Parallel Data Processing†

Introduction to Databases

CompSci 316 Fall 2017

DUKE
COMPUTER SCIENCE

†Most contents are drawn and adapted from slides by Madga Balazinska at U. Washington

Announcements (Thu., Dec. 5)

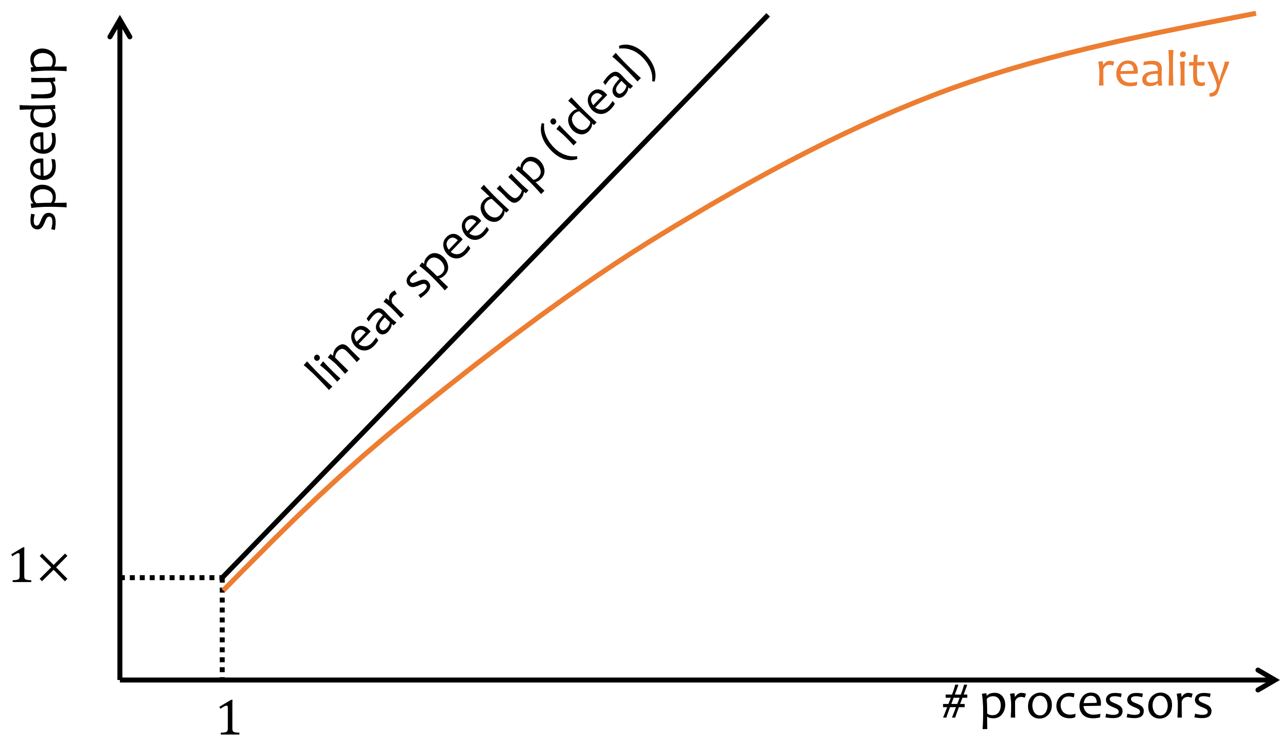
- Homework #4 sample solution to be posted
- Final exam Sat. Dec. 16 2-5pm
  - **This room**
  - Open-book, open-notes
  - Comprehensive, but with strong emphasis on the second half of the course
  - Sample final + solution posted on Sakai
- Project demos starting
  - Check your email for schedule
  - Submit report/code before demo
  - Today: ***LegiToken***, by Josh, Alex, Austin, Oscar, Stuart, and Trenton

Parallel processing

- Improve performance by executing multiple operations in parallel
- Cheaper to scale than relying on a single increasingly more powerful processor
- Performance metrics
  - Speedup, in terms of completion time
  - Scaleup, in terms of time per unit problem size
  - Cost: completion time × # processors × (cost per processor per unit time)

