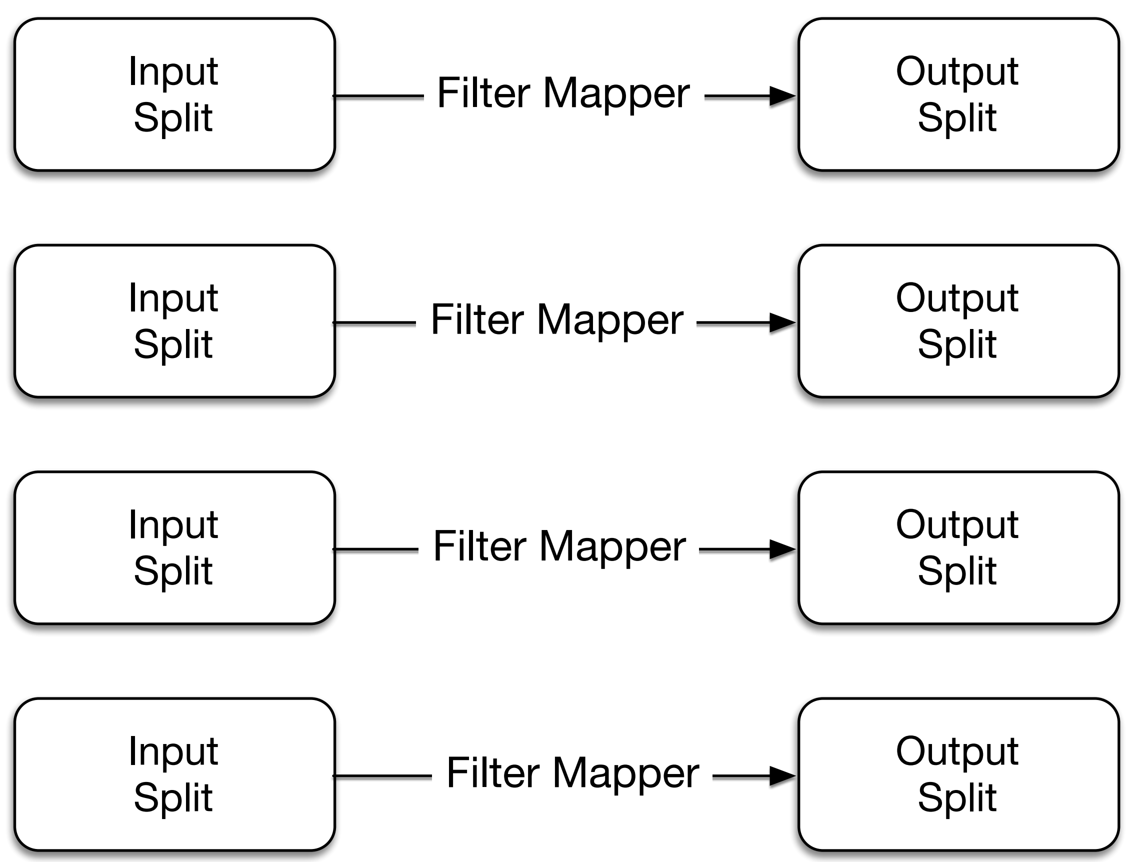
Filtering Patterns

- Simple filtering:
  - User defined function or condition is a boolean
    - Decides whether record is to be kept or not
  - Very generic pattern

```
map(key, record):
    if(user_condition(record){
        emit key, value
```

Filtering Patterns

- Simple Filtering



Filtering Patterns

- Simple Filtering
  - There is no “reduce” operation because there is no aggregation
  - If output splits are saved, they can serve as new inputs

Filtering Patterns

- Simple Filtering in Pig
  - Uses the FILTER keyword
  - b = **FILTER** a BY value < 3

Filtering Patterns

- Because there are no reducers
  - Data never has to be transmitted
  - There is no sort phase and no reduce phase

Filtering Patterns

- Filtering pattern:
    - Grep: filtering for a regular expression

Filtering Patterns

- Getting a random sample
  - Simple random sampling (SRS)
    - Grab a random subset of data
  - Can get `filter_percentage` property:
    - `context.getConfiguration().get(“filter_percentage”)`
  - Mapper writes objects with a given probability
  - There neither combiner nor reducer

Excurse: Bloom Filters

- Bloom filters (1970 Burton Howard Bloom)
  - Use to test membership in a set
  - Idea:
    - A data structure that can quickly decide whether an element does **not** belong to a large set
    - And probabilistically whether an element is present
      - With a low probability of error

Excurse: Bloom Filters

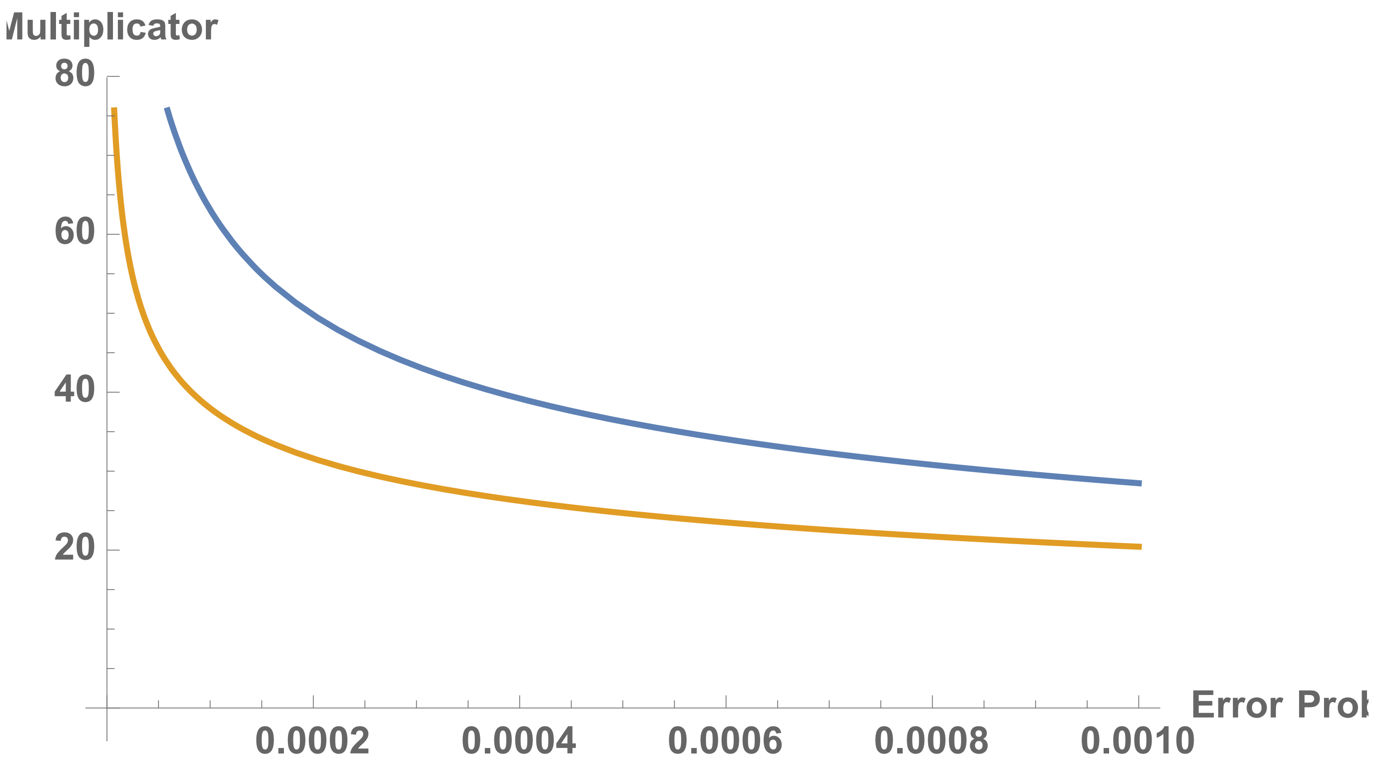
- Idea: A bloom filter is a large bit array
  - (How large: Deduplication proposes sizes of several GB)
  - Uses a good hash function
  - For each element in the set:
    - Calculate $h(\textbf{ele},0)$ $h(\textbf{ele},1)$ $h(\textbf{ele},2)$
    - Change the resulting bits in the bit array

Excurse: Bloom Filters

- To test for the presence of x in the set S
  - Calculate $h(x,0)$ $h(x,1)$ $h(x,2)$
  - Check whether the corresponding bits are set.
    - Bits are set, but $x \notin S$
      - Then bits were set by other elements.
      - If $|S| = n$ and there are N elements in the bit array, this happens with probability

$$\left(1 - (1 - \frac{1}{N})^{3n}\right)^3 \approx \left(1 - \exp(\frac{-3n}{N})\right)^3$$

