POLITECNICO
MILANO 1863

Distributed Platforms for Data Analytics

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Data science

"Data science is an interdisciplinary field that uses scientific methods, processes, algorithms and systems to extract knowledge and insights from data in various forms, both structured and unstructured"

Wikipedia

Data science

- Data science is made possible by the increasing availability of large volumes of data
  - Big data

- Examples
  - Recommender algorithms (Netflix)
    - Based on historical data
  - Google translate
    - Based on snippets of books in different languages
  - Genomic data
    - Correlation between genes and diseases
  - Medicine
    - Lifestyle and environment variables monitored through smart devices (smartphones, watches, bands, …)

Technical perspective

- Collect all the data
  - The more the better → statistical relevance
  - Keeping all is cheaper than deciding what to keep
- Decide independently what to do with data
  - Run experiments on data when question arises
- Huge difference with respect to traditional information systems
  - Decide upfront what data to keep and why

Consequences

- Volume: data at rest
  - It is going to be a lot of data!
- Velocity: data in motion
  - It is going to arrive fast
- Variety: many different formats
  - Different versions, different sources
- Veracity: not always correct

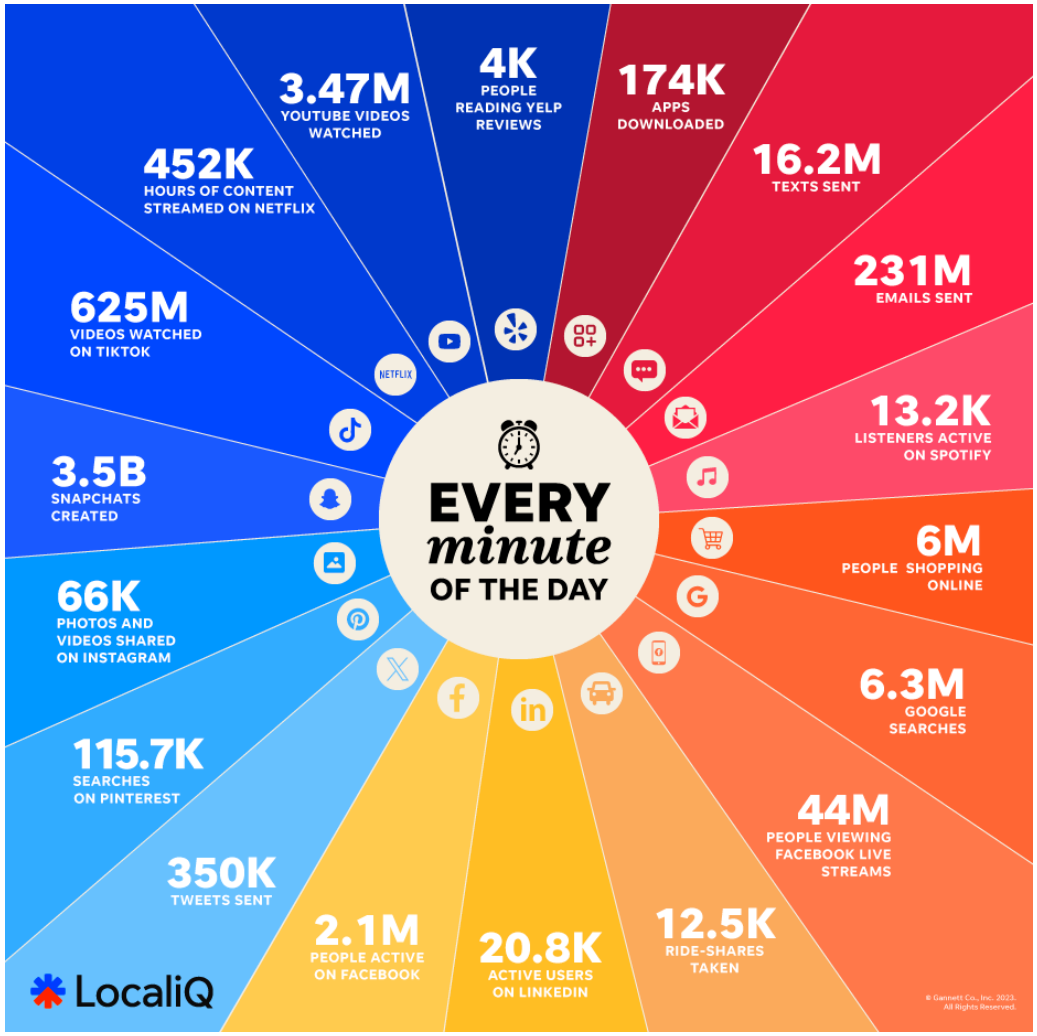
Volume

- Back in 2008, Google was processing 20 PB (20k TB) of data every day

- Source:
  - Dean, Ghemawat, *MapReduce: simplified data processing on large clusters*

- Exponential grows over the years

Velocity



Internet minute [2024]

Velocity

- In many domains, information is relevant when it's fresh …
- … and loses value as it becomes old
- We need to process data and extract valuable knowledge as soon as possible!

Problem scope

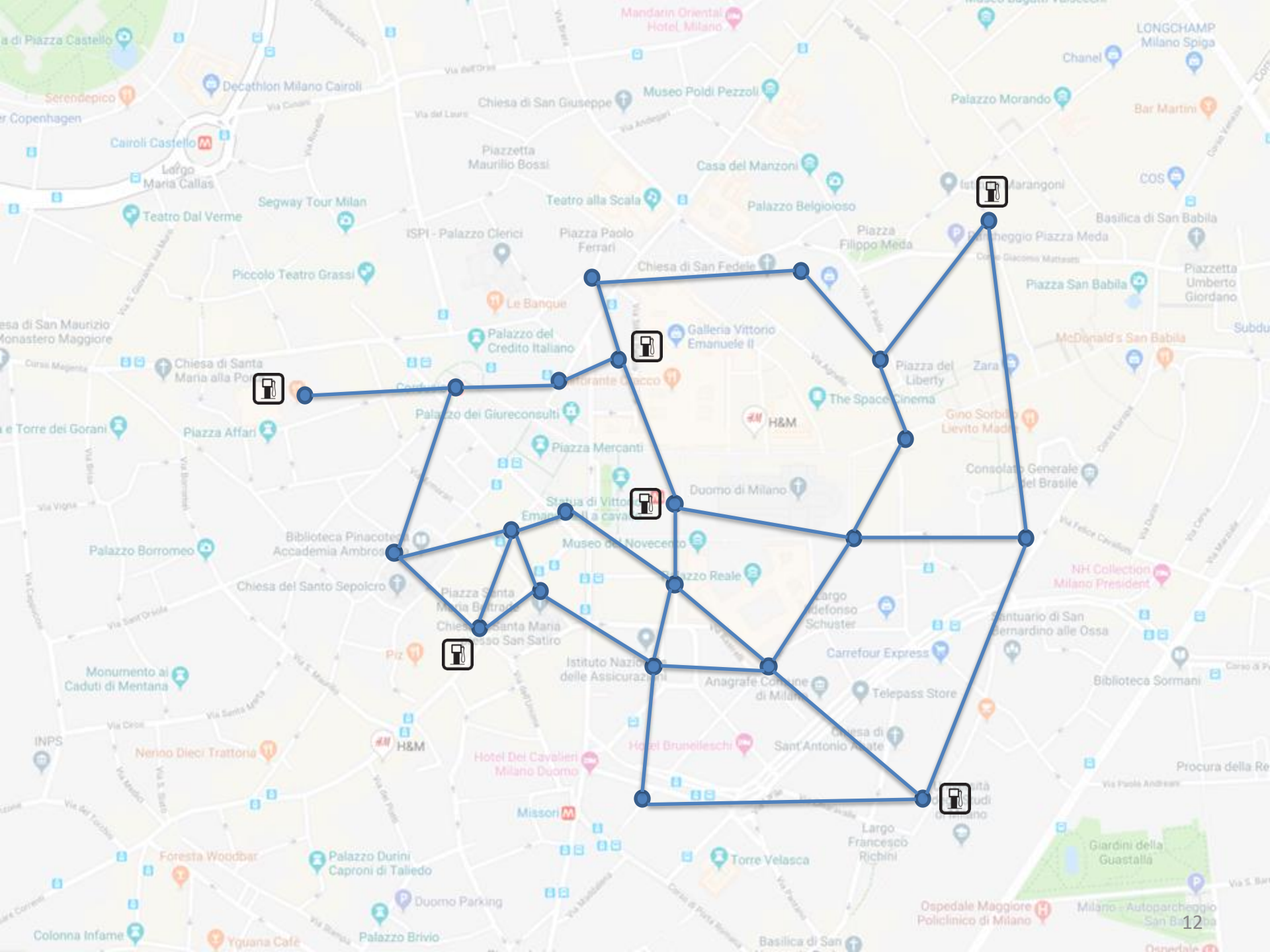
- Scalability to large data volumes
- Support for quickly changing data
- Required functions
  - Automatic parallelization & distribution
  - Fault-tolerance
  - Status and monitoring tools
  - A clean abstraction for programmers

