 

# Abstractions for Massively Parallel Dataflow Processing

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*with slides from Reza Zadeh

# Overview

- A little bit of history: From Relational Databases to Massively Parallel Dataflow Processing

- Distributed Shared-Nothing Filesystems

- Abstractions for Massively Parallel Dataflow Processing
  - MapReduce
  - Parallelization Contracts & Iterative Dataflows
  - Resilient Distributed Datasets

- Summary

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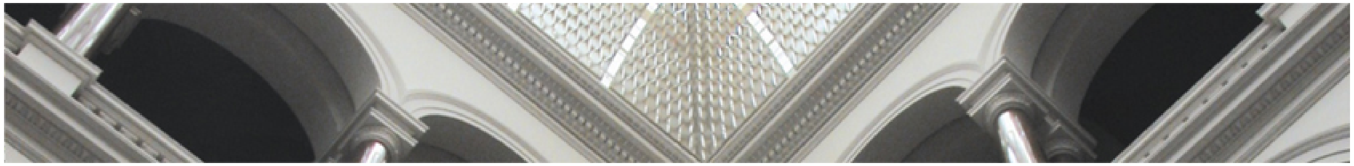
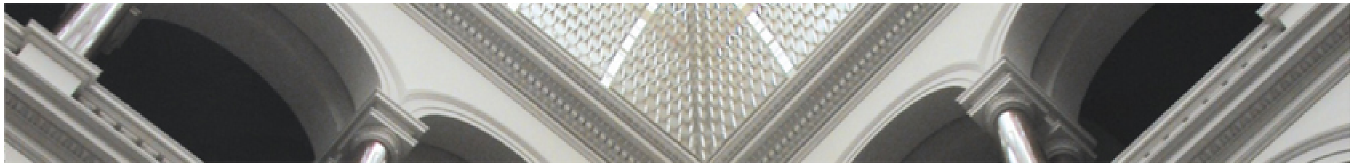


# From Relational Databases to Massively Parallel Dataflow Systems

- **relational model** (Codd 1970) gives rise to relational database management systems

- large data processing challenges in enterprise data management
  - enterprises collect historical business data in **data warehouses**
  - **reporting and business analytics** on this data

- scalability issues lead to development of **parallel database systems** in the mid 1980s
  - **shared-nothing architecture**: autonomous machines that only communicate over the network via message passing
  - introduction of **'divide-and-conquer' parallelism** based on hash-**partitioning the data** for storage and relational query processing
  - **commercial adoption** of these systems in the mid 1990s
  - database community considered **parallel query processing solved**



# From Relational Databases to Massively Parallel Dataflow Systems

- **rise of the world wide web** in the 1990s produces growing need to query and index the data available online
- search engine companies found **database technology neither well suited nor cost-effective**
  - ACID paradigm of relational data processing **mismatch for web search:**
    - mostly **read-only queries**
    - **high availability** much more important than consistency
  - **dirty, semi-structured web data** hard to fit into clearly defined relational schema
  - **new types of 'queries'** very different from traditional SQL-based data analysis, e.g.,
    - ranking of search results based on link structure of the web (**graph processing**)
    - personalized advertising (**machine learning**)

## From Relational Databases to Massively Parallel Dataflow Systems

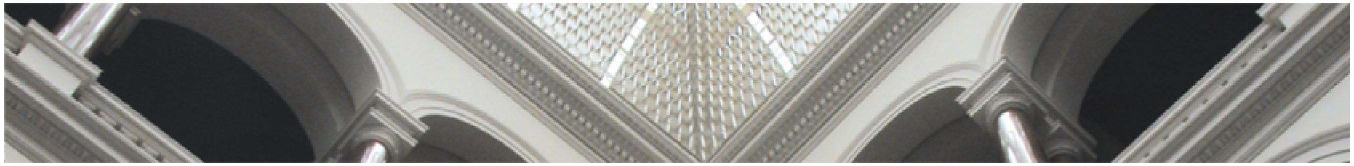
- **Google developed a new breed of storage and data processing systems**
  - aimed at cost-effective shared-nothing clusters built from commodity hardware

  - **Google File System (GFS)**: distributed, web-scale storage system
  - **MapReduce**: simple programming model and execution paradigm for parallel data processing

- Google's publications gave birth to **Apache Hadoop**, an open-source variant of these systems

- **huge ecosystem** evolved (Pig, Hive, Mahout, Jaql, Zookeeper, Hbase, ...)

- currently, **second generation of distributed data processing engines** coming up
  (Apache Spark, Apache Flink)



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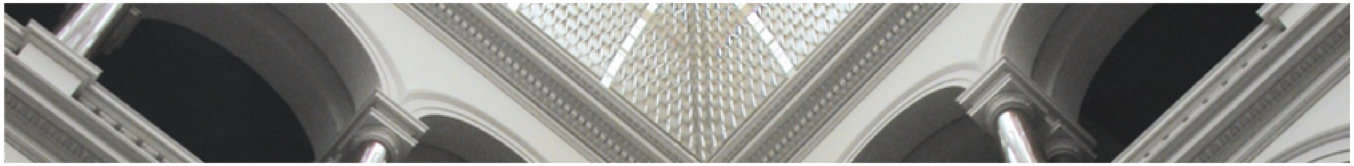
- **Distributed Shared-Nothing Filesystems**

- Abstractions for Massively Parallel Dataflow Processing
  - MapReduce
  - Parallelization Contracts & Iterative Dataflows
  - Resilient Distributed Datasets

- Discussion: Large-Scale Machine Learning on Dataflow Systems





# Distributed Shared-Nothing Filesystems

- most modern massively parallel data processing engines work on large datasets stored in distributed filesystems modeled after **Google's File System (GFS)**

- GFS is a **scalable, shared-nothing filesystem** for distributed data-intensive applications

- design decisions and goals:

  - **high fault tolerance** in clusters of **hundreds and thousands of machines,** high failure rates
  - storage of **large, multi-gigabyte files**
  - write workload: **large sequential writes**, no random access
  - read workload: **large streaming reads**, few small random reads
  - favoring high bandwidth for bulk reads over low latency access to individual files

# Distributed Shared-Nothing Filesystems

- GFS uses a **master-slave architecture**
- files are divided into **chunks** with a typical size of several dozen megabytes

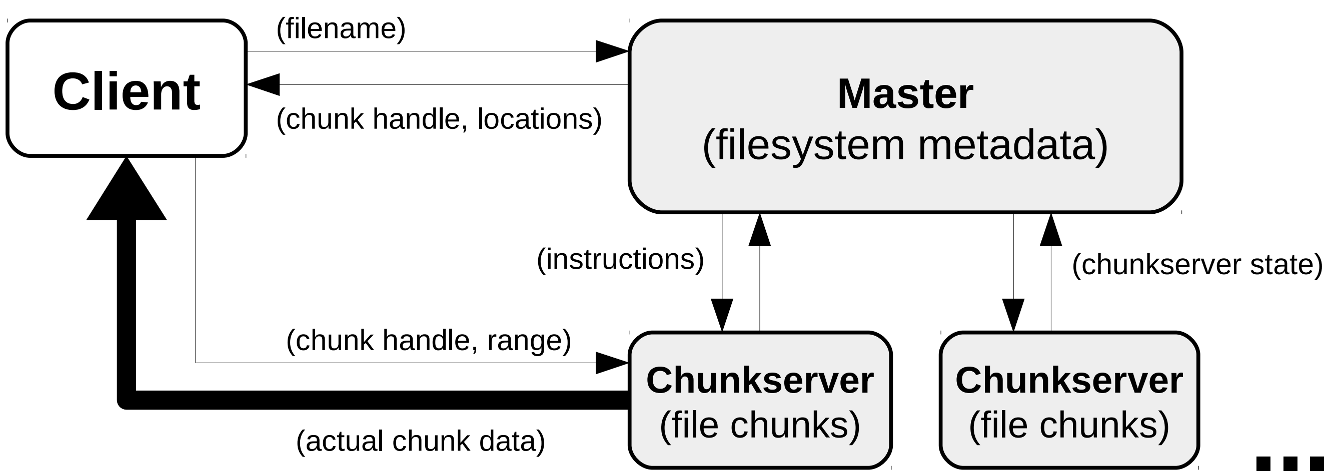
- **master server**
  - orchestrates file operations
  - store the metadata of the filesystem

- **slaves (chunk servers)**
  - store replicas of the chunks on their local disks

- **fault tolerance**
  - master maintains replicated write-ahead log of critical metadata changes
  - master regularly sends heartbeat messages to chunk servers
  - master initiates re-replication of chunks in case of  machine failures or data corruption

# Distributed Shared-Nothing Filesystems

- clients communicate with master for metadata only (e.g., location of chunks)
- master redirects client to chunk servers
- client directly conducts read and write operations on chunk servers