Excurse: Bloom Filters



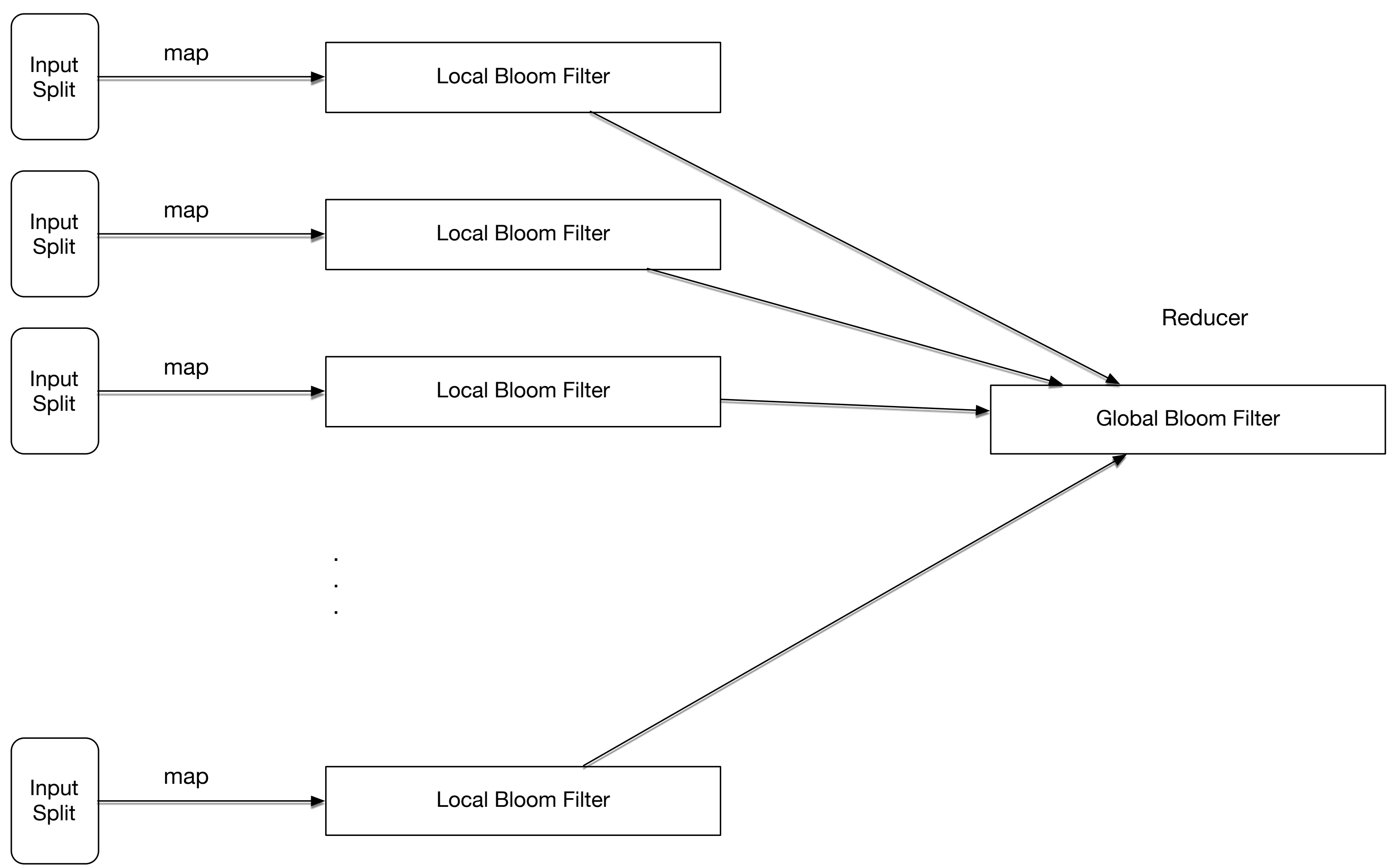
Number of bits = number of set elements times multiplicator
needed to achieve a certain error probability with 3 and 4 hashes

Filtering Patterns

- Bloom Filtering pattern:
    - Need to accept a few false positives
- Creating Bloom Filter
- Using Bloom Filter

