Map Reduce Design Patterns

Caveat

- MapReduce is a **framework** not a tool
  - You have to fit your solution into the framework of map and reduce
  - It might be challenging in some situations
- Need to take the algorithm and break it into **filter/aggregate steps**
  - Filter becomes part of the map function
  - Aggregate becomes part of the reduce function
- Sometimes we may need **multiple** Map Reduce **stages**
- Map Reduce is **not a solution to every problem**, not even every problem that profitably can use many compute nodes operating in parallel!
- It makes sense only when:
  - files are **very large** and are **rarely updated**
  - We need to **iterate** over all the files to **generate** some interesting property of the data in those files

Design Patterns

- Intermediate data reduction
- Matrix generation and multiplication
- Selection and filtering
- Joining
- Graph algorithms

Intermediate Data

- Written locally
  - Transferred from mappers to reducers over network
- Issue
  - Performance bottleneck
- Solution
  - Reduce data
  - Use combiners
  - Use In-Mapper Combining

In-Mapper Combining (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)
```

In-Mapper Combining (II)

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

In-Mapper Combining (III)

```
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

- **Advantages**:
  - **Complete** local aggregation **control** (how and when)
  - **Guaranteed** to execute
  - Direct **efficiency control** on intermediate data creation
  - Avoid **unnecessary** objects creation and destruction (before combiners)
- **Disadvantages**:
  - **Breaks** the functional programming background (state)
  - Potential ordering-dependent **bugs**
  - **Memory** scalability **bottleneck** (solved by memory **foot-printing** and flushing)

Matrix Generation

- Common problem:
  - Given an input of size *N*, generate an output of size *N x N*
- Example: word co-occurrence matrix
  - Given a document collection, emit the bigram frequencies
- Two solutions
  - **Pairs**: generating $O(N^2)$ data in $O(1)$ space
  - **Stripes**: generation $O(N)$ data in $O(N)$ space

Pairs

```
class Mapper
    method Map(docid a, doc d)
        for all term w ∈ doc d do
            for all term u ∈ Neighbors(w) do
                Emit(pair (w, u), count 1)          ▷ Emit count for each co-occurrence
```

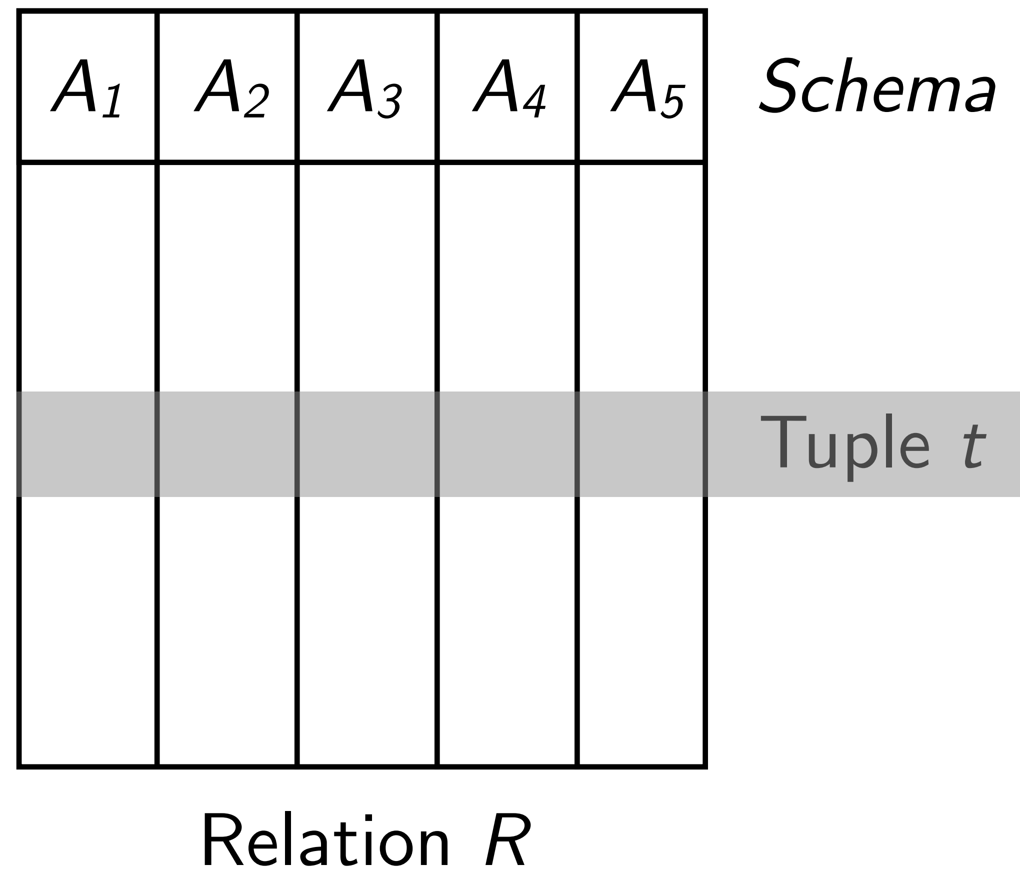
```
class Reducer
    method Reduce(pair p, counts [c1, c2, ...])
        s ← 0
        for all count c ∈ counts [c1, c2, ...] do
            s ← s + c                               ▷ Sum co-occurrence counts
        Emit(pair p, count s)
```

