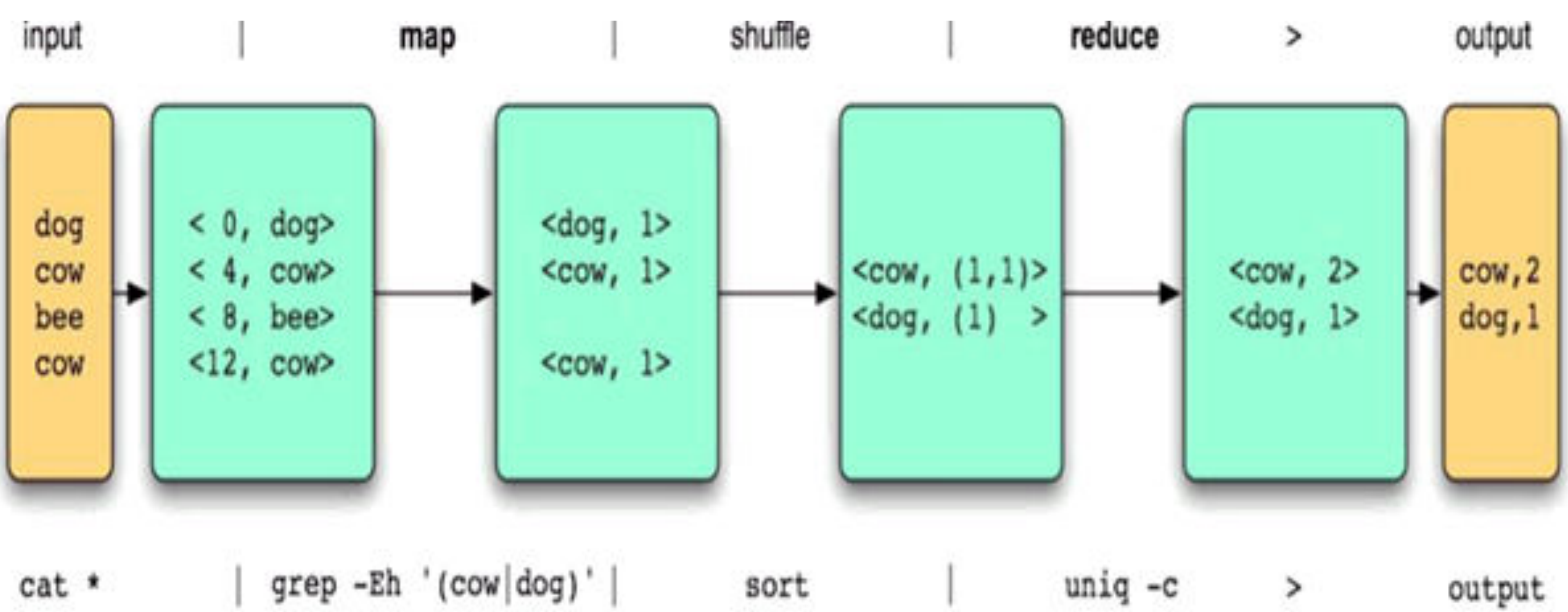
MapReduce Patterns



Intermediate Data

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

Original Word Count

```
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)
```

- How many intermediate keys per mapper?
- How can we improve this?
- Is it a “real” improvement?

Stateless In-Mapper Combining

```
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})
```

- Custom local aggregator
- Coding overhead
- Is it a “real” improvement?

Stateful In-Mapper Combining

```
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})
```

- Custom local aggregator
- Coding overhead
- Is it a “real” improvement?