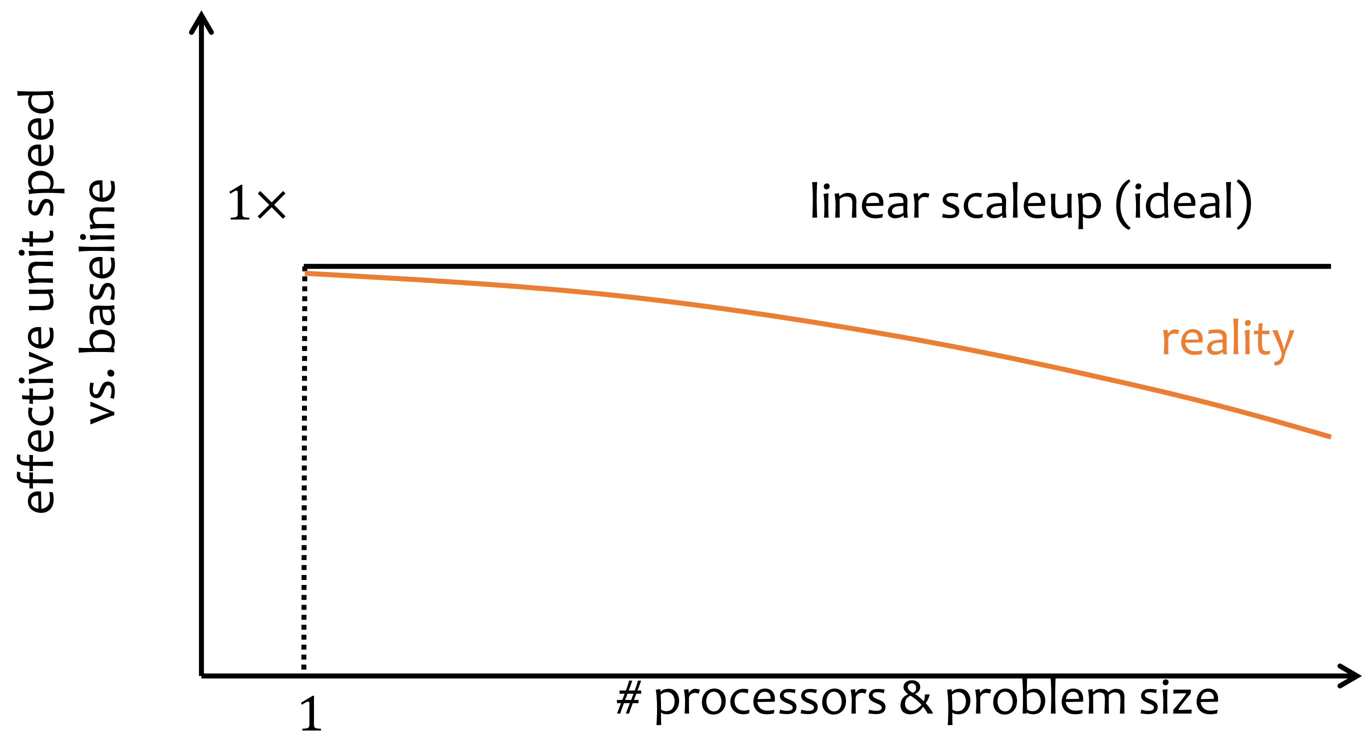
Speedup

- Increase # processors → how much faster can we solve the same problem?
  - Overall problem size is fixed



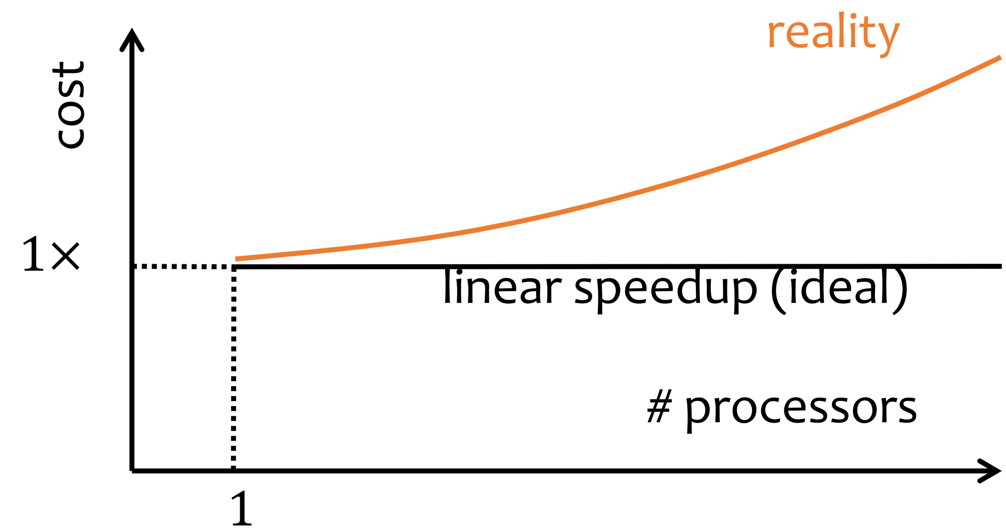
Scaleup

- Increase # processors and problem size proportionally → can we solve bigger problems in the same time?
  - Per-processor problem size is fixed