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# MapReduce

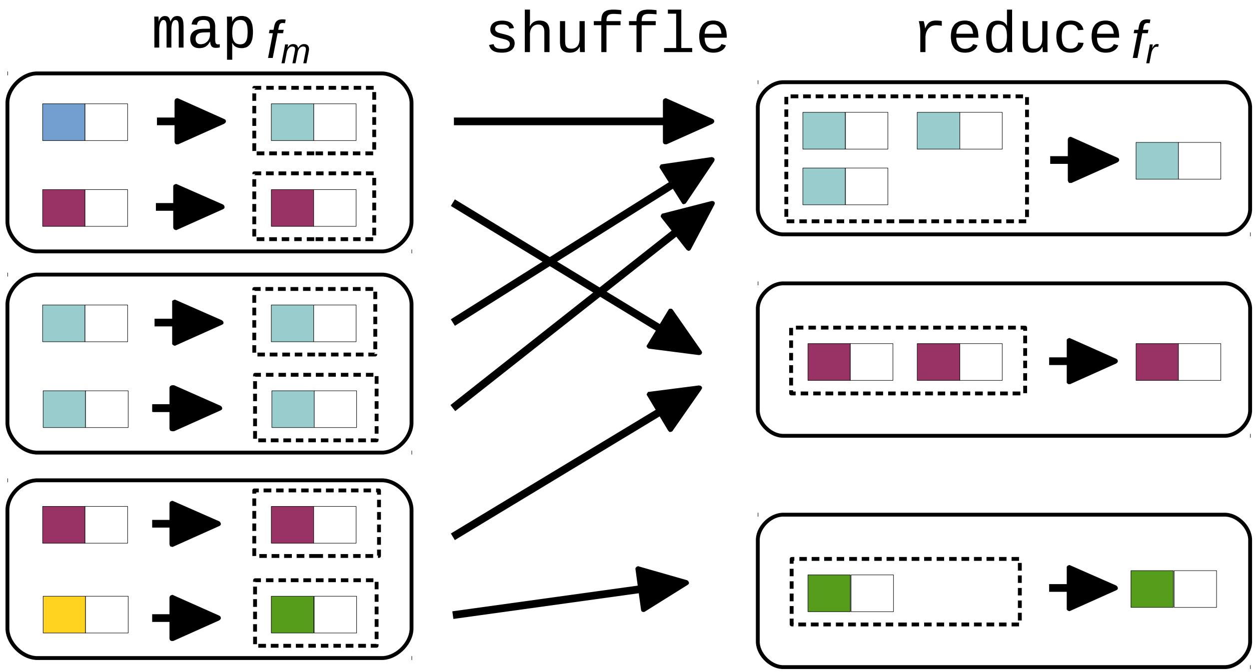
- programming model and paradigm for distributed data processing based on **two second-order functions map and reduce**
- program expressed by **two first order functions $f_m$ and $f_r$** which operate on key-value pairs

$$f_m : (k_1, v_1) \rightarrow list(k_2, v_2)$$

$$f_r : (k_2, list(v_2)) \rightarrow list(k_2, v_2)$$

- execution in three phases
  - **map-phase:** system individually applies $f_m$ to all input key-value pairs in parallel
  - **shuffle phase:** systems groups all key-value pairs emitted in the map-phase by key $k_2$
  - **reduce-phase:** system applies $f_r$ to all groups in parallel

# MapReduce



# Wordcount Example

- **Task:** count the number of occurrences of every word in a large set of documents with MapReduce
- proxy for many workloads related to large search engines
  (e.g. inverted index generation, calculation of tf-idf score)

```
function f_m (document):
  words = tokenize(document)
  for (word in words):
    emit(word, 1)

function f_r(word, counts):
  num_occurrences = sum(counts)
  emit(word, num_occurrences)
```

# WordCount

“Hello World”

“Hello Galaxy”

“Hello Moon”

“Hello World”