MAP REDUCE

Problem

- We have a map represented as a graph
  - Nodes are points of interest
  - Edges are roads

- We want to compute the shortest path from each point to the nearest gas station


Mandarin Oriental Hotel Milano
Decathlon Milano Cairoli
Museo Poldi Pezzoli
Chiesa di San Giuseppe
Cairoli Castello
Piazzetta Maurilio Bossi
Casa del Manzoni
Teatro alla Scala
Palazzo Belgioioso
Segway Tour Milan
Teatro Dal Verme
ISPI - Palazzo Clerici
Piazza Paolo Ferrari
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Piccolo Teatro Grassi
Le Banque
Palazzo del Credito Italiano
Galleria Vittorio Emanuele II
Piazza del Liberty
Zara
The Space Cinema
H&M
Palazzo dei Giureconsulti
Piazza Affari
Piazza Mercanti
Duomo di Milano
Museo del Novecento
Palazzo Reale
Biblioteca Pinacoteca Accademia Ambros
Palazzo Borromeo
Chiesa del Santo Sepolcro
Piazza Santa Maria Beltrade
Chiesa di Santa Maria Passo San Satiro
Istituto Nazionale delle Assicurazioni
Anagrafe Comune di Milano
Carrefour Express
Telepass Store
Largo Cardinale Alfonso Schuster
Santuario di San Bernardino alle Ossa
Biblioteca Sormani
NH Collection Milano President
Monumento ai Caduti di Mentana
INPS
Nerino Dieci Trattoria
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Hotel Brunelleschi
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Missori
Largo Francesco Richini
Torre Velasca
Foresta Woodbar
Palazzo Durini Caproni di Taliedo
Duomo Parking
Palazzo Brivio
Colonna Infame
Yguana Café
Giardini della Guastalla
Ospedale Maggiore Policlinico di Milano
Basilica di San Babila
Piazza San Babila
Piazza Filippo Meda
Parcheggio Piazza Meda
Piazzetta Umberto Giordano
McDonald's San Babila
Bar Martini
LONGCHAMP Milano Spiga
Chanel
Palazzo Morando
COS
Basilica di San Babila
Consolato Generale del Brasile
Gino Sorbillo Lievito Madre
Procura della Re
Chiesa di San Maurizio Monastero Maggiore
Chiesa di Santa Maria alla Po
Torre dei Gorani
Serendepico
Copenhagen

Solutions?

- Compute the shortest path between each gas station and each node
  - This is the single-source shortest path problem
  - Well known algorithms (Dijkstra, Johnson, ...)
  - If you are curious about the complexity: the best-known algorithm works in O((N + E) log N), where N is the number of nodes and E is the number of edges, and we need to do that for each gas station

Notice that we are in the 2000's, so we only had hard disk, so in case of parallelism the reading of the data could be the bottleneck

- Then, for each node, we need to compare the distance computed from each gas station and keep only the minimum
  - E.g., we can store the best-known solution for each node and update it as we discover better paths

Solutions?

- Possible optimization: we can discard nodes that are too far away
  - E.g., we assume that the maximum distance between any node and the nearest gas station is 50 km and we discard paths that are longer than that

Solutions?

- Did we ask ourselves the right questions?

- We implicitly made some strong assumptions
  - We can easily access the entire input data
  - We can easily store and update the state of the computation
    - Discovered paths, current minimum for each node, …
  - They fit in memory …
  - … or at least on the disk of a single node
    - Random access can then become a problem

Scalability

- In general, some problems only appear "at scale"
  - Data-intensive applications
- Reading input and reading/storing the intermediate state of the computation can easily become the bottleneck
- If input/state do not fit in one machine, we need distributed solutions …
- … and then the coordination, communication can become the bottleneck

Scalability

- We need to consider
  - The scale of the problem
    - For now, let's focus on the volume of data only
  - The computing infrastructure we have

- Our story takes place in a datacenter of Google in the early 2000s

Assumptions: scale of the problem

- Terabytes or more
- Does not fit into a single disk
  - Or it is too expensive to read from a single disk
  - Sadly, there were no SSDs at that time …
- For sure does not fit in memory

Assumptions: computing infrastructure

- Cluster of "normal" computers
- Hundreds to thousands of nodes
- No dedicated hardware
  - Less expensive
  - Easy to update frequently and incrementally
  - Not reliable! Hardware failures are common!

Back to the problem

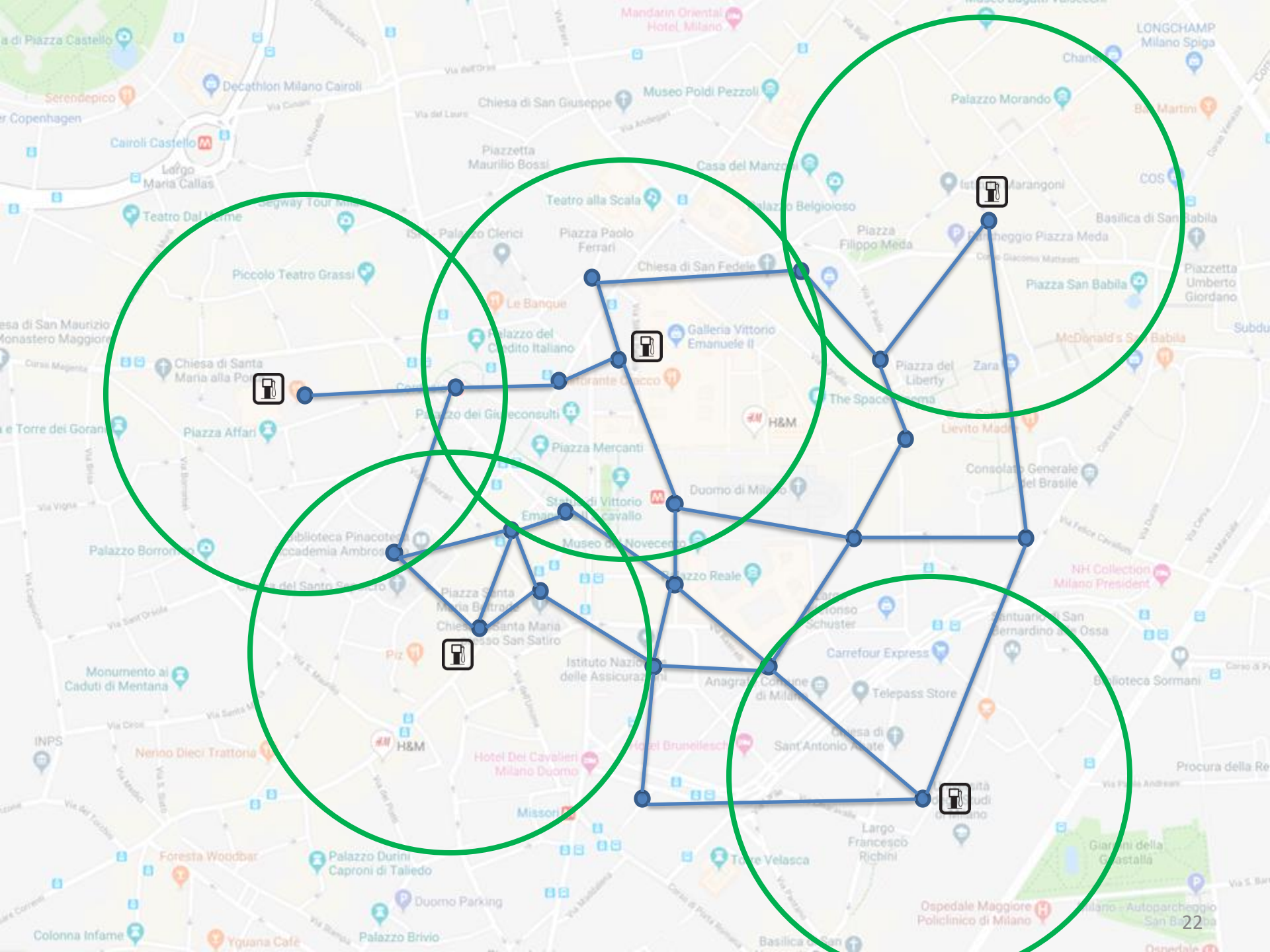
- Now we have a clear picture of the assumptions …

- … better solutions?