Stripes

```
class Mapper
    method Map(docid a, doc d)
        for all term w ∈ doc d do
            H ← new AssociativeArray
            for all term u ∈ Neighbors(w) do
                H{u} ← H{u} + 1                        ▷ Tally words co-occurring with w
            Emit(Term w, Stripe H)

class Reducer
    method Reduce(term w, stripes [H1, H2, H3, . . .])
        Hf ← new AssociativeArray
        for all stripe H ∈ stripes [H1, H2, H3, . . .] do
            Sum(Hf, H)                                  ▷ Element-wise sum
        Emit(term w, stripe Hf)
```

Relational Algebra Operators



- SELECTION: Select from relation R tuples satisfying condition $c(t)$
- PROJECTION: For each tuple in relation R, select only certain attributes A_i
- UNION, INTERSECTION, DIFFERENCE: Set operations on two relations with same schema
- NATURAL JOIN
- GROUPING and AGGREGATION

Selection and projection

- **Map**: each tuple t in R, if condition $c(t)$ is satisfied, is outputted as a (t, t) pair
- **Reduce**: for each (t, t) pair in input, output $(t, \perp)$

- **Map**: each tuple t in R, create a new tuple t' containing only the projected attributes and output a (t', t') pair
- **Reduce**: for each (t', t') pair in input, output $(t', \perp)$

Selection and projection

- **Map**: for each tuple t in R, if condition $c(t)$ is satisfied, output a (t, t) pair
- **Reduce**: for each (t, t) pair in input, output $(t, \perp)$

- **Map**: for each tuple t in R, create a new tuple t' containing only the projected attributes and output a (t', t') pair
- **Reduce**: for each $(t', [t', t', t', t'])$ pair in input, output $(t', \perp)$

Union, intersection and difference

- **Map**: for each tuple t in R, output a *(t, t)* pair
- **Reduce**: for each input key t, there will be 1 or 2 values equal to t. Coalesce them in a single output $(t, \perp)$

- **Map**: for each tuple t in R, output a *(t, t)* pair
- **Reduce**: for each input key t, there will be 1 or 2 values equal to t. If there are 2 value, coalesce them in a single output $(t, \perp)$ otherwise do nothing

- **Map**: for each tuple t in R, output (t , `R`) and for each tuple t in S, output (t , `S`)
- **Reduce**: for each input key t, there will be 1 or 2 values. If there is 1 value equal to (t , `R`) output $(t, \perp)$, otherwise do nothing

Natural Join

For simplicity, assume we have two relations *R(A,B)* and *S(B,C)*. Find tuples that agree on the *B* attribute values and output them.

- **Map**: for each tuple *(a, b)* from *R*, output *(b, (*`R`*, a))* and for each tuple *(b, c)* from *S*, produce *(b, (*`S`*, c))*
- **Reduce**: For each input key *b*, there will a list of values of the form *(*`R`*, a)* or *(*`S`*, c)*. Construct all pairs and output them together with *b*