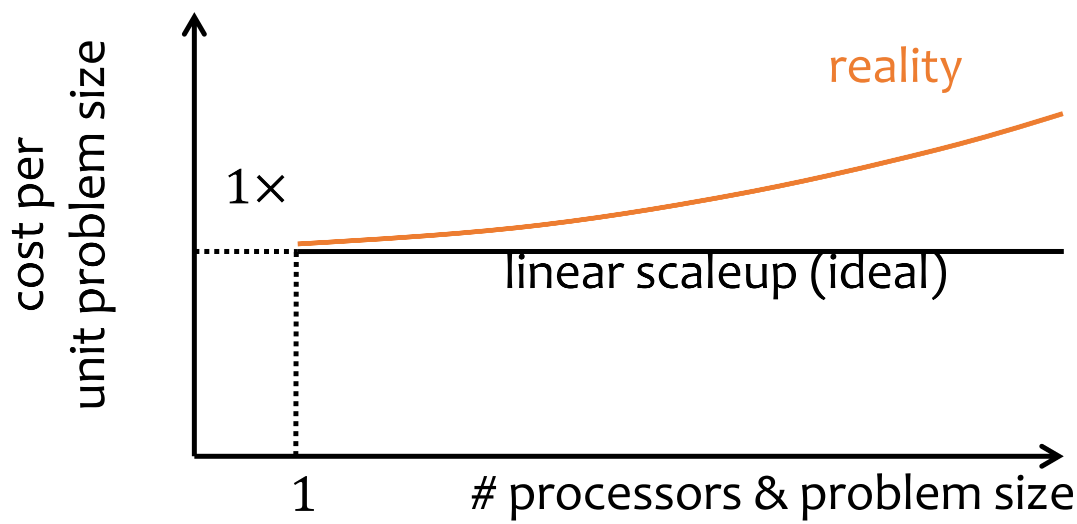


Cost

- Fix problem size



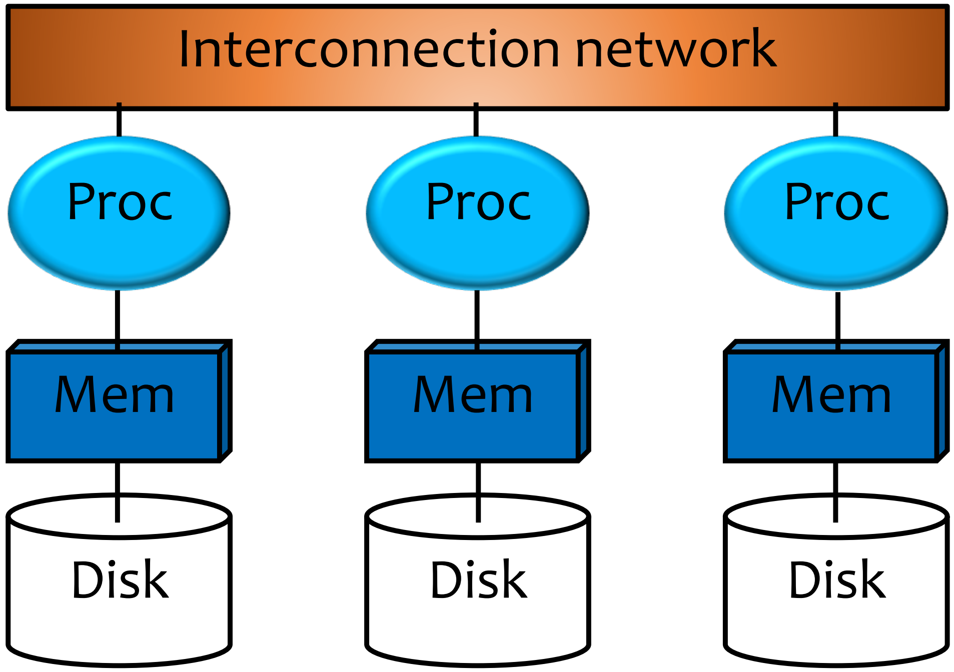
- Increase problem size proportionally with # processors



Why linear speedup/scaleup is hard

- Startup
  - Overhead of starting useful work on many processors
- Communication
  - Cost of exchanging data/information among processors
- Interference
  - Contention for resources among processors
- Skew
  - Slowest processor becomes the bottleneck

Shared-nothing architecture



- Most scalable (vs. shared-memory and shared-disk)
  - Minimizes interference by minimizing resource sharing
  - Can use commodity hardware
- Also most difficult to program

Parallel query evaluation opportunities

- Inter-query parallelism
  - Each query can run on a different processor
- Inter-operator parallelism
  - A query runs on multiple processors
  - Each operator can run on a different processor
- Intra-operator parallelism
  - An operator can run on multiple processors, each working on a different "split" of data/operation