In-Mapper Combining Analysis

- **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 matrix of size N x N
- **Example**: word co-occurrence matrix
  - Given a document collection, emit the bigram frequencies

“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)
```

- We must use custom key type
- Intermediate overhead? Bottlenecks?
- Can we use the reducer as a combiner?
- Keys space?

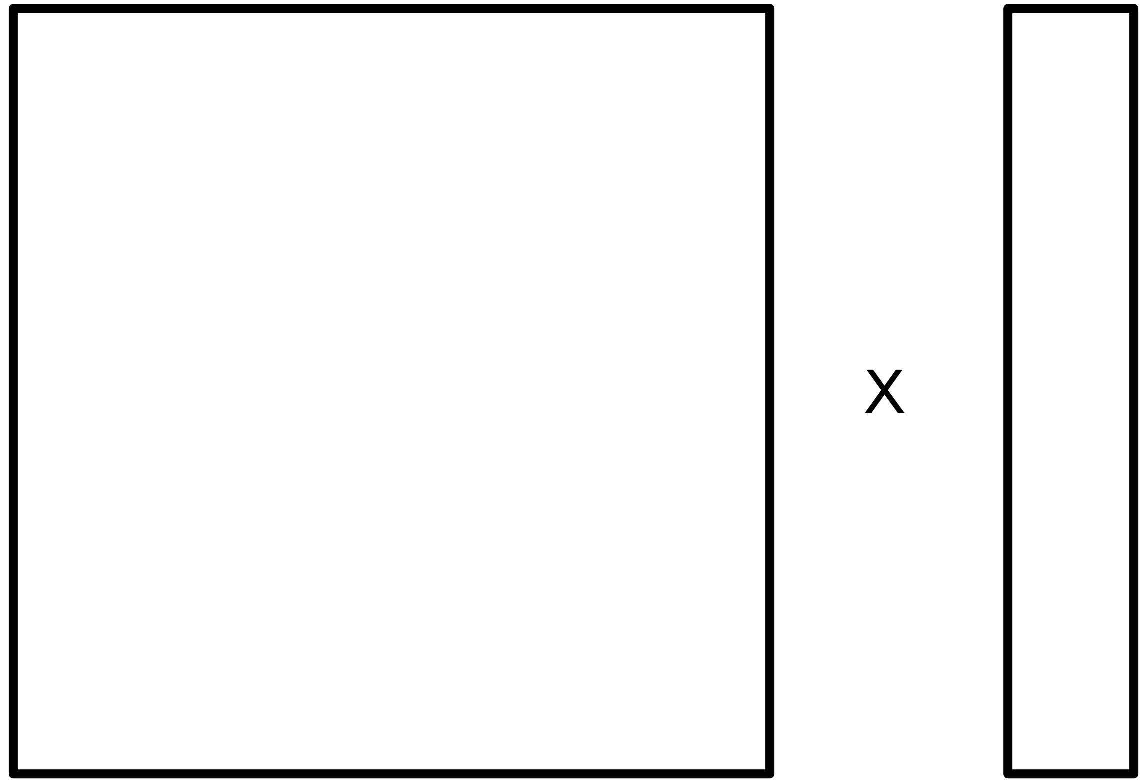
“Stripes”