Grouping and aggregation

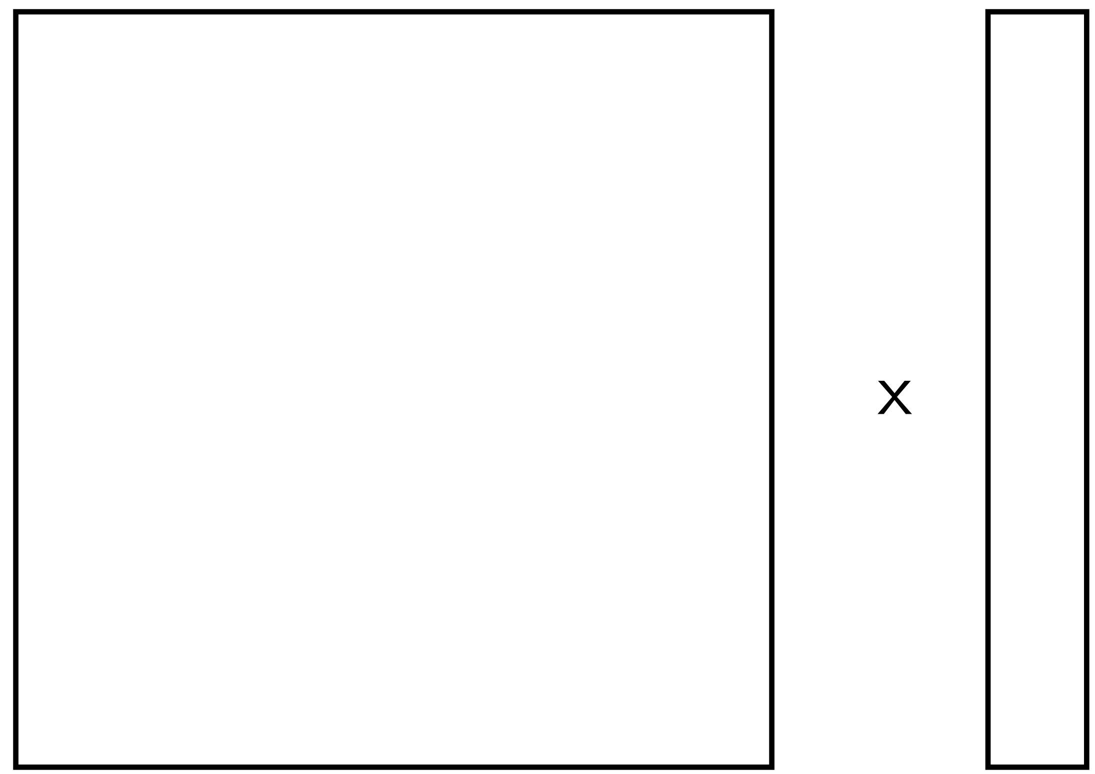
For simplicity, assume we have the relation *R(A,B,C)* and we want to group-by *A* and aggregate on *B*, disregarding C.

- **Map**: for each tuple *(a, b, c)* from *R*, output *(a, b)*. Each key a represents a group.
- **Reduce**: apply the aggregation operator to the list of *b* values associated with group keyed by *a*, producing *x*. Then output *(a, x)*.

Stage Chaining

- As map reduce calculations get **more complex**, it's useful to break them down into **stages**, with the output of one stage serving as input to the next
- Intermediate output may be useful for **different outputs** too, so you can get some reuse
- The intermediate records can be saved in the data store, forming a **materialized view**
- **Early stages** of map reduce operations often represent the **heaviest amount** of data access, so building and save them once as a basis for many downstream uses saves a lot of work