A brief tour of two systems

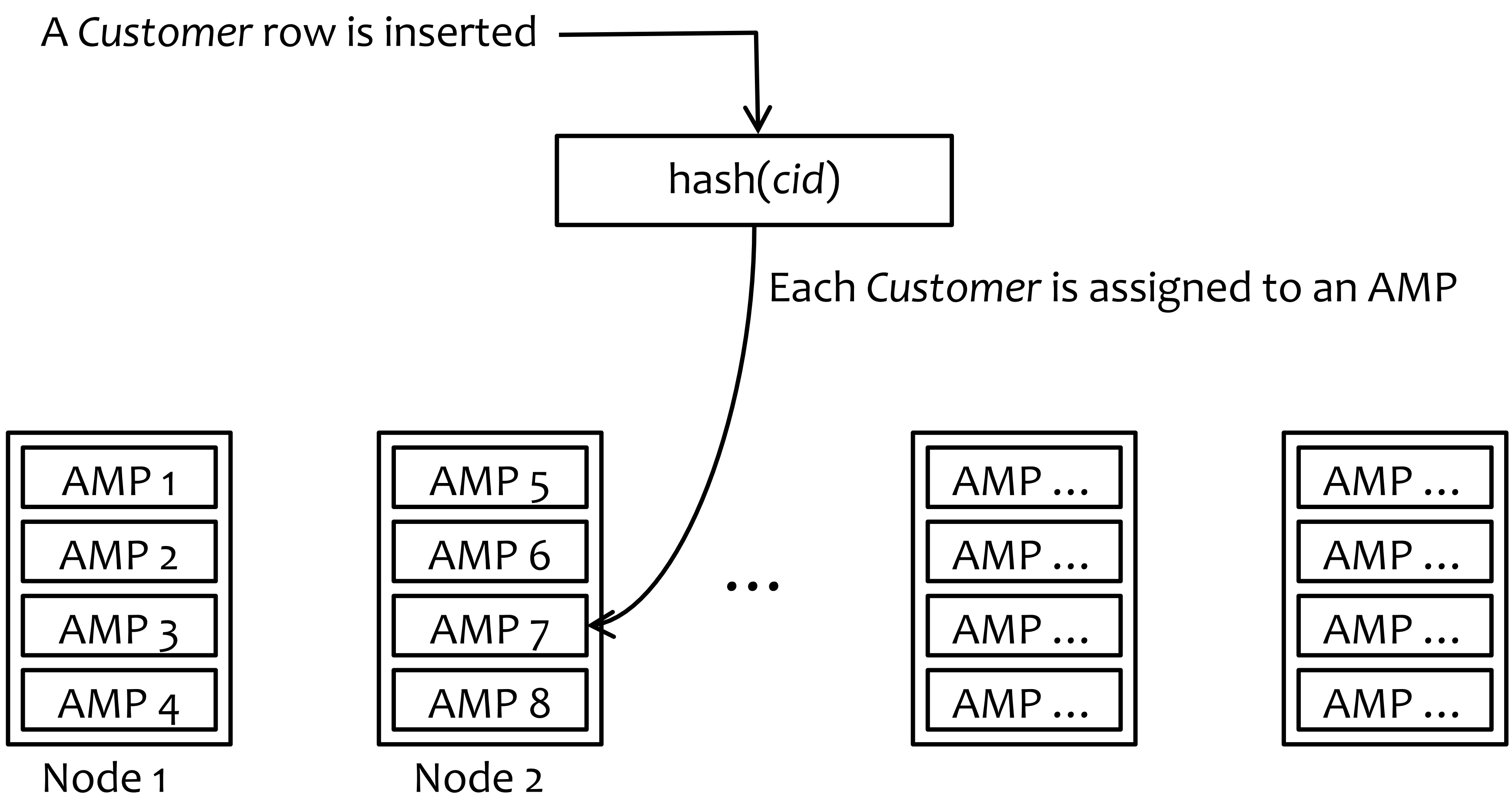
- Parallel DBMS (e.g.,. Teradata)
  - Provides the same abstractions (e.g., relational data model, SQL, transactions) as a regular DBMS
  - Parallelization handled behind the scene
- MapReduce (e.g., Hadoop)
  - Supports easy scaling out (e.g., adding lots of commodity servers) and failure handling
  - Does not require loading data into tables
  - Exposes parallelism to programmers
    - Other tools built on top of MapReduce can provide higher-level abstractions

Horizontal data partitioning

- Split a table R into p chunks, each stored at one of the p processors
- Splitting strategies:
  - Round robin assigns the i-th row assigned to chunk $(i \bmod p)$
  - Hash-based partitioning on attribute A assigns row r to chunk $(h(r.A) \bmod p)$
  - Range-based partitioning on attribute A partitioning the range of $R.A$ values into p ranges, and assigns row r to the chunk whose corresponding range contains $r.A$

