Map-Reduce (Part II)

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Thanks for source slides and material to: J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets (http://www.mmds.org)

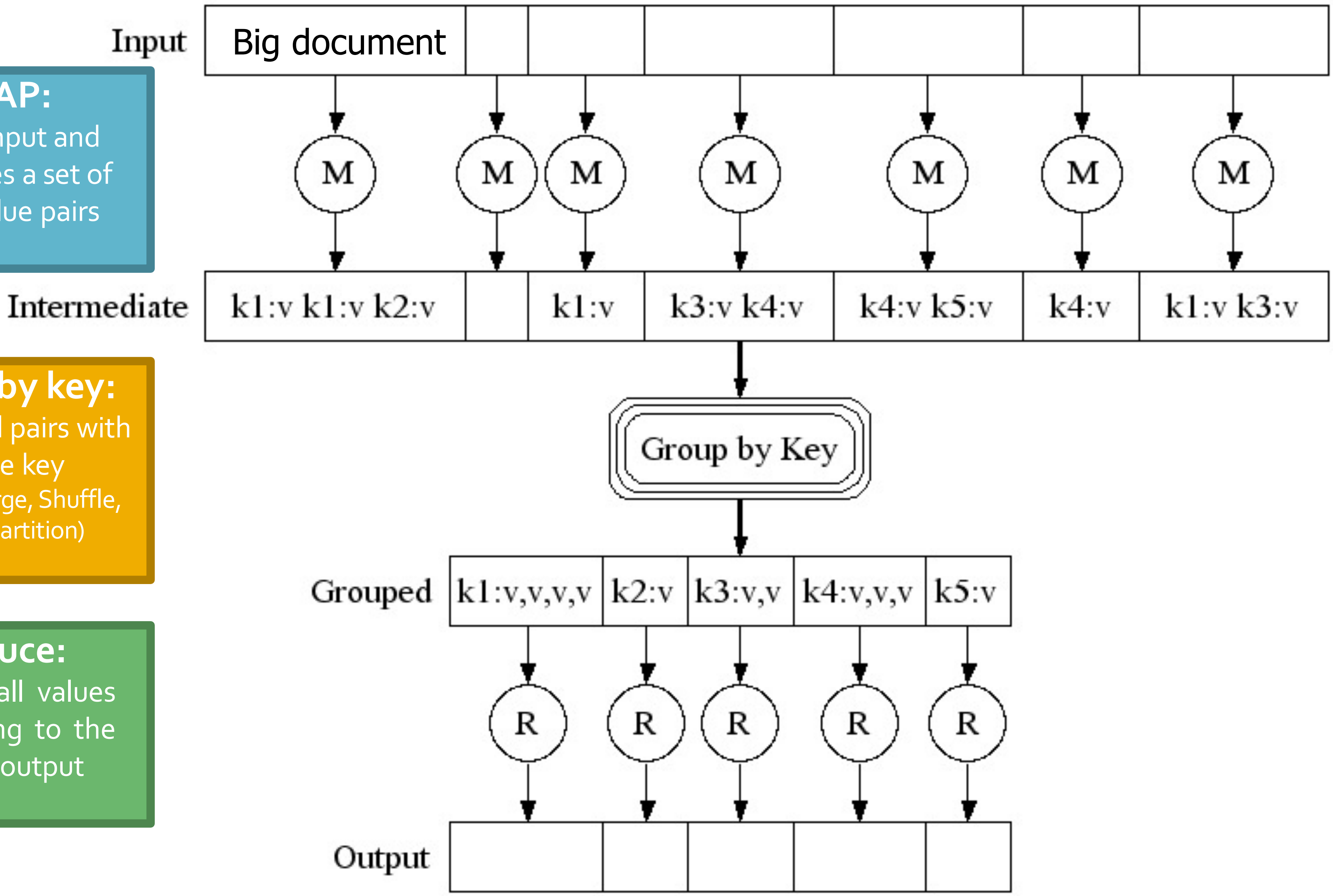
Also slides from Yijun Lin, Ann Chervenak, and Wensheng Wu