Matrix Vector Multiplication



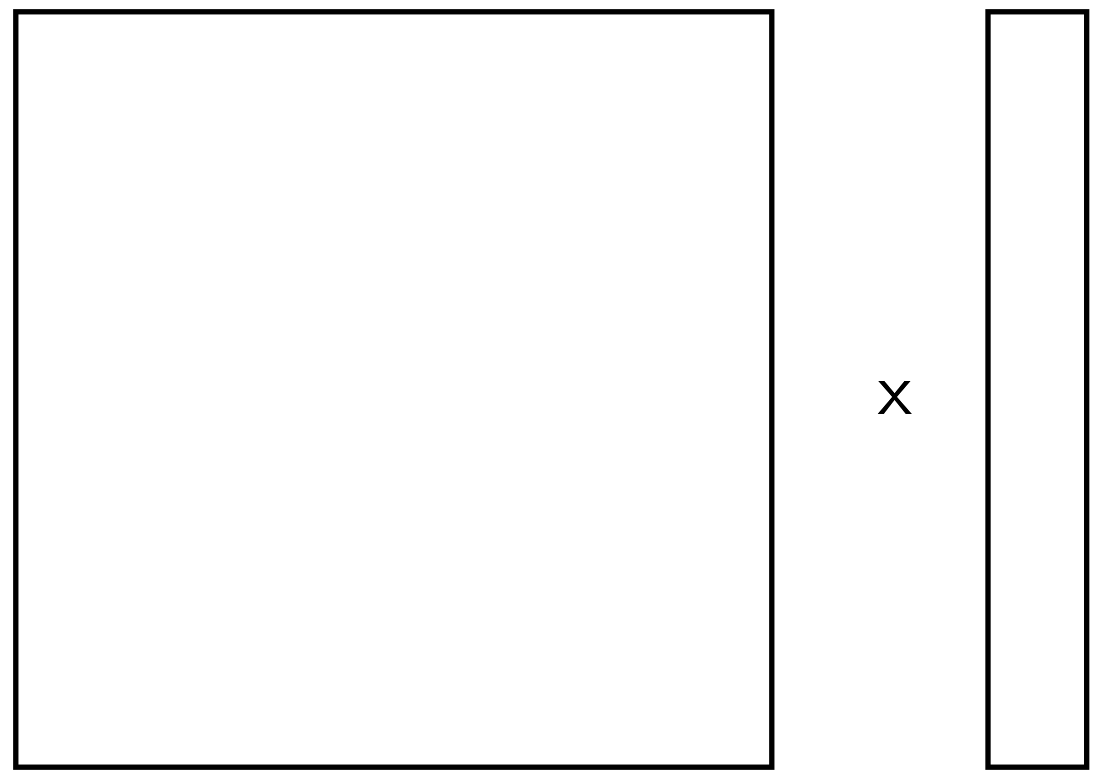
Matrix M size m x n

Vector v size n x 1

The matrix does not fit in memory, and

1. The vector v **does fit** in a machine's memory
2. The vector v **does not fit** in machine's memor

Vector does fit



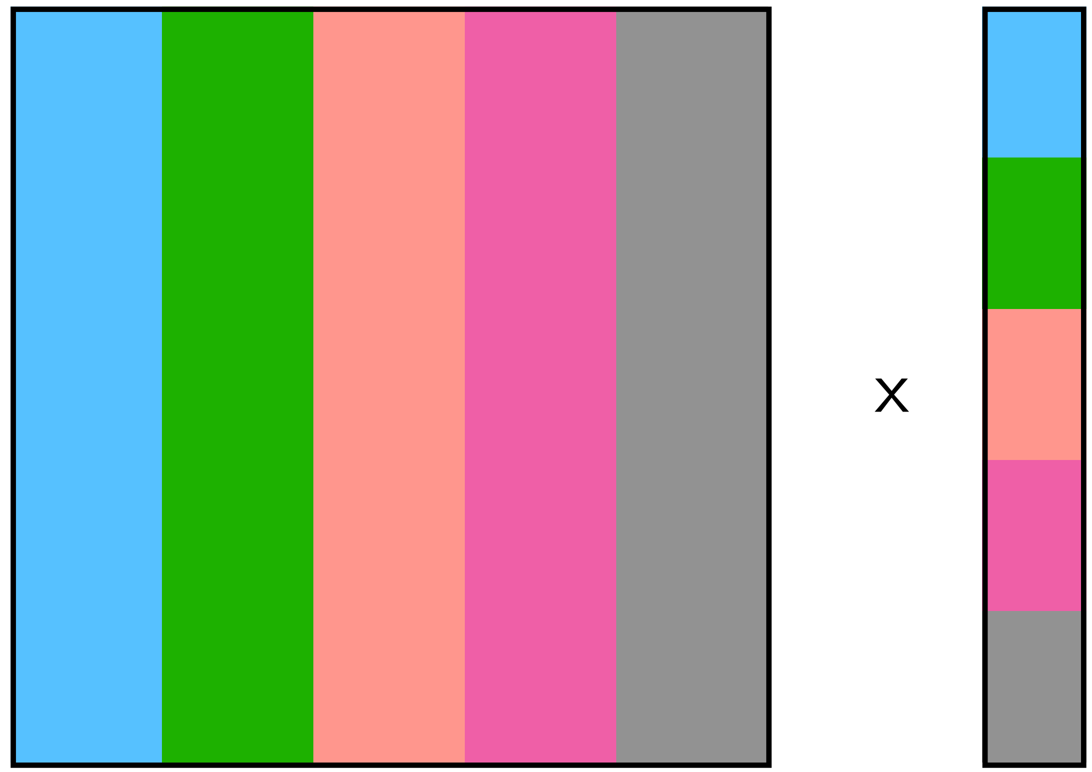
Matrix M size m x n

Vector v size n x 1

The matrix is stored in HDFS as a list of (i, j, m_{ij}) tuples

- The elements v_j of v are **available to all mappers**
- **Map**: ((i, j), m_{ij}) pair → (i, $m_{ij}v_j$) pair
- **Reduce**: (i, [$m_{i1}v_1$, $m_{i2}v_2$, ..., $m_{in}v_n$]) pair → (i, $m_{i1}v_1 + m_{i2}v_2 + ... + m_{in}v_n$) pair