Back to the problem

- Assuming that the maximum distance between any point and the nearest gas station is 50 km …

- … we can split the dataset into blocks
  - Each block b_i centered around gas station i
  - Different blocks can be stored on different computers
  - For each block b_i, we can compute the distance between gas station i and any node in the block
    - The computation is independent for each block
    - Blocks can be processed entirely in parallel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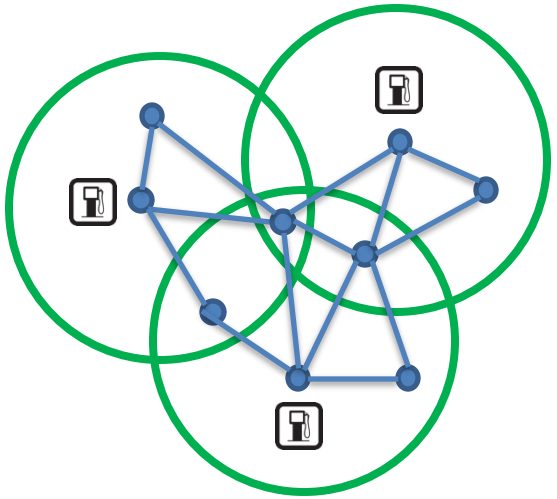
Ospedale Maggiore Policlinico di Milano
Procura della Re
INPS

Back to the problem

- Next, we need to determine the closest gas station and the shortest path for each node

- This requires communication, because a point can be at the intersection of several blocks

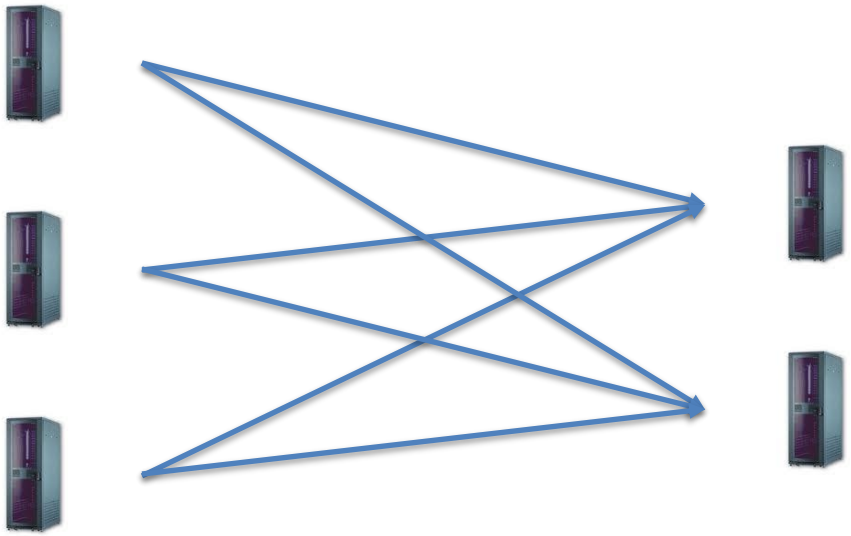


Back to the problem

- We can repartition the data by node

- Again, the shortest path (minimum distance) can be computed independently for each node
  - Each node can be processed in parallel on a different machine

The solution



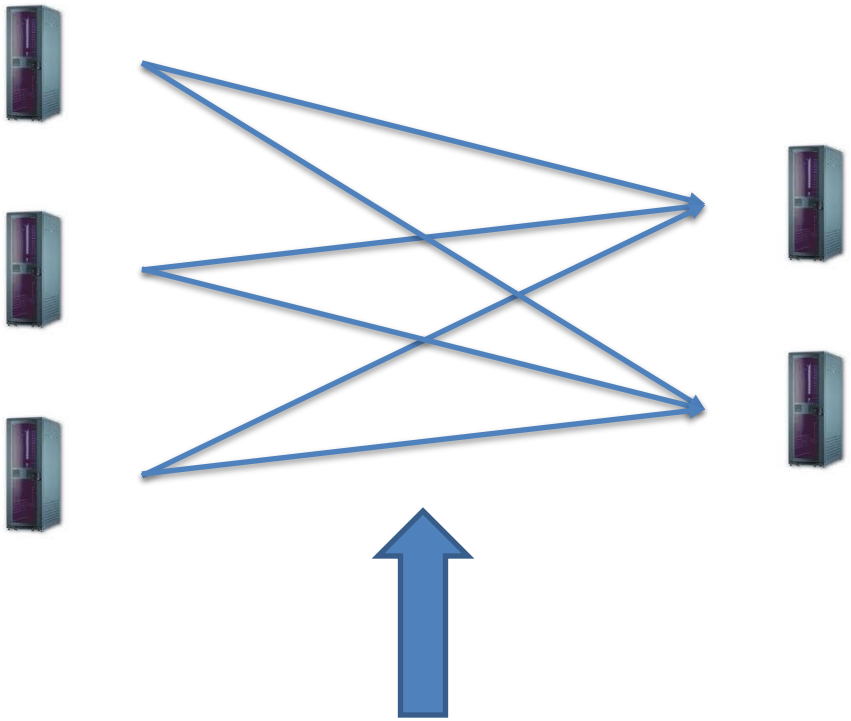
Computation of paths

- Data split by gas station
- Each gas station can be processed in parallel
- Nodes can read input blocks in parallel

Computation of shortest paths

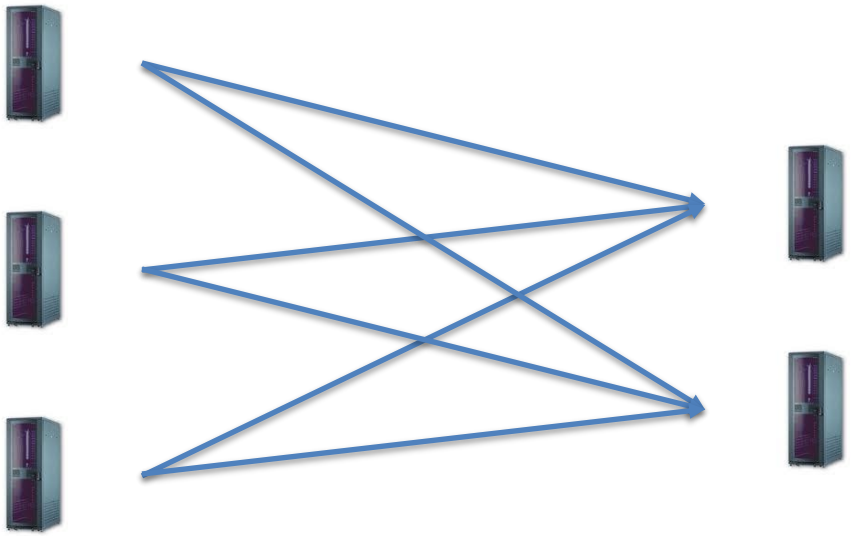
- Data split by node
- Each node can be processed in parallel

The solution



From global and *mutable state* to transformations of *immutable data*

The solution



Different channels

- Distributed filesystem
- Messages (e.g., TCP)
- Queues (e.g., Kafka)

MapReduce

- The previous example exemplifies MapReduce
  - Programming model introduced by Google in 2004
  - Enables application programs to be written in terms of high-level operations on immutable data
  - The runtime system controls scheduling, load balancing, communication, fault tolerance, …

MapReduce

- The computation is split into two phases
  - Map and Reduce
- Map processes individual elements
  - For each of them outputs one or more <key, value> pairs

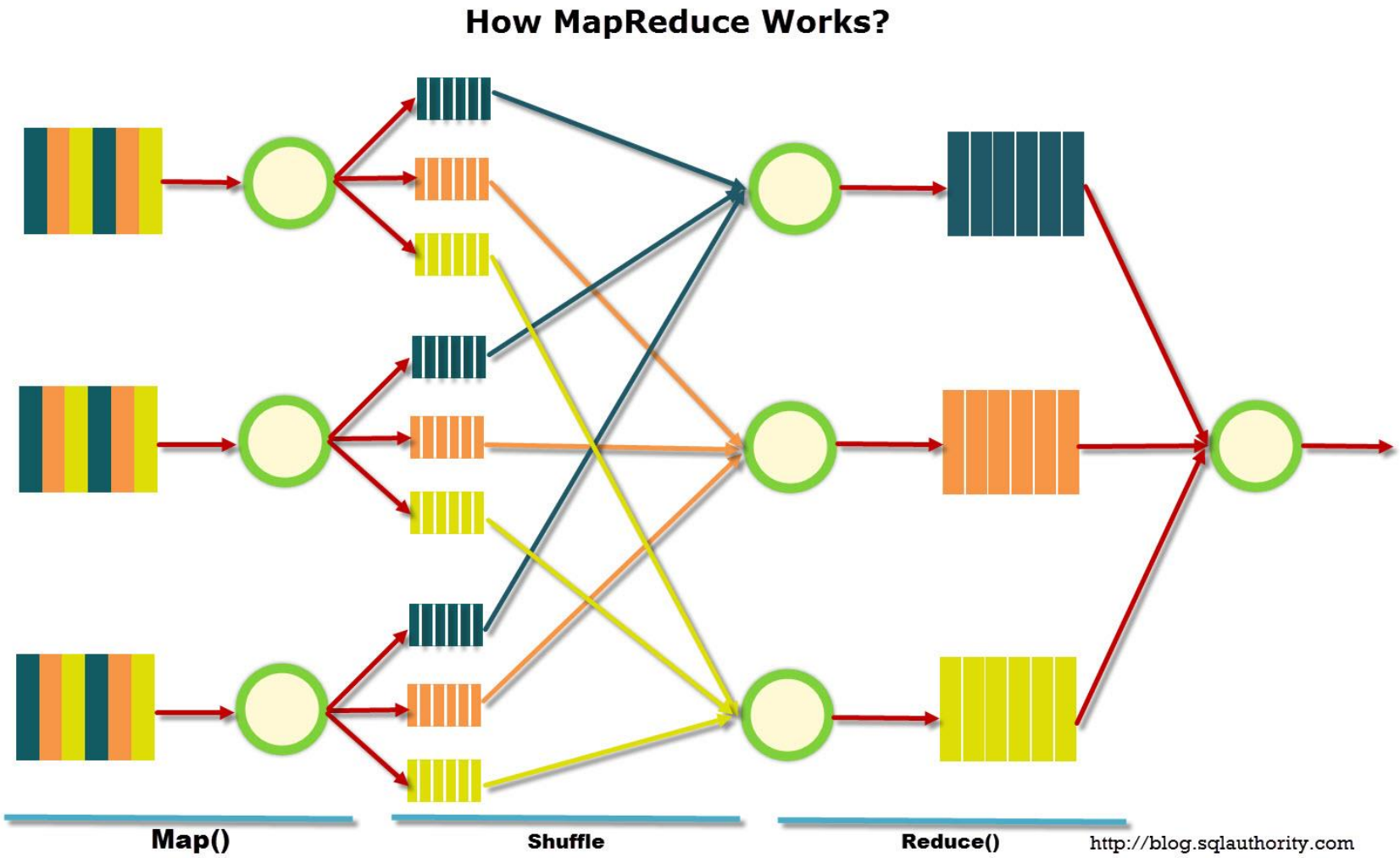
: they are automatically spawned by the system, only thing to specify is how many of them there are