```
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)
```

- We must use custom key and value types
- Intermediate overhead? Bottlenecks?
- Can we use the reducer as a combiner?
- Keys space?

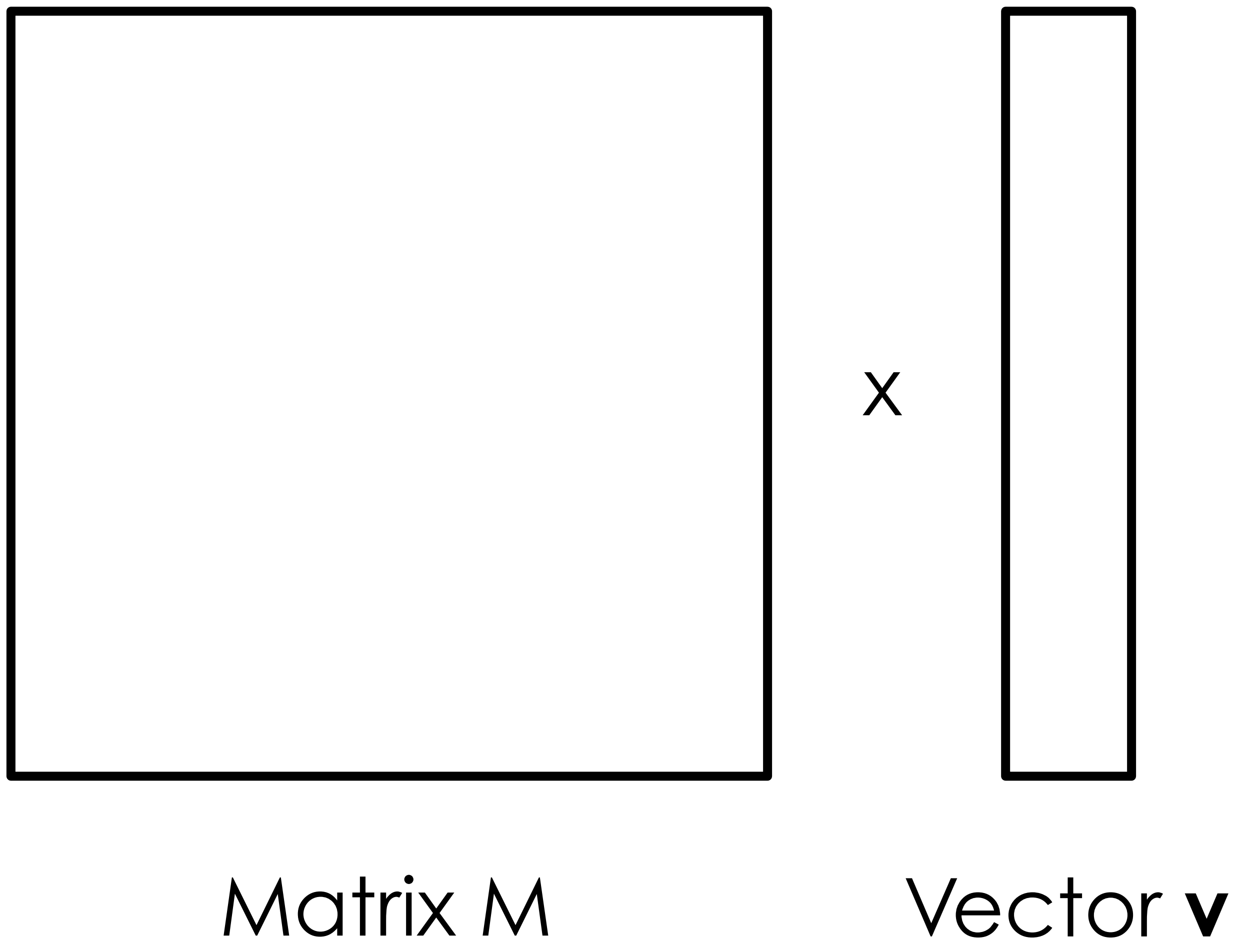
Matrix Vector Multiplication



Matrix M   Vector **v**

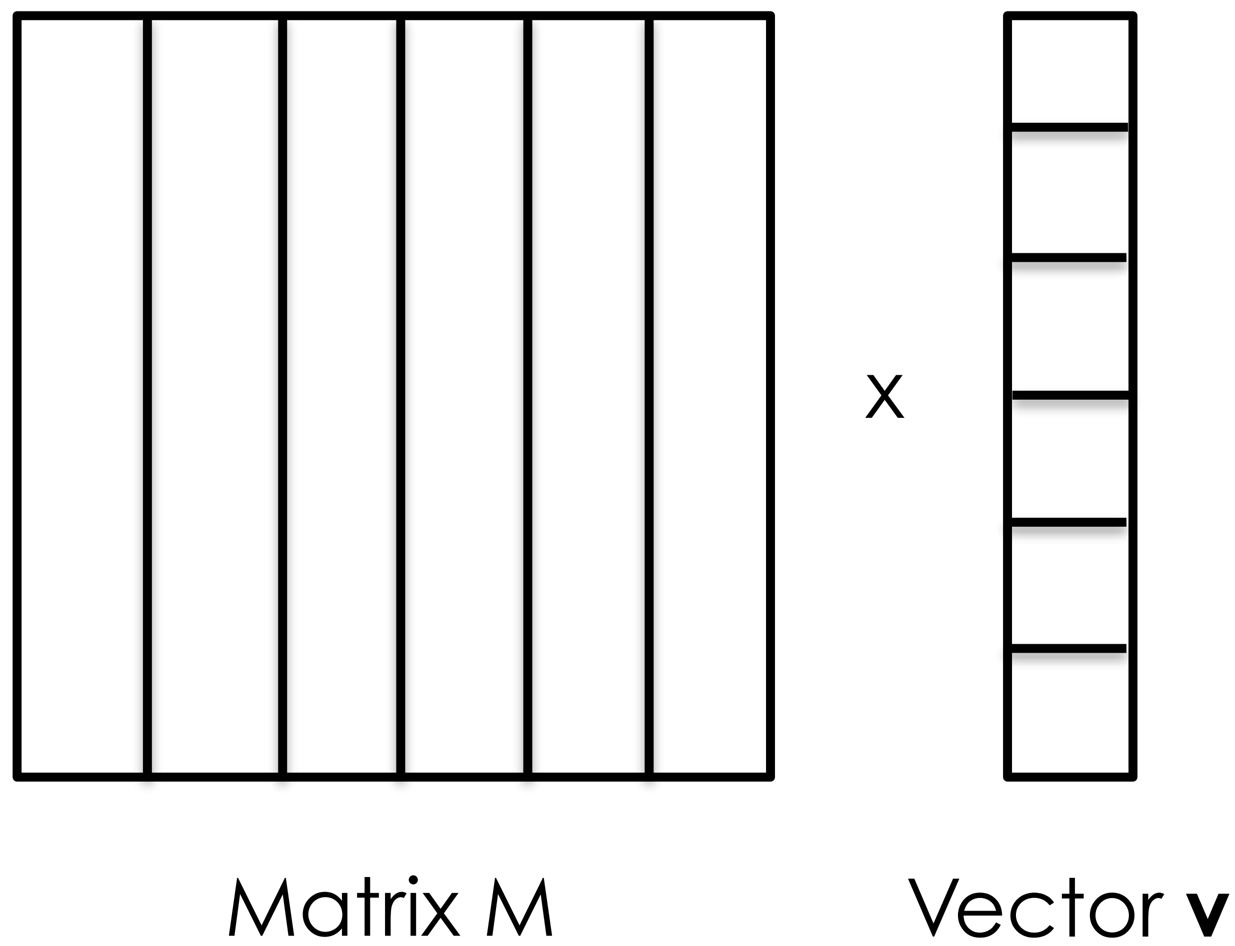
- The matrix does not fit in memory
  - 1 case: vector **v** fits in memory
  - 2 case: vector **v** does not fit in memory

Vector fits in memory



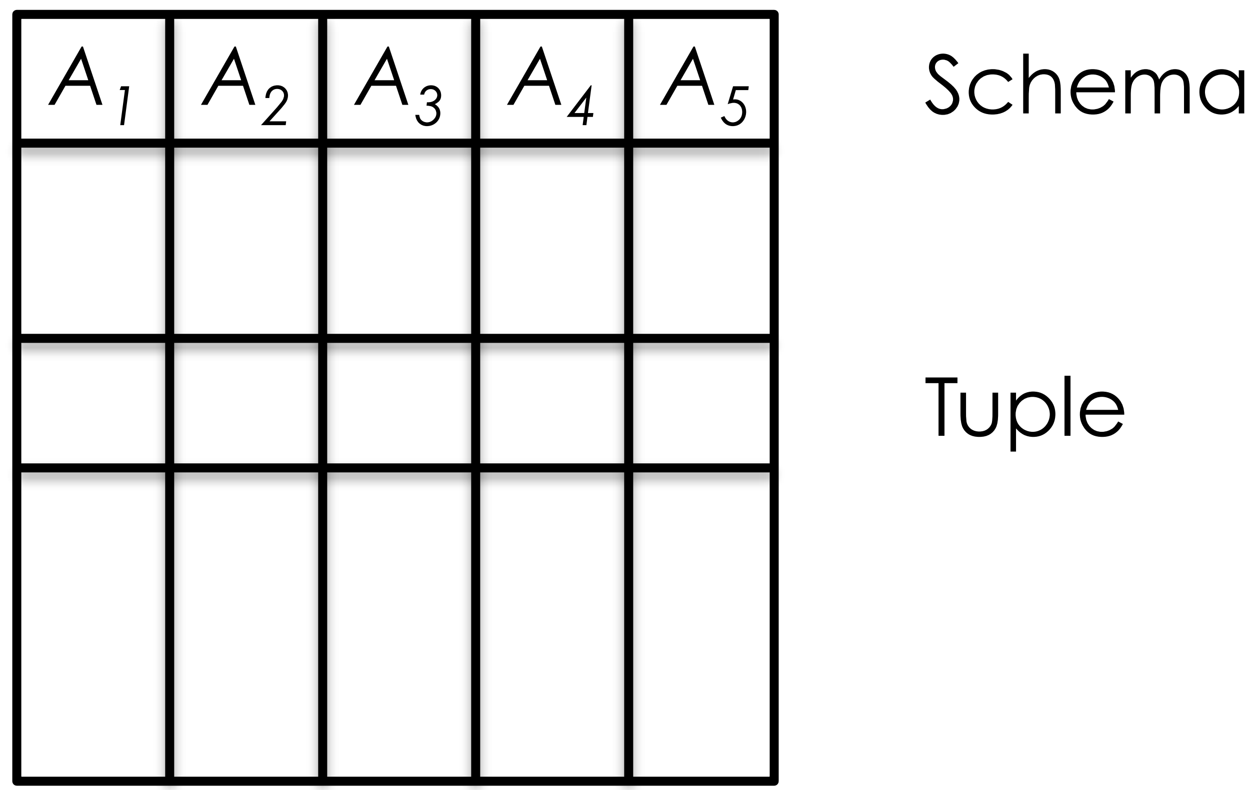
- Map
  - input = (*, chunk of matrix M)
  - vector v read from memory
  - output = (i, mijvj)
- Reduce
  - sum up all the values for the given key i

Vector does not in memory



- 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

Relational Databases



Relation *R*

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