Map-Reduce: A diagram

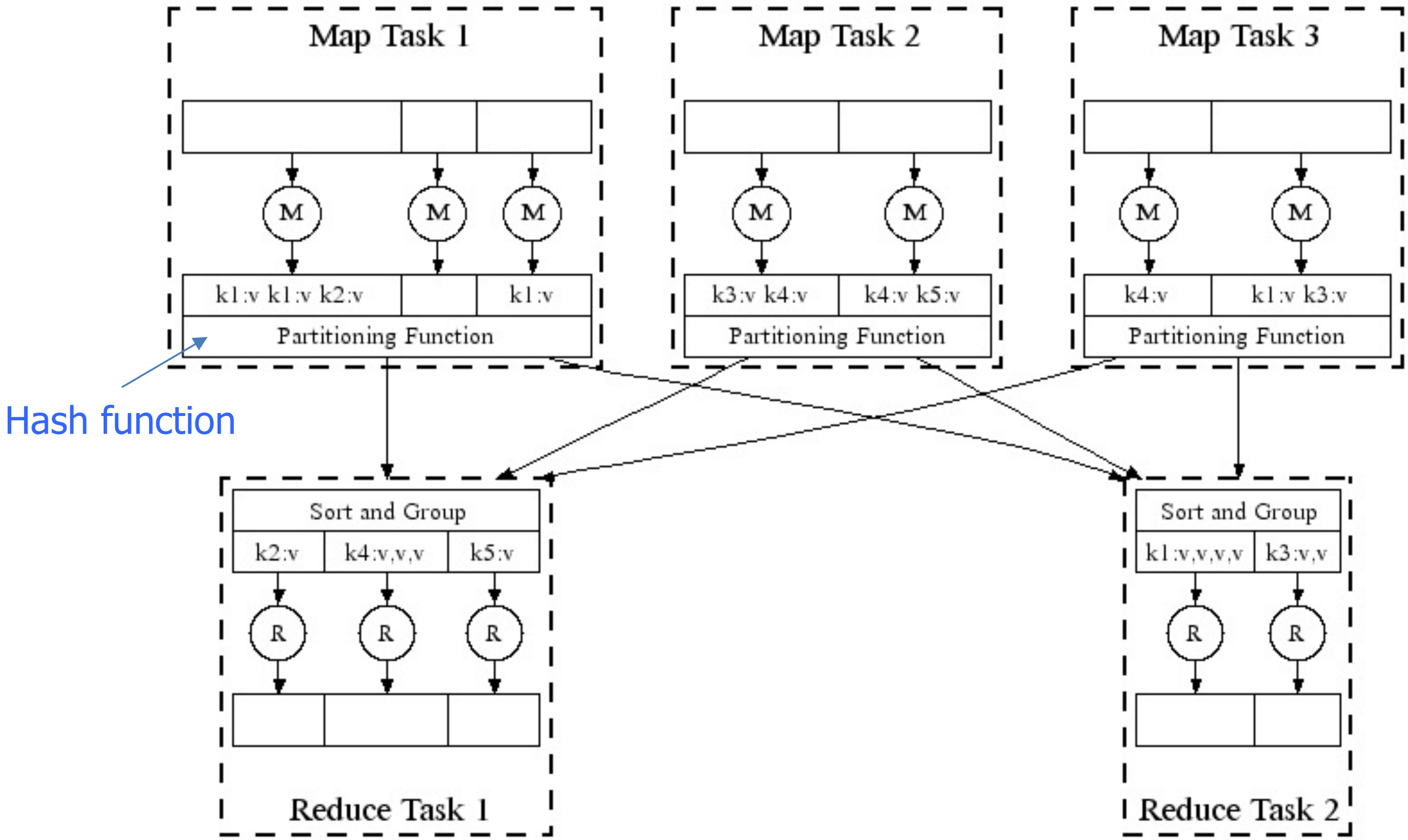
MAP:
Read input and produces a set of key-value pairs

Group by key:
Collect all pairs with same key
(Hash merge, Shuffle, Sort, Partition)