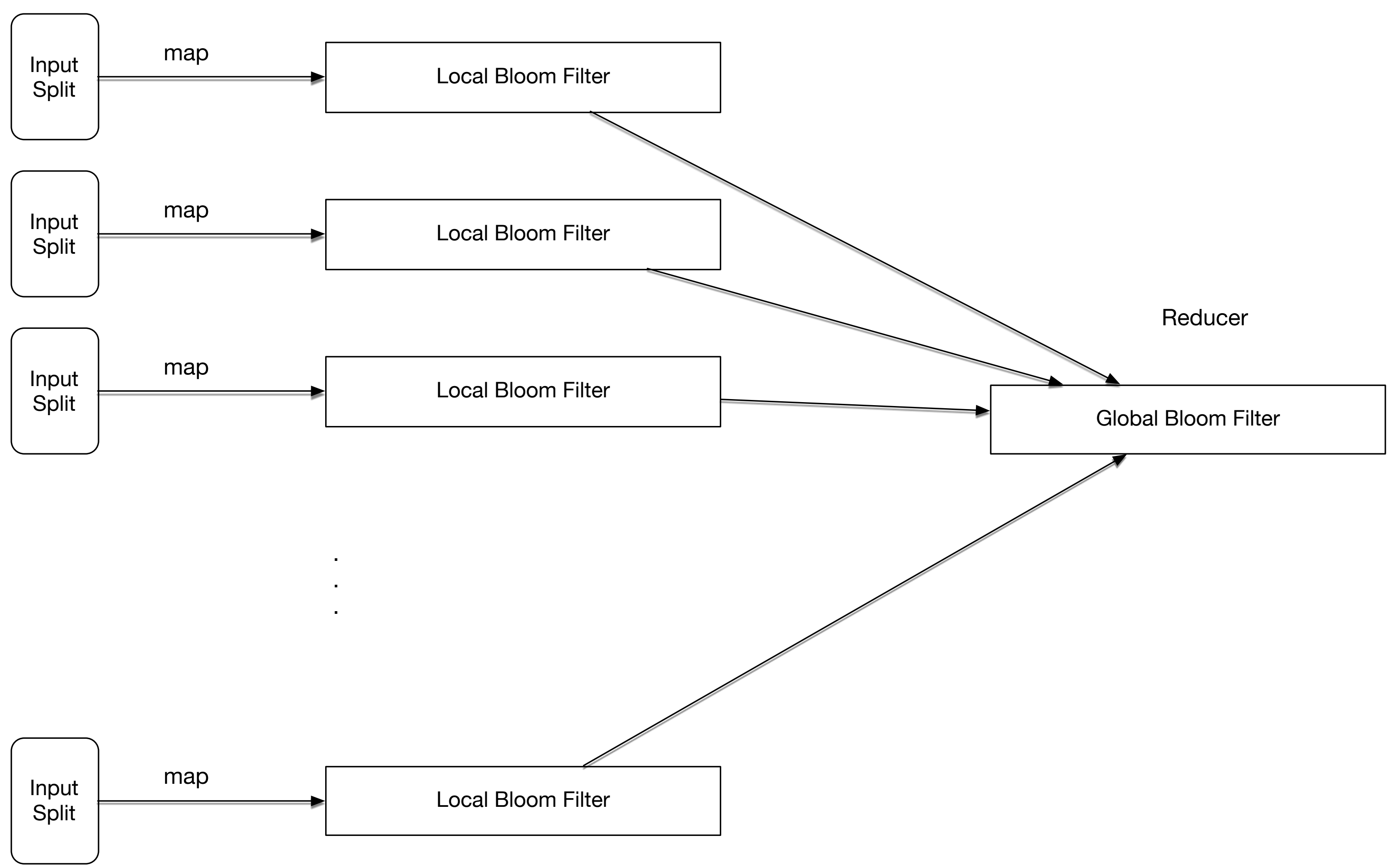
Filtering Patterns

- Mappers create local bloom filter
- Reducer combines them



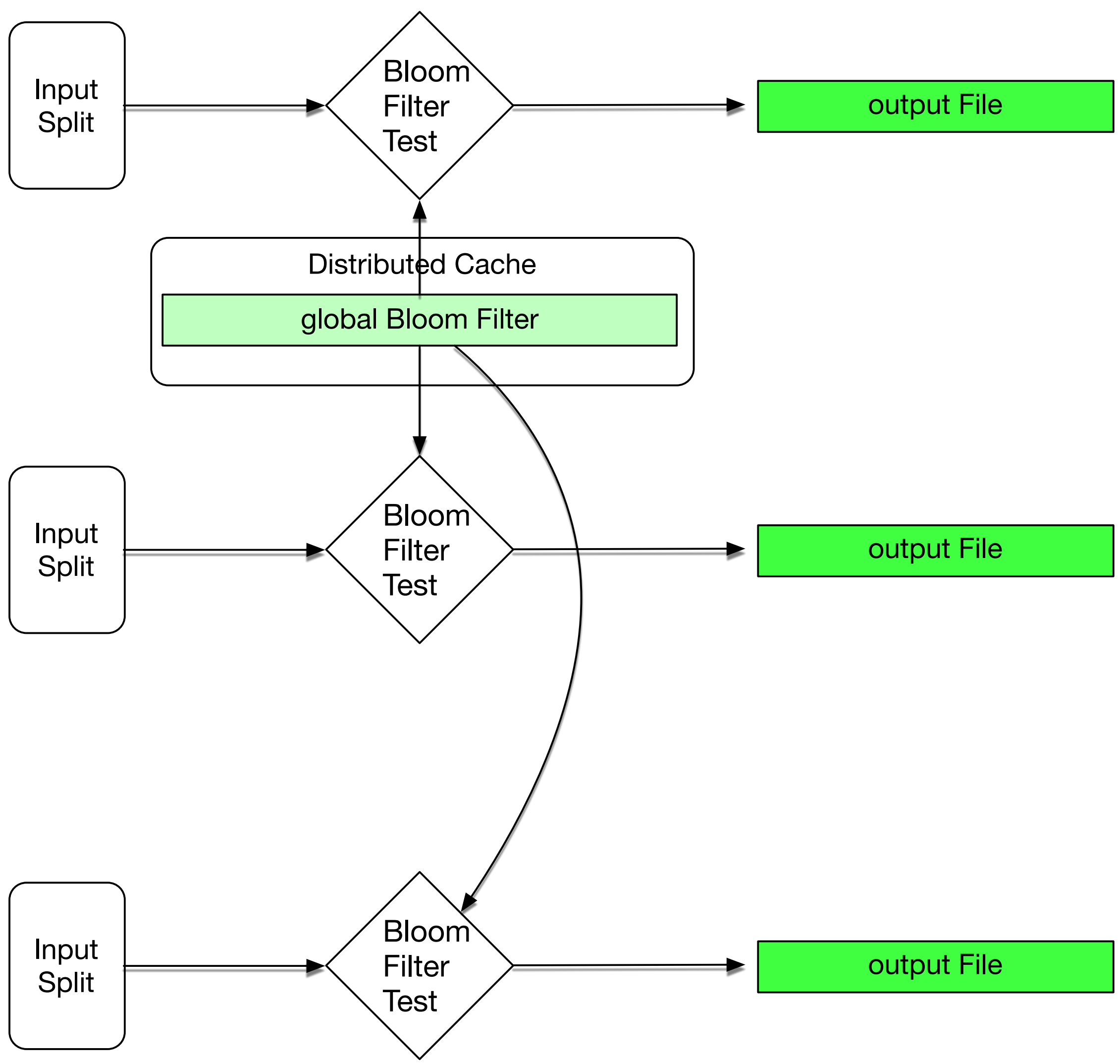
Filtering Patterns

- Could use more than one reducer by breaking up local bloom filter into ranges



Filtering Patterns

- Bloom Filtering



Filtering Patterns

- Bloom Filtering is used for
  - Removing (almost all of) unwatched items
  - Prefiltering data

- Pig: Need to implement Bloom filtering as user-defined functions

Filtering Patterns

- Top-ten
  - Retrieve the records that have the *k* largest values in a certain attribute

- Group Exercise

Filtering Patterns

- A set of distinct records
  - Example: Web page log
    - Want to have records where user-name, device, or browser are different, but we don’t care about time stamps

Filtering Patterns

- Unique records:
  - Use the map-reduce grouping properties
    - Mapper group by the attributes we are interested in
    - Combiners emit one value for each group
    - Reducer only emits one value for each group

```
map(key, record):
      emit record, null

reduce(key, records):
      emit key
```

Filtering Patterns

- Unique records
  - Pig:

```
b = distinct a;
```

Data Organization Patterns

- Problem:
  - Transform data to a different format
    - Row-based data to hierarchical format such as JSON or XML

Data Organization Patterns

- Example
  - StackOverflow data
    - Posts and comments are separated
      - Lines in an XML document
    - Hierarchy combines posts and comments
  - Hierarchical data model allows us to correlate length of posts with number of comments, etc.

```
Posts
   Post
      Comment
      Comment
   Post
   Post
      Comment
      Comment
      Comment
```

Data Organization Patterns

- Often, the data to be combined comes from different data sets
  - Hadoop class `MultipleInputs` from org.apache.hadoop.mapreduce.lib.input
  - Allows to specify different input paths and different mappers for each input
  - Configuration is done in the driver

Data Organization Patterns

- Multiple sources to hierarchical Pattern
  - Mappers load data and parse it into a cohesive format
  - Output key corresponds to root of hierarchical record
    - E.g. StackOverflow: root is post_id
  - Need to identify the source for each mapper output
    - E.g. StackOverflow: is this a post or a comment
  - Combiners are pretty useless because we create large strings

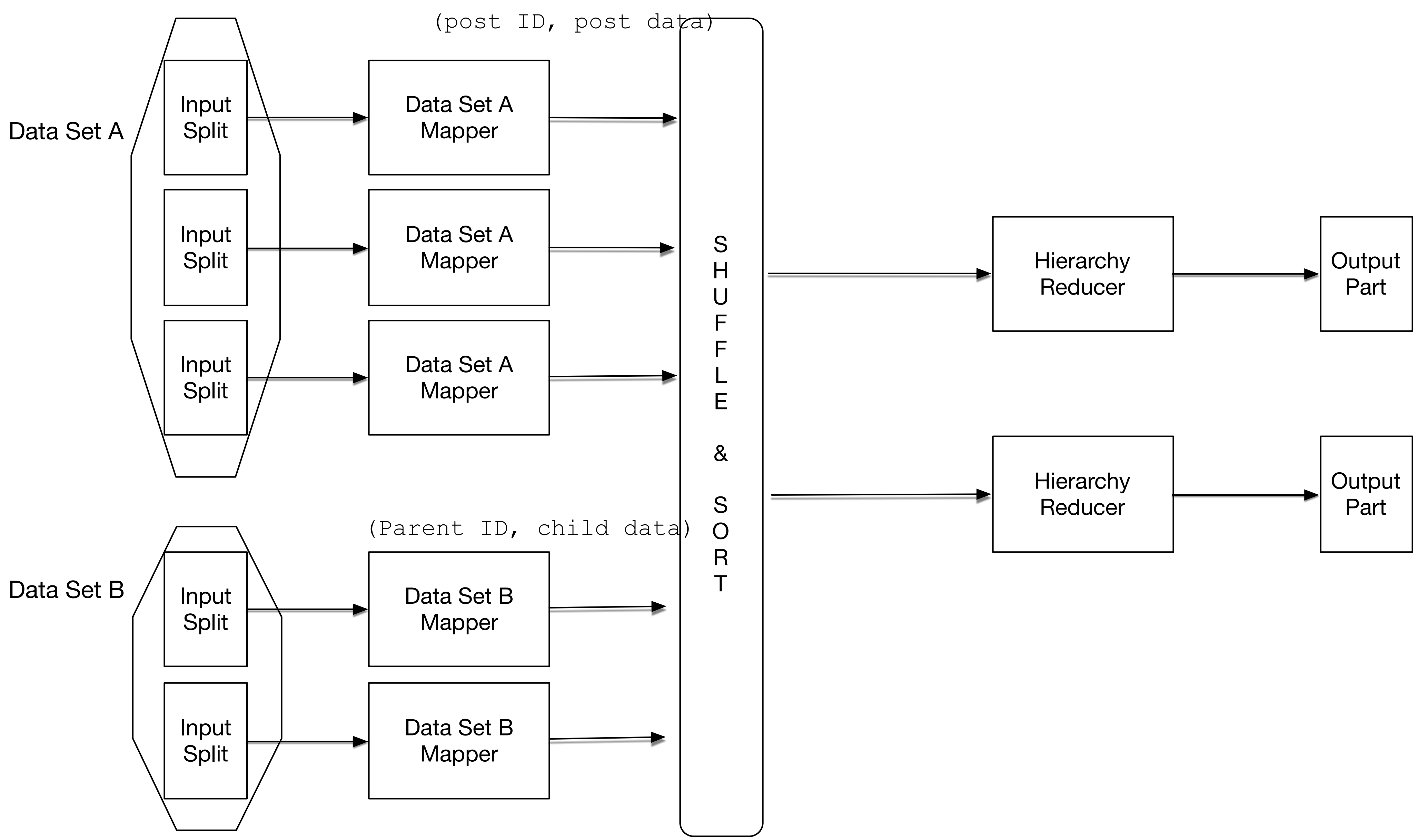
Data Organization Patterns

- Multiple sources to hierarchical Pattern
  - Reducers receive data from different sources key by key
  - For each key, can now build hierarchical data structure