Teradata: an example parallel DBMS

- Hash-based partitioning of *Customer* on *cid*

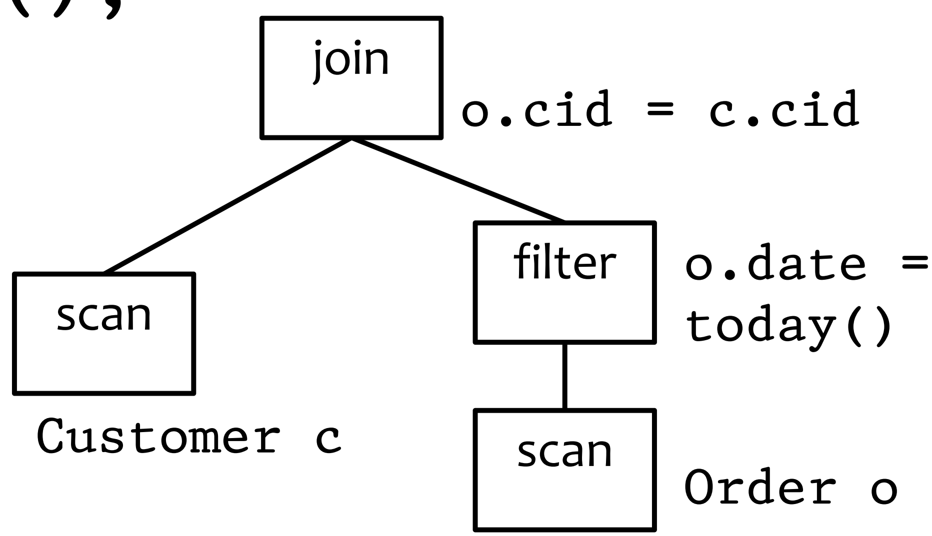


AMP = unit of parallelism in Teradata

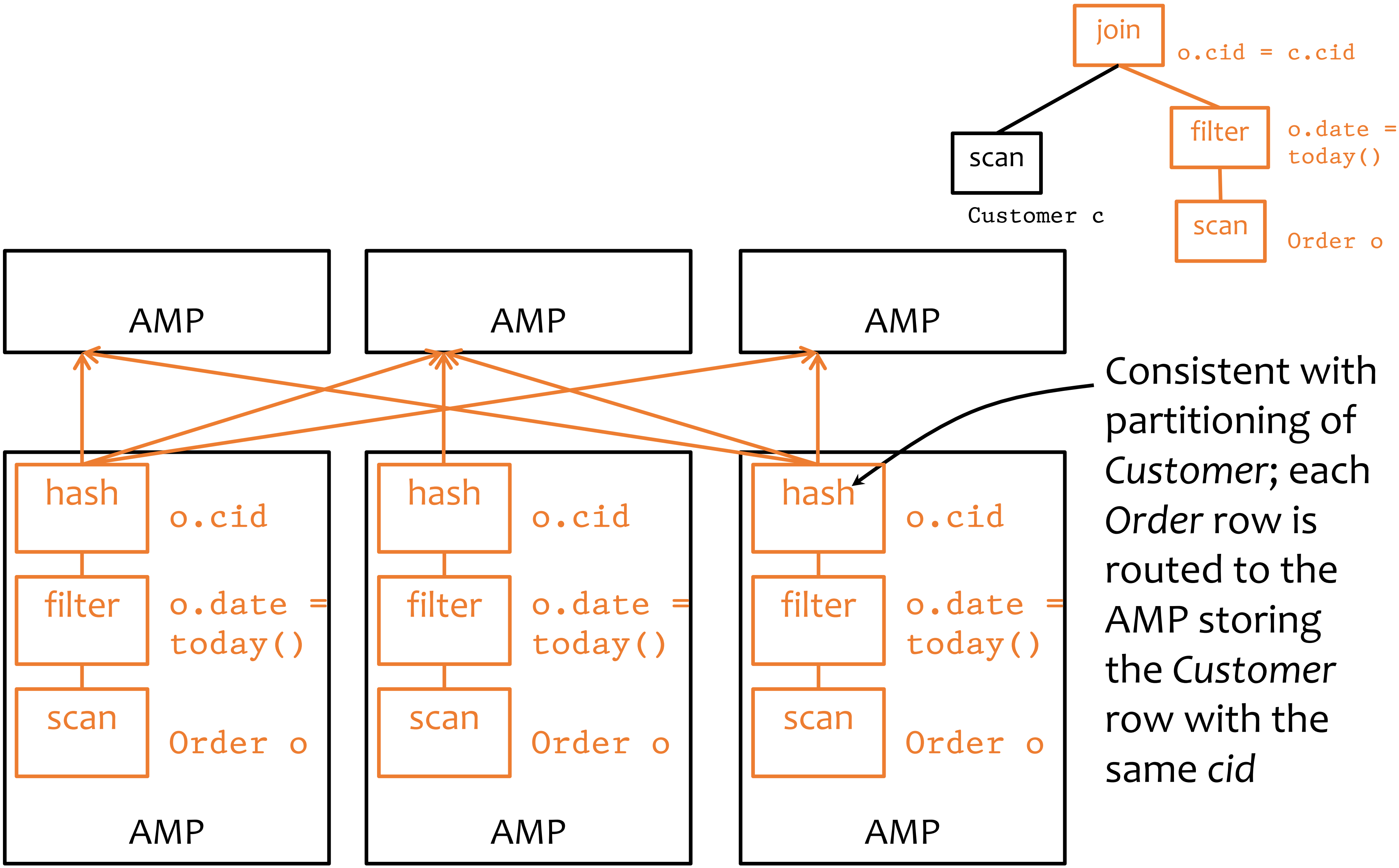
Example query in Teradata

- Find all orders today, along with the customer info

```
SELECT *
FROM Order o, Customer c
WHERE o.cid = c.cid
AND o.date = today();
```