Reduce:
Collect all values belonging to the key and output



Map-Reduce: In Parallel

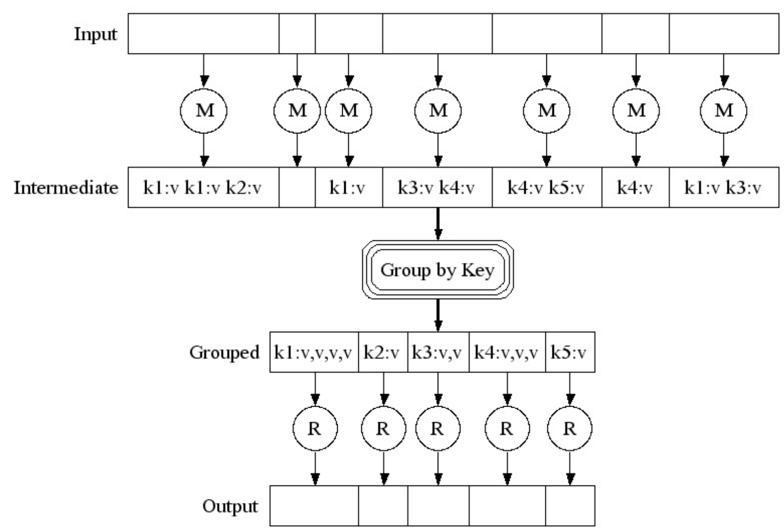


All phases are distributed with many tasks doing the work

Map-Reduce: Environment

MapReduce environment takes care of:

- **Partitioning** the input data
- **Scheduling** the program's execution across a set of nodes
- Performing the **group by key** step
- Handling machine **failures**
- Managing required inter-machine **communication**



Data Flow

- Input and final output are stored **on a distributed file system (DFS)**
  - Scheduler tries to schedule map tasks “close” to physical storage location of input data
- Intermediate results are stored **on local file system of Map workers**

  e.g., output of the map step
- Output is often input to another Map-Reduce task

Coordination: Primary

- Primary node takes care of coordination:
  - **Task status:** idle, in-progress, completed
  - **Idle tasks** get scheduled as workers become available
  - When a map task completes, it sends the **primary** the **location** and **sizes** of its R intermediate files, one for each reducer (R = number of reducers)
  - **Primary pushes this info to reducers**
- Primary pings workers periodically to detect failures

Dealing with Failures

- **Map worker failure**
  - Map tasks **completed or in-process** at worker are reset to idle
  - Idle tasks eventually rescheduled on other worker(s)

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  - Idle Reduce tasks restarted on other worker(s)

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- **Reduce worker failure**
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- **Primary failure**
  - Map-reduce task is aborted and client is notified

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- *M* map tasks, *R* reduce tasks