Data Organization Patterns

- Multiple sources to hierarchical Pattern
  - Result is in hierarchical form
  - Probably need to add header and footer so that it is well-formed

Data Organization Patterns



Data Organization Patterns

- Multiple sources to Hierarchical Pattern
  - Performance problems
    - Need enough reducers
    - Reducers might see a lot of skew:
      - Some are busy, others are not
    - Hot spots can result in humongous strings moved between mappers and reducers
      - Could take up the heap of a Java Virtual Machine

Data Organization Patterns

- Needs two mappers: one for comments, one for posts
- Both: extract post-id to use as output key
- Append “P” or “C” to distinguish between sources

Data Organization Patterns

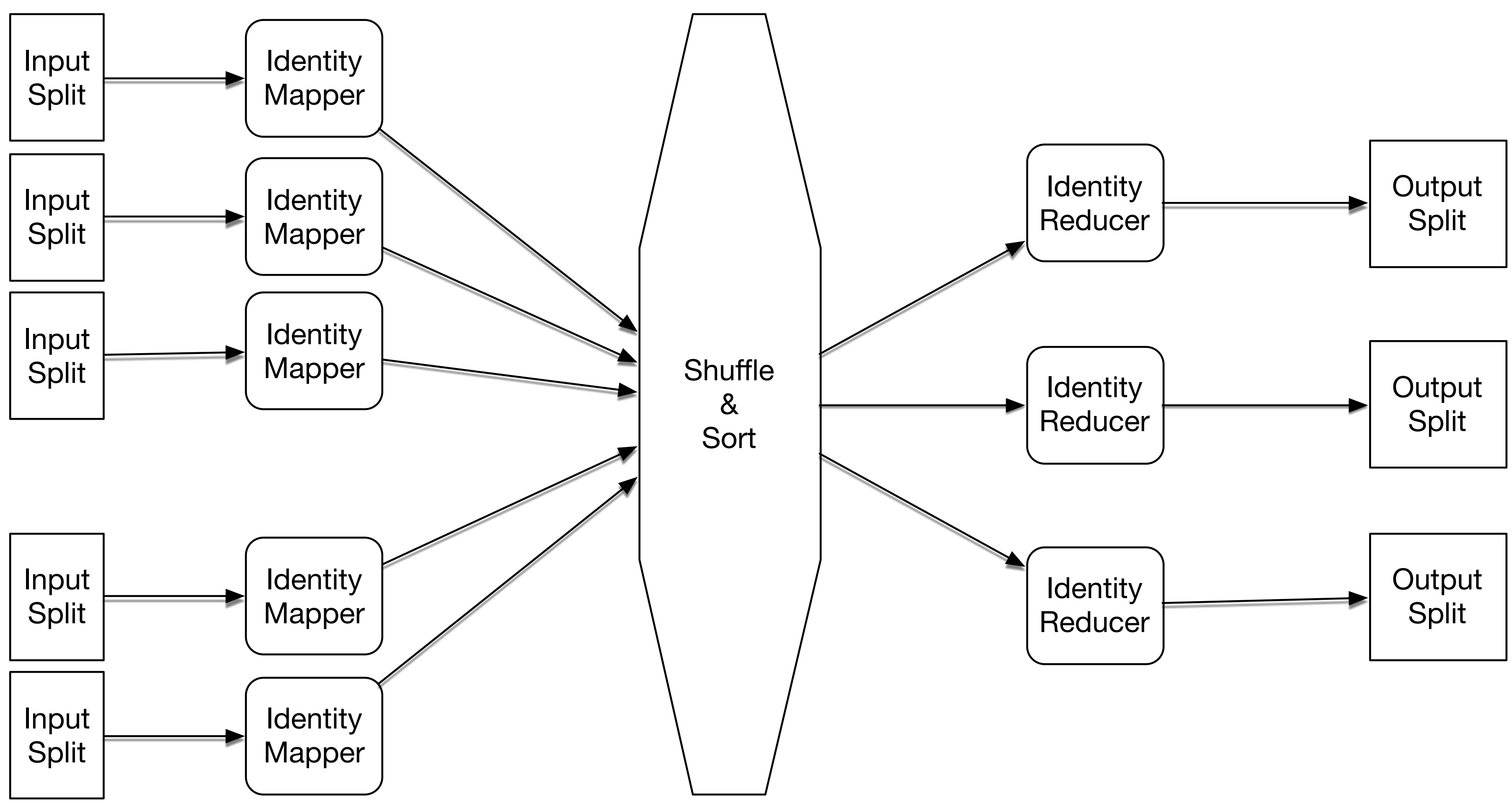
- Reducer:
  - Reducers receive post-id + marker as key and text as value
    - For each post-id with “P” marker:
      - Create a post entry in the XML
      - For each post-id with “C” marker:
        - Create child

Data Organization Patterns

- Partitioning
  - Moves records into shards, but does not care about ordering
    - Example: partitioning by date
  - Need to know number of partitions ahead of time

Data Organization Patterns

- Partitioning: Let the partitioner do the job

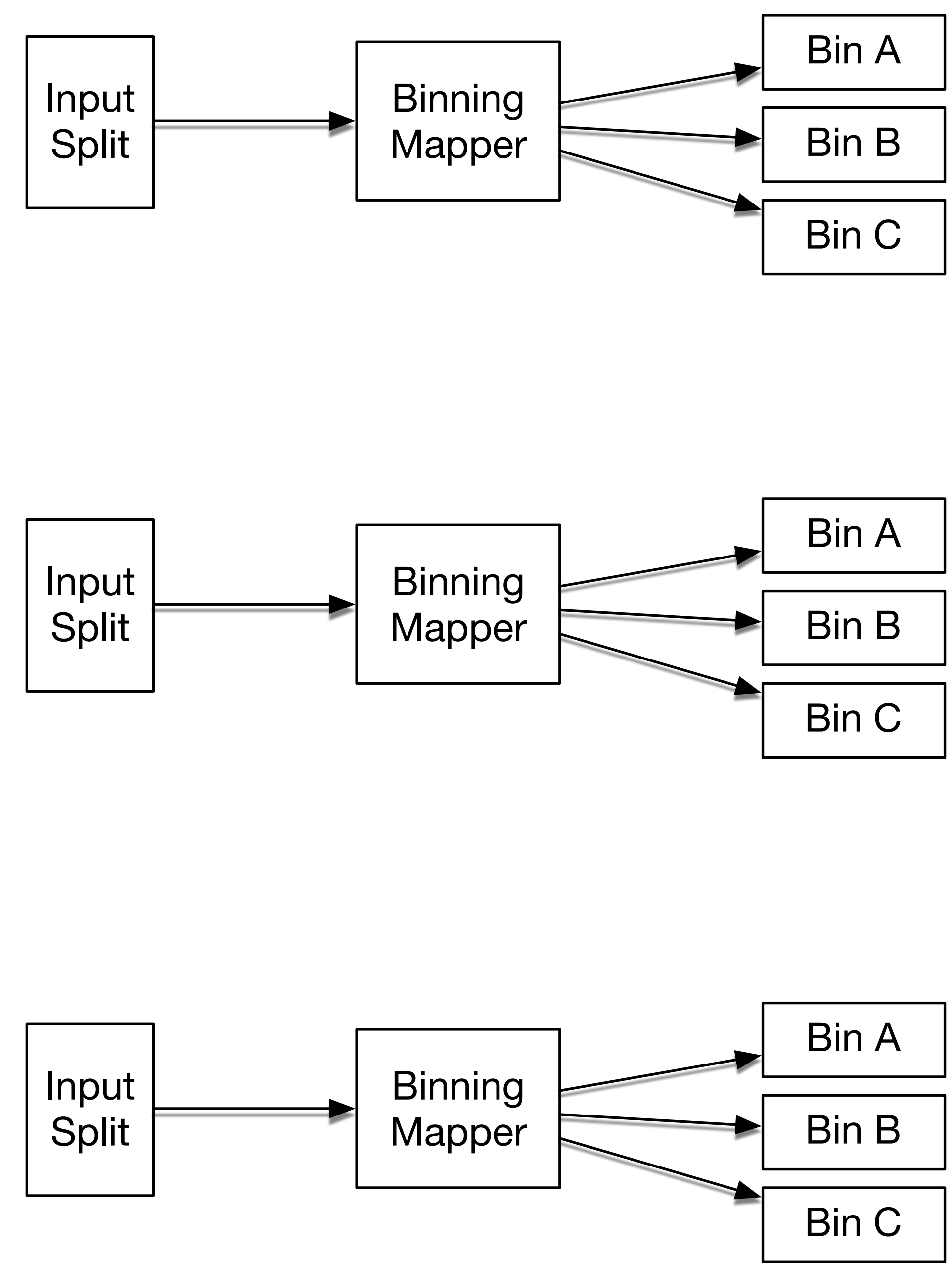


Data Organization Patterns

- Binning:
  - Moves records into categories irrespective of order
  - Related to partitioning
    - Which one works better depends on the system
    - Binners do not use reducers