- Reduce processes all the values with the same key and outputs a value
- The developers need only specify the behavior of these two functions

-How to compute the nearest gas station
-How to aggregate data about gas station in intersections

-Concurrency is abstracted away
-Managing of the data is ''

MapReduce


How MapReduce Works?
Map()
Shuffle
Reduce()
http://blog.sqlauthority.com

Another example: word count

- We want to count the number of occurrences of each word in a large document

- Example: "All you need is love", The Beatles
  - All you need is love
    All you need is love
    All you need is love, love
    Love is all you need

- The document is split into blocks, and each block is given to a different "Map" node

In our case we split by document (every line of the song is a document)

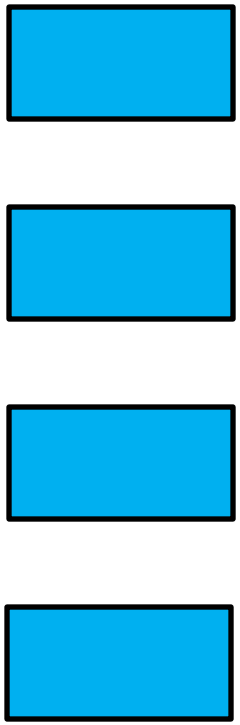
Another example: word count

All you need is love

All you need is love

All you need is love, love

Love is all you need



Map

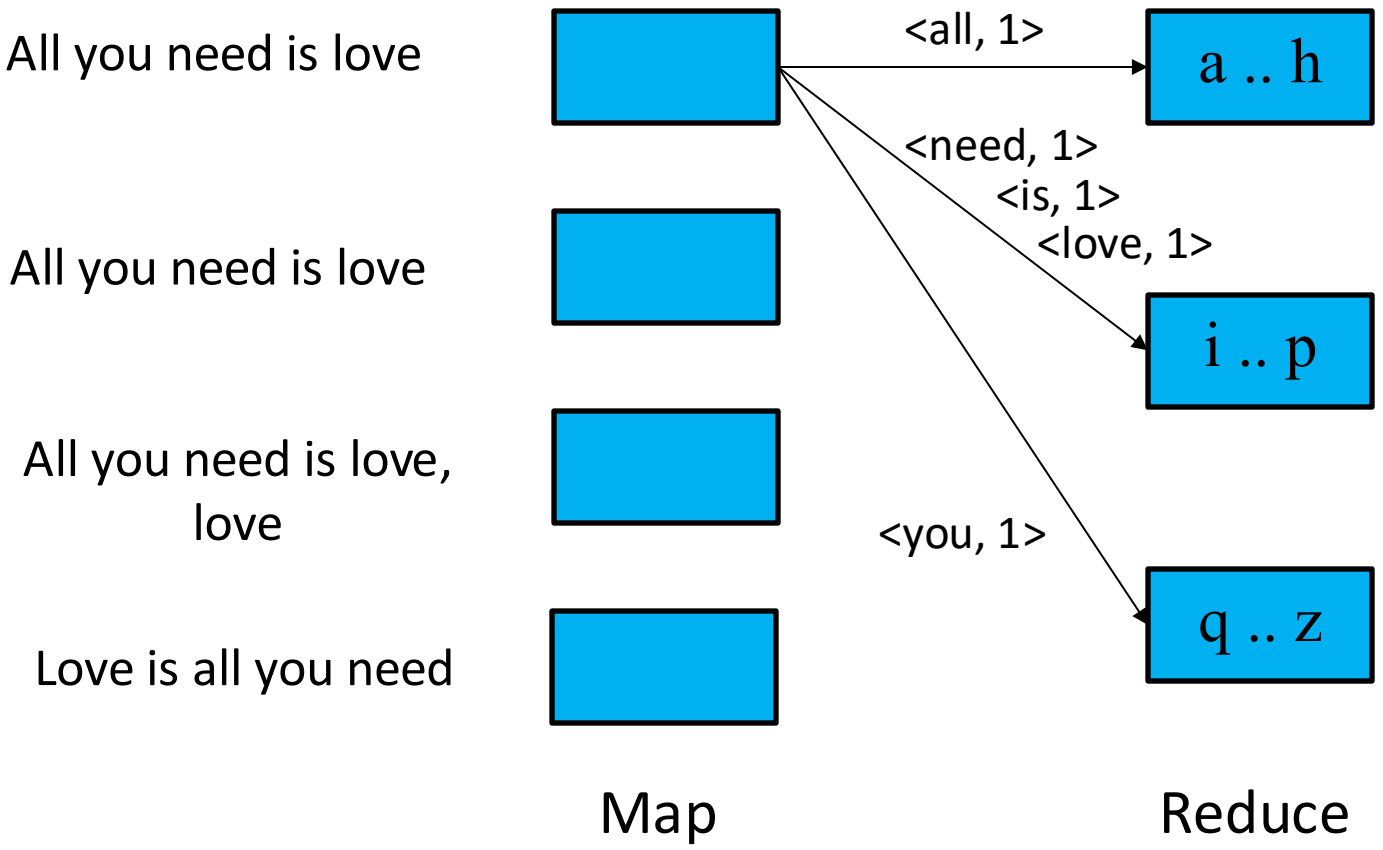
Another example: word count

- For each word w in its part of the document, the map function outputs the tuple <w, c>
  - w is the key
  - c is the count

- The map function is stateless: its output depends only on the specific word that it receives in input

- Tuples with the same key are guaranteed to be received by the same receiver

Another example: word count



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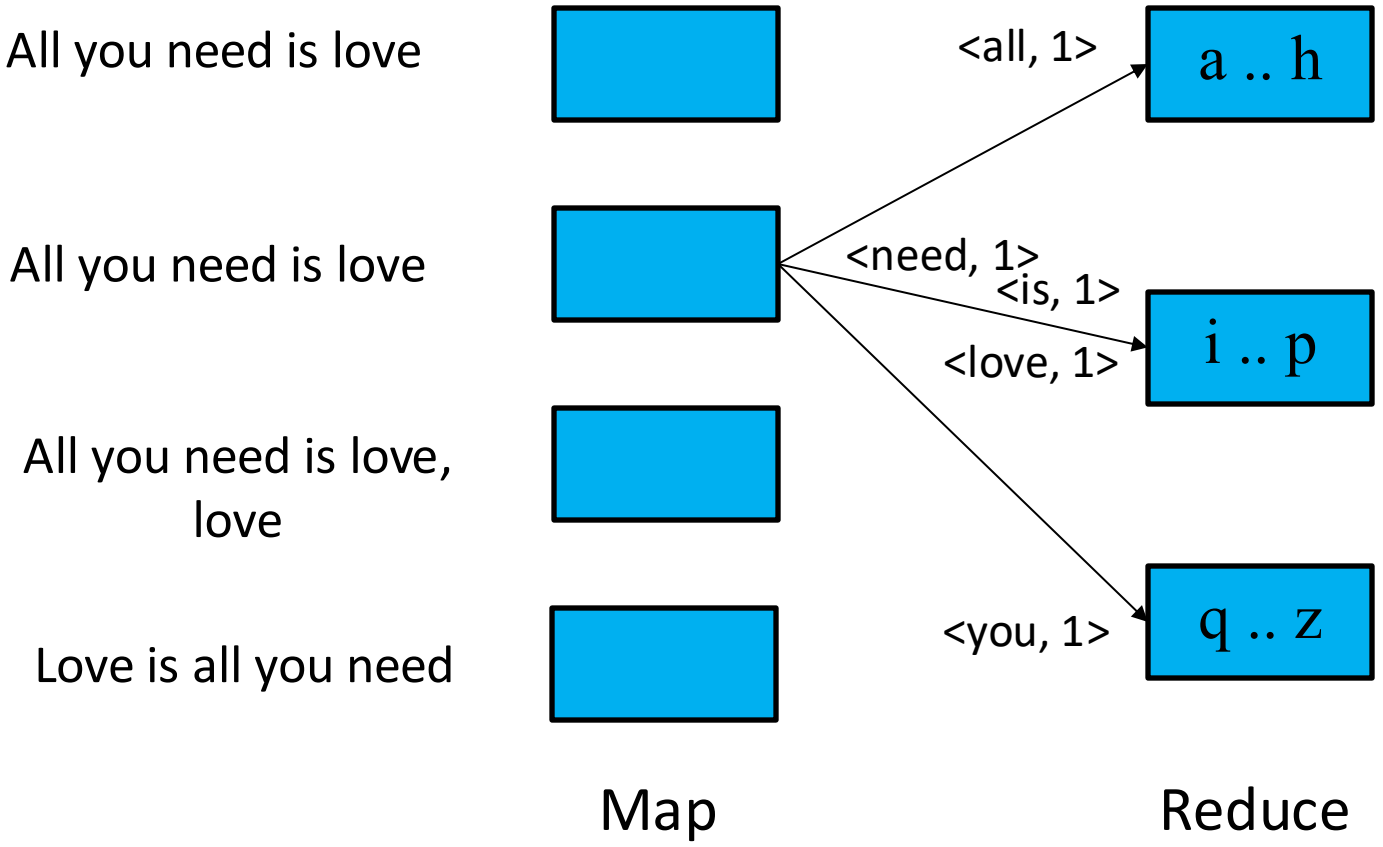

