Part A:
Massive Parallelism with MapReduce

- Introduction
- Model
- Implementation issues

Acknowledgements

The material is largely based on

- material from the Stanford cources CS246, CS345A and CS347 (http://infolab.stanford.edu)
- the freely available textbook "Data-Intensive Text Processing with MapReduce"
- the "Mining of Massive Datasets" book .

Of course, all errors are mine!

MapReduce in a nutshell

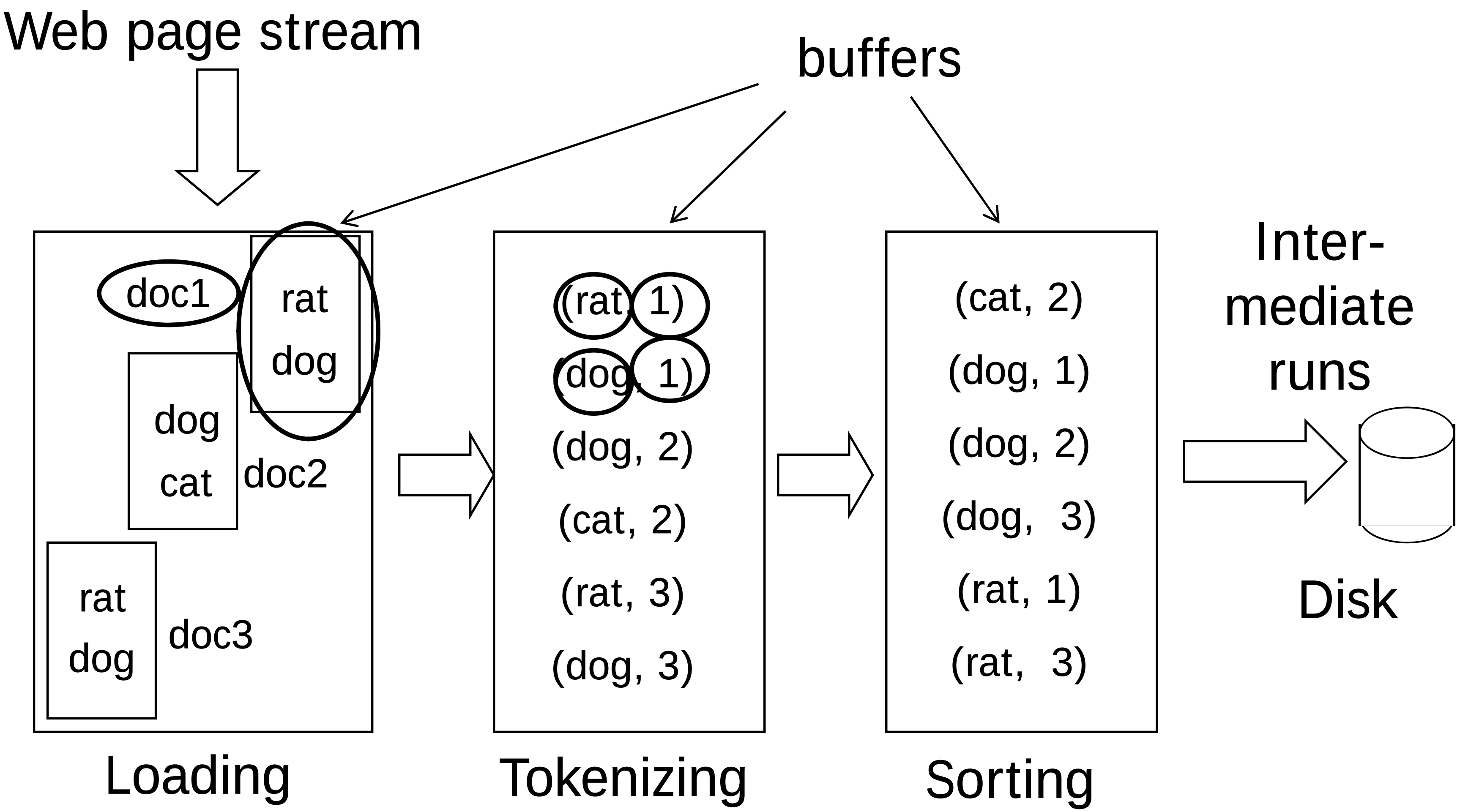
- It is a programming model
- that is suitable for processing very large volumes of data on top of distributed infrastructures.
- It is based on ideas, principles and notions that are known since decades!
  - map and reduced are *adapted* from functional programming
- Initially, it was developed by Google;
  - nowadays most people use the Hadoop open source implementation.