Data Organization Patterns

- Binning
    - Number of outputs = Number of mappers times Number of bins



Data Organization Patterns

- Binning:
  - Pig
    - Split data INTO eights IF col1==8, bigs IF col1>8, smalls IF col1<8;

Data Organization Patterns

- Total Order Sorting
  - Data needs to be sorted by a given comparator
  - Result is a set of shards that are ordered
    - Need to know the distribution of data first
      - Run an analyze phase first

Data Organization Patterns

- Total order sorting:
    - Analyze phase
        - Mapper does random sampling
        - Only outputs the key after which we sort
        - Use only one reducer which will give us the sort keys in order

Data Organization Patterns

- Total order sorting:
  - Order phase
    - Mapper extracts the sort key and stores the record as a value
    - Custom partitioner is loaded based on the results of the analysis phase
      - TotalOrderPartitioner in Hadoop
      - Takes the data ranges prescribed and uses them to partition
    - Reducer simply outputs the values
    - Shuffle and sort has already done all the work

Data Organization Patterns

- Total Ordering in Pig
  - c = order b by col1;

Data Organization Patterns

- Shuffling
  - Randomizes the order of a set of records

Data Organization Patterns

- Shuffling
  - Mapper maintains the records, but creates a random key
  - Reducer sort according to random keys
  - Only record is printed out

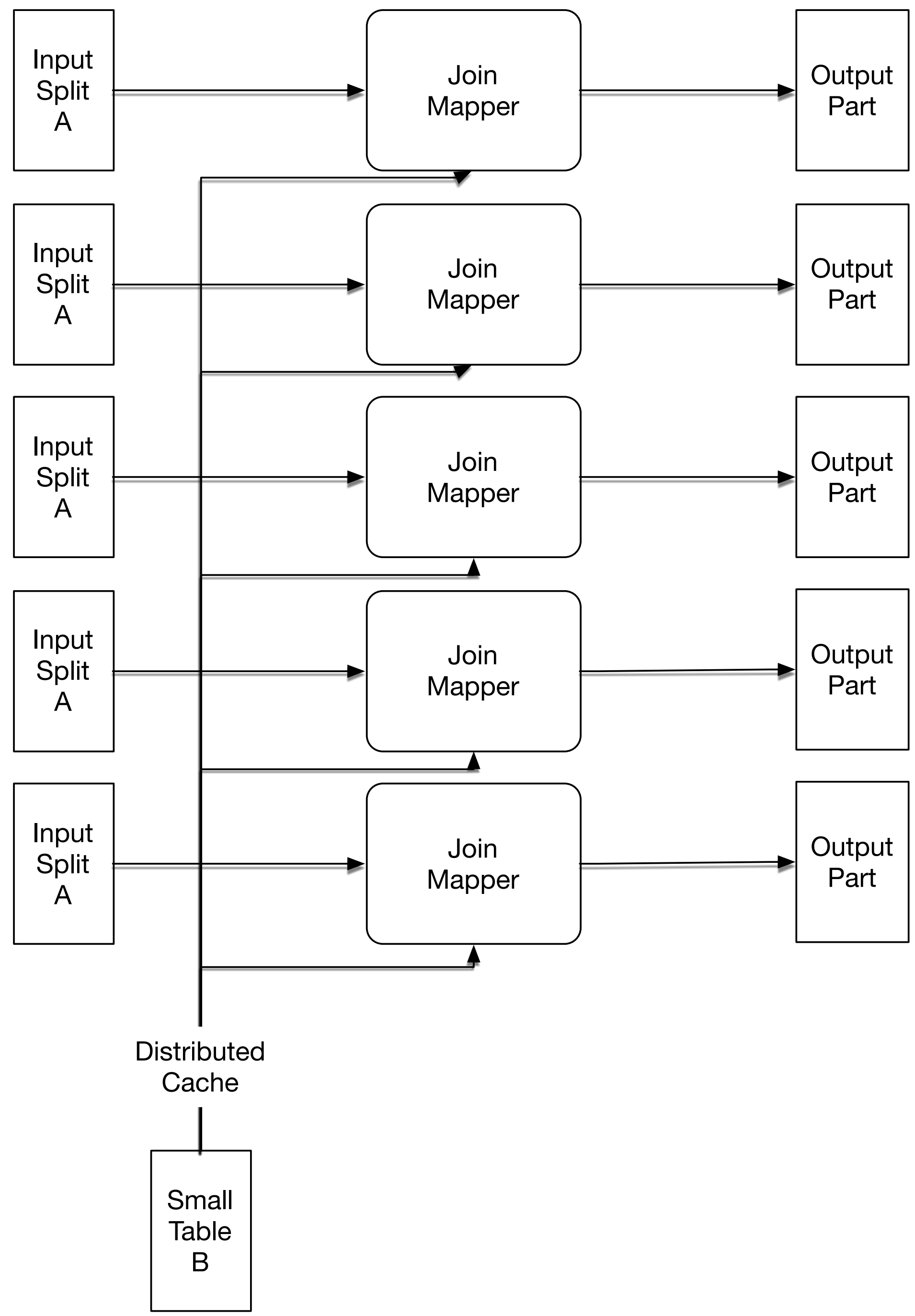
Data Organization Patterns

- Shuffling
  - Pig:
    - c = Group b by Random( );
    - d = FOREACH c generate Flatten(b);

Join Patterns

- Join Pattern
  - Different cases
    - Simplest Case: Join with a small table
      - Send small table to all mappers
      - Mappers calculate local join
      - Reducers