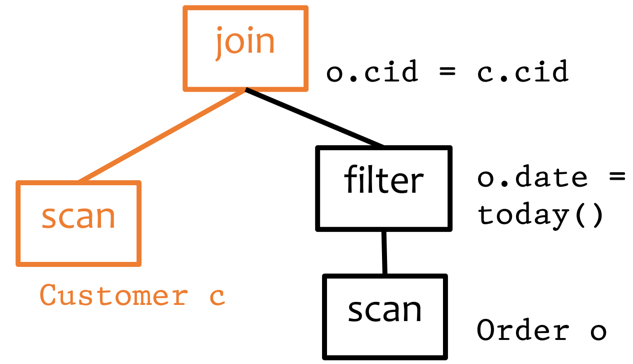


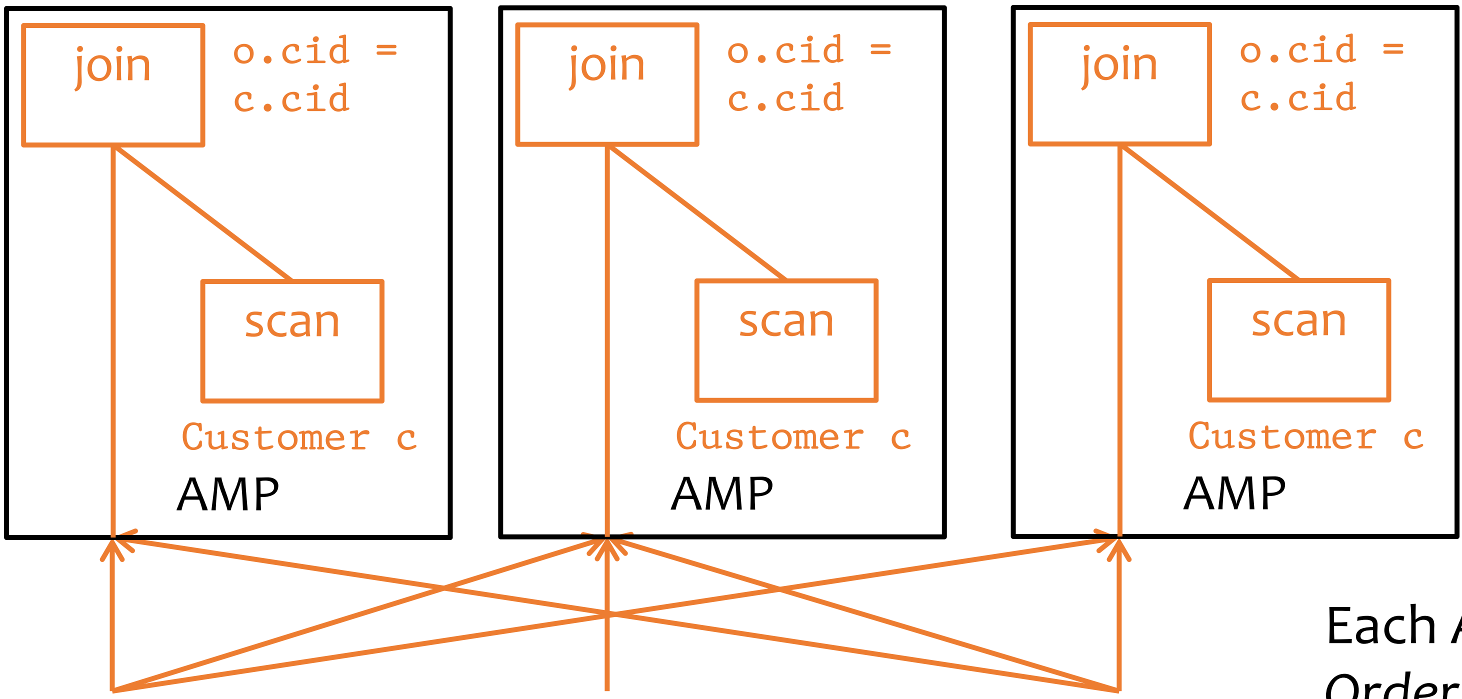
Teradata example: scan-filter-hash



Consistent with partitioning of *Customer*; each *Order* row is routed to the AMP storing the *Customer* row with the same *cid*

Teradata example: hash join





Each AMP processes *Order* and *Customer* rows with the same *cid* hash

MapReduce: motivation

- Many problems can be processed in this pattern:
  - Given a lot of unsorted data
  - Map: extract something of interest from each record
  - Shuffle: group the intermediate results in some way
  - Reduce: further process (e.g., aggregate, summarize, analyze, transform) each group and write final results