Selection and Projection

- MAP: Each tuple t, if condition C is satisfied, is outputted as a (t, t) pair
- REDUCE: Identity

- MAP: For each tuple t, create a new tuple t’ containing only projected attributes. Outpu is (t’, t’) pair
- REDUCE: Coalesce input (t’, [t’ t’ t’ t’]) in output (t’,t’)

Union, Intersection, Difference

- MAP: Each tuple t is outputted as a (t, t) pair
- REDUCE: For each key t, there will be 1 or 2 values t. Coalesce them in a single output (t,t)

- MAP: Each tuple t is outputted as a (t, t) pair
- REDUCE: For each key t, there will be 1 or 2 values t. If 2 values, coalesce them in a single output (t,t), else ignore

- MAP: For each tuple t in R, produce (t, “R”). For each tuple t in S, produce (t, “S”).
- REDUCE: For each key t, there will be 1 or 2 values t. If 1 value, and being ”R”, output (t,t), else ignore

Natural Join

- We have two relations R(A,B) and S(B,C). Find tuples that agree on B components

- MAP: For each tuple (a,b) from R, produce (b,(“R”,a)). For each tuple (b,c) from S, produce (b,(“S”,c)).
- REDUCE: For each key b, there will a list of values of the form (“R”,a) or (“S”,c). Construct all pairs and output them with b.

Grouping and Aggregation

- We have the relation R(A,B,C) and we **group-by** A and **aggregate** on B.

- 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 associate with group a, producing x. Output (a,x).

Graph Algorithms

- 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

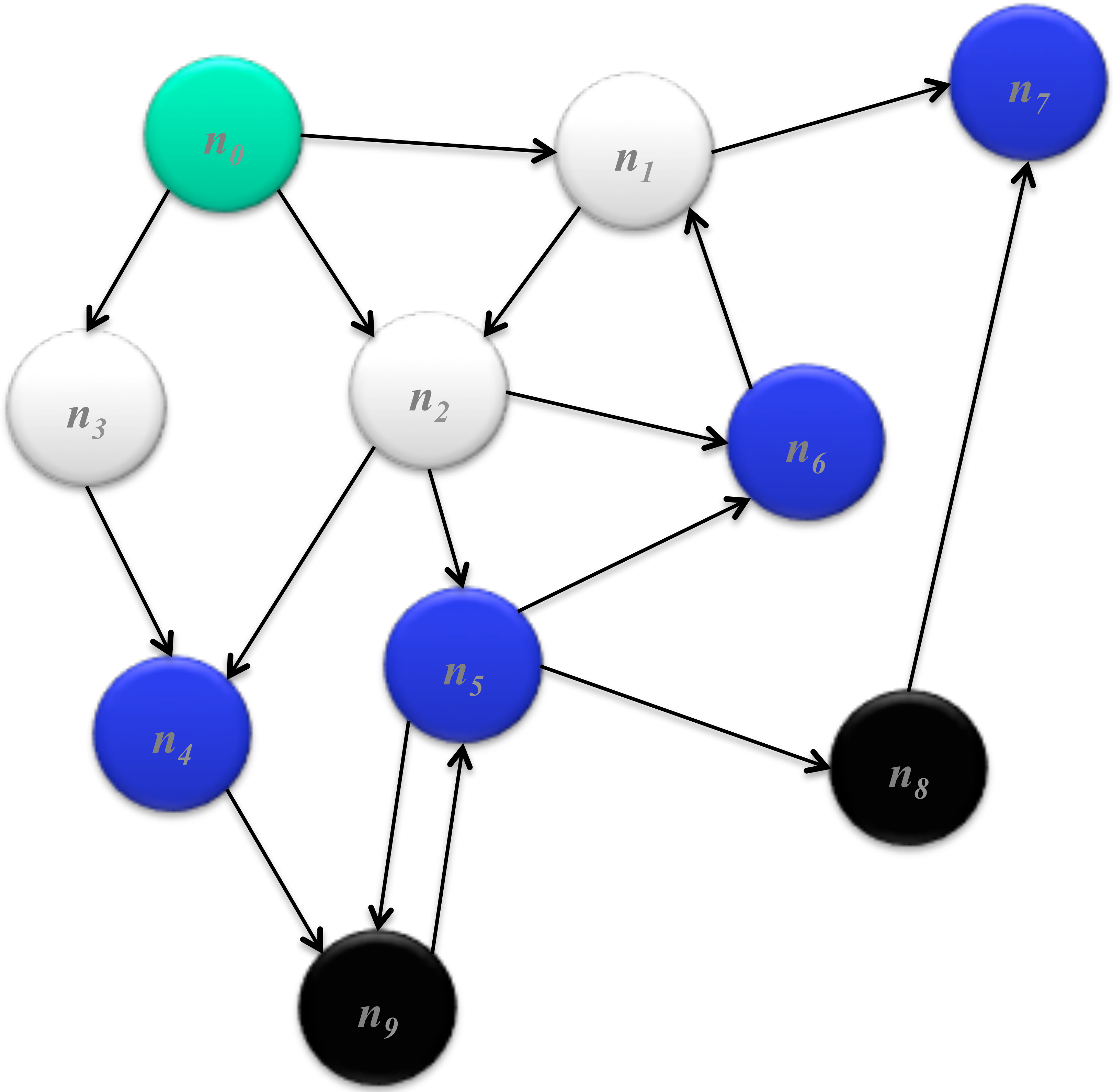
- Consider simple case of equal edge weights
- Solution to the problem can be defined inductively
- Here’s the intuition:
    - Define: b is reachable from a if b is on adjacency list of a

      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



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:
  - m 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

- 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

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, [d1, d2, ...])
        dmin ← ∞
        M ← ∅
        for all d ∈ counts [d1, d2, ...] do
            if IsNode(d) then
                M ← d                                   ▷ Recover graph structure
            else if d < dmin then                       ▷ Look for shorter distance
                dmin ← d
        M.Distance ← dmin                               ▷ Update shortest distance
        Emit(nid m, node M)
```

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