Join Patterns



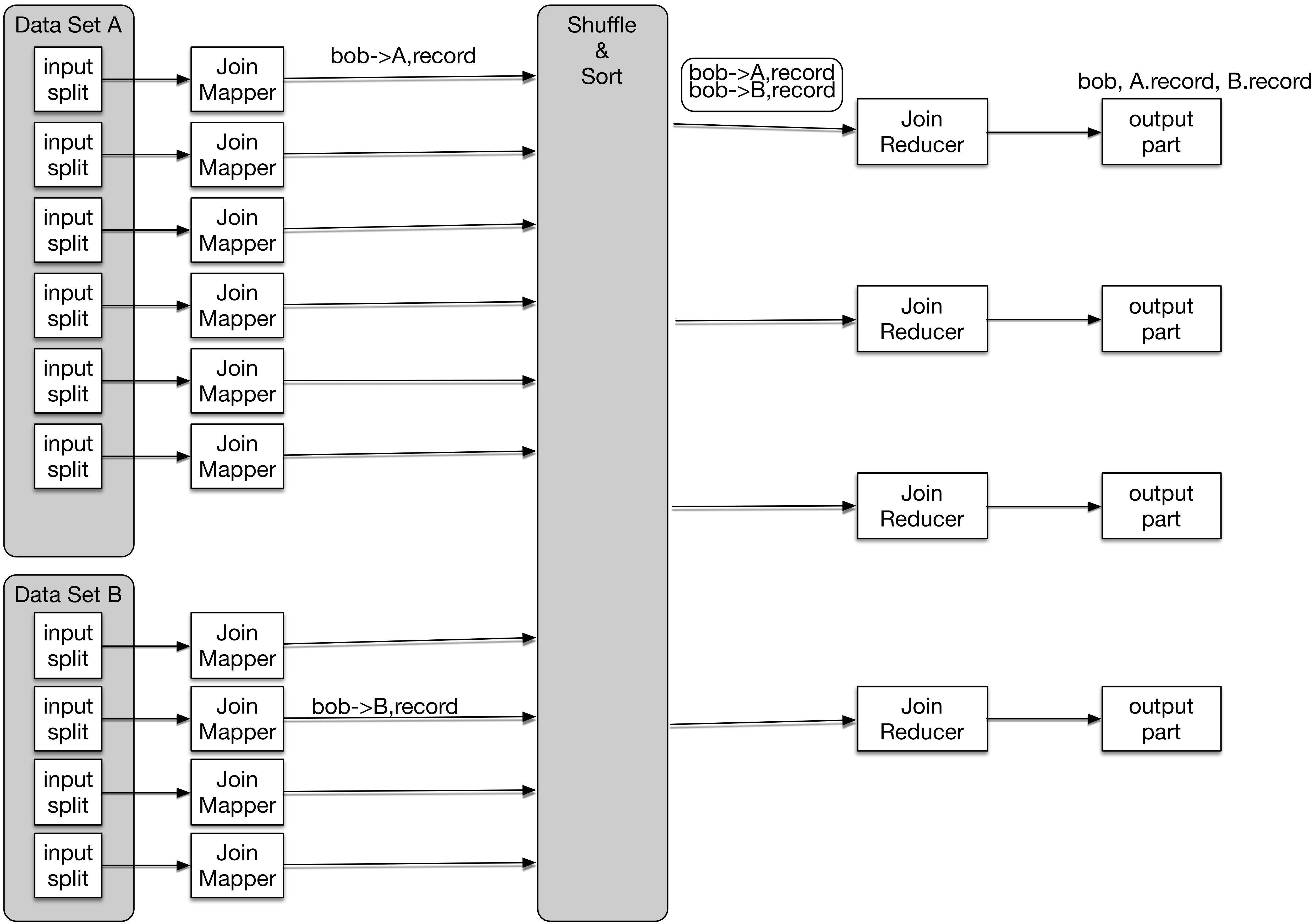
Join Patterns

- Pig allows you to give hints for joins

```
huge = LOAD ‘huge.txt’ AS (h1,h2);
smallest = LOAD ‘smallest.txt’ AS (ss1, ss2);
small = LOAD ‘small.txt’ AS (s1,s2);
A = JOIN huge BY h1, small BY s1, smallest BY ss1 USING
‘replicated’;
```

Join Patterns

- Reduce Side Join
  - Join large multiple data sets together by some foreign key
  - Structure:
    - Mapper goes through all records in both data sets
    - Mapper creates pairs
      - foreign key —> source, rest of record
      - source is the name of the table
    - Can use hash partitioner or a customized partitioner
    - Reducer combines values of each input group into two lists



Data Set A
input split
input split
input split
input split
input split
input split
Join Mapper
Join Mapper
Join Mapper
Join Mapper
Join Mapper
Join Mapper
bob->A,record
Shuffle & Sort
bob->A,record
bob->B,record
Join Reducer
Join Reducer
Join Reducer
Join Reducer
bob, A.record, B.record
output part
output part
output part
output part
Data Set B
input split
input split
input split
input split
Join Mapper
Join Mapper
Join Mapper
Join Mapper
bob->B,record

Join Patterns

- The reducer is given within the input group all records with a foreign key
- This allows the reducer to create many types of joins based on equality

Join Patterns

- Inner join:
  - Records from Table A and Table B are joined if they share the same foreign key

Table A

foreign key	attribute 1	attribute 2

Table B

foreign key	attribute 1	attribute 2	attribute 3

Inner Join

Join Patterns

- Outer Join
  - If the foreign key is not present in one table than the lacking values are made into Null values

Table A

foreign key	attribute 1	attribute 2

Table B

foreign key	attribute 1	attribute 2	attribute 3

Outer Join

			NULL	NULL	NULL

Join Patterns

- Optimization with Bloom Filters
    - If we calculate an inner join with map-reduce, a mapper does not have to create a key-value pair if the foreign key value is not present in the other table

Table A

foreign key	attribute 1	attribute 2
value		

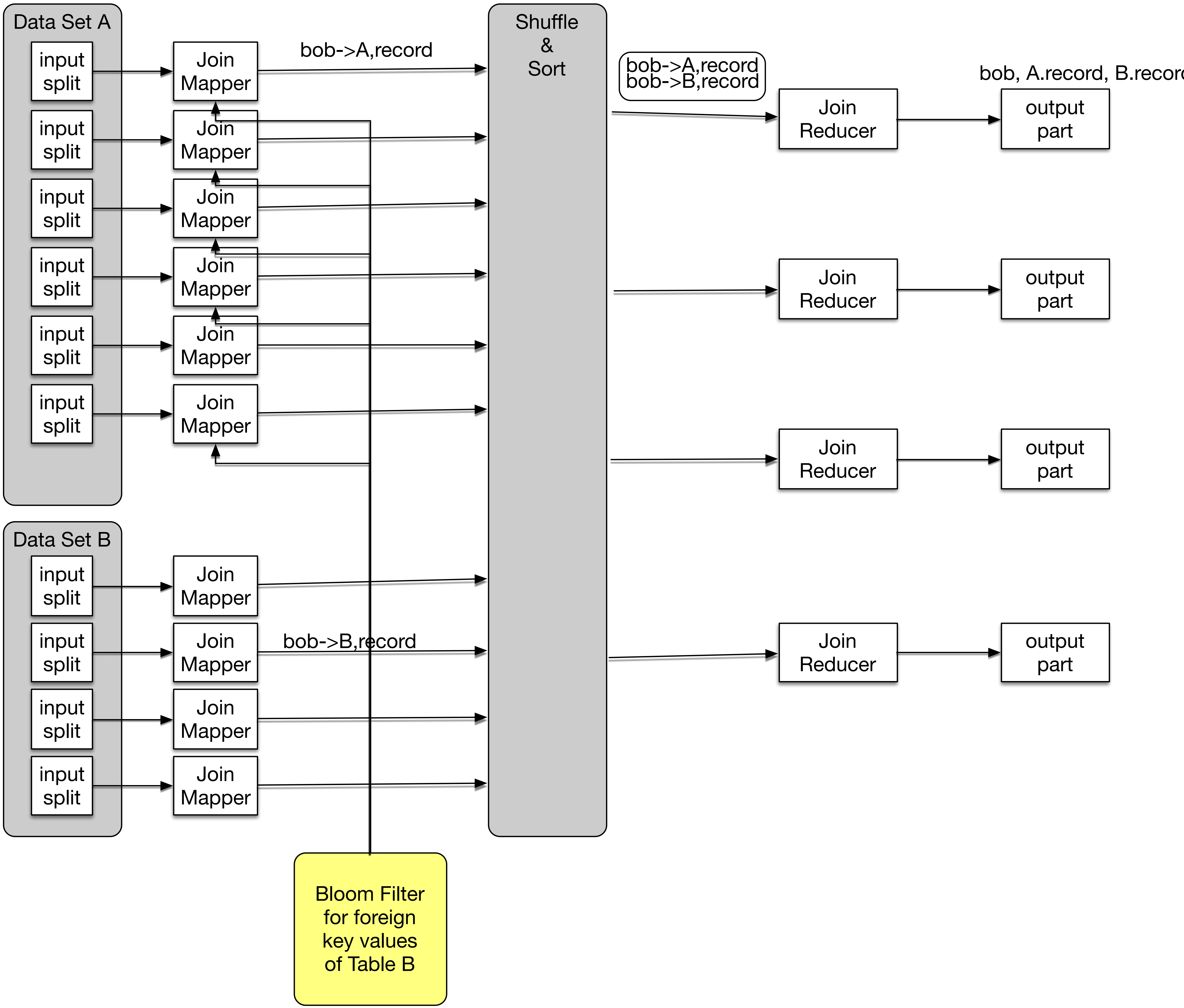
Table B

foreign key	attribute 1	attribute 2	attribute 3

value not present

Join Patterns

- Create a Bloom Filter for both sets (or for only one)
- Put Bloom filter in distributed cache or send it to all mappers for the other table
- Then only send records to the reducer when we know that the foreign key value is also present in the other table



Data Set A
input split
input split
input split
input split
input split
input split
Join Mapper
Join Mapper
Join Mapper
Join Mapper
Join Mapper
Join Mapper
bob->A,record
Data Set B
input split
input split
input split
input split
Join Mapper
Join Mapper
Join Mapper
Join Mapper
bob->B,record
Shuffle & Sort
bob->A,record
bob->B,record
Join Reducer
Join Reducer
Join Reducer
Join Reducer
bob, A.record, B.record
output part
output part
output part
output part
Bloom Filter for foreign key values of Table B