Motivation

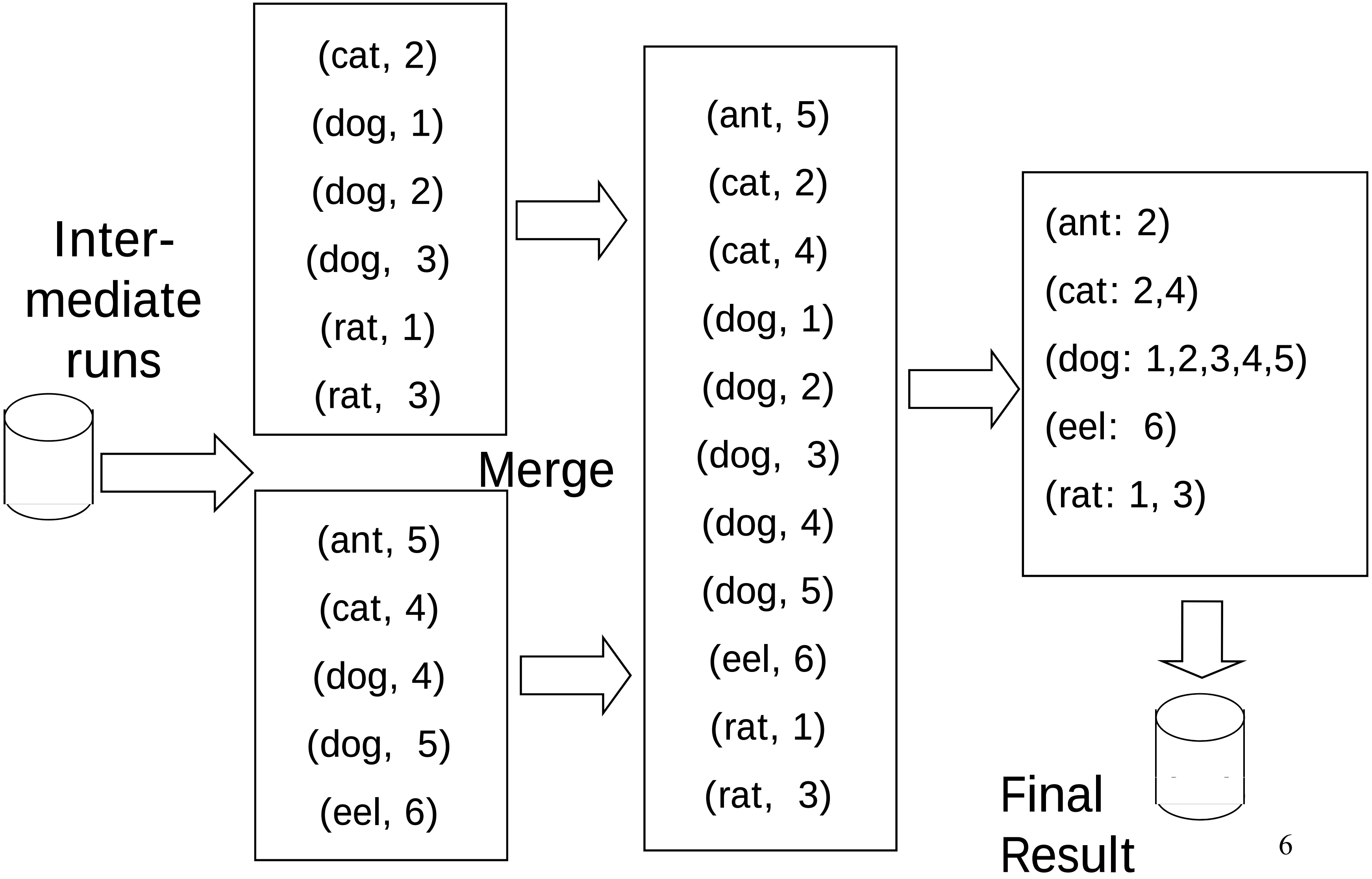
- Huge Data:
  - Google: 100TB/day in 2004, 20PB/day in 2008.
  - eBay (2009): $170 \cdot 10^{12}$ records, $150 \cdot 10^{9}$ new records daily, 2-6,5 PB user data.
  - Facebook(2009): 2,5PB, 15 TB daily.
  - LHC: 15PB/year.

- *Note that many algorithms based on training (e.g., machine learning) perform better if they are trained with more data.*