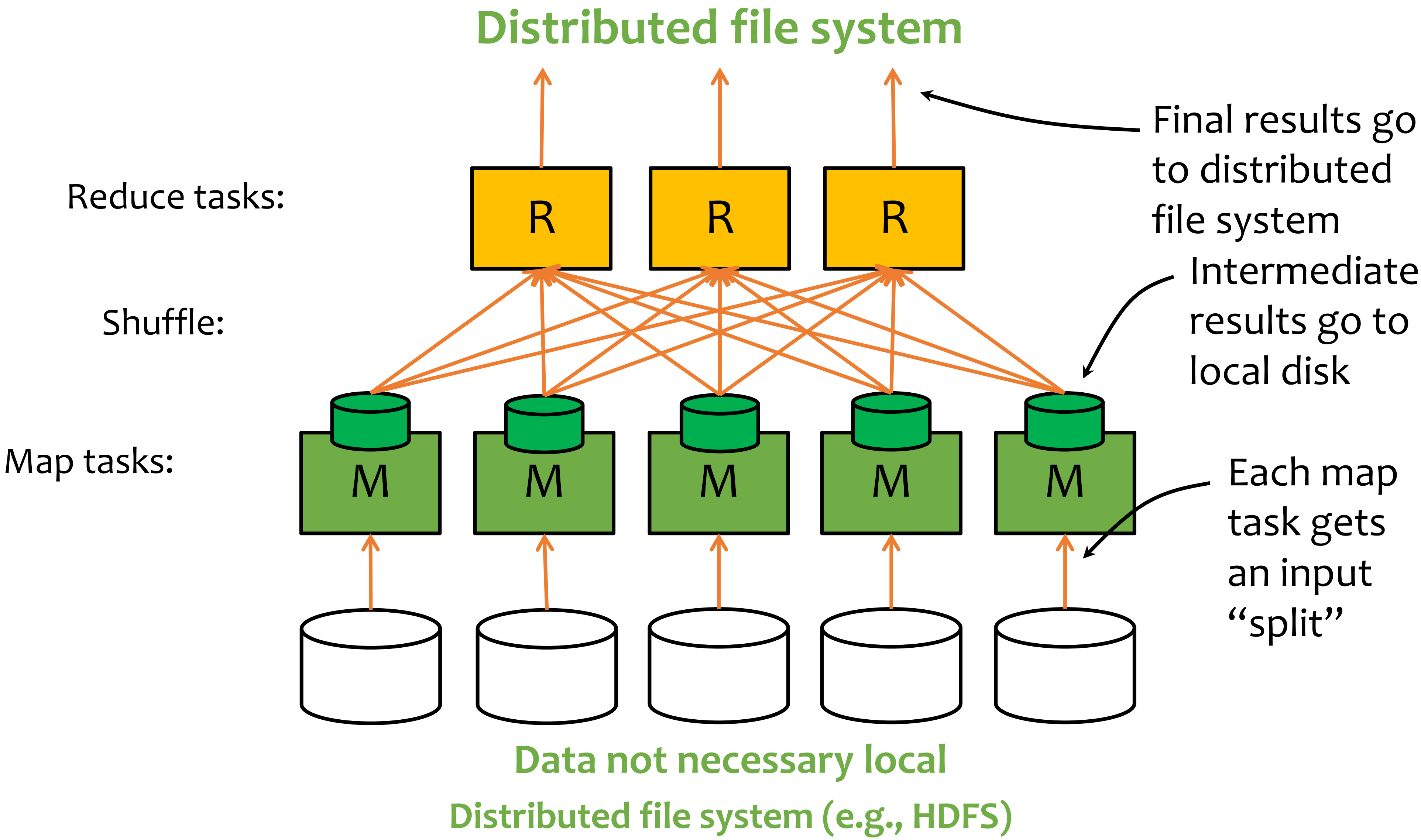
  (Customize map and reduce for problem at hand)

☞ Make this pattern easy to program and efficient to run
  - Original Google paper in *OSDI* 2004
  - Hadoop has been the most popular open-source implementation

M/R programming model

- Input/output: each a collection of key/value pairs
- Programmer specifies two functions
  - $\mathrm{map}(k_1, v_1) \to \mathrm{list}(k_2, v_2)$
    - Processes each input key/value pair, and produces a list of intermediate key/value pairs
  - $\mathrm{reduce}\big(k_2, \mathrm{list}(v_2)\big) \to \mathrm{list}(v_3)$
    - Processes all intermediate values associated with the same key, and produces a list of result values (usually just one for the key)