Join Patterns

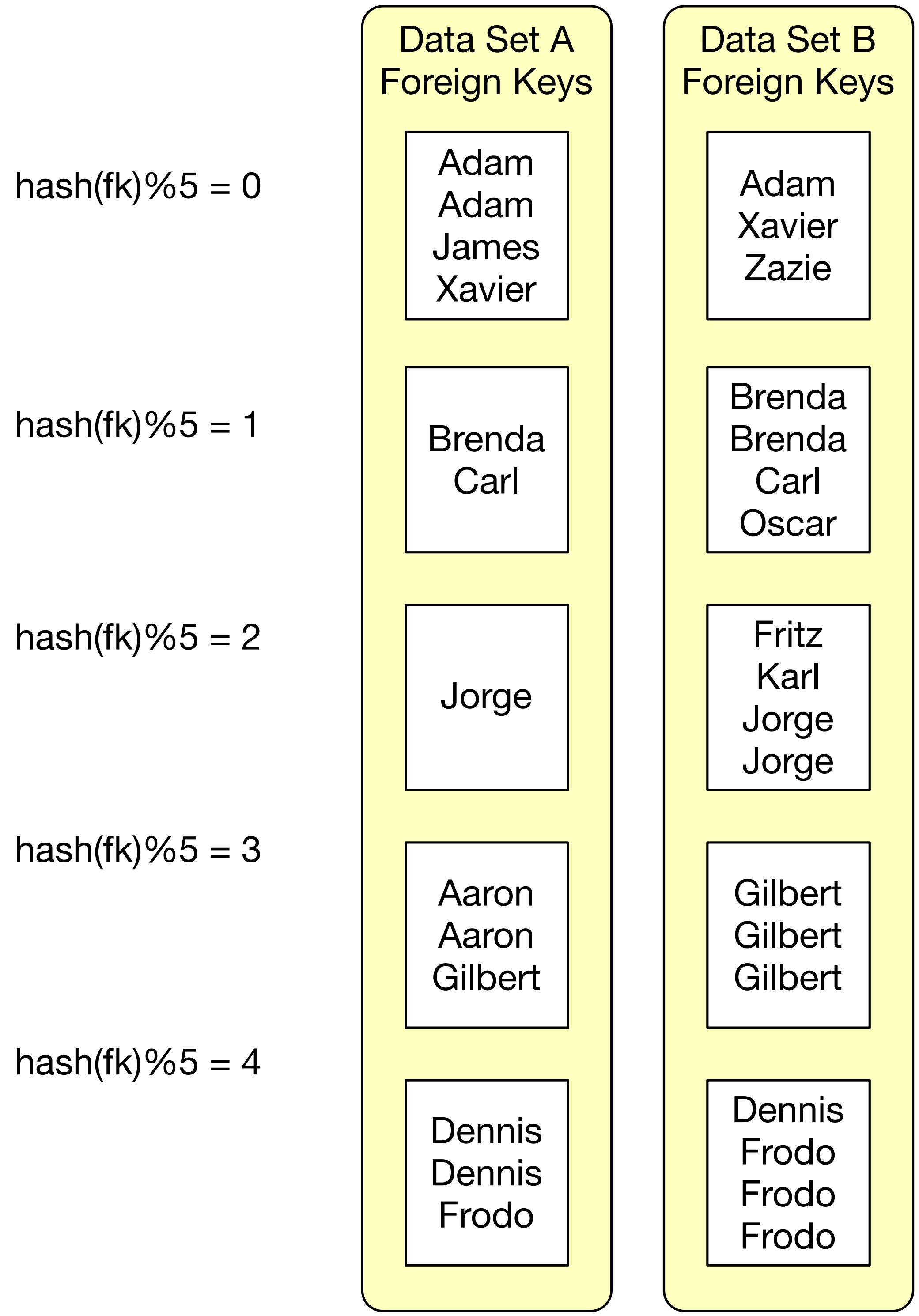
- Bloom filter does not need to be very good to be efficient
  - Bloom filter does not have false negatives, only false positives
- Bloom filter needs to be created before it can be used, making this into a two phase job

Join Patterns

- Composite Join
  - Supported by Hadoop: CompositeInputFormat
- Idea:
  - Preprocess all table contents to create input shards that are sorted and partitioned by foreign key.
  - This is somewhat similar to the idea of the hash-join
- Two-phase job again

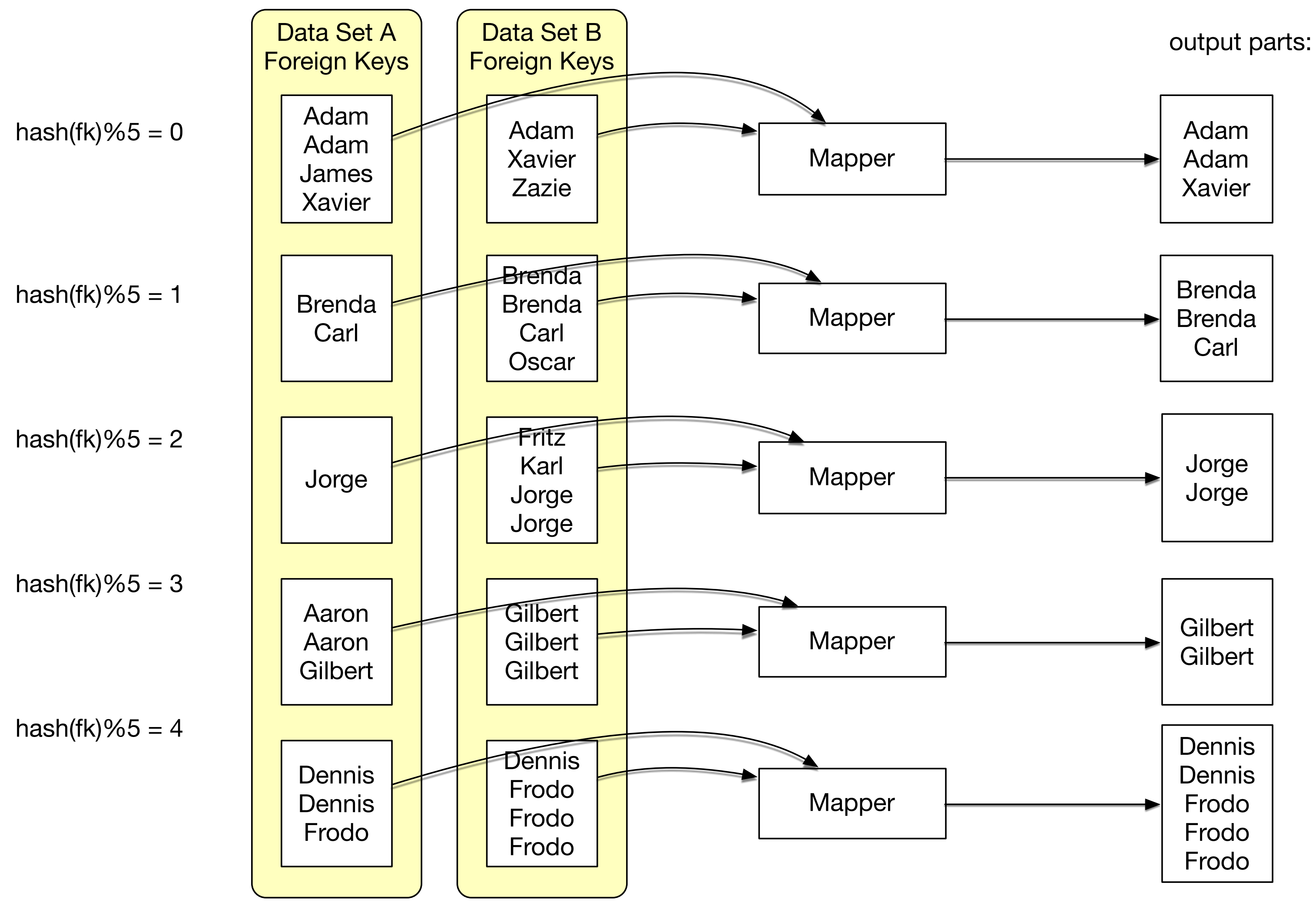
Join Patterns

- Create hash buckets for records based on foreign keys
- Buckets are sorted



Join Patterns

- Send all buckets in the hash to the same mapper
- Mappers then combine
- There are no reducers involved