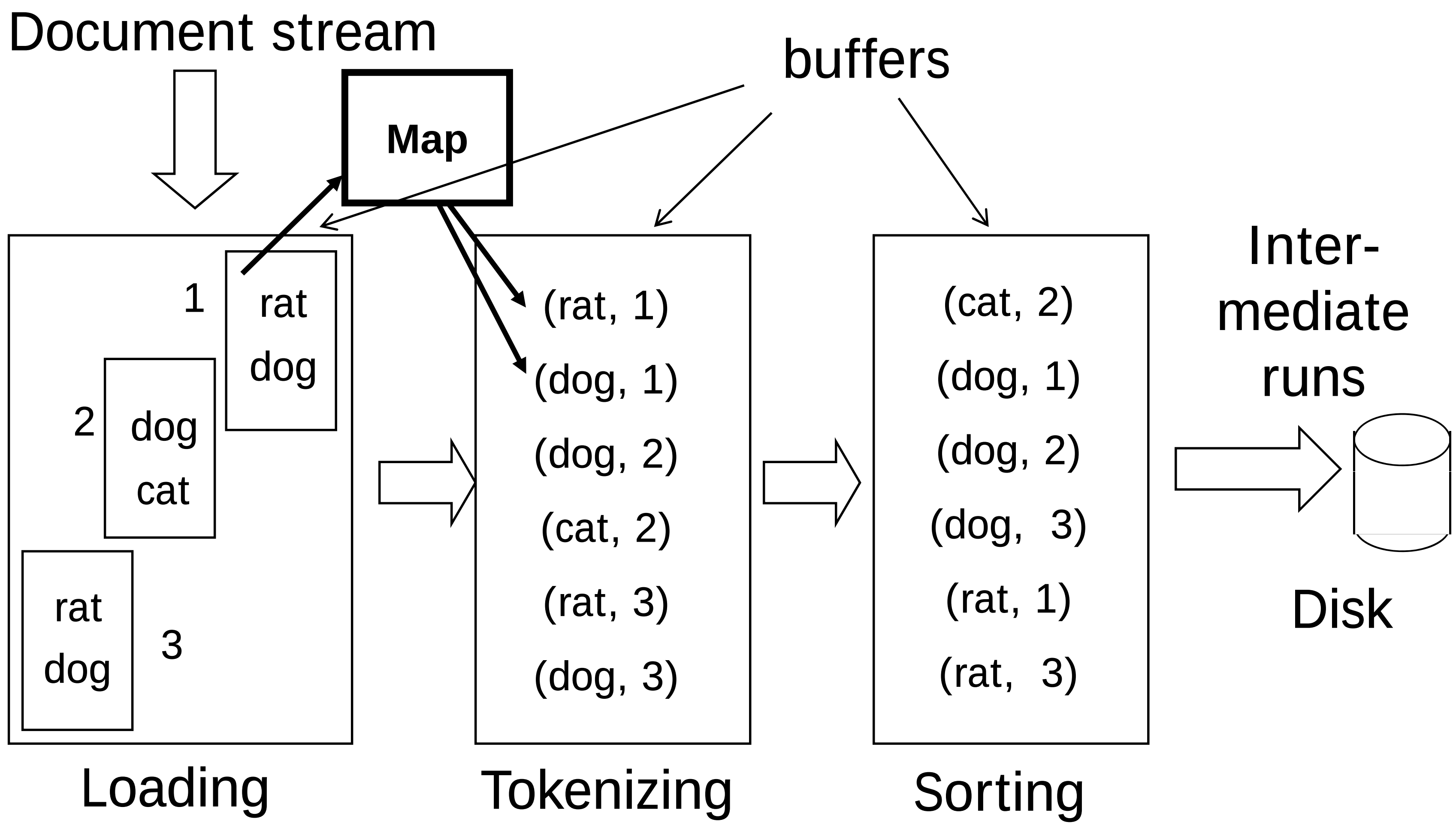
Building a text index- I



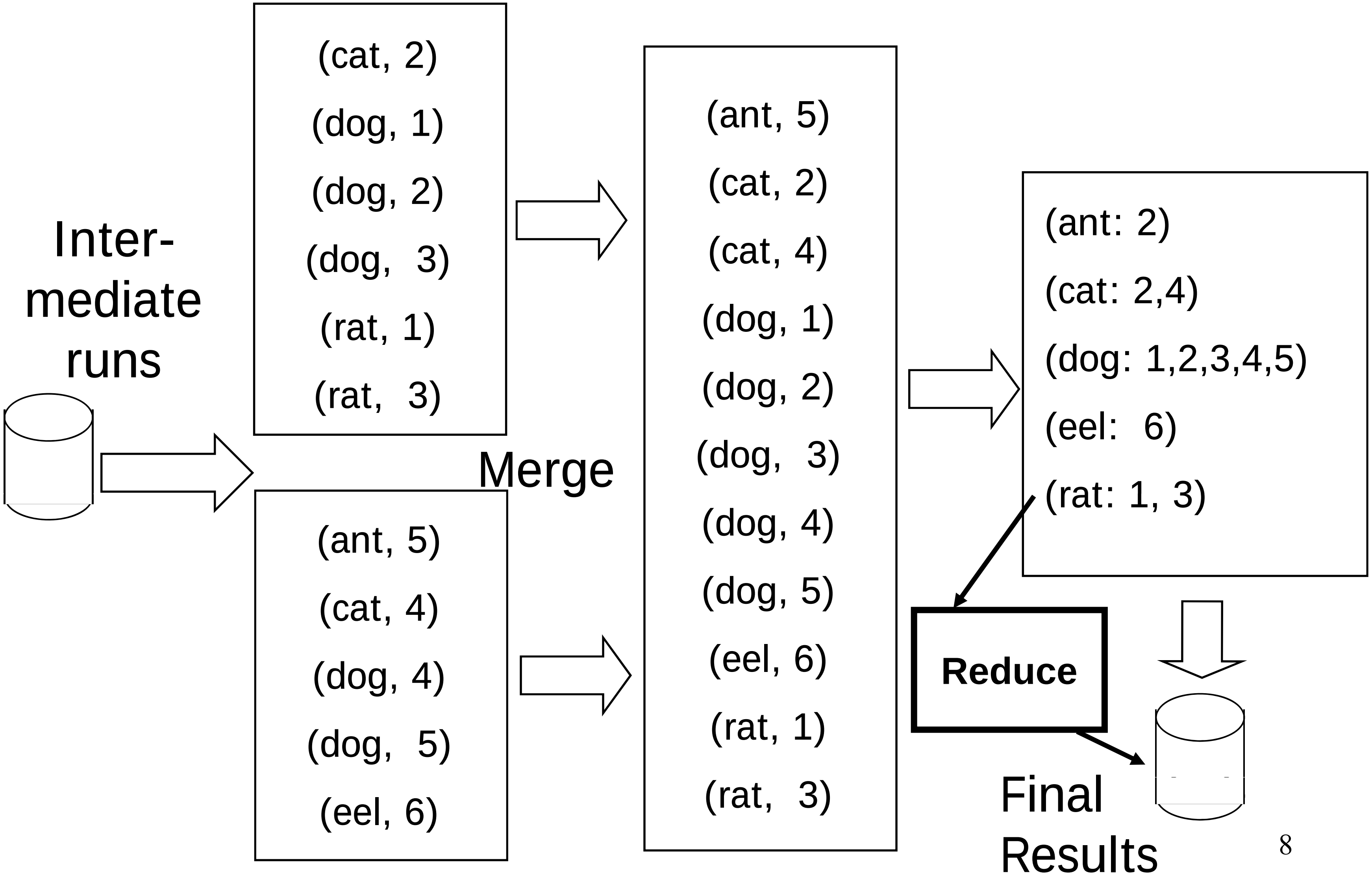
Building a text index- II



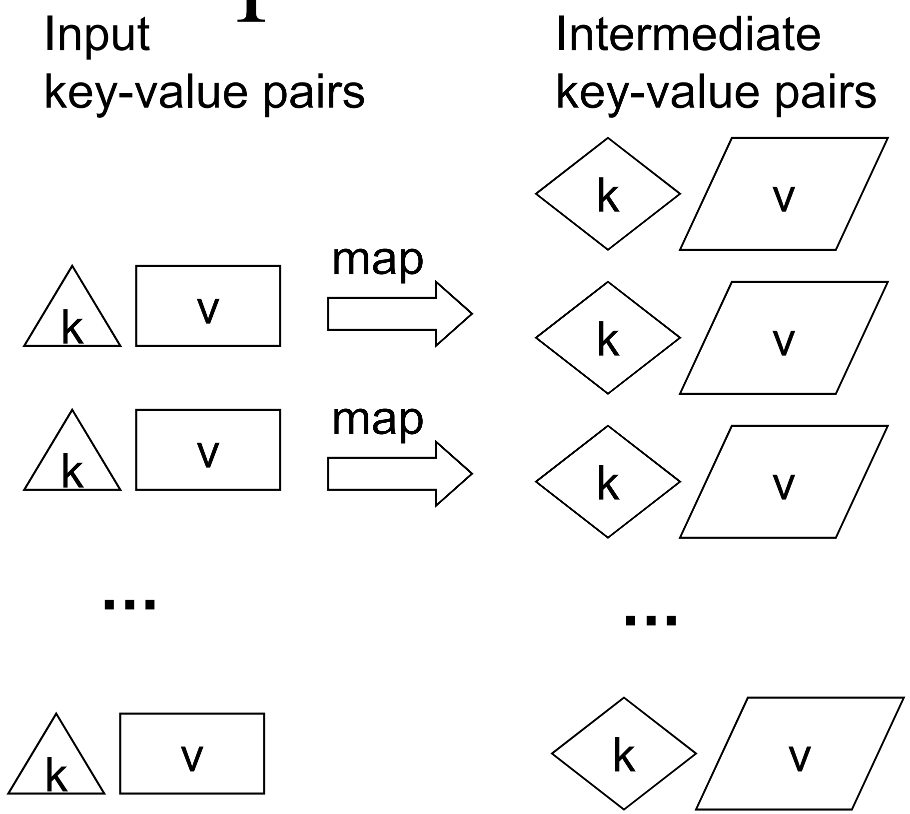
Generic Processing Model: Map



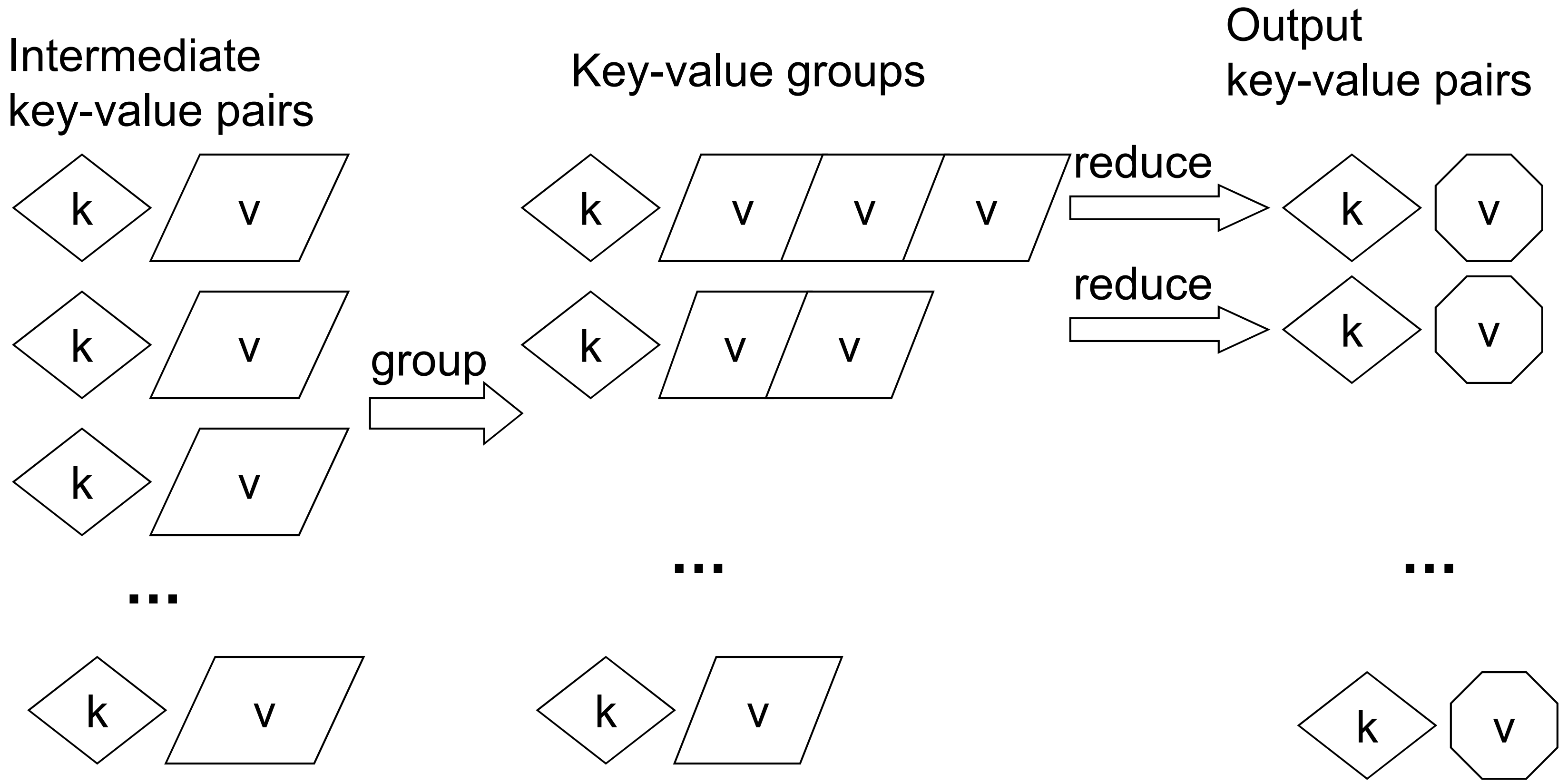
Generic Processing Model : Reduce



MapReduce: The Map Step



MapReduce: The Reduce Step



Short Interface Description

- Map: (key1, value) → (key2, value2) list
- Reduce: (key2, list of values2) → list of final_values

Alternatively:

- Map: (key1, value1) → [(key2, value2)]
- Reduce: (key2, [value2]) → [value3]   // in Hadoop, we may
  // change key2 to key3