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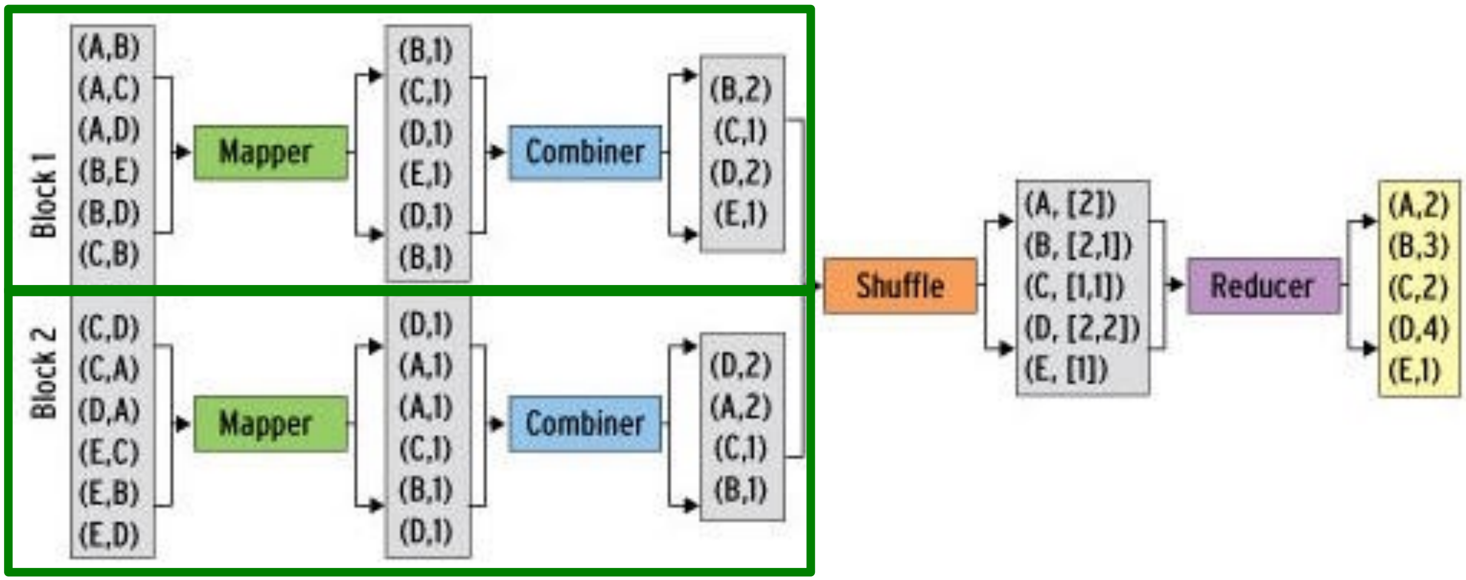
- **Rule of a thumb:**
  - Make *M* **much larger** than the number of nodes in the cluster
  - One DFS chunk per map task is common
  - Improves dynamic load balancing and speeds up recovery from worker failures

How many map and reduce jobs?

- ***M*** **map tasks,** ***R*** **reduce tasks**
- **Rule of a thumb:**
  - Make *M* **much larger** than the number of nodes in the cluster
  - One DFS chunk per map task is common
  - Improves dynamic load balancing and speeds up recovery from worker failures
- **Usually** ***R*** **is smaller than** ***M***
  - Output is spread across *R* files
  - Google example: Often use 200,000 map tasks, 5000 reduce tasks on 2000 machines

Refinement: Combiners

- **Combiner** combines the values of all keys of a single mapper (single node)



Much less data needs to be copied and shuffled!

Works if reduce function is commutative and associative

Refinement: Partition Function

- **Control how keys get partitioned**
  - Reduce needs to ensure that records with the same intermediate key end up at the same worker

- System uses a default partition function:
  - **hash(key) mod *R***

- Sometimes useful to override the hash function:
  - E.g., **hash(hostname(URL)) mod *R*** ensures URLs from a host to end up in the same output file

Implementations

- **Google's MapReduce**
  - Not available outside Google
- **Hadoop**
  - Open-source implementation in Java
  - Uses HDFS for stable storage
  - Download: http://hadoop.apache.org/releases.html
- **Spark**

Example: Relational Join

Employee

Name	SSN
Sue	999999999
Tony	777777777

Assigned Departments

EmpSSN	DepName
999999999	Accounts
777777777	Sales
777777777	Marketing

Emplyee ⋈ Assigned Departments

Name	SSN	EmpSSN	DepName
Sue	999999999	999999999	Accounts
Tony	777777777	777777777	Sales
Tony	777777777	777777777	Marketing

Example: Relational Join

- Map Task: Emit (key, value) pair
  - **Key is key used for join**
  - **Value is a tuple** with all fields from table (including the table name)

Employee

Name	SSN
Sue	999999999
Tony	777777777

Assigned Departments

EmpSSN	DepName
999999999	Accounts
777777777	Sales
777777777	Marketing

key=999999999, value=(Employee, Sue, 999999999)
key=777777777, value=(Employee, Tony, 777777777)
key=999999999, value=(Department, 999999999, Accounts)
key=777777777, value=(Department, 777777777, Sales)
key=777777777, value=(Department, 777777777, Marketing)