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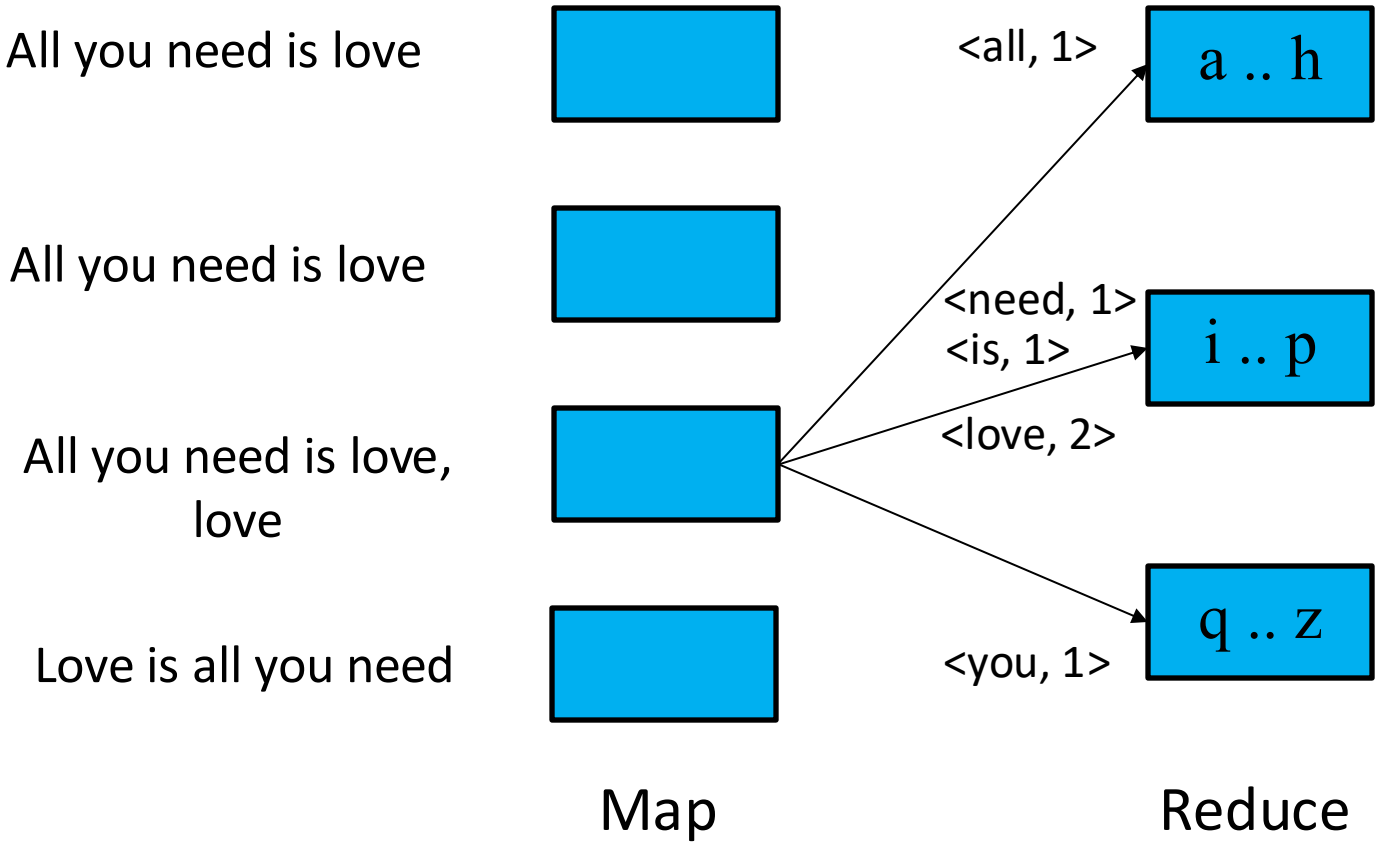
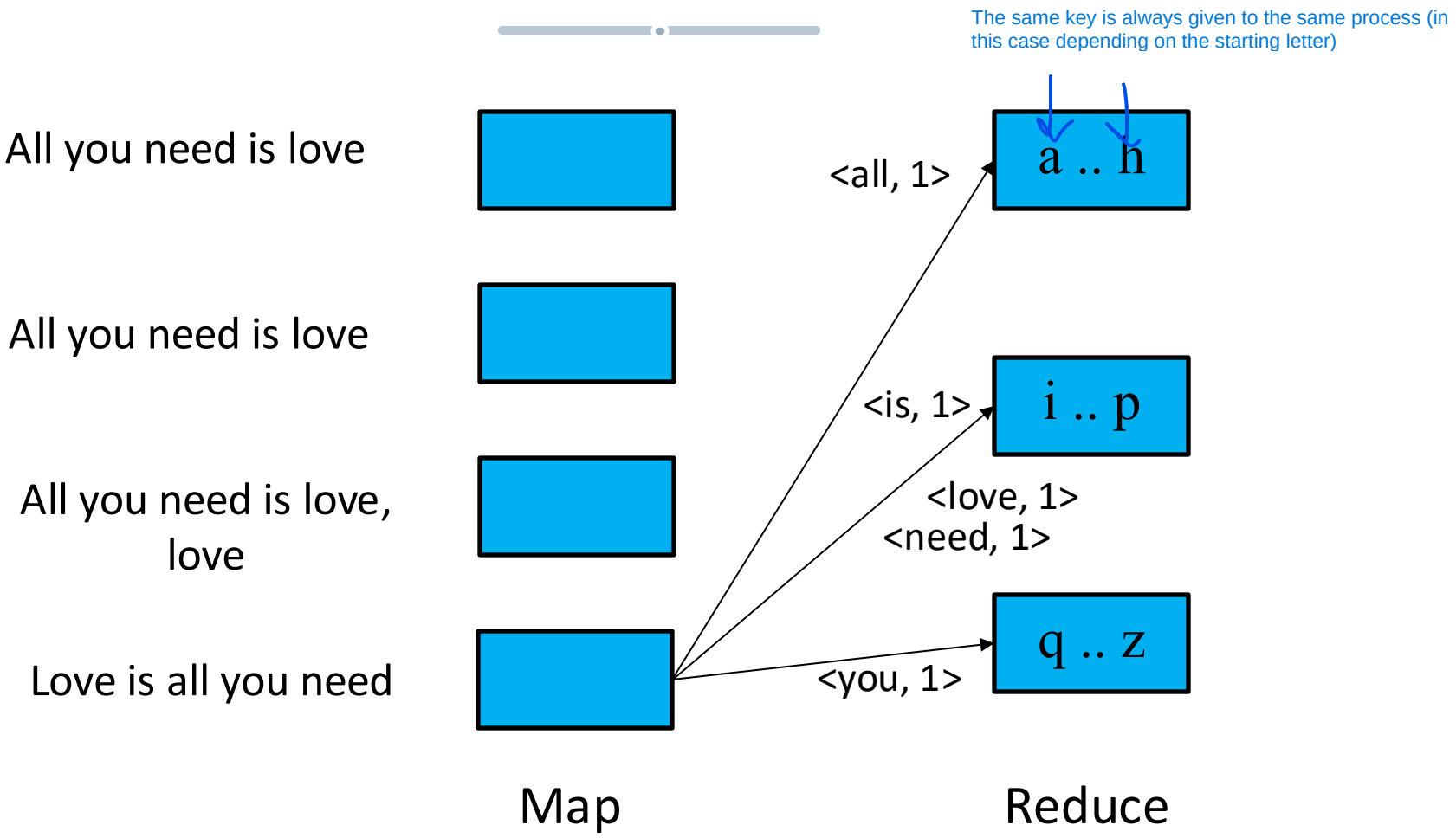