- Key should not be understood in the strict database sense; more than one values can share the same key.

The famous Wordcount example

```
map(String doc, String value);
  // doc: document name
  // value: document content
  for each word w in value:
     EmitIntermediate(w, “1”);
```

Example:

map(doc, “cat dog cat bat dog”) emits
  [cat 1], [dog 1], [cat 1], [bat 1], [dog 1]

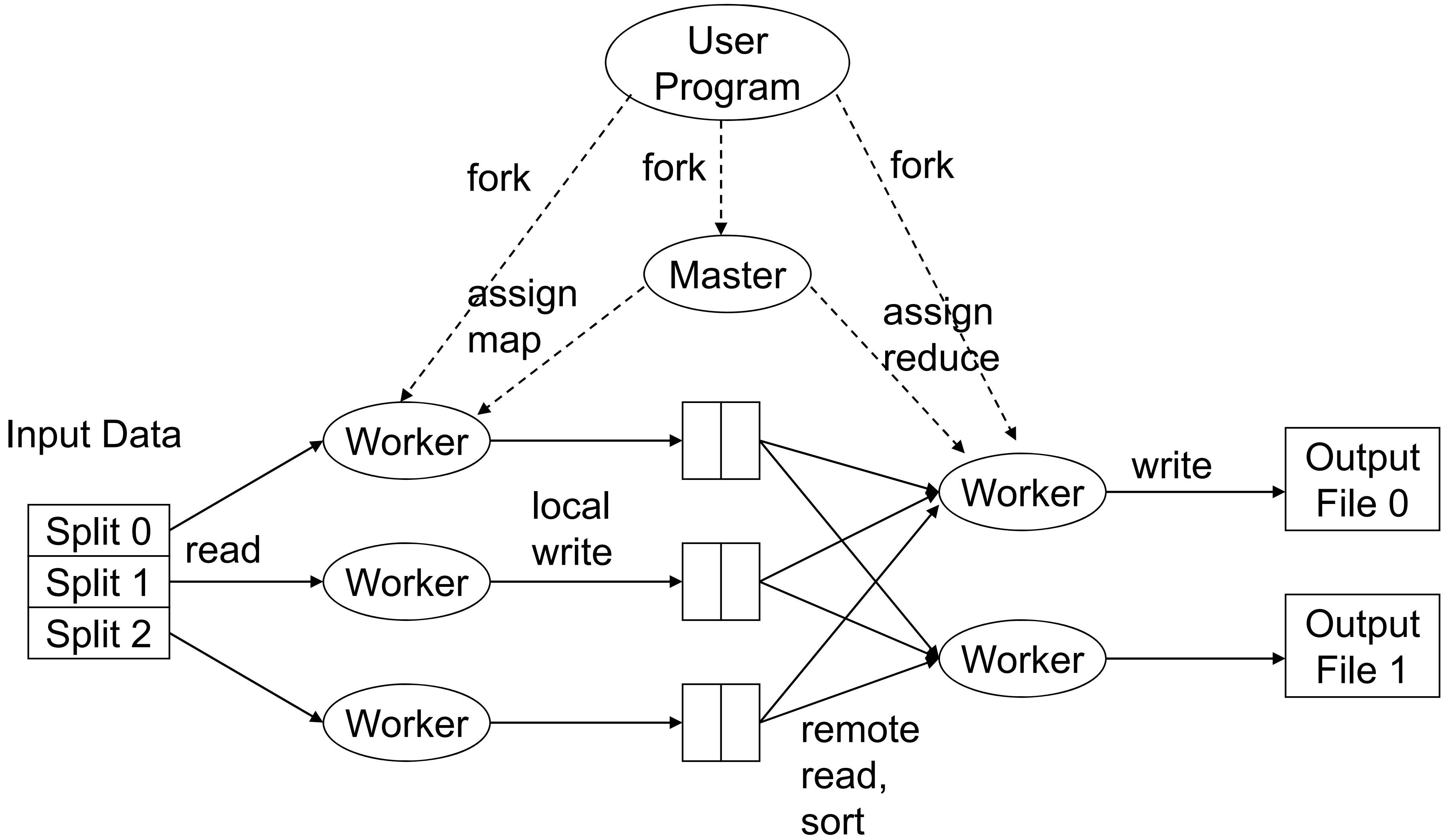
The famous Wordcount example – cont'd

```
reduce(String key, Iterator values);
   // key: word
   // values:  counter list
   int result = 0;
   for each v in values:
       result += ParseInt(v)
   Emit(AsString(result));
```