Example: Relational Join

- **Group by Key:** groups together all values (tuples) associated with each key
- **Reduce task:** emit joined values (without table names)

key=999999999, values=[(Employee, Sue, 999999999),
(Department, 999999999, Accounts)]

Sue, 999999999, 999999999, Accounts

key=777777777, values=[(Employee, Tony, 777777777),
(Department, 777777777, Sales),
(Department, 777777777, Marketing)]

Tony, 777777777, 777777777, Sales
Tony, 777777777, 777777777, Marketing

Example: Distributed Sort

- Goal: Sort a very large list of (firstName, lastName) pairs by lastName followed by firstName

- Map task:

- Reduce task:

Example: Distributed Sort

- Map task
  - Emit (lastName, firstName)

- Group by keys:
  - Group together entries with same last name
  - **Divide into non-overlapping alphabetical ranges** (sorting)
  - Keys are sorted in alphabetical order

- Reduce task
  - Processes one key at a time
  - For each (lastName, list(firstName)), emit (lastName, firstName) in alphabetical order **(sorting)**
  - Merge output from all Reduce tasks (e.g., write)

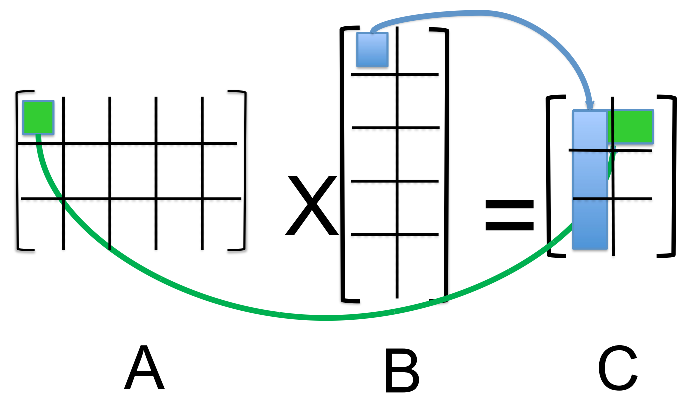
Example: Matrix Multiplication

- Assume two matrices A and B, and AB = C
- A_{ij} is the element in **row *i*** and **column *j*** of matrix A
  - Similarly for B and C
- **$C_{ik} = \sum_j A_{ij} \times B_{jk}$**
  - C_{ik} depends on the i^{th} row of A, that is A_{ij} for all j, and the k^{th} column of B, that is B_{jk} for all j

$$\underset{A}{\begin{bmatrix} 1 & 3 & 2 \\ 4 & 0 & 1 \end{bmatrix}} \underset{B}{\begin{bmatrix} 1 & 3 \\ 0 & 1 \\ 5 & 2 \end{bmatrix}} = \underset{C}{\begin{bmatrix} 11 & 10 \\ 9 & 14 \end{bmatrix}}$$

e.g., $C_{11} = 1 \times 1 + 3 \times 0 + 2 \times 5 = 11$

Matrix Multiplication Map-Reduce (One phase)



C = A X B

A has dimensions L x M

B has dimensions M x N

C has dimensions L x N

Matrix Multiplication: C[i, k] = SUM_j (A[i, j] x B[j, k])

Map task:

Reduce task:

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Map task:

for each element (i,j) of A, emit **((i,k), A[i,j])** for **k in 1..N**

e.g., For A[1, 1] emit ((1, 1), 1), ((1, 2), 1)

For A[1, 2] emit ((1, 1), 3), ((1, 2), 3)

For A[2, 1] emit ((2, 1), 4), ((2, 2), 4)