Vector does not fit

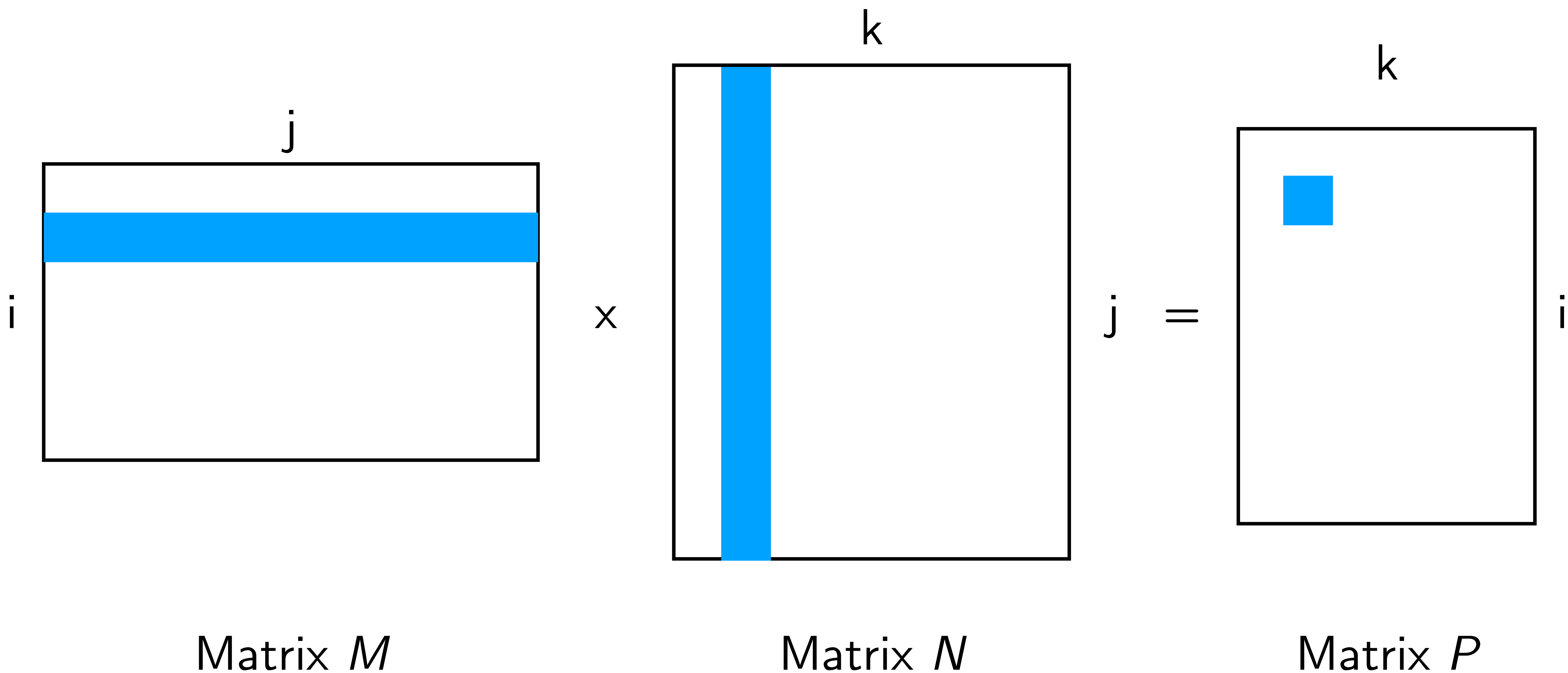


Matrix *M*
size *m* x *n*

Vector *v*
size *n* x *1*

- Divide the vector in equal-sized **subvectors** that can fit in memory
- According to that, divide the matrix in **stripes**
- Stripe i and subvector i are **independent** from other stripes/subvectors
- Use the **previous algorithm** for each stripe/subvector pair

Matrix Matrix Multiplication (I)



$$p_{ik} = \sum_j m_{ij} n_{jk}$$

Matrix Multiplication (II)

- A matrix can be seen as a 3 attributes relation:
  - (row index, column index, value) tuples
  - $M \rightarrow (i, j, m_{ij})$, $N \rightarrow (j, k, n_{jk})$
- As large matrices are often sparse (0's) we omit such tuples
- The product MN can be seen as a natural join over attribute j, followed by product computation, followed by grouping and aggregation
  - Start with *(i, j, v)* and *(j, k, w)*
  - Compute *(i, j, k, v, w)*
  - Compute *(i, j, k, v x w)*
  - Compute $(i, k, \Sigma_j\ v \times w)$

Matrix Multiplication (III)

- First stage
  - **Map**: given (i, j, m_{ij}) produce $(j, (\mathtt{M}, i, m_{ij}))$

    given (j, k, n_{jk}) produce $(j, (\mathtt{N}, k, n_{jk}))$
  - **Reduce**: given $(j, [(\mathtt{M}, i, m_{ij}), (\mathtt{N}, k, n_{jk})])$ produce $((i, k), m_{ij} \times n_{jk})$

    otherwise do nothing
- Second stage
  - **Map**: identity
  - **Reduce**: produce the sum of the list of values associated with the key

Matrix Matrix Multiplication (IV)

Algorithm 1: The Map Function

for *each element* m_{ij} *of* M **do**

  produce $(key, value)$ pairs as $((i,k),(M,j,m_{ij}))$, for $k = 1,2,3,..$ up to the number of columns of N

for *each element* n_{jk} *of* N **do**

  produce $(key, value)$ pairs as $((i,k),(N,j,n_{jk}))$, for $i = 1,2,3,...$ up to the number of rows of M

return *Set of (key, value) pairs that each key,* (i,k)*, has a list with values* (M,j,m_{ij}) *and* (N,j,n_{jk}) *for all possible values of* j