Example:

reduce("dog", "1 1 1 1") emits "4"

Summary of Parallel Execution



Coordination – master node

- The master mode
  - Checks if a task is
    - idle,
    - in-progress,
    - or completed.
  - Tasks are scheduled as soon as workers become available.
  - When a map task completes, the master is informed about the location and the size of intermediate results.
  - The master notifies the reducers.
- The master periodically pings all the workers
  - To detect failures.

Implementation issues

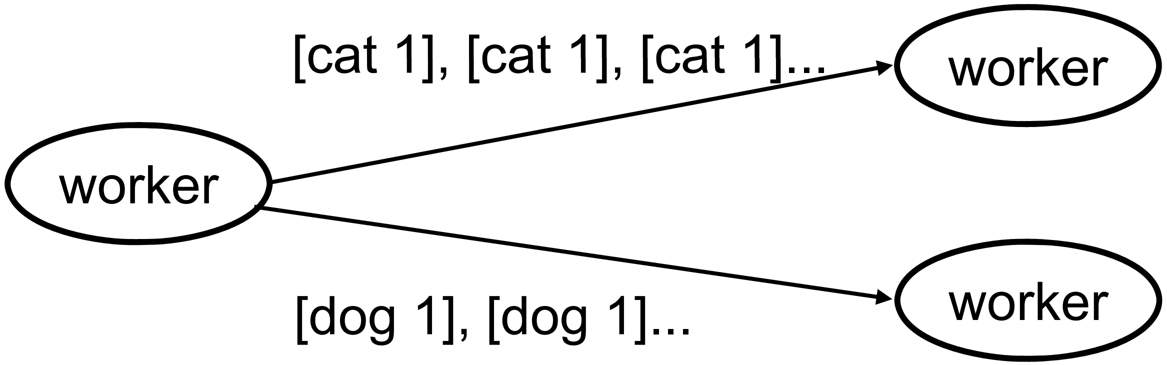
- Combine functions
- DFS
- Input/key partitioning
- Failures
- Backup Tasks
- Result sorting

Methods and Classes

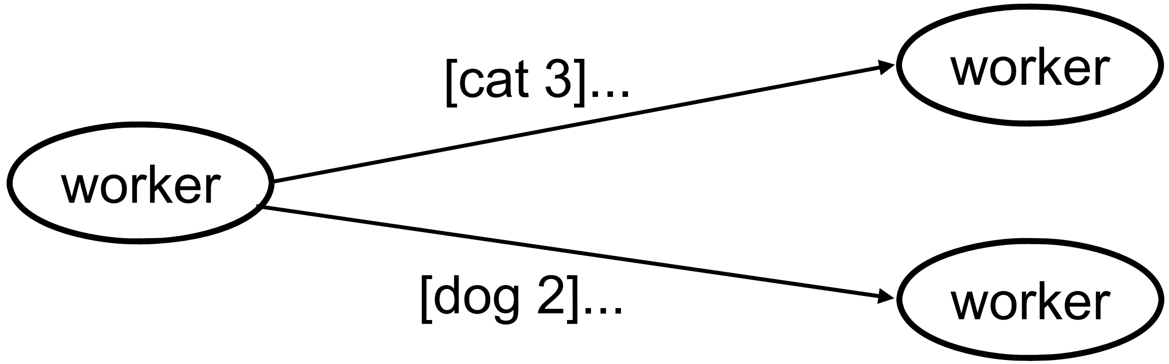
```
class Mapper
    method Map(docid a, doc d)
        for all term t ∈ doc d do
            Emit(term t, count 1)

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)
```

- Each MR job is split into tasks that comprise sequences of key-value pairs.
- For each task, we create a mapper object, which calls the map method for each key-value pair.

Combine functions



Same as if a *local* reduce is executed.



Distributed File System

All data transfers are done via the DFS.

Each reducer had access to the mappers' local disk space.

Each worker accesses part of the global input (in splits)

Each reduce worker can write in the same file.