Another example: word count



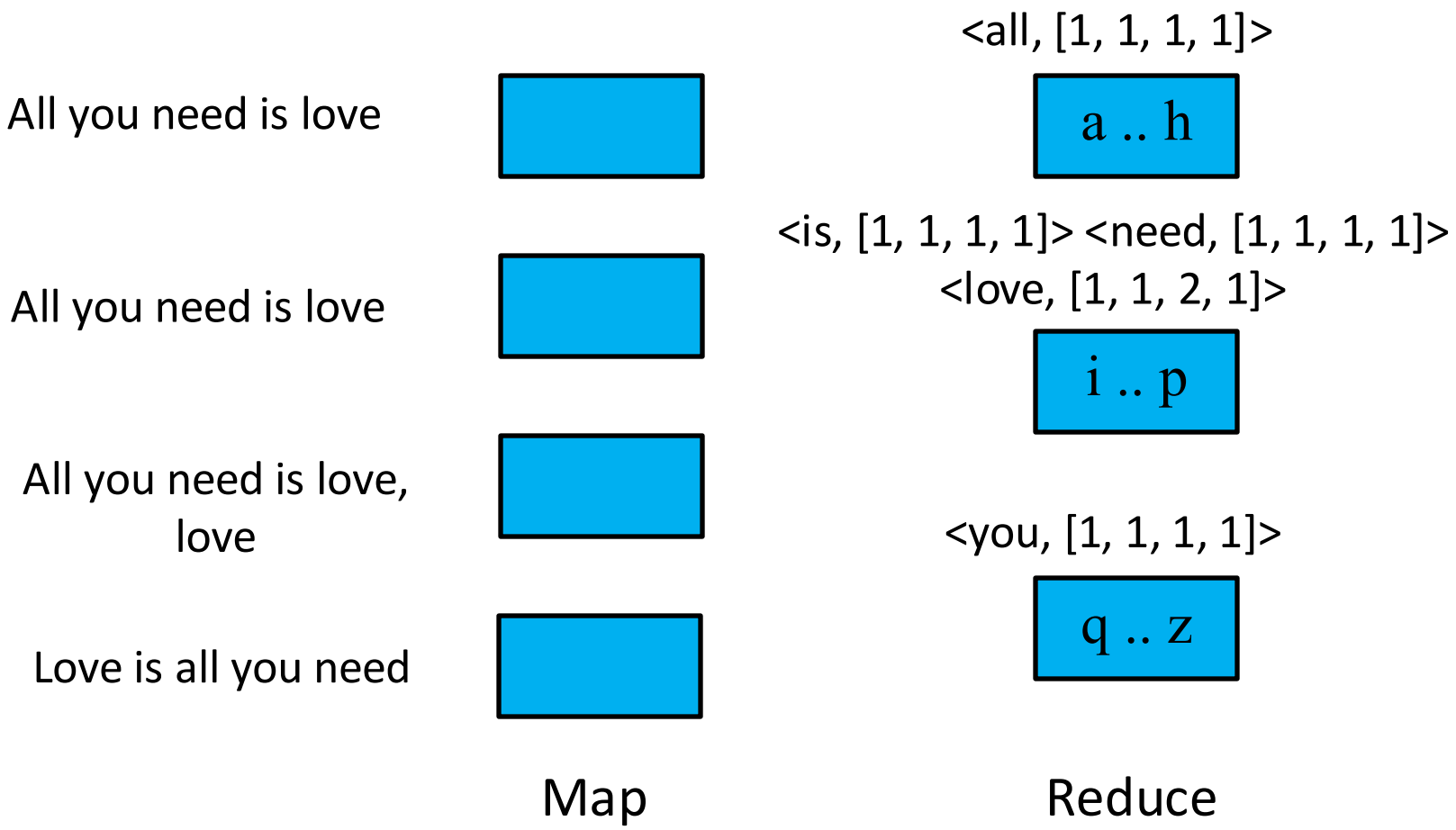
Another example: word count

- Reducers receive an immutable list (actually, an iterator) over the values associated to each key
  - Why? To ensure that the data is read sequentially, from the disk, only once

- The "reduce" function iterates over the list and outputs one or more values for each key

- In our case, it outputs the sum of the elements in the list

Another example: word count



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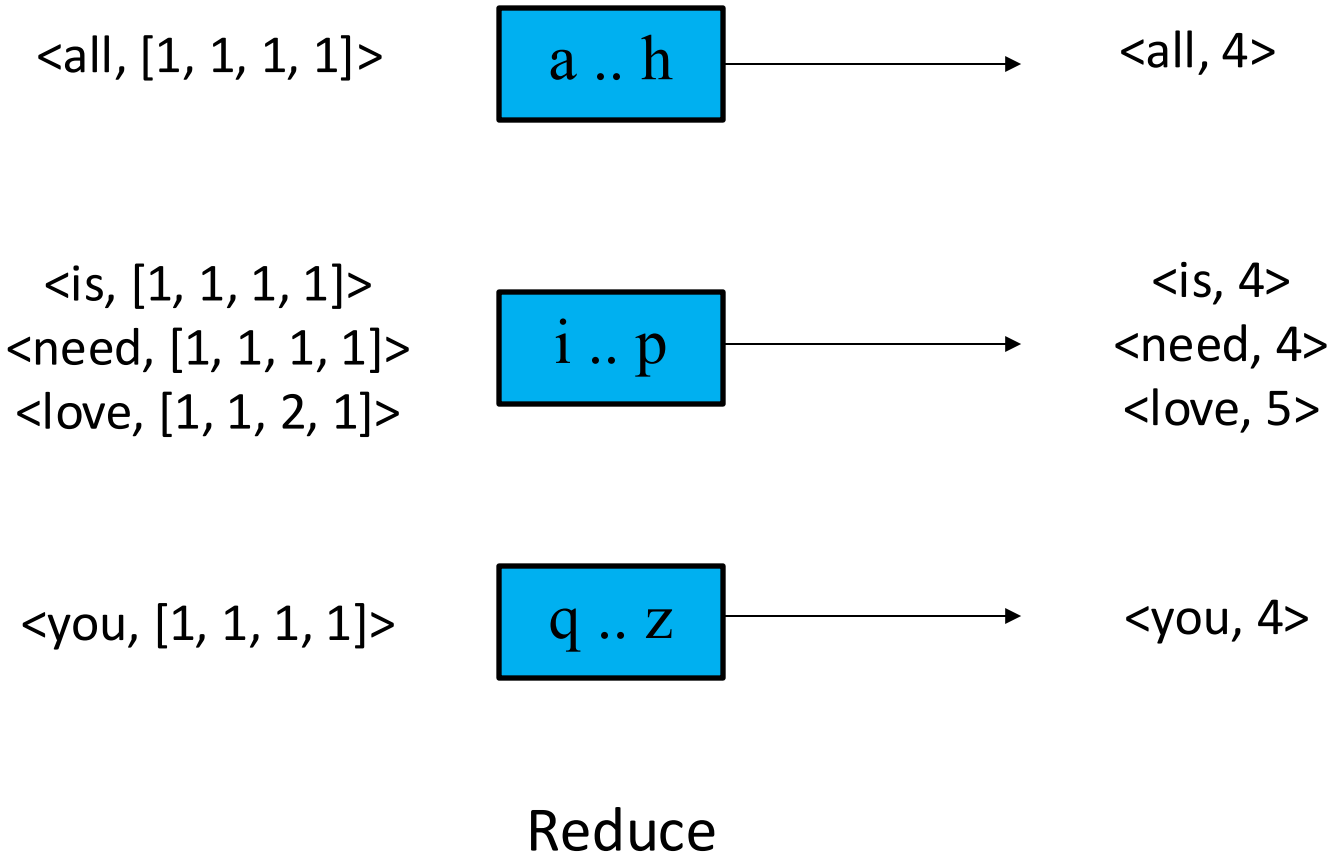


Another example: word count

- What does the programmer need to write?
- For the map function, what a mapper has to do with its part of the document
- For the reduce function, how to process the list of values associated to a given key

Another example: word count

```
// key: document name
// value: document contents
def map(key: String, value: String):
      count = []
      for w in value:
            if not w in count:
                  count[w] = 1
            else:
                  count[w] = count[w] + 1

      for w in count:
            emit(w, count[w])
```

Another example: word count

```
// key: a word
// values: a list of counts
reduce(key: String, values: Iterator):
      result = 0
      for v in values:
            result += v

      emit(result)
```

MapReduce

- What does the platform do?
- Scheduling: allocates resources for mappers and reducers
- Data distribution: moves data from mappers to reducers
- Fault tolerance: transparently handles the crash of one or more nodes

MapReduce scheduling

- One master, many workers
  - Input data split into M map tasks (typically 64 MB)
  - Reduce phase partitioned into R reduce tasks (hash(k) mod R)
  - Tasks are assigned to workers dynamically

- Master assigns each map task to a free worker
  - Considers locality of data to worker when assigning a task
  - Worker reads task input (often from local disk)
  - Worker produces R local files containing intermediate k/v pairs