Algorithm 2: The Reduce Function

for *each key (i,k)* **do**

  sort values begin with M by j in $list_M$

  sort values begin with N by j in $list_N$

  multiply m_{ij} and n_{jk} for j_{th} value of each list

  sum up $m_{ij} * n_{jk}$

return $(i,k), \sum_{j=1} m_{ij} * n_{jk}$

Matrix Matrix Multiplication (III)

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} a & b \\ c & d \\ e & f \end{bmatrix} \longrightarrow \begin{bmatrix} 1a+2c+3e & 1b+2d+3f \\ 4a+5c+6e & 4b+5d+6f \end{bmatrix}$$

$(i,k),(M,j,m_{ij})$

$m_{11} = 1$
$(1,1),(M,1,1)k = 1$
$(1,2),(M,1,1)k = 2$

$m_{12} = 2$
$(1,1),(M,2,2)k = 1$
$(1,2),(M,2,2)k = 2$
....

$m_{23} = 6$
$(2,1),(M,3,6)k = 1$
$(2,2),(M,3,6)k = 2$

$(i,k),(N,j,n_{jk})$

$n_{11} = a$
$(1,1),(N$
$(2,1),(N$

$n_{21} = c$
$(1,1),(N,2,c)i = 1$
$(2,1),(N,2,c)i = 2$

$n_{31} = e$
$(1,1),(N,3,e)i = 1$
$(2,1),(N,3,e)i = 2$
....

$n_{32} = f$
$(1,2),(N,3,f)i = 1$
$(2,2),(N,3,f)i = 2$

$((i,k),[(M,j,m_{ij}),(M,j,m_{ij}),...,(N,j,n_{jk}),(N,j,n_{jk}),....])$
$(1,1),[(M,1,1),(M,2,2),(M,3,3),(N,1,a,(N,2,c),(N,3,e)]$
$(1,2),[(M,1,1),(M,2,2),(M,3,3),(N,1,b,(N,2,d),(N,3,f)]$
$(2,1),[(M,1,4),(M,2,5),(M,3,6),(N,1,a,(N,2,c),(N,3,e)]$
$(2,2),[(M,1,4),(M,2,5),(M,3,6),(N,1,b,(N,2,d),(N,3,f)]$

$[(M,1,1),(M,2,2),(M,3,3),(N,1,a,(N,2,c),(N,3,e)]$

$list_M = [(M,1,1),(M,2,2),(M,3,3)]$
$list_N = [(N,1,a),(N,2,c),(N,3,e)]$

$P(1,1) = 1a + 2c + 3e$

$P(1,1) = 1a + 2c + 3e$
$P(1,2) = 1b + 2d + 3f$
$P(2,1) = 4a + 5c + 6e$
$P(2,2) = 4b + 5d + 6f$

Graphs

- G = (V,E), where
  - V represents the set of **vertices** (nodes)
  - E represents the set of **edges** (links)
  - Both vertices and edges may contain **additional information**
- Graph algorithms typically involve:
  - **Performing computations at each node**: based on node features, edge features, and local link structure
  - **Propagating computations**: “traversing” the graph
- Key questions:
  - How do you **represent graph data** in MapReduce?
  - How do you **traverse a graph** in MapReduce?

Representing Graphs (I)

- **Adjacency matrix**
  - Represent a graph as an n x n square matrix M
  - $n = |V|$
  - $m_{ij} = 1$ means a link from node i to j
- Advantages:
  - Amenable to mathematical manipulation
  - Iteration over rows and columns corresponds to computations on outlinks and inlinks
- Disadvantages:
  - Lots of zeros for sparse matrices
  - Lots of wasted space