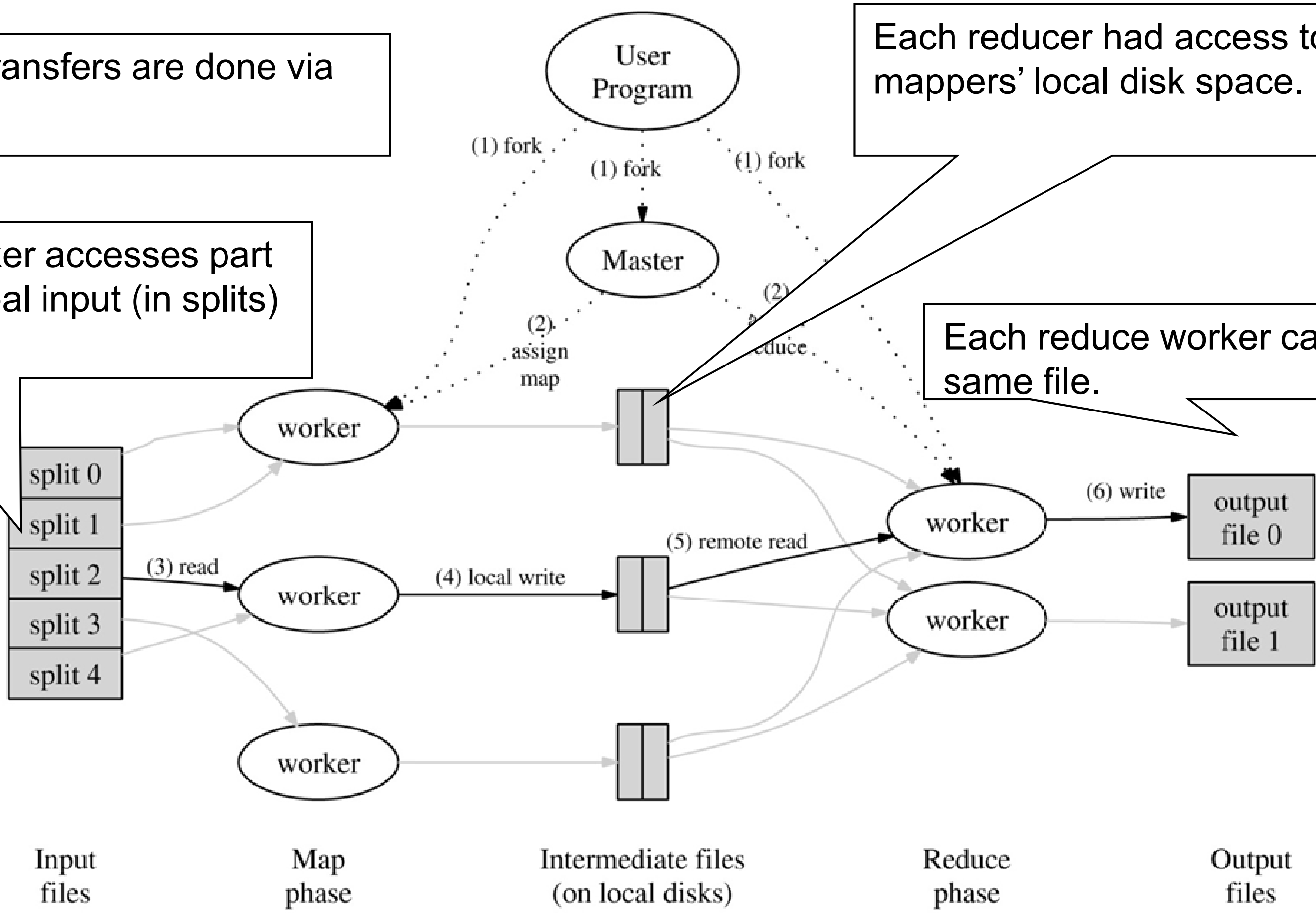


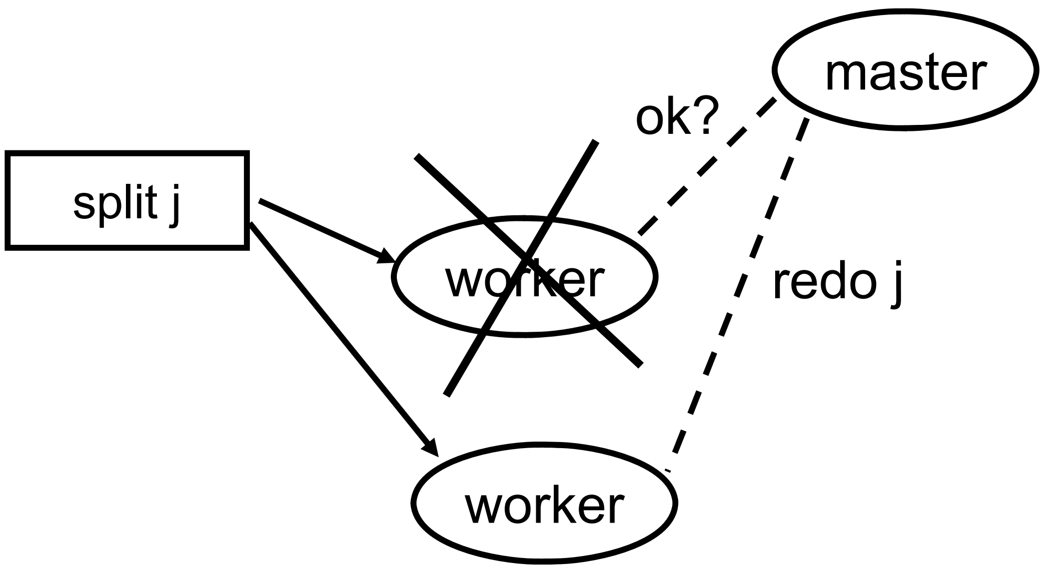
Figure 1: Execution overview

Input partitioning

- Number of workers
  - We prefer to have many input splits per worker for load balancing and failure recovery purposes.
- How many splits?
  - More than the number of map workers,
  - Which may be already high.
  - Typically, an input split has roughly the same size as a DFS chunk, which is 64MB in most of Google’s applications.
- Try to benefit from data locality when assigning map tasks to workers
  - When this is possible.

Failures

- The master node, upon failure detection, re-allocates the tasks to another node.
- If failures are due to erroneous data, then the relevant split is removed.



Backup Tasks

- Some machines are relevantly slow, e.g., due to a broken disk. These machines are called stragglers.
- Stragglers may slow down the entire execution.
  - In parallel execution, the total running time depends on the slowest machine.
- Solution: near the end of execution, the master schedules redundant tasks.
  - At least one such task should complete normally.
  - Such an approach requires mechanisms to handle duplicate results.

Result sorting

- Sorting is performed automatically (i.e., as a built-in feature).