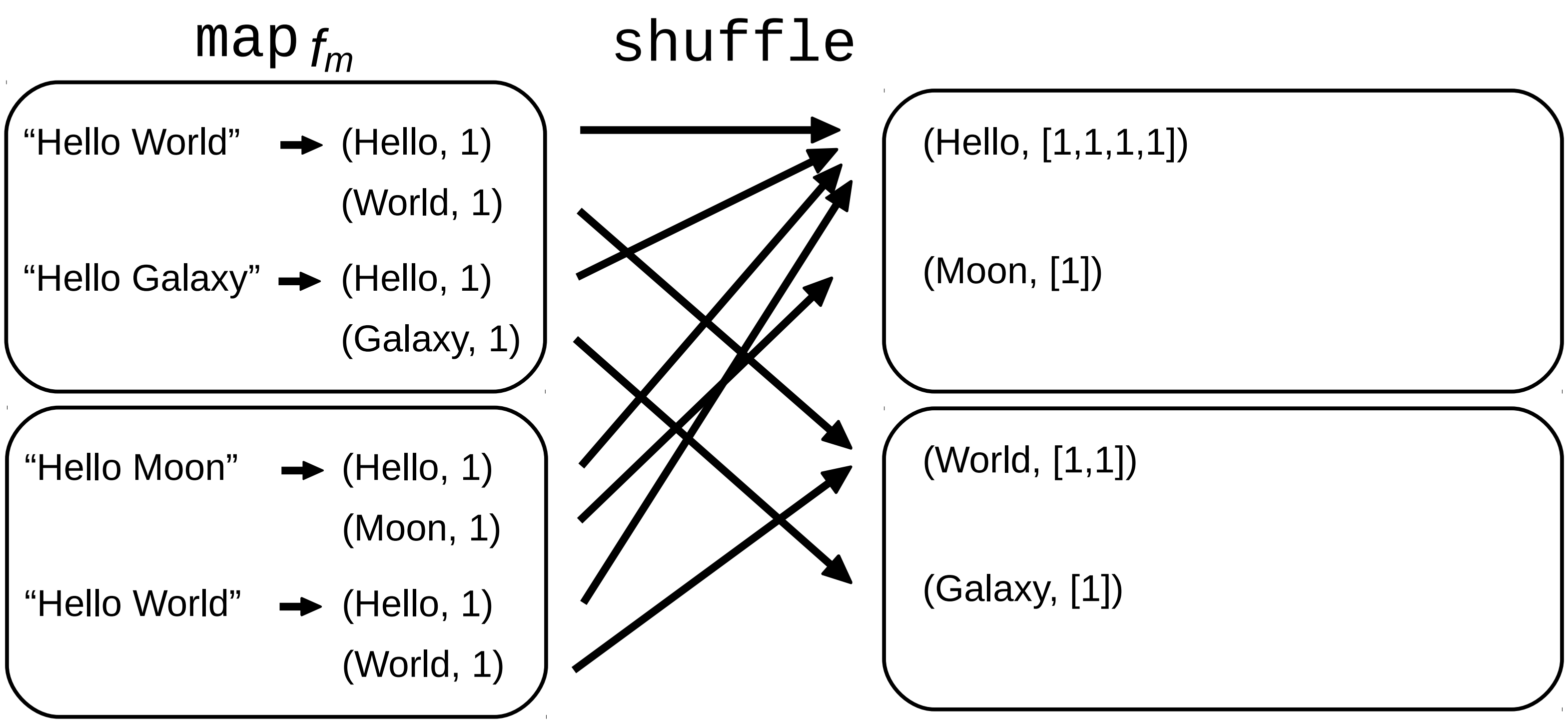
# WordCount: Map-Phase

map $f_m$

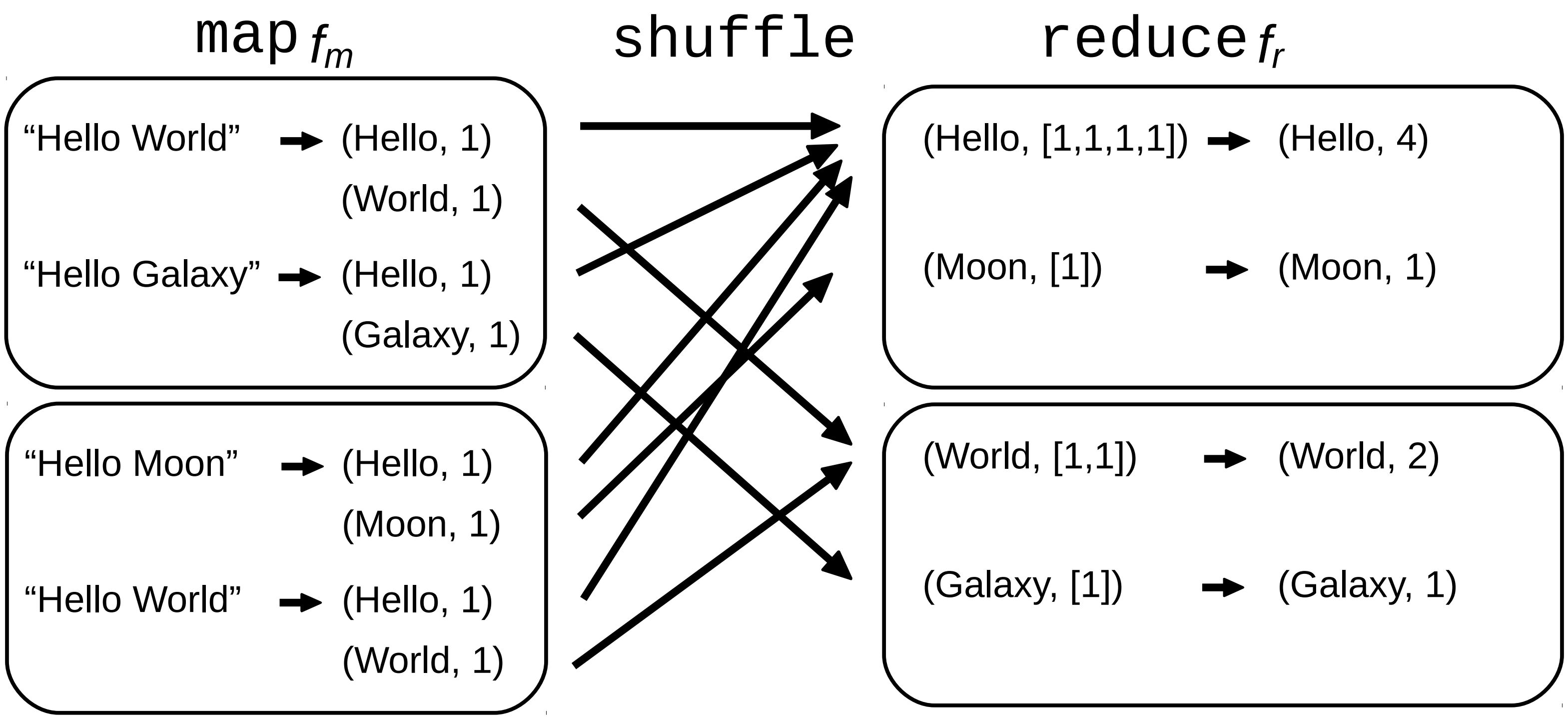
| | | |
|---|---|---|
| “Hello World” | → | (Hello, 1) |
| | | (World, 1) |
| “Hello Galaxy” | → | (Hello, 1) |
| | | (Galaxy, 1) |

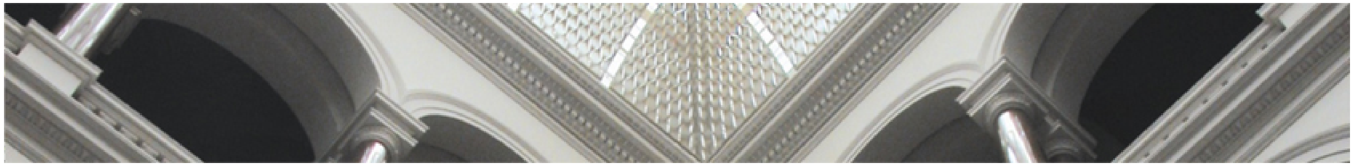
| | | |
|---|---|---|
| “Hello Moon” | → | (Hello, 1) |
| | | (Moon, 1) |
| “Hello World” | → | (Hello, 1) |
| | | (World, 1) |

# WordCount: Shuffle-Phase



# WordCount: Reduce-Phase







# MapReduce

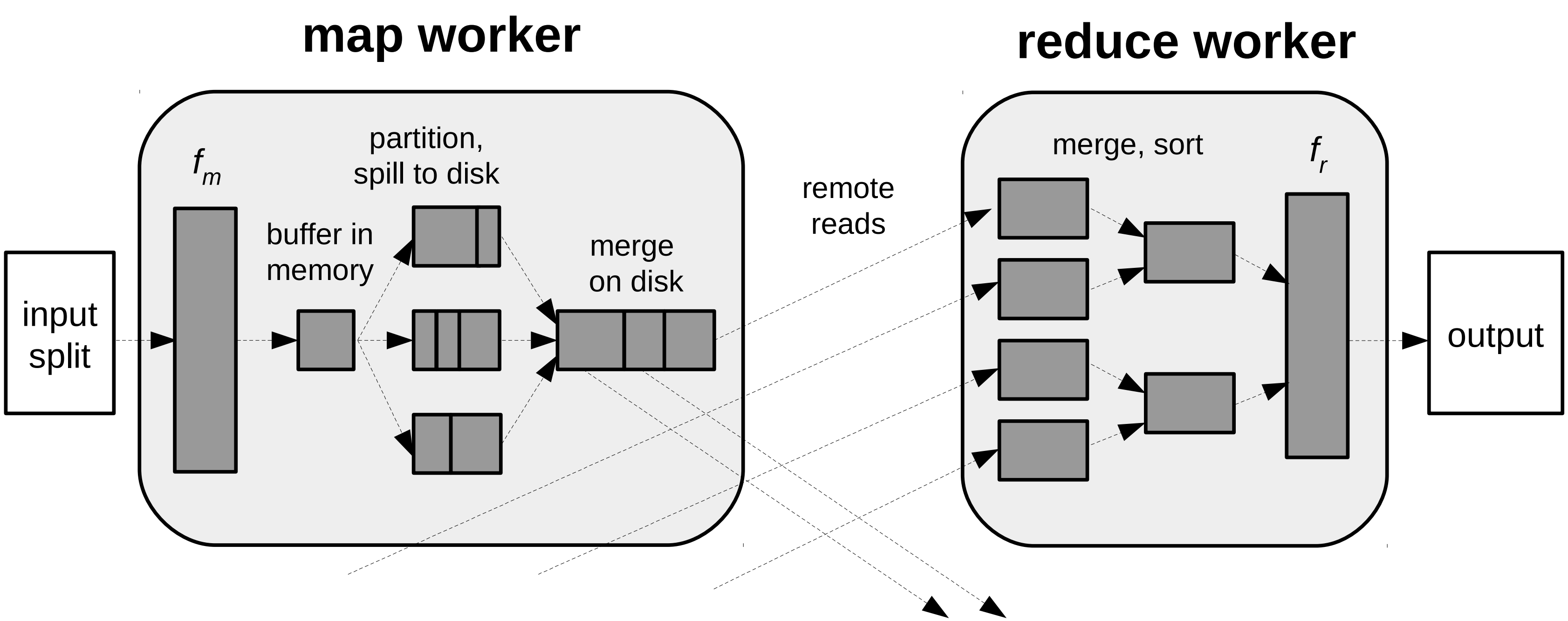
- system implemented with a **master-slave architecture** complementary to the architecture of the underlying distributed filesystem

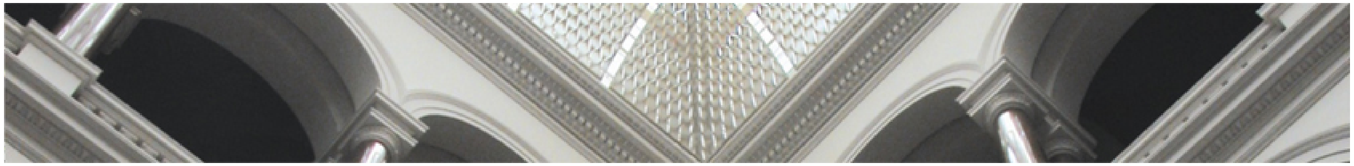
- **master** orchestrates system
  - **schedules individual map and reduce tasks** on slaves
  - monitors progress and reacts to failures
  - tries to exploit **data locality**

- **slaves execute map and reduce tasks**

- extremely simple way to achieve **fault tolerance**
  - regular heartbeat to check slaves presence, **rescheduling of failed map and reduce tasks**
  - atomic commits for intermediate map and reduce outputs to avoid corruption

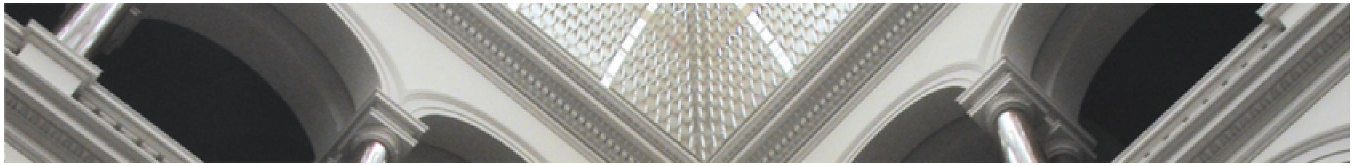
# MapReduce


map worker
reduce worker
input split
$f_m$
buffer in memory
partition, spill to disk
merge on disk
remote reads
merge, sort
$f_r$
output



# MapReduce

- drawbacks of MapReduce
  - **performance problems**
    - always uses **disk-backed execution**
    - **no global view of programs** consisting of many MR jobs (missing optimization potential)
    - **low performance for iterative computations** (e.g., no caching of loop-invariant data)
  - difficult to program
    - **no operators for combining multiple datasets** (e.g., joins)
    - very **low level interface**