- Master assigns each reduce task to a free worker
  - Worker reads intermediate k/v pairs from map workers
  - Worker sorts & applies user's reduce operation to produce the output

MapReduce data locality

- Goal: limit the usage of network bandwidth
- In GFS, data files are divided into 64MB blocks and 3 copies of each are stored on different machines
- Master program schedules map() tasks based on the location of these replicas
  - Put map() tasks physically on the same machine as one of the input replicas (or, at least on the same rack / network switch)
- This way, thousands of machines can read input at local disk speed
  - Otherwise, rack switches would limit read rate

MapReduce fault tolerance

- On worker failure
  - Master detects failure via periodic heartbeats
  - Both completed and in-progress map tasks on that worker should be re-executed
    - Output stored on local disk
  - Only in-progress reduce tasks on that worker should be re-executed
    - Output stored in global file system
  - All reduce workers will be notified about any map re-executions
- On master failure
  - State is check-pointed to GFS: new master recovers & continues
- Robustness

MapReduce: stragglers

- Stragglers = tasks that take long time to execute
  - Slow hardware, poor partitioning, bug, …

- When done with most tasks …
- … reschedule any remaining executing task
  - Keep track of redundant executions
  - Significantly reduces overall run time

MapReduce: conclusions

- Typical MapReduce application
  - Sequence of steps, each requiring map & reduce
  - Series of data transformations
  - Iterating until reach convergence
    - E.g., Google PageRank

MapReduce: conclusions

- Strengths
  - The developers write simple functions
  - The system manages complexities of allocation, synchronization, communication, fault tolerance, stragglers, …
  - Very general
  - Good for large-scale data analysis

- Limitations
  - High overhead
  - Lower raw performance than HPC
  - Very fixed paradigm
    - Each MapReduce step must complete before the next one can start

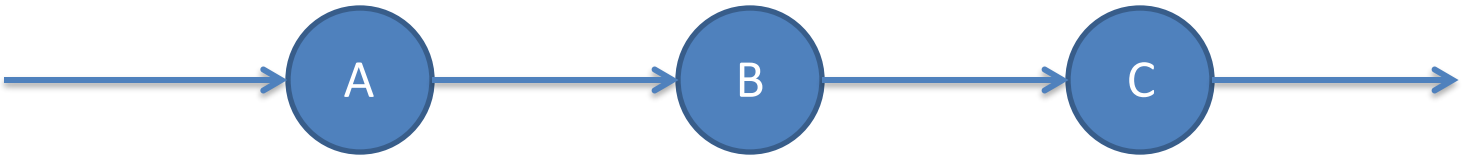
Dataflow platforms

BEYOND MAP REDUCE

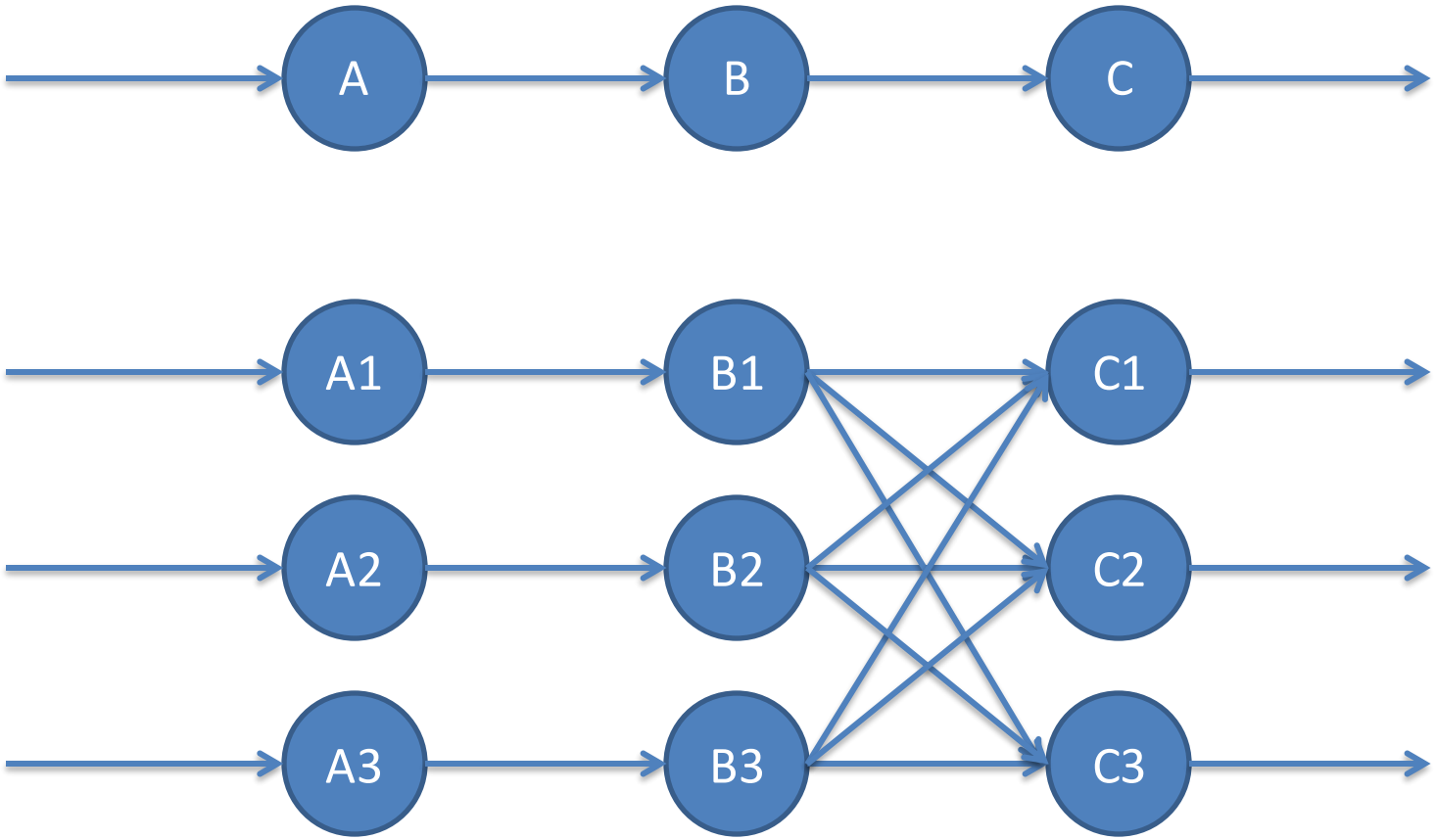
Beyond MapReduce

- In the last decade, many systems extended and improved the MapReduce abstraction in many ways
  - From two processing steps to arbitrary acyclic graphs of transformations
    - Dataflow model
    - In some cases, support for iterative computations
  - From batch processing to stream processing
    - Not only process large datasets with high throughput …
    - … also, low latency
  - From disk to main-memory or hybrid approaches