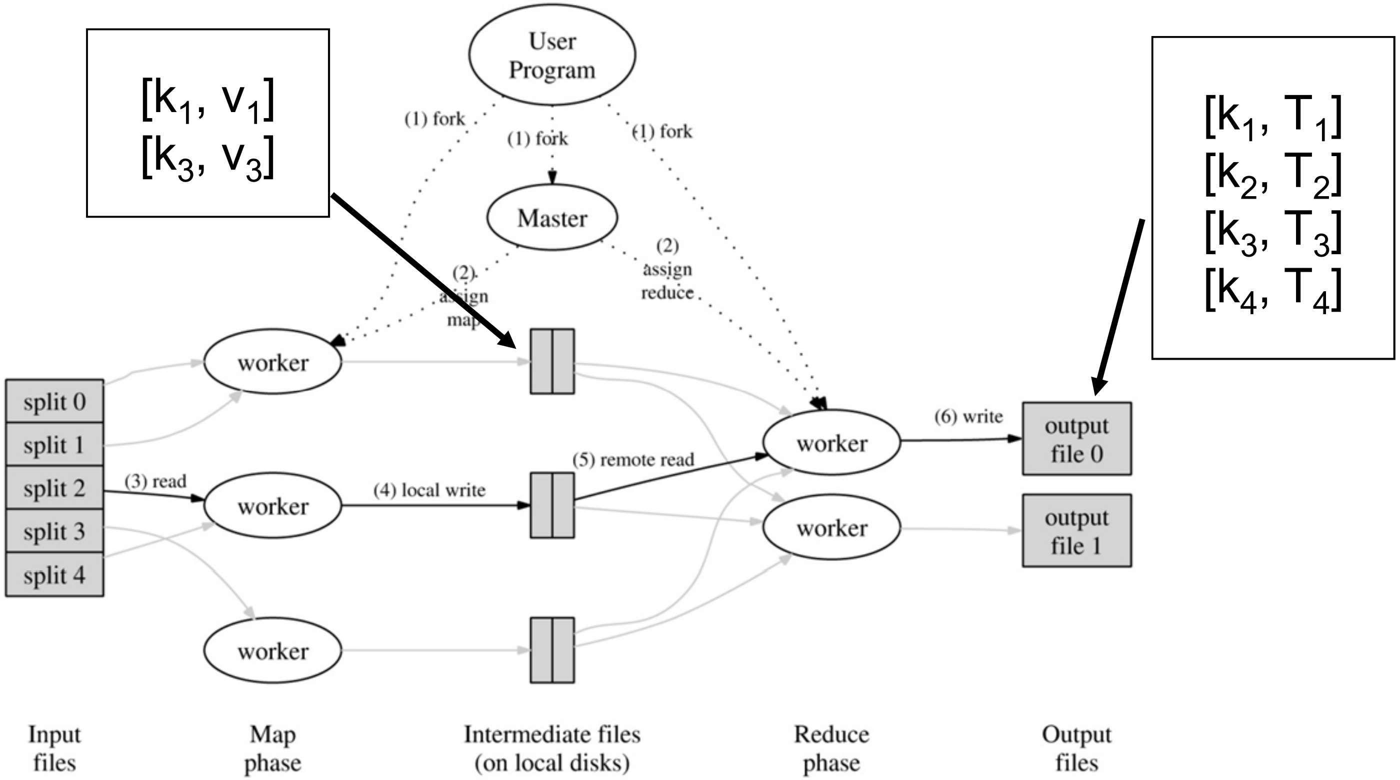


Figure 1: Execution overview

Pros

- All technical details w.r.t parallelism and fault tolerance are hidden.
- Although the system is simple, it is flexible enough to support many problems.
- MR applications can scale to thousands of machines.
  - Note that other parallel models, including some forms of shared nothing databases, can exhibit similar scalability.

Cons

- Not arbitrary scenarios can be supported, at least in an elegant/straightforward manner.
  - Due to the single input, two-stage processing model.
- Need to write code even for the simplest tasks.
  - Task declaration is at a much lower level than in SQL.
- The fact that the code inside map and reduce functions is treated as a black box, prohibits optimizations.

Part B:
Algorithm design and basic data management operators in MR

- Design Techniques
- Relational operators
- Matrix Multiplication

Reminder: Methods and Classes

```
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 [c_1, c_2, ...])
        sum ← 0
        for all count c ∈ counts [c_1, c_2, ...] do
            sum ← sum + c
        Emit(term t, count sum)
```

- Each MR job is split into tasks that comprise sequences of key-value pairs.
- For each task, we create a mapper object, which calls the map method for each key-value pair.

Improvement of Mapper

class MAPPER
    method MAP(docid a, doc d)
        $H \leftarrow$ new ASSOCIATIVEARRAY
        for all term $t \in$ doc d **do**
            $H\{t\} \leftarrow H\{t\} + 1$
        for all term $t \in H$ **do**
            EMIT(term t, count $H\{t\}$)

- Instead of emitting a key-value pair for each term in *d*, this version emits a key-value pair for each unique term in *d*.

Further Improvement

```
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
    method CLOSE
        for all term t ∈ H do
            EMIT(term t, count H{t})
```

- In-mapper combining:
  - Full control of local aggregations;
  - More efficient because it emits less pairs;
  - But breaks the functional programming model and requires more memory

Another combiner example

class MAPPER
  method MAP(string t, integer r)
    EMIT(string t, pair $(r, 1)$)

class COMBINER
  method COMBINE(string t, pairs $[(s_1, c_1), (s_2, c_2) \ldots]$)
    $sum \leftarrow 0$
    $cnt \leftarrow 0$
    for all pair $(s, c) \in$ pairs $[(s_1, c_1), (s_2, c_2) \ldots]$ **do**
      $sum \leftarrow sum + s$
      $cnt \leftarrow cnt + c$
    EMIT(string t, pair (sum, cnt))

class REDUCER
  method REDUCE(string t, pairs $[(s_1, c_1), (s_2, c_2) \ldots]$)
    $sum \leftarrow 0$
    $cnt \leftarrow 0$
    for all pair $(s, c) \in$ pairs $[(s_1, c_1), (s_2, c_2) \ldots]$ **do**
      $sum \leftarrow sum + s$
      $cnt \leftarrow cnt + c$
    $r_{avg} \leftarrow sum/cnt$
    EMIT(string t, integer r_{avg})

Computes the average of values for each key

Following in-mapper combining design

```
class Mapper
    method Initialize
        S ← new AssociativeArray
        C ← new AssociativeArray
    method Map(string t, integer r)
        S{t} ← S{t} + r
        C{t} ← C{t} + 1
    method Close
        for all term t ∈ S do
            Emit(term t, pair (S{t}, C{t}))
```

Relational operators

- Selections
- Projections
- Union, Intersection, and Difference
- Joins
- Grouping and Aggregation

Selections

- $\sigma_C(R)$
- Map: For each tuple *t* in R, test C.
  - If it satisfies the predicate emit *(t,t) ;*
  - *or (t,NULL), so that all the info is in the key*
- Reduce: nothing to be done

Projections

- $\pi_C(R)$
- Map: For each tuple *t* in R, produce *t'* and emit *(t',t')*
- Reduce: receive *(t',[t',t',t'....,t'])* and emit *(t',t')*
  - We perform duplicate elimination

Alternatively:

- Map: For each tuple *t* in R, produce *t'* and emit *(t',1)*
- Reduce: receive *(t',[1,1,1....,1])* and emit *(t',NULL)*
  - We perform duplicate elimination

Unions

- $R(X,Y) \cup S(Y,Z)$
- Map: For each tuple *t* either in R or in S, and emit *(t,t)*
- Reduce: either receive *(t,[t,t]) or (t,[t])*
  - Always emit (t,t)
  - We perform duplicate elimination

Alternatively:

- Map: For each tuple *t* in R, produce *t'* and emit *(t',1)*
- Reduce: receive *(t',[1,1]) or (t',[1])* and emit *(t',NULL)*
  - We perform duplicate elimination

Intersections

- $R(X,Y) \cap S(Y,Z)$
- Map: For each tuple t either in R or in S, emit (t,t)
- Reduce: either receive $(t,[t,t])$ *or* $(t,[t])$
  - Emit (t,t) in the former case and nothing in the latter.