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  - Resilient Distributed Datasets
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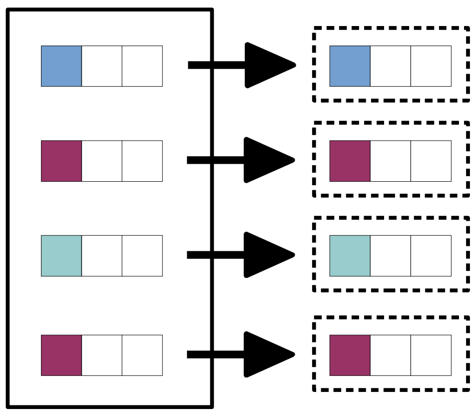
# Parallelization Contracts (PACTs) and Iterative Dataflows

- core abstraction of the **distributed data processing system Apache Flink** (formerly Stratosphere)

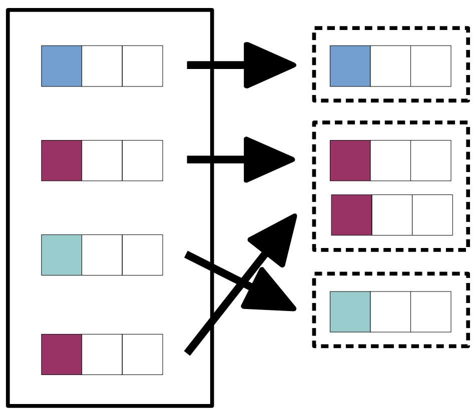
- main differences to MapReduce
  - **wide variety of operators** with support for combinining multiple datasets
  - **automatic optimization** of programs
  - dedicated **support for iterative computations**

- core operators (second-order functions, generalization of MapReduce)
  - **Map**
  - **Reduce**
  - **Cross** (cartesian product + UDF)
  - **Join** (equi join + UDF)
  - **CoGroup**

## Parallelization Contracts (PACTs) and Iterative Dataflows

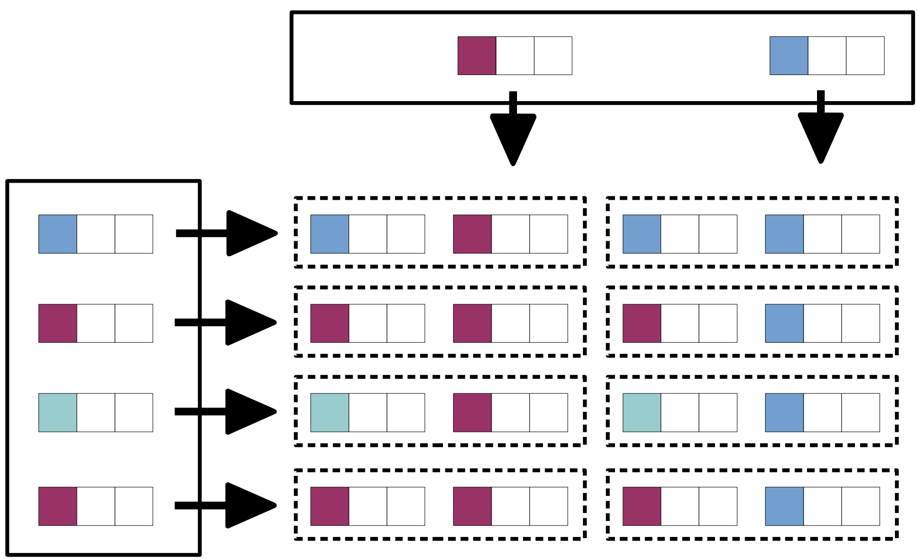


*map*



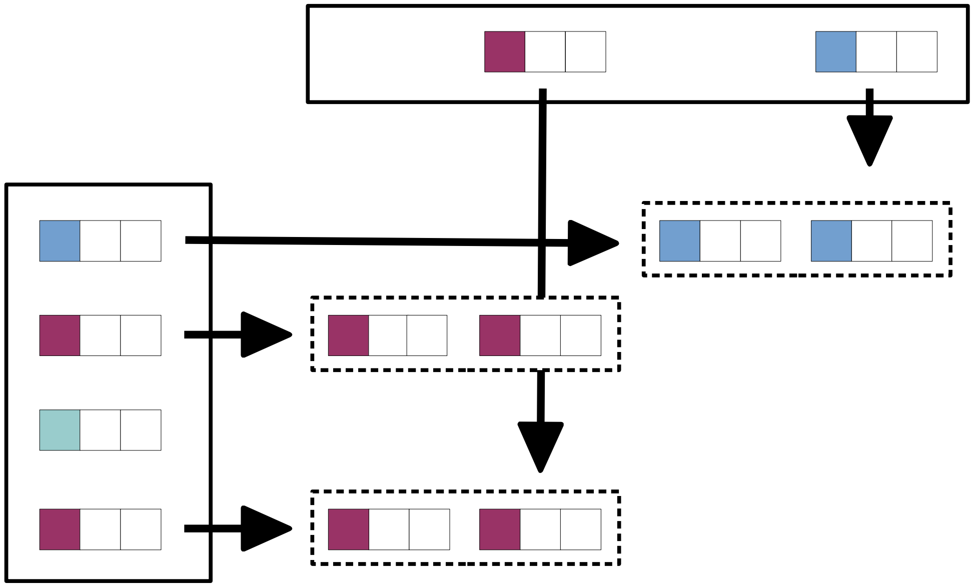
*reduce*

# Parallelization Contracts (PACTs) and Iterative Dataflows



***cross***

# Parallelization Contracts (PACTs) & Iterative Dataflows



***join***

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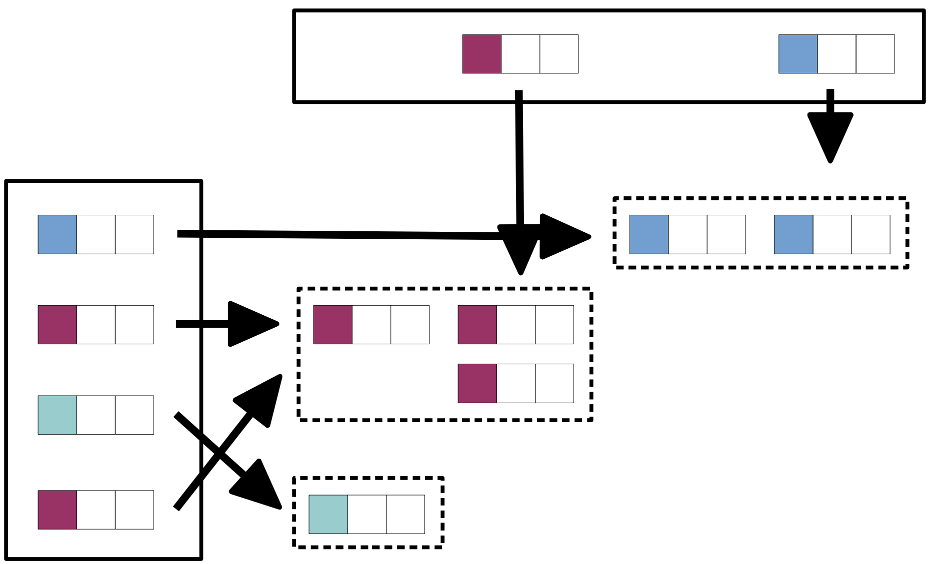
# Parallelization Contracts (PACTs) & Iterative Dataflows



***cogroup***

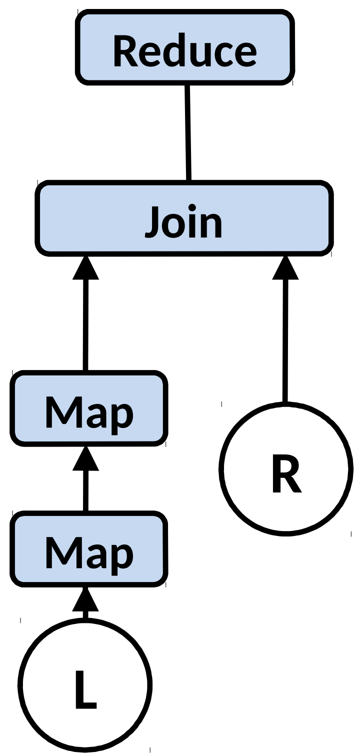
# Parallelization Contracts (PACTs) & Iterative Dataflows

- a **PACT program consists of a directed acyclic graph (DAG)**
  - vertices: PACT operators and their corresponding UDFs
    edges: represent exchange of data between operators

- **transformation of PACT program into a low level job graph** of the distributed processing engine Nephele

- **optimization** inspired by optimizers of parallel database systems
  - logical plan equivalences, cost models, interesting properties

- optimization much **more difficult than in relational setting**
  - non-fully specified semantics due to UDFs, hard to derive estimates for intermediate result sizes
  - no predefined schema present



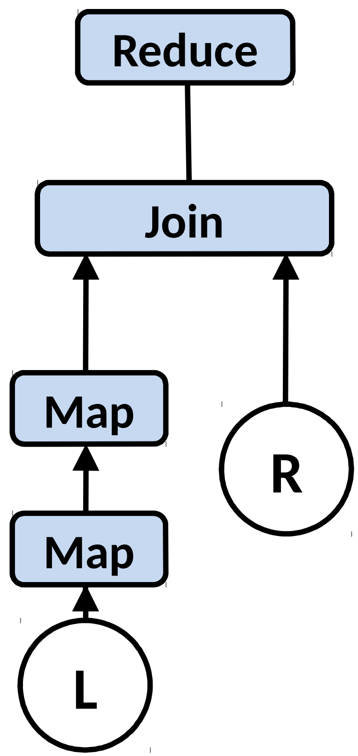
# Parallelization Contracts (PACTs) & Iterative Dataflows