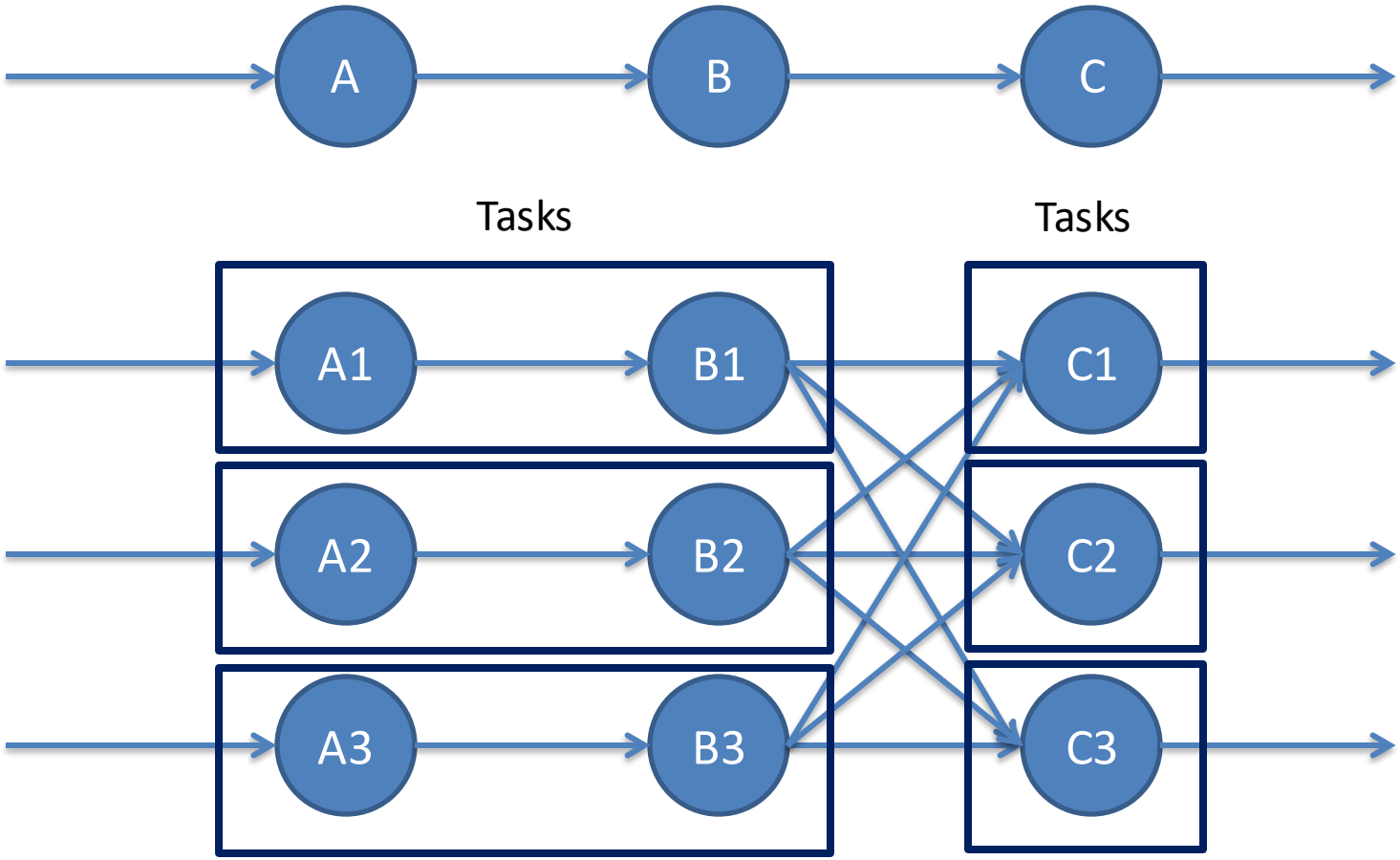
Dataflow programming model



Dataflow programming model



Dataflow programming model

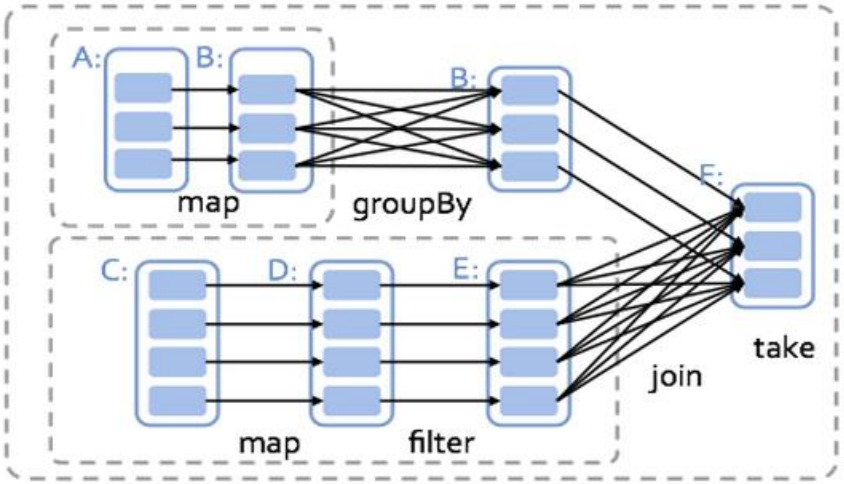


Beyond MapReduce

- We consider two systems as representatives of two different architectural approaches
- They differ in how / when they allocate tasks onto nodes
  - Apache Spark (see https://spark.apache.org)
    - Scheduling of tasks
    - Batch (or micro-batch) processing
  - Apache Flink (see https://flink.apache.org)
    - Pipelining of tasks
    - Continuous processing

Apache Spark

- Similar to MapReduce
  - Instead of only two stages (map and reduce) …
  - … arbitrary number of stages
- Intermediate results can be cached in main memory if they are reused multiple times
- Scheduling of tasks (stages) ensures that the computation takes place close to the data



Apache Spark

- Support for streaming data through the micro-batch approach
- The input data stream is split into small batches of data
  - Processed independently …
  - … but some state can persist across batches
    - For example, in a streaming word count, the count of each word is persisted and updated by each new micro-batch
    - State stored as an additional input for the next micro-batch

Apache Flink

- A job is not split into stages that are scheduled

- Instead, all the operators are instantiated as soon as the job is submitted
  - They communicate using TCP channels
  - An operator can start processing as soon as it has some data available from the previous ones
    - Pipeline architecture where multiple operators are simultaneously running

Apache Flink

- Ideal for stream processing
  - Data flows into the system without waiting for the operators to be scheduled
  - Lower latency

- Same approach used for batch processing
  - By "streaming" the entire batch through the operators

Comparison: latency

- The pipeline approach of Flink provides lower latency
  - Relevant for stream processing scenarios where new data is continuously generated
  - New data elements are ingested into the network of processing operators as they become available
  - No need to accumulate (micro-)batches
  - No need to schedule tasks

Comparison: throughput

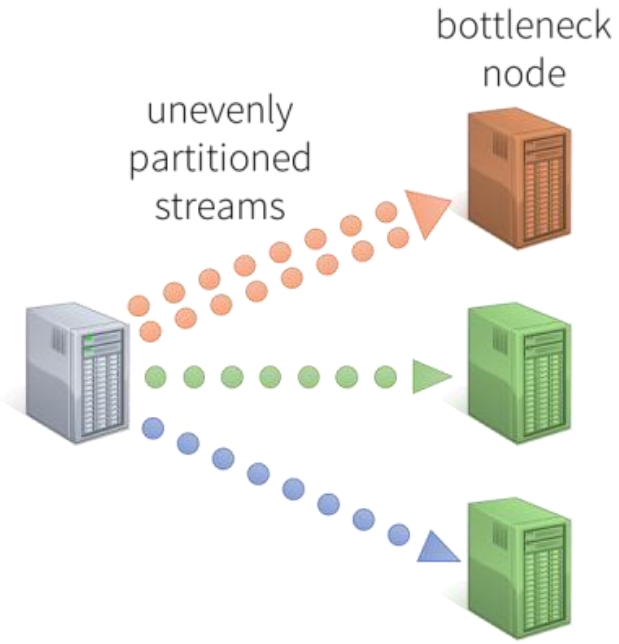
- A scheduling approach offers more opportunities to optimize throughput
  - Moving larger data blocks can be more efficient
    - Smaller overhead from the network protocols
    - More opportunities for data compression
  - Scheduling decisions can consider data distribution
    - See the comparison on load balancing below

Comparison: load balancing

- The scheduling approach of Spark simplifies load balancing
  - Dynamic scheduling decisions can consider data distribution
  - This is not possible in the case of a pipelined approach
    - Allocation of tasks to operators is decided statically when the job is deployed
  - Also relevant for streaming workloads
    - The distribution of data may change over time

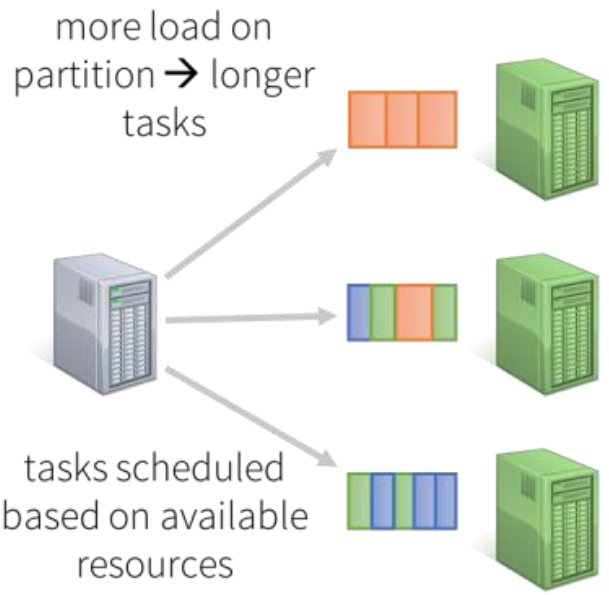
Comparison: load balancing

Traditional systems



static scheduling of continuous operators to nodes can cause bottlenecks

Spark Streaming



dynamic scheduling of tasks ensures even distribution of load

Comparison: elasticity

- Big data processing platforms are often offered as a service
- The actual cost of the service depends on the amount of resources being used
- In the case of continuous/streaming jobs, the load can change over time
- Elasticity indicates the possibility of a system to dynamically adapt resource usage to the load of the system

Comparison: elasticity

- Scheduling approaches are better for elasticity
  - Scheduling decisions take place dynamically at runtime
  - It is possible to dynamically change the set of physical resources being used for deployment
    - This may require moving intermediate state in the case of stream processing jobs
- Elasticity is simply not possible in pipelined approaches
  - Only opportunity: take a snapshot of the system and restart it on a different set of physical nodes

Comparison: fault-tolerance

- What happens if a node fails?
- Scheduled processing
  - Re-schedule the task
- Apache Spark relies on the lineage
  - No replication of intermediate results
  - If a data element is lost …
  - … simply recompute it
  - If the data it depends on is lost …
  - … simply recompute it
  - … and so on ...

Comparison: fault-tolerance

- In pipelined processing, periodically checkpoint to (distributed) file system
- In the case of failure, replay from the last checkpoint
- Apache Flink relies on checkpointing
  - You have seen the Chandy Lamport fault tolerance algorithm in detail in previous lectures