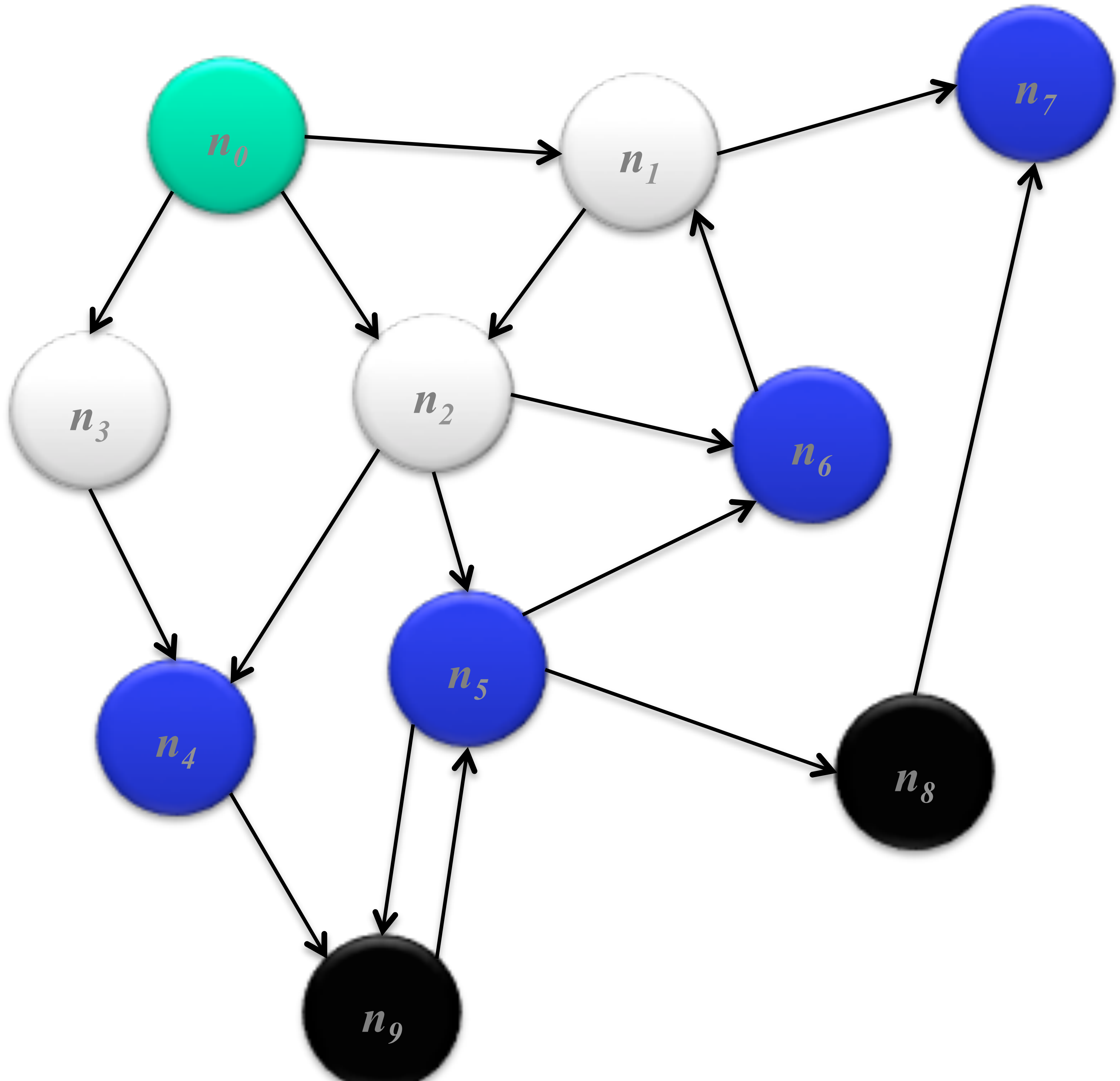
Representing Graphs (II)

- **Adjacency list**
  - Take adjacency matrices...
  - and throw away all the zeros
- Advantages:
  - Much more compact representation
  - Easy to compute over outlinks
- Disadvantages:
  - Much more difficult to compute over inlinks

Shortest Path Algorithm

- Consider simple case of equal edge weights
- Solution to the problem can be defined inductively
- Here's the intuition:
  - Define: b is reachable from a if b is on adjacency list of a
    DISTANCETO(s) = 0
  - For all nodes p reachable from s,
    DISTANCETO(p) = 1
  - For all nodes n reachable from some other set of nodes M,
    DISTANCETO(n) = 1 + min(DISTANCETO(m), m M)