- WordCount in Flink's Scala API

```
val counts = corpus
  .flatMap { document => document.split("\\W+") }
  .map { term => (term, 1) }
  .groupBy(0)
  .sum(1)
```

# Parallelization Contracts (PACTs) & Iterative Dataflows

- optimization conducted in two phases
  - **logical plan rewriting**
    - generation of **equivalent plans by reordering operators**
    - conditioned on conflicting value accesses and preservation of group cardinalities
  - **physical optimization**
    - **cost-based approach** to pick strategies for **data shipping** and **local operator execution** (e.g., broadcast- or repartition-based data shipping, sort- or hash-based join execution)
    - optimizer keeps track of **interesting properties** such as sorting, grouping and partitioning



# Parallelization Contracts (PACTs) & Iterative Dataflows

```
case class Order(id: Int, priority: Int, …)
case class Item(id: Int, price: Double, …)
case class PricedOrder(...)
```

```
val orders = DataSource(…)
val items = DataSource(…)

val filtered = orders filter { … }

val priced = filtered join items where { _.id } isEqualTo { _.id }
                      map { (o, i) => PricedOrder(o.id, o.priority, i.price) }

val sales = priced groupBy { p => (p.id, p.priority) } aggregate ({ _.price}, SUM)
```

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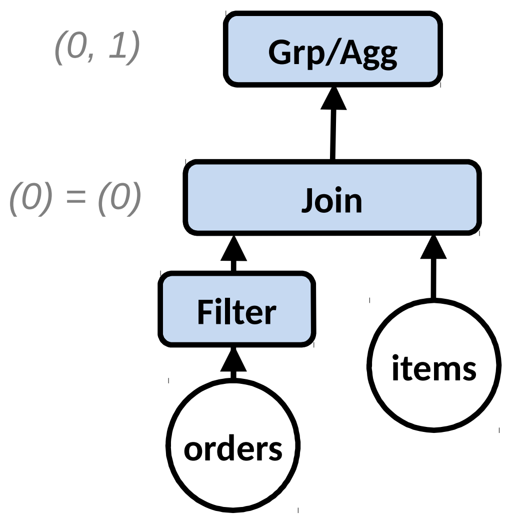

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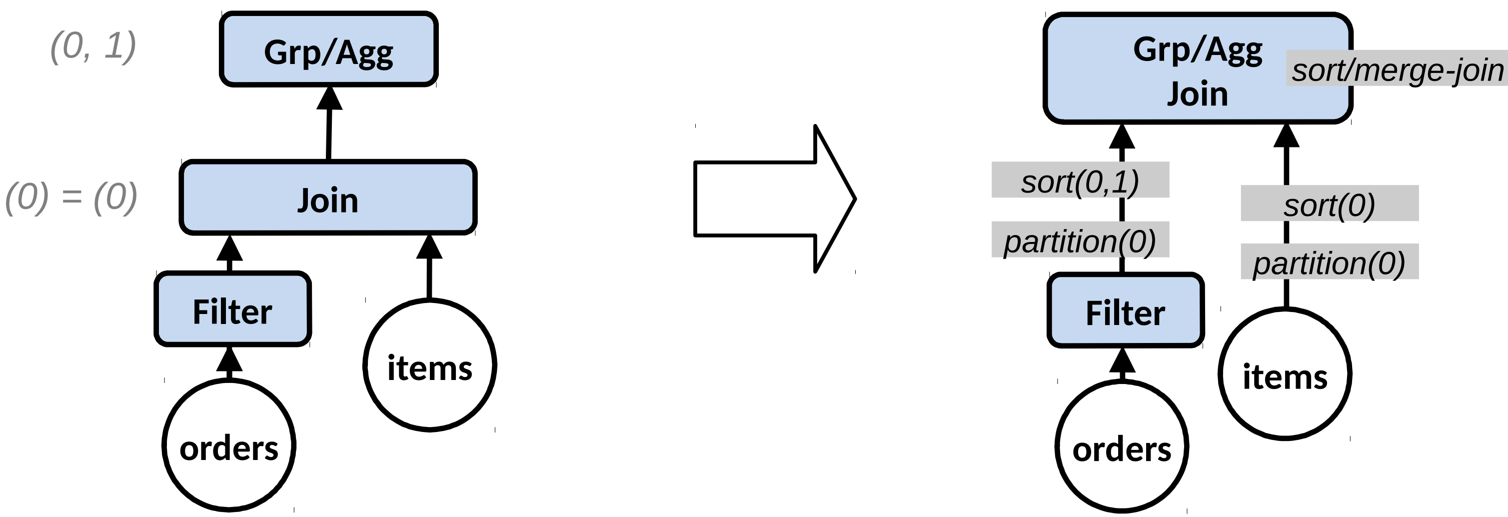
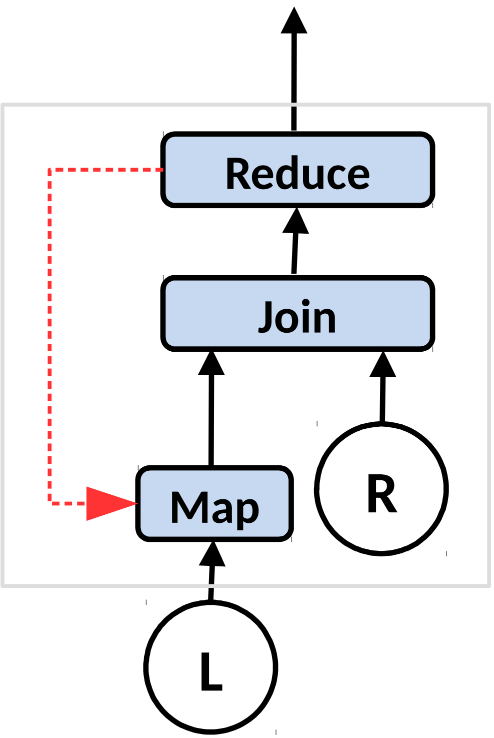


# Parallelization Contracts (PACTs) & Iterative Dataflows

- **efficient execution of iterative computations is crucial** for graph processing and machine learning workloads
- PACTs offer special support for embedding iterative computations into a DAG

- abstraction: iteration starts with initial state $s^{(0)}$, step function $f$ is repeatedly applied until **fixpoint $s^* = f(s^*)$** is reached

- **Iterative Dataflows**
  - user marks part of the DAG is iterative
  - **system repeatedly executes this part of the DAG** by feeding back the output of its last operator to its first operator until a convergence criterion is met *(bulk iterations)*
  - special mode for iterative computations that only recompute parts of the state in each iteration *(delta iterations)*



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  - **Resilient Distributed Datasets**
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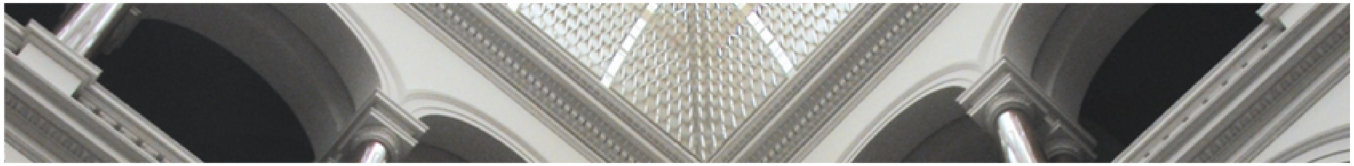
# Resilient Distributed Datasets (RDDs)

- core abstraction of the distributed **data processing engine Apache Spark**

- motivated by growing need to **efficiently execute applications that re-use intermediate results** multiple across multiple operations (e.g., machine learning, graph processing, ad-hoc data analysis)

- **distributed, shared-memory abstraction for MapReduce-like computations**
- **corse-grained transformations** rather than fine-grained updates for simple fault tolerance
- parallel computations on RDDs using a set of **high level operators** and UDFs (analogous to PACTs and MapReduce)
- system automatically handles parallelization, work distribution and fault tolerance



# Resilient Distributed Datasets (RDDs)

- **read-only, fault-tolerant, partitioned, parallel data structures**

- allow users to
  - **explicitly persist intermediate results** in memory
  - **control the partitioning** of the data for placement optimization
  - create new RDDs from stable storage or by transforming existing RDDs using a **rich set of operators**

- **immutability and bulk operations** enable
  - straggler mitigation through speculative execution
  - graceful out-of-core execution for bulk reads under memory pressure
  - scheduling based on data locality
  - **lineage-based recovery** for fault tolerance

# Resilient Distributed Datasets (RDDs)

- WordCount in Spark's Scala API

```
val counts = documents
  .flatMap(document => document.split("\\W+"))
  .map(term => (term, 1))
  .reduceByKey(_ + _)
```