M/R execution



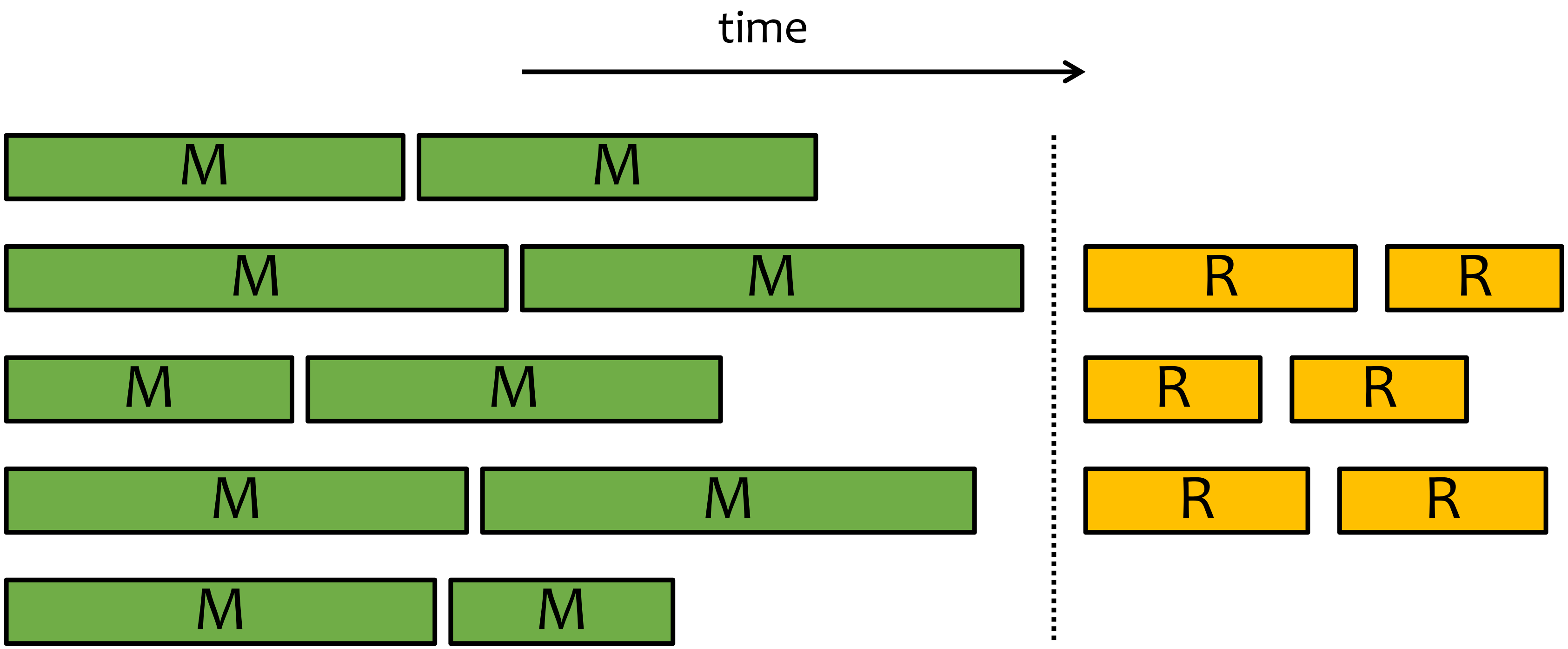
M/R example: word count

- Expected input: a huge file (or collection of many files) with millions of lines of English text
- Expected output: list of (word, count) pairs
- Implementation
  - $\text{map}(\_, \text{line}) \rightarrow \text{list}(\text{word}, \text{count})$
    - Given a line, split it into words, and output $(w, 1)$ for each word w in the line
  - $\text{reduce}\left(\text{word}, \text{list}(\text{count})\right) \rightarrow (\text{word}, \text{count})$
    - Given a word w and list L of counts associated with it, compute $s = \sum_{\text{count} \in L} \text{count}$ and output (w, s)
  - Optimization: before shuffling, map can pre-aggregate word counts locally so there is less data to be shuffled
    - This optimization can be implemented in Hadoop as a "combiner"

Some implementation details

- There is one "master" node
- Input file gets divided into m "splits," each a contiguous piece of the file
- Master assigns m map tasks (one per split) to "workers" and tracks their progress
- Map output is partitioned into r "regions"
- Master assigns r reduce tasks (one per region) to workers and tracks their progress
- Reduce workers read regions from the map workers' local disks

M/R execution timeline



- When there are more tasks than workers, tasks execute in “waves”
  - Boundaries between waves are usually blurred
- Reduce tasks can’t start until all map tasks are done

More implementation details

- Numbers of map and reduce tasks
  - Larger is better for load balancing
  - But more tasks add overhead and communication
- Worker failure
  - Master pings workers periodically
  - If one is down, reassign its split/region to another worker
- “Straggler”: a machine that is exceptionally slow
  - Pre-emptively run the last few remaining tasks redundantly as backup

M/R example: Hadoop TeraSort

- Expected input: a collection of (key, payload) pairs
- Expected output: sorted (key, payload) pairs
- Implementation
  - Using a small sample of input, find $r - 1$ key values that divides the key range into r subranges where # pairs is roughly equal across them
  - $\mathrm{map}(k, \mathrm{payload}) \rightarrow (j, \langle k, \mathrm{payload} \rangle)$
    - If k falls within the j-th subrange
  - $\mathrm{reduce}\big(j, \mathrm{list}(\langle k, \mathrm{payload} \rangle)\big) \rightarrow \mathrm{list}(k, \mathrm{payload})$
    - Sort the list of $(k, \mathrm{payload})$ pairs by k and output

Parallel DBMS vs. MapReduce

- Parallel DBMS
  - Schema + intelligent indexing/partitioning
  - Can stream data from one operator to the next
  - SQL + automatic optimization
- MapReduce
  - No schema, no indexing
  - Higher scalability and elasticity
    - Just throw new machines in!
  - Better handling of failures and stragglers
  - Black-box map/reduce functions → hand optimization

  ☞ But newer systems (e.g., Hive, Spark SQL) have added schema, declarative languages, indexing, and automatic optimization