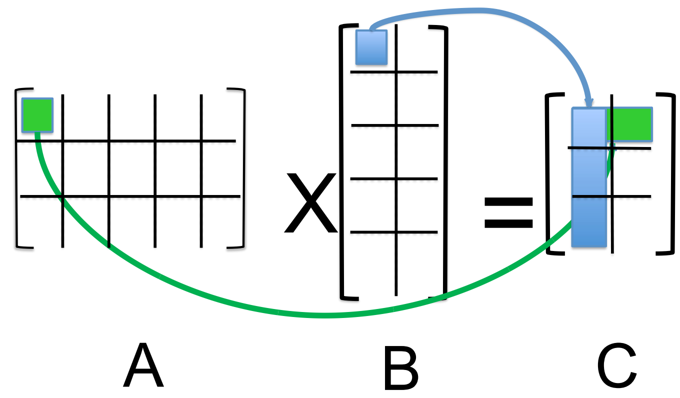
for each element (j,k) of B, emit **((i,k), B[j,k])** for **i in 1..L**

e.g., For B[1, 1] emit ((1, 1), 1), ((2, 1), 1)

For B[2, 1] emit ((1, 1), 0), ((2, 1), 0)

For B[1, 2] emit ((1, 2), 3), ((2, 2), 3)

Matrix Multiplication
Map-Reduce (One phase)



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Map task:

for each element (i,j) of A, emit **((i,k), A[i,j])** for **k in 1..N**

Better: emit ((i,k), ('A', i, j, A[i,j])) for k in 1..N

Or just emit ((i,k), ('A', j, A[i,j])) for k in 1..N

for each element (j,k) of B, emit **((i,k), B[j,k])** for **i in 1..L**

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Matrix Multiplication
Map-Reduce (One phase)

C = A X B

A has dimensions L x M

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Matrix Multiplication: C[i, k] = SUM$_j$ (A[i, j] x B[j, k])

$$\underset{A}{\begin{bmatrix} 1 & 3 & 2 \\ 4 & 0 & 1 \end{bmatrix}} \underset{B}{\begin{bmatrix} 1 & 3 \\ 0 & 1 \\ 5 & 2 \end{bmatrix}} = \underset{C}{\begin{bmatrix} 11 & 10 \\ 9 & 14 \end{bmatrix}}$$

Map task:

for each element (i,j) of A, emit **((i,k), (‘A’, i, j, A[i,j]))** for k in 1..N

e.g., For A[1, 1] emit ((1, 1), (‘A’, 1, 1, 1)), ((1, 2), (‘A’, 1, 1, 1))

For A[1, 2] emit ((1, 1), (‘A’, 1, 2, 3)), ((1, 2), (‘A’, 1, 2, 3))

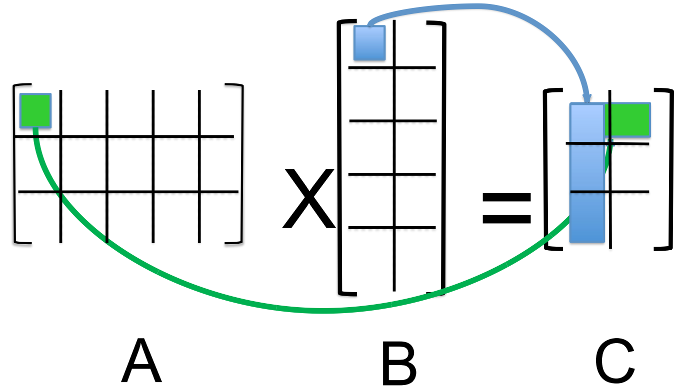
For A[2, 1] emit ((2, 1), (‘A’, 2, 1, 4)), ((2, 2), (‘A’, 2, 1, 4))

for each element (j,k) of B, emit **((i,k), (‘B’, j, k, B[j,k]))** for i in 1..L

e.g., For B[1, 1] emit ((1, 1), (‘B’, 1, 1, 1)), ((2, 1), (‘B’, 1, 1, 1))

For B[2, 1] emit ((1, 1), (‘B’, 2, 1, 0)), ((2, 1), (‘B’, 2, 1, 0))

For B[1, 2] emit ((1, 2), (‘B’, 1, 2, 3)), ((2, 2), (‘B’, 1, 2, 3))



C[i,k] = Sum$_j$ (A[i,j] x **B[j,k]), C is L** x **N**

In the map phase:

- for each element (i,j) of A, emit **((i,k), ('A', i, j, A[i,j]))** for k in 1..N
- for each element (j,k) of B, emit **((i,k), ('B', j, k, B[j,k]))** for i in 1..L

e.g.,

C[1,1] = A[1,1] * B[1,1] + **A[1,2]** * B[2,1] + A[1,3] * **B[3,1]** + A[1,4] * B[4,1] + A[1,5] * B[5,1]

C[1,2] = A[1,1] * B[1,2] + **A[1,2]** * B[2,2] + A[1,3] * B[3,2] + A[1,4] * B[4,2] + A[1,5] * B[5,2]

C[2,1] = A[2,1] * B[1,1] + A[2,2] * B[2,1] + A[2,3] * **B[3,1]** + A[2,4] * B[4,1] + A[2,5] * B[5,1]

C[3,1] = A[3,1] * B[1,1] + A[3,2] * B[2,1] + A[3,3] * **B[3,1]** + A[3,4] * B[4,1] + A[3,5] * B[5,1]

Map phase: For **A[1,2]**, emit ((1, k), ('A', 1, 2, A[1,2])) for k in 1..2

emit ((1,1)('A', 1, 2, A[1,2])) ((1,2)('A', 1, 2, A[1,2]))

For **B[3,1]**, emit ((i, 1), ('B', 3, 1, B[3,1])) for i in 1..3

emit ((1,1), ('B', 3, 1,B[3,1])), ((2,1)('B', 3, 1,B[3,1])), ((3,1)('B', 3, 1,B[3,1]))

Matrix Multiplication
Map-Reduce (Two phase)

Idea: 1, Multiply the appropriate values in 1st MapReduce phase
2, Add up in 2nd MapReduce phase

Try this tonight!

General Characteristic of Good Problem for Map-Reduce

Data set is truly "big"

- Terabytes, not tens of gigabytes
- Hadoop/MapReduce designed for terabyte/petabyte scale computation
- Most real-world problems process less than 100 GB of input
  - Microsoft, Yahoo: median job under 14 GB
  - Facebook: 90% of jobs under 100 GB

Source: "To Hadoop or Not to Hadoop" by Anand Krishnaswamy 8/13/2013

General Characteristic of Good Problem for Map-Reduce

Don’t need fast response time

- When submitting jobs, Hadoop latency can be 1 min
- Not well-suited for problems that require faster response time
  - online purchases, transaction processing
- A good pre-computation engine
  - E.g., pre-compute related items for every item in inventory

Source: “To Hadoop or Not to Hadoop” by Anand Krishnaswamy 8/13/2013

General Characteristic of Good Problem for Map-Reduce

- Good for applications that work in **batch mode**
- Runs over entire data set
  - Takes time to initiate, run;
  - Shuffle step can be time-consuming;
- Does not provide good support for random access to datasets
  - Extensions: Hive, Dremel, Shark, Amplab

Source: "To Hadoop or Not to Hadoop" by Anand Krishnaswamy 8/13/2013

General Characteristic of Good Problem for Map-Reduce

- Best suited for data that can be expressed as key-value pairs without losing context, dependencies
  - Graph data is hard to process using Map-Reduce
    - Implicit relationships: edges, sub-trees, child/parent relationships, weights, etc.
  - Graph algorithms need information about the entire graph for each iteration
    - Hard to break into independent chunks for Map tasks
  - Alternatives: Google's Pregel, Apache Giraph

Source: "To Hadoop or Not to Hadoop" by Anand Krishnaswamy 8/13/2013

General Characteristic of Good Problem for Map-Reduce

Other problems/data NOT suited for MapReduce

- Tasks that need results of intermediate steps to compute results of current step
  - Interdependencies among tasks
  - Map tasks must be independent
- Some machine learning algorithms
  - Gradient-based learning

Source: “To Hadoop or Not to Hadoop” by Anand Krishnaswamy 8/13/2013

General Characteristic of Good Problem for Map-Reduce

Summary: Good candidates for Map-Reduce:

- Jobs that process huge quantities of data and either summarize or transform the content
- Collected data has elements that can easily be captured with an identifier (key) and corresponding value

Source: “To Hadoop or Not to Hadoop” by Anand Krishnaswamy 8/13/2013