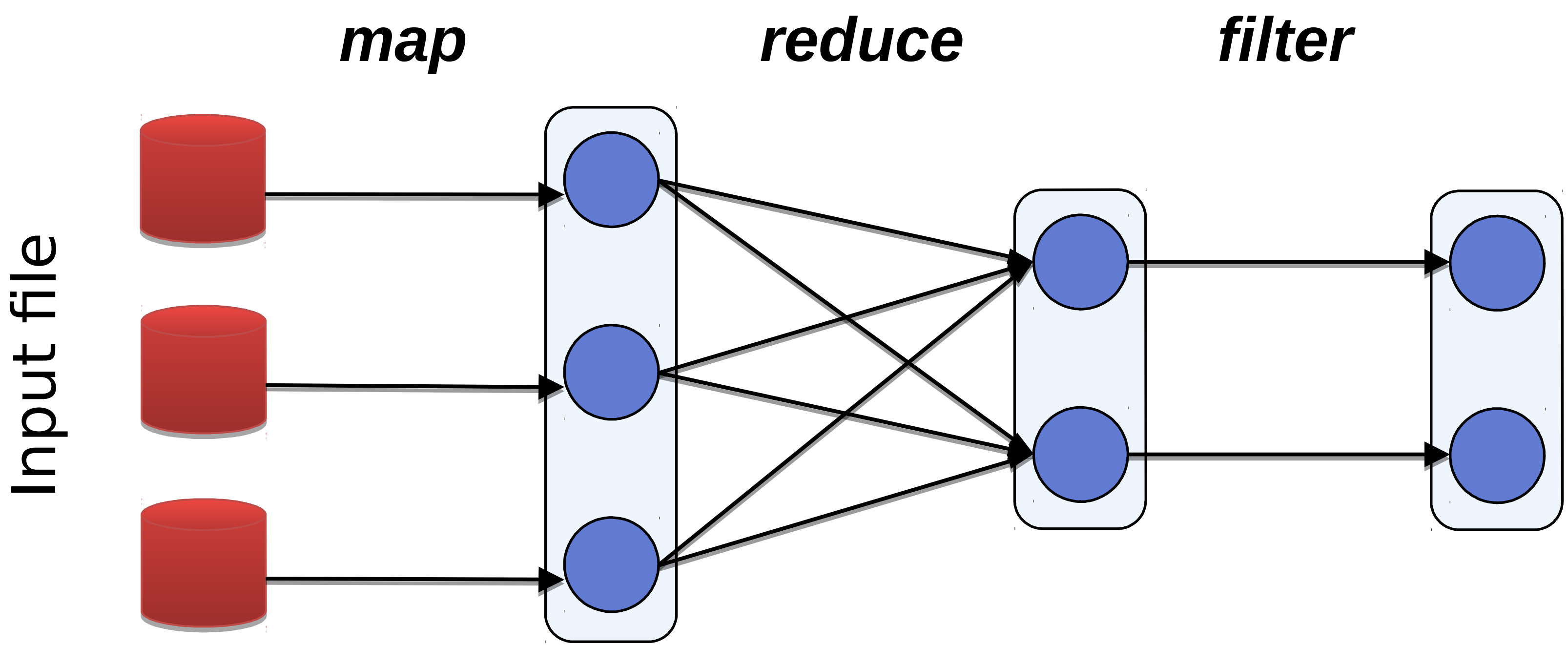
# Resilient Distributed Datasets (RDDs)

- main idea of **lineage-based recovery:** log transformations applied to data instead of the resulting data itself,

- **system represents lineage as a graph**
  - vertices: individual partitions of RDDs
  - edges: data dependencies of transformations between RDDs

- two kinds of dependencies
  - *narrow dependencies*: **one-to-one relation between partitions of parent and child RDD**, (map transformations or joins on co-partitioned data)
    → simply re-compute lost partitions in case of failures
  - *wide dependencies*: **all-to-all relation between partitions of parent and child RDD**, (transformations that require to re-partition the data)
    → require full re-computation of partitions of parent RDD in case of failures

# Lineage-based Recovery



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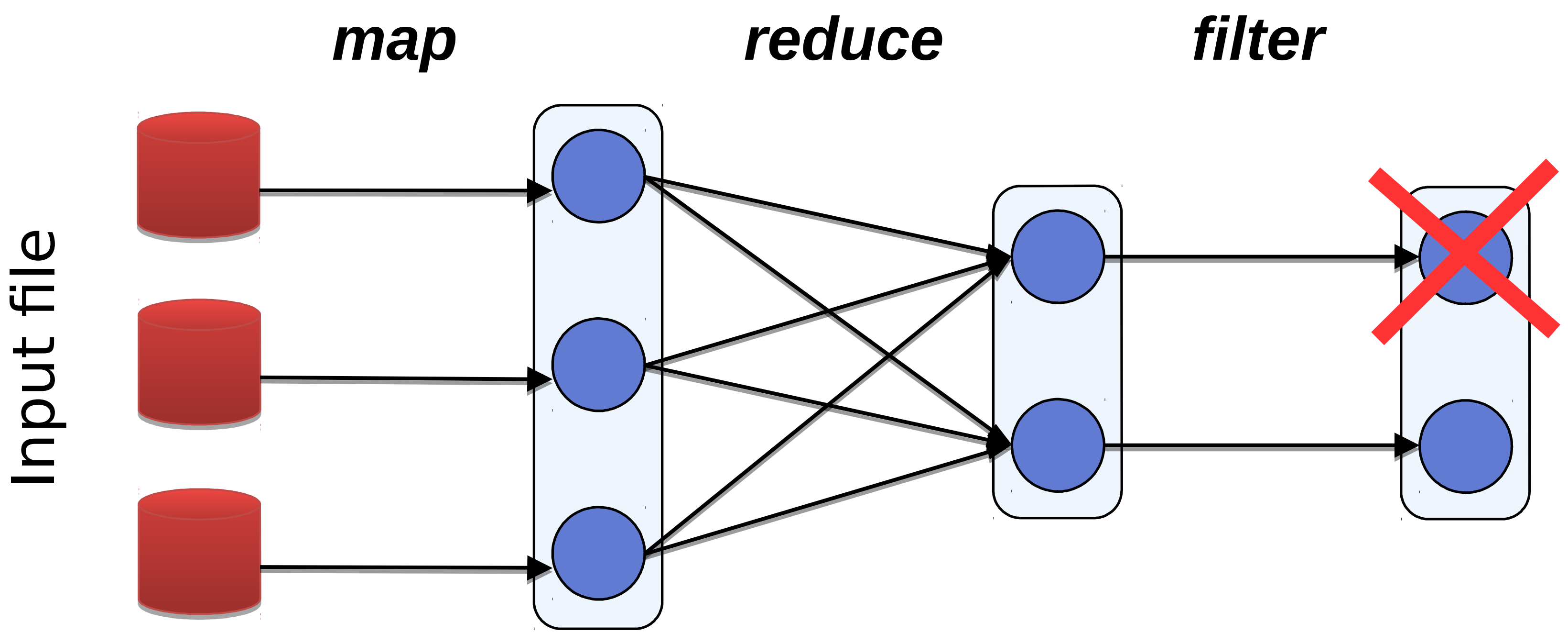

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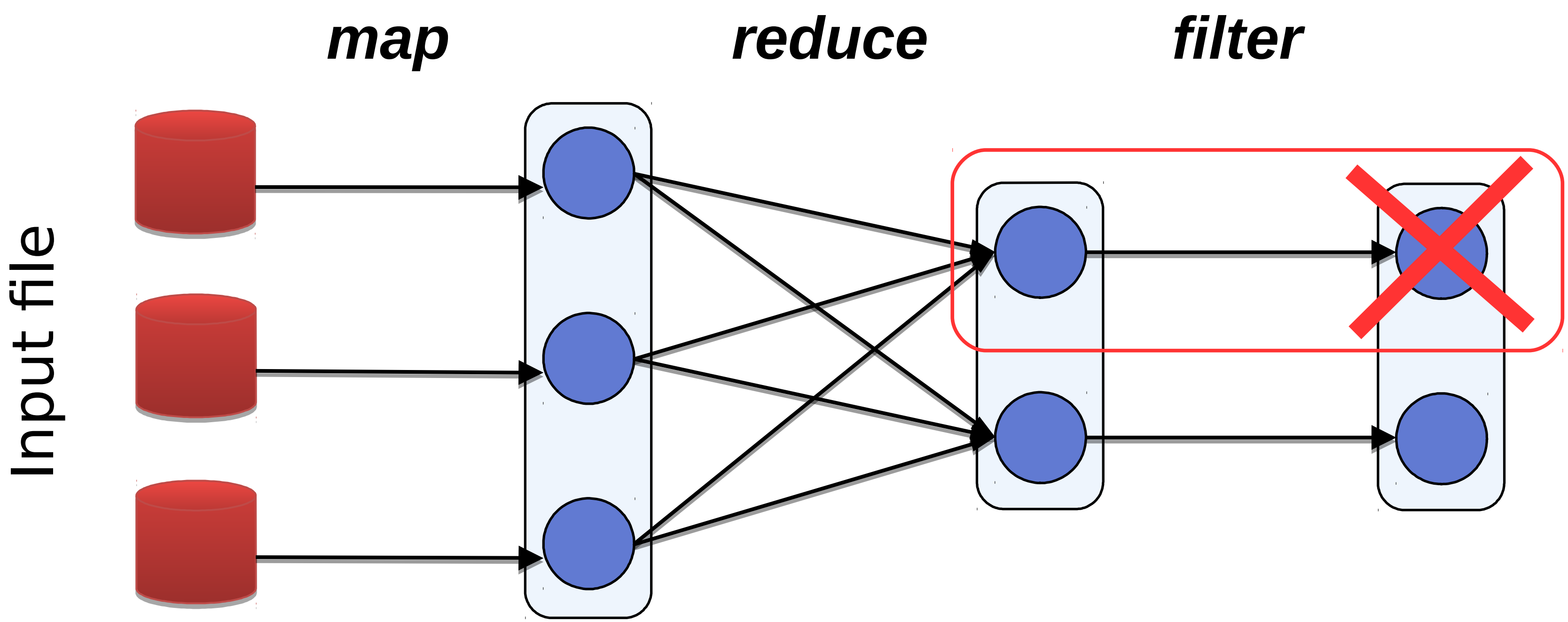