Differences

- *R(X,Y) - S(Y,Z)*
- Map: For each tuple *t* either in R or in S, emit *(t,R or S)*
- Reduce: receive *(t,[R]) or (t,[S]) or (t,[R,S])*
  - Emit (t,t) only when received *(t,[R])*

Simple group-by queries

- Employees(id, dno, salary).

```
Select dno, SUM(salary)
from employees
where salary>1000
group by dno
```

- Map: for each tuple s.t. `salary>1000`, emit a pair `(dno,salary)`
- Reduce: for each value of *`dno`*, compute the sum of the associated list with the multiple values of `salary`.

Reduce-Side Joins

- $R(X,Y) \bowtie S(Y,Z)$.
  - Map:
    - Input: (relation name *R or S,* tuples *t)*
    - Output: list (*Y value*,
      list (relation name, remainder of tuples *X or Z*)).
  - Reduce: for each *Y,* create all pairs *XYZ.*
  - *Secondary sort:*
    - *Extends the key with part of the value.*
    - *Allows the reducer to receive input in specific order.*
    - *Good for 1-to-many joins.*
    - *Requires a partitioner.*

Map-Side Joins

- $R(X,Y) \bowtie S(Y,Z)$.
  - Less generic
  - Assume that both relations are sorted by the join key.
  - Assume that both relations have identically split inputs.
  - Similar to merge-join.
  - Map: local merge join, receive as input a split from one relation and read the corresponding partition from the other relation within map.
  - Reduce: nothing.

Comparison

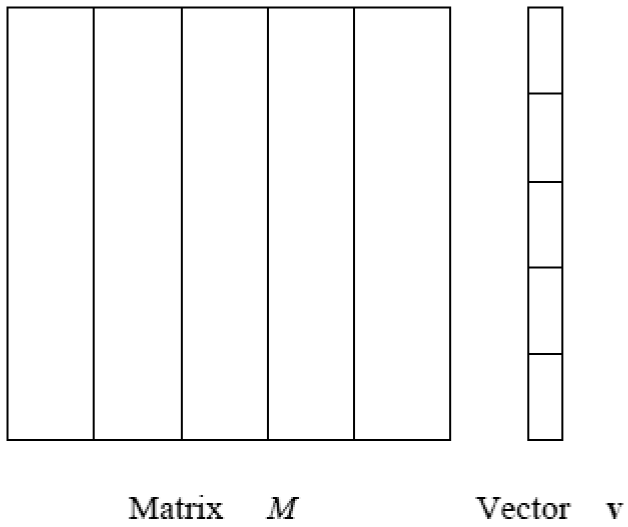
- Map-side
  - (+) can reduce intermediate data significantly if highly selective
  - (-) requires identically keyed/split inputs
- Reduce-side
  - (+) works with any input
  - (+) may be easier to use if number of inputs is expected to increase
  - (-) intermediate data size ~ input size

Matrix –Vector Multiplication

- It is essential in algorithms such as PageRank
- Suppose we have an $n \, X \, n$ matrix (M) and a vector v of length n
- $Mv=x$, where $x_i=\Sigma m_{ij} v_j$
- Map:
  - read a chunk of M and all v.
  - For each element of M, m_{ij}, produce $(i, m_{ij}v_j)$
- Reduce: sum all values with a given key i.

Matrix –Vector Multiplication

- If *v* does not fit in main memory:



Matrix –Matrix Multiplication in 2 steps

- Relational Representation
- Suppose we have an (i X j) matrix M and a (j X k) matrix N
- $M \rightarrow (i,j,m_{ij})$, $N \rightarrow (j,k,n_{jk})$
- Map1: for each element m_{ij} emit $(j,(M,i,m_{ij}))$. Similarly, do the same for n_{jk} values.
- Reduce 1: For each key j, produce $(j, (i,k\ m_{ij}n_{jk})$ –similarities with join.
- Map2: for each $(i,k\ m_{ij}n_{jk})$ value, emit $((i,k), m_{ij}n_{jk})$.
- Reduce2: for each (i,k) key, sum the values.

Matrix –Matrix Multiplication in 1 step

- Relational Representation
- Suppose we have an (i X j) matrix M and a (j X k) matrix N
- $M \rightarrow (i,j,m_{ij})$, $N \rightarrow (j,k,n_{jk})$
- Map1: for each element m_{ij} emit k pairs: $((i,k'),(M,j,m_{ij}))$
  - k': 1..k
- Similarly, for each n_{jk} emit i pairs: $((i',k),(N,j,n_{ik}))$
  - $i'=1..i$
- Reduce 1: For each key:
  - Multiply m_{ij} with n_{ik} if they have the same j value;
  - Sum the products.

Part C:
Data Mining Examples

- URL access frequency
- Friend Recommendation
- Frequent itemsets

URL access frequency

- We assume log files that contain the URL visited.
- Map: process log files and emit <URL, 1> for each log entry.
- Reduce: sum all values for a given URL key, thus producing <URL, total count> .

Frequent Itemsets

- Map 1: find all frequent itemsets using any main-memory algorithm in a split with transaction records; output a key-value pair (L,1) for each itemset *L* found frequent in the split. The exact support value does not play any role.

- Reduce 1: do nothing with the value → eliminate duplicate keys, i.e., locally frequent itemsets. The result contains a list of *C* candidate frequent itemsets.

- Map 2: read a) all output *C* of Reduce1, and b) an input split. For each candidate itemset *c* in *C,* emit its support in that split in the form (c,support)

- Reduce2: sum the supports for each key *c* of Map2; if the sum is not smaller than the support threshold, emit *(c,sum)*

Friend Recommendation

- Suppose that friend connections in a social network are stored as an adjacency list (graph representation)
  - E.g., p245: p125,p246,p347,p893,p899
- Recommend friend links if both persons have mutual friends; rate the recommendations.
- Map:
  - Process records of the form *p_id: n1,n2,n3,...,n_M*
  - Emit all pairs *(p_id,(ni,0))* , *(ni,(nk,1)), i<>k and i,k:1..M*
- Reduce:
  - For each pair *(a,(b,count))* sum the counts for each *a-b* combination if there is no zero value (why?) and sort by the sum.