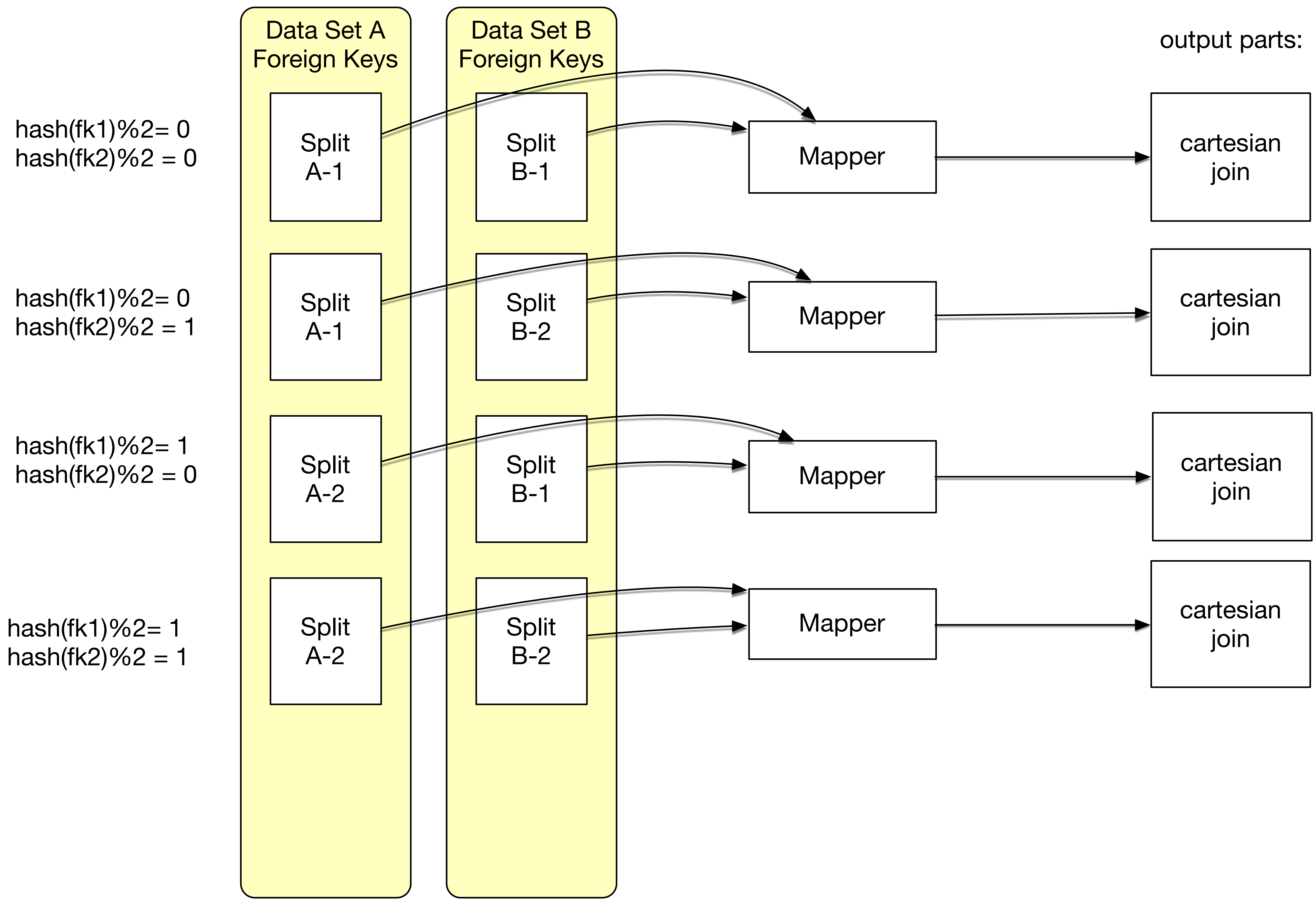


Join Patterns

- Composite Join Performance
  - Most of the work in the creation of the Composite Join Splits

Join Patterns

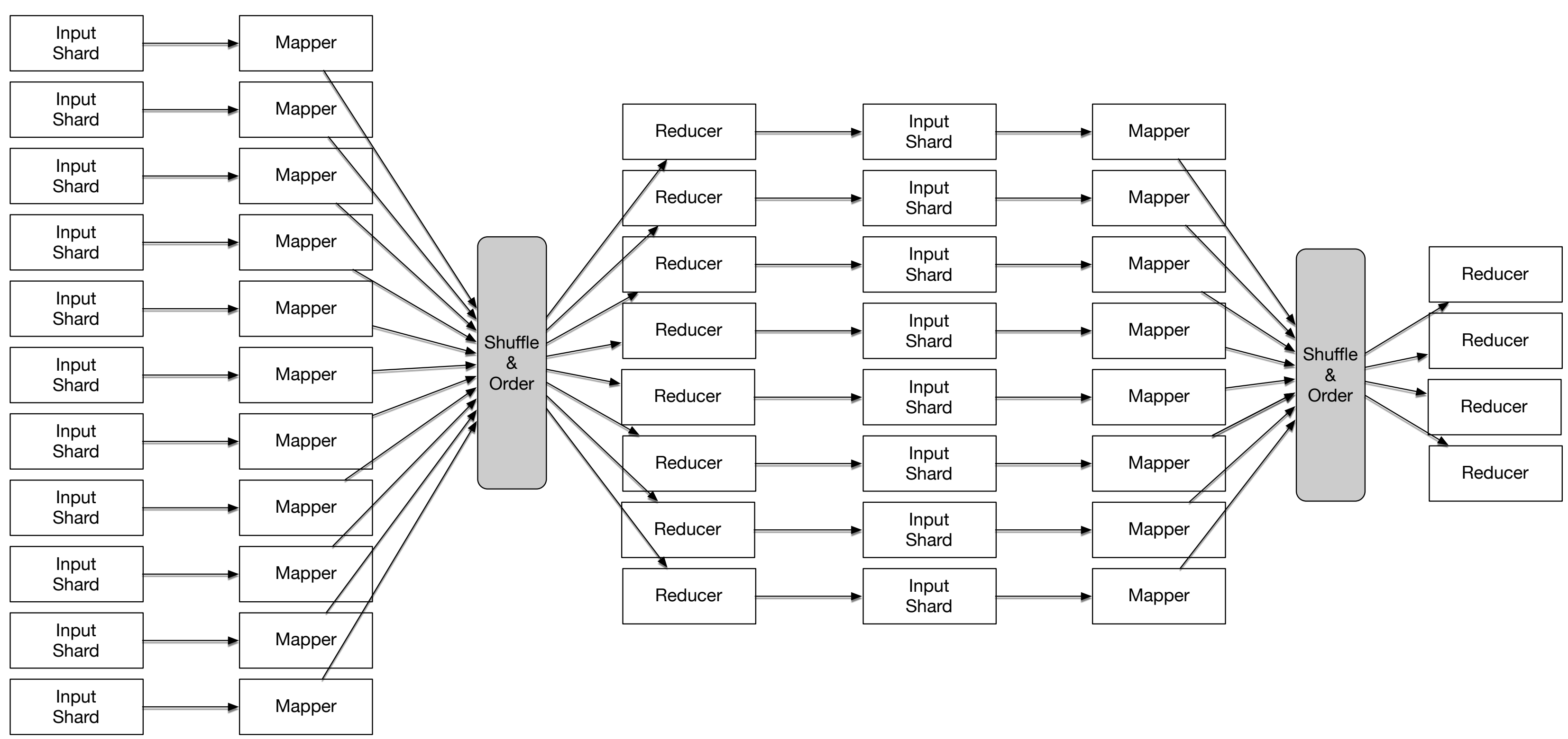
- Cartesian Product
  - Cartesian product combines all values in one table with all values in one other table
  - Easily create gigantic results
  - With huge execution times
- Uses essentially the composite join pattern
  - Each mapper receives an input split from Table A and an input split from Table B
  - If we break Table A into *n* pieces and Table *B* into *m* pieces, then we need $n \times m$ mappers



Data Set A Foreign Keys
Data Set B Foreign Keys
output parts:
hash(fk1)%2= 0
hash(fk2)%2 = 0
Split A-1
Split B-1
Mapper
cartesian join
hash(fk1)%2= 0
hash(fk2)%2 = 1
Split A-1
Split B-2
Mapper
cartesian join
hash(fk1)%2= 1
hash(fk2)%2 = 0
Split A-2
Split B-1
Mapper
cartesian join
hash(fk1)%2= 1
hash(fk2)%2 = 1
Split A-2
Split B-2
Mapper
cartesian join

Meta Patterns

- Job Chaining
  - Run two or more map-reduce jobs
  - Output of the first is input to the second



Meta Patterns

- Map-Reduce framework is not very good at this
  - Special frameworks exist
    - Oozie —Apache Project Workflow Engine
      - Java web application
      - Workflow - collection of actions
        - Map-reduce jobs, Pig jobs arranged in a DAG
        - Uses XML-based Hadoop Process Definition Language for workflow specifications
    - Oozie coordinates jobs

Meta Patterns

- Doing it yourself
  - Using Java
  - Map-reduce drivers are simple Java classes
  - Take the drivers of the individual Map-reduce jobs and call them in sequence
    - Output and input paths need to match
  - Use Job.Submit( ), JobisComplete( ), and Job.waitForCompletion( )

Meta Patterns

- Doing it yourself
  - Scripting
  - Using JobControl

Chain Folding

- Opportunities for optimization
  - Mappers work in isolation
  - A record can be submitted to multiple mappers or to a reducer-mapper combination
- Avoids transfer of files

Chain Folding

- Chain folding patterns
  - Multiple mapping phases are adjacent
    - Fold them into single mappers
  - If a job ends with a map phase
    - Push into the preceding reducer phase
  - Split mappers that reduce data and mappers that increase data
  - Filter data as early as possible

Job Merging

- If two unrelated map-reduce jobs use the same input set
  - Can combine the mappers and reducers
  - Data is loaded and parsed now only once