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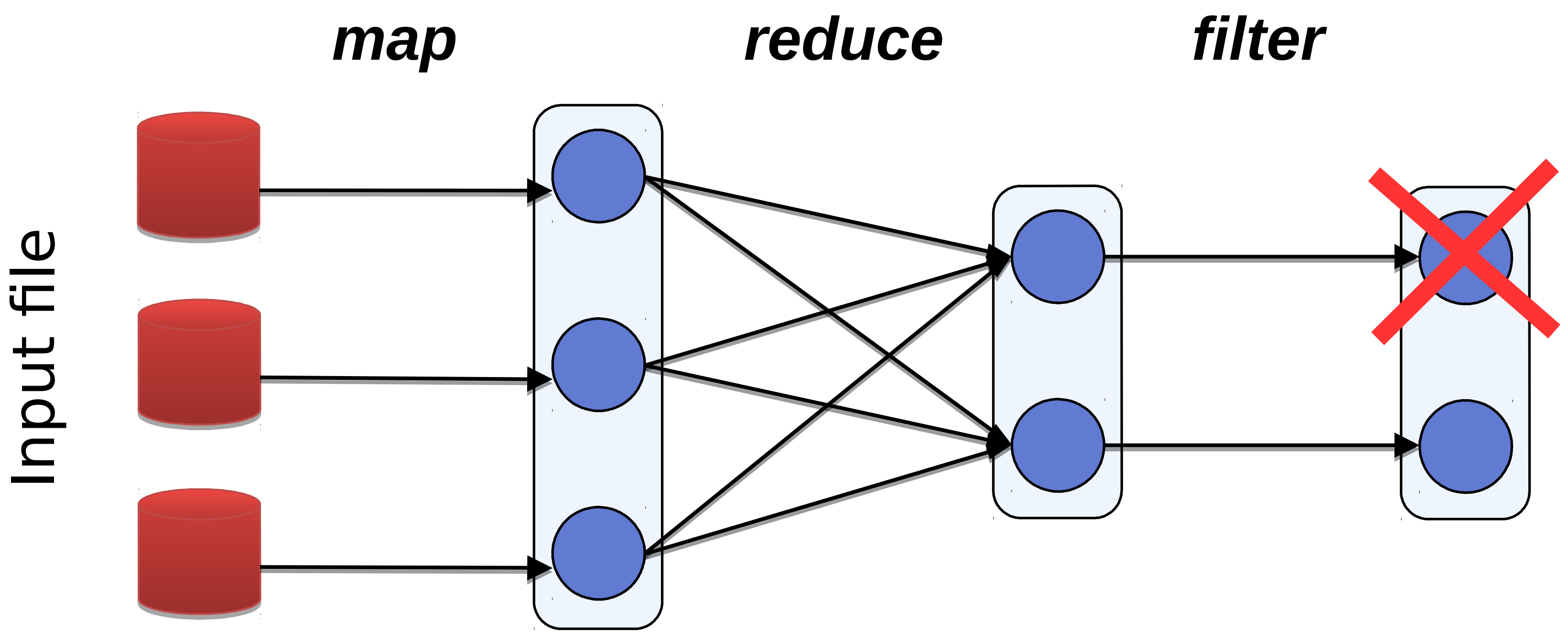

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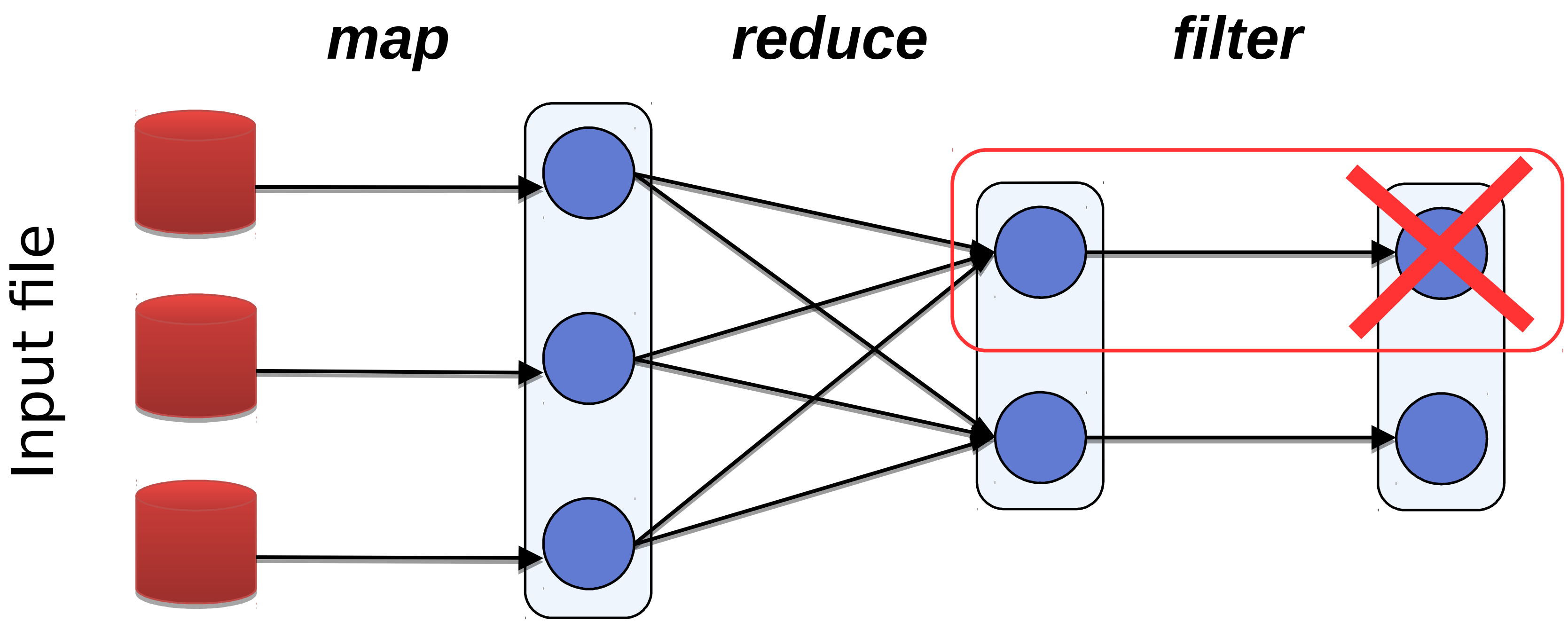