Shortest Path



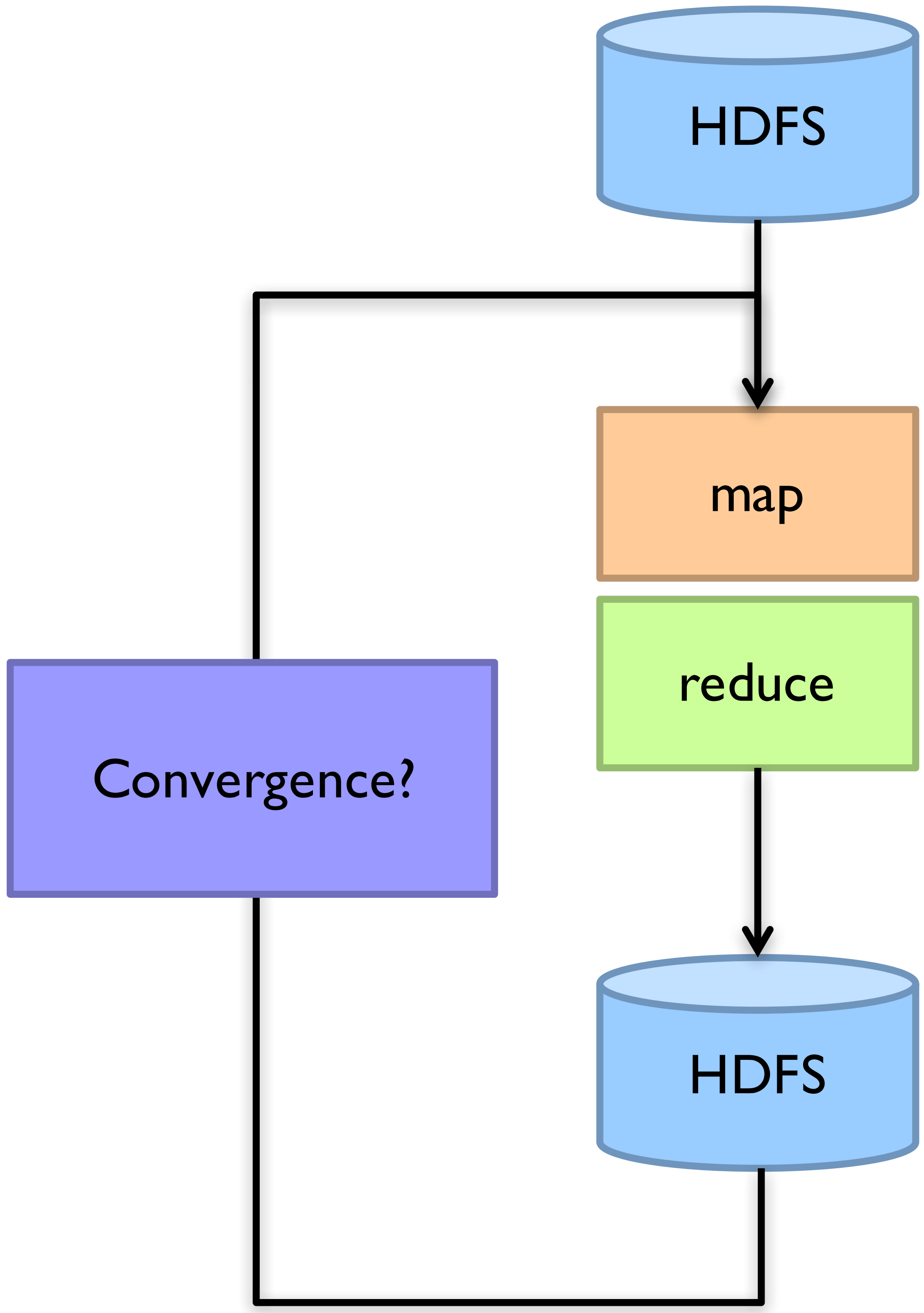
Shortest Path Algorithm

- Data representation:
  - key: node n
  - value: d (distance from start), adjacency list (list of nodes reachable from n)
  - Initialization: for all nodes except for start node, d = infinity
- Mapper:
  - Selects minimum distance path for each reachable node
  - Additional bookkeeping needed to keep track of actual path
  - adjacency list: emit (m, d + 1)
- Sort/Shuffle
  - Groups distances by reachable nodes
- Reducer:
  - Selects minimum distance path for each reachable node
  - Additional bookkeeping needed to keep track of actual path

Details (I)

- Each MapReduce iteration advances the "known frontier" by one hop
  - Subsequent iterations include more and more reachable nodes as frontier expands
  - Multiple iterations are needed to explore entire graph
- Preserving graph structure:
  - Problem: Where did the adjacency list go?
  - Solution: mapper emits (n, adjacency list) as well

Details (II)



Pseudocode

```
class Mapper
    method Map(nid n, node N)
        d ← N.Distance
        Emit(nid n, N)                                  ▷ Pass along graph structure
        for all nodeid m ∈ N.AdjacencyList do
            Emit(nid m, d + 1)                          ▷ Emit distances to reachable nodes
```

```
class Reducer
    method Reduce(nid m, [d_1, d_2, ...])
        d_min ← ∞
        M ← ∅
        for all d ∈ counts [d_1, d_2, ...] do
            if IsNode(d) then
                M ← d                                   ▷ Recover graph structure
            else if d < d_min then                      ▷ Look for shorter distance
                d_min ← d
        M.Distance ← d_min                              ▷ Update shortest distance
        Emit(nid m, node M)
```

Graph Algorithm Recipe

- Graph algorithms typically involve:
  - Performing computations at each node: based on node features, edge features, and local link structure
  - Propagating computations: “traversing” the graph
- Generic recipe:
  - Represent graphs as adjacency lists
  - Perform local computations in mapper
  - Pass along partial results via outlinks, keyed by destination node
  - Perform aggregation in reducer on inlinks to a node
  - Iterate until convergence: controlled by external “driver”
  - Don’t forget to pass the graph structure between iterations