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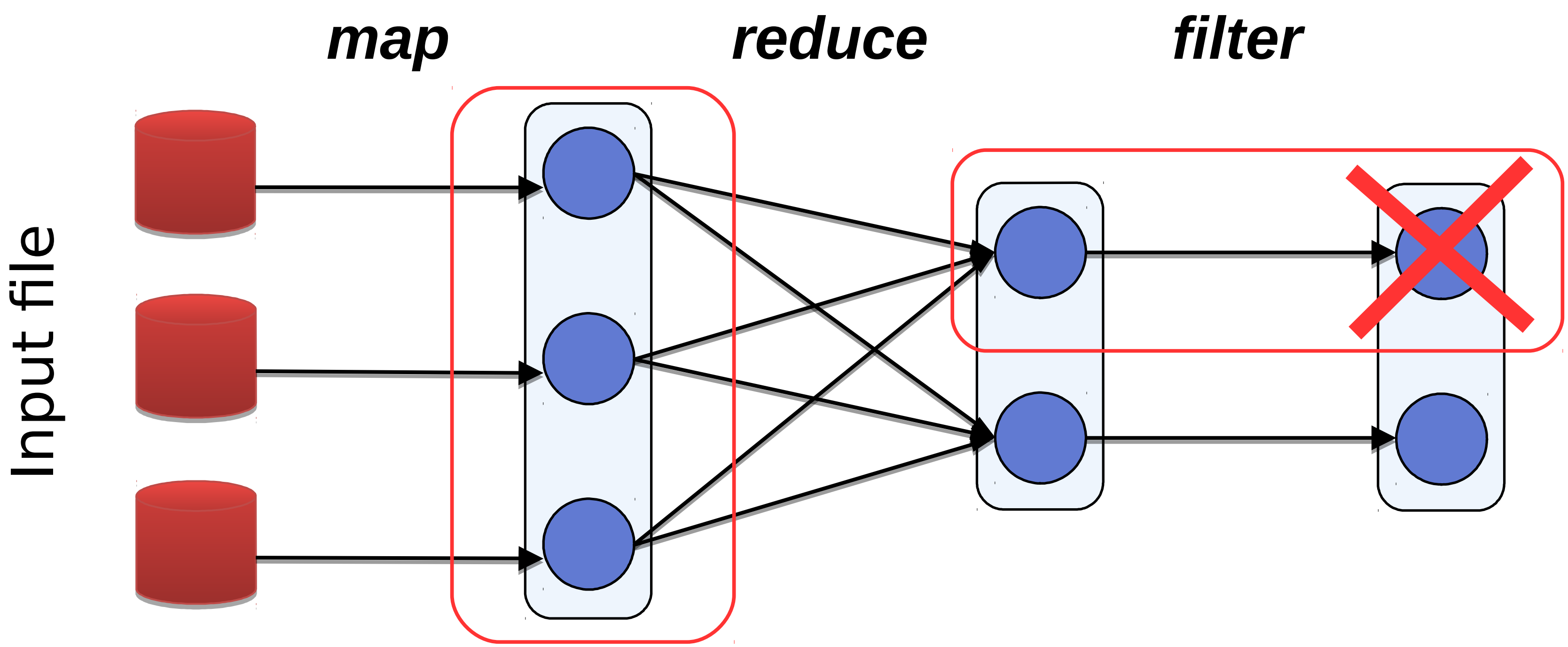

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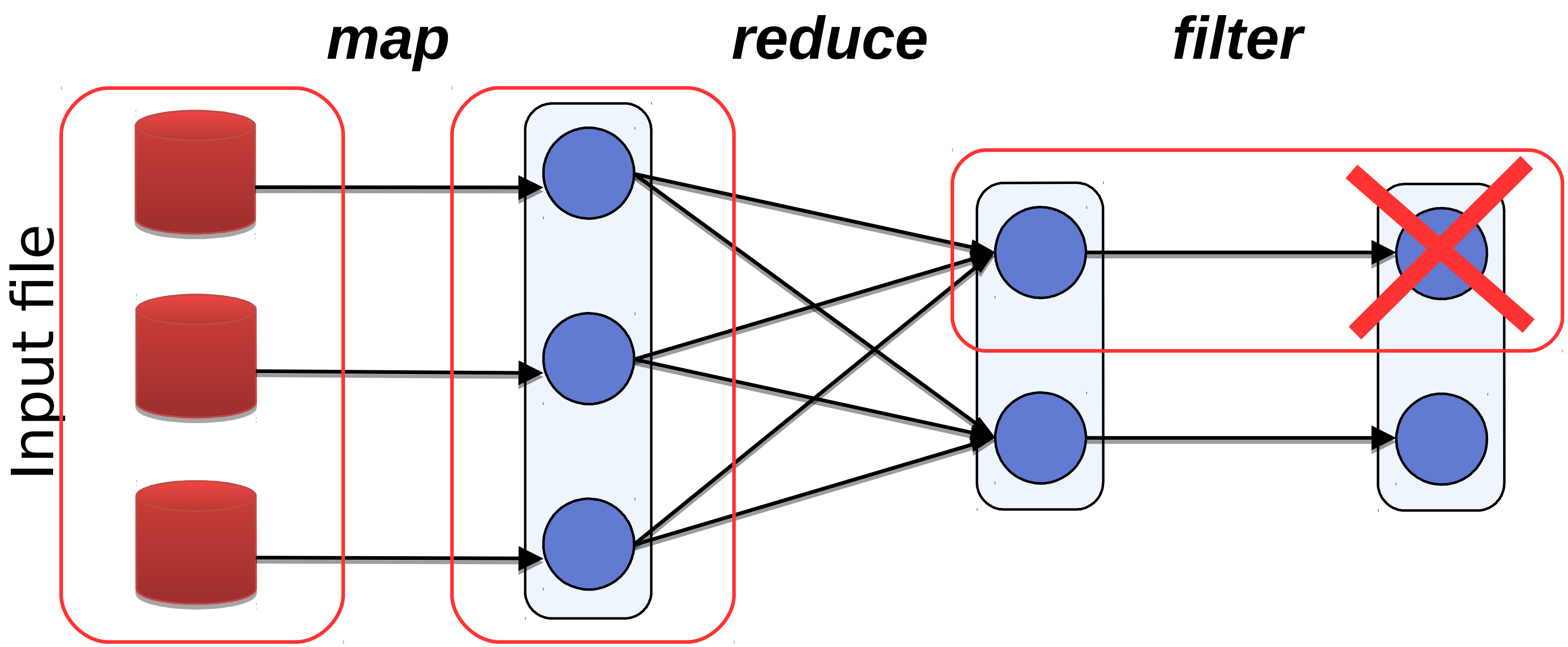

# Resilient Distributed Datasets (RDDs)

- **master-slave architecture** used for execution
- **driver program** connects to master and a cluster of workers, issues instructions to create and transform RDDs
- **execution is deferred** until an *action* is requested (an operation that either sends data to the driver program or requires to materialize an RDD)
- **driver tracks lineage**, workers store and process partitioned RDDs
- **execution divided** into *stages*: all pipelineable transformations with narrow dependencies until a transformation with wide dependencies is encountered

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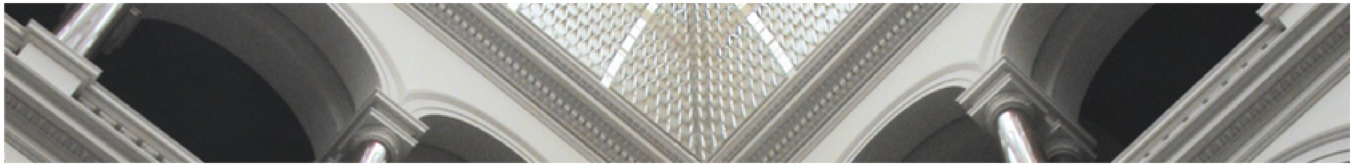

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- **parallel query processing solved** in the 1990s for relation data processing
- **rise of the internet** produces new data processing challenges:
  - large clusters built from commodity hardware for **scalability**
  - dirty, **semi-structured data** from the web
  - **new workloads** (search engines, machine learning, graph processing)

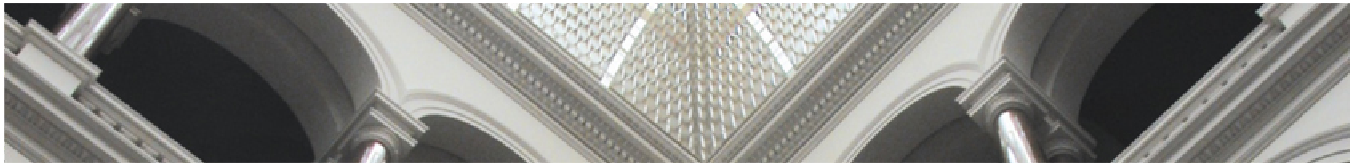
- distributed shared-nothing filesystems
  - designed to store extremely large datasets with **high fault tolerance guarantees**
  - exploitation of high sequential bandwidth of spinning disks

- MapReduce
  - **simple programming model and execution paradigm for distributed data processing**
  - based on **second-order functions** *map* and *reduce*
  - automatically handles parallelization, scalability, failures and concurrency

# Summary

- Parallelization Contracts & Iterative Dataflows
  - **generalization of the second-order function paradigm** of MapReduce
  - programs consist of **large dataflow graphs**
  - **automatic optimization**
  - dedicated abstraction for iterative computations

- Resilient Distributed Datasets
  - **distributed, shared-memory abstraction for MapReduce-like computations**
  - **corse-grained transformations**
  - simple fault tolerance via **lineage-based recovery**



# Further Reading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- Jeffrey Dean and Sanjay Ghemawat. *MapReduce: simplified data processing on large clusters.* Communication of the ACM, 51, pp. 107–113, 2008.
- Alexander Alexandrov, Rico Bergmann, Stephan Ewen,et al. *The stratosphere platform for big data analytics.* Journal on Very Large Data Bases, 23(6), pp. 939–964, 2014.
- Matei Zaharia, Mosharaf Chowdhury, Tathagata Das, et al. *Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing.* USENIX Conference on Networked Systems Design and Implementation, pp. 2–2., 2012.