REX: MACHINE LEARNING WITH SPARK

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CONTEXT

Moore's Law: computing power doubled every two years from 1975 to 2012. Nowadays, every two and a half year.

Rapid growth of datasets: internet activity, genomics, astronomy, censor networks, etc.

Data size trends: doubles every year according to IDC executive summary.

Data grows faster than Moore's law. How do we scale the training of a statistical model?

SCALING-UP

Keywords: *High Performance Computing (HPC), parallel computing*

Scale-up means using a bigger machine. Can lead to huge performance increase for medium scale problems

Very expensive, require specialized machines able to handle lots of processors and memory.

Challenges: side effects.

An expression has a side effects if it modifies some state or has an observable interaction with calling functions or the outside world.

Solution? Locks to limit access to resources, which ensures that only one thread is accessing a specific resource all at once.

Some rare algorithms, such as Hogwild!, exploit side effects to improve performance.

Does not scale at some point to very big datasets.

WAIT... WHAT IS BIG? SOME FIGURES...

Big data examples:

- facebook daily logs: 60TB
- 1000 genomes project: 200TB
- Google web index: 10+ PB

Cost of 1Tb of storage: ~$35

Time to read 1Tb from disk: 3hours (100MB/s)

Data is streamed from the disk to the different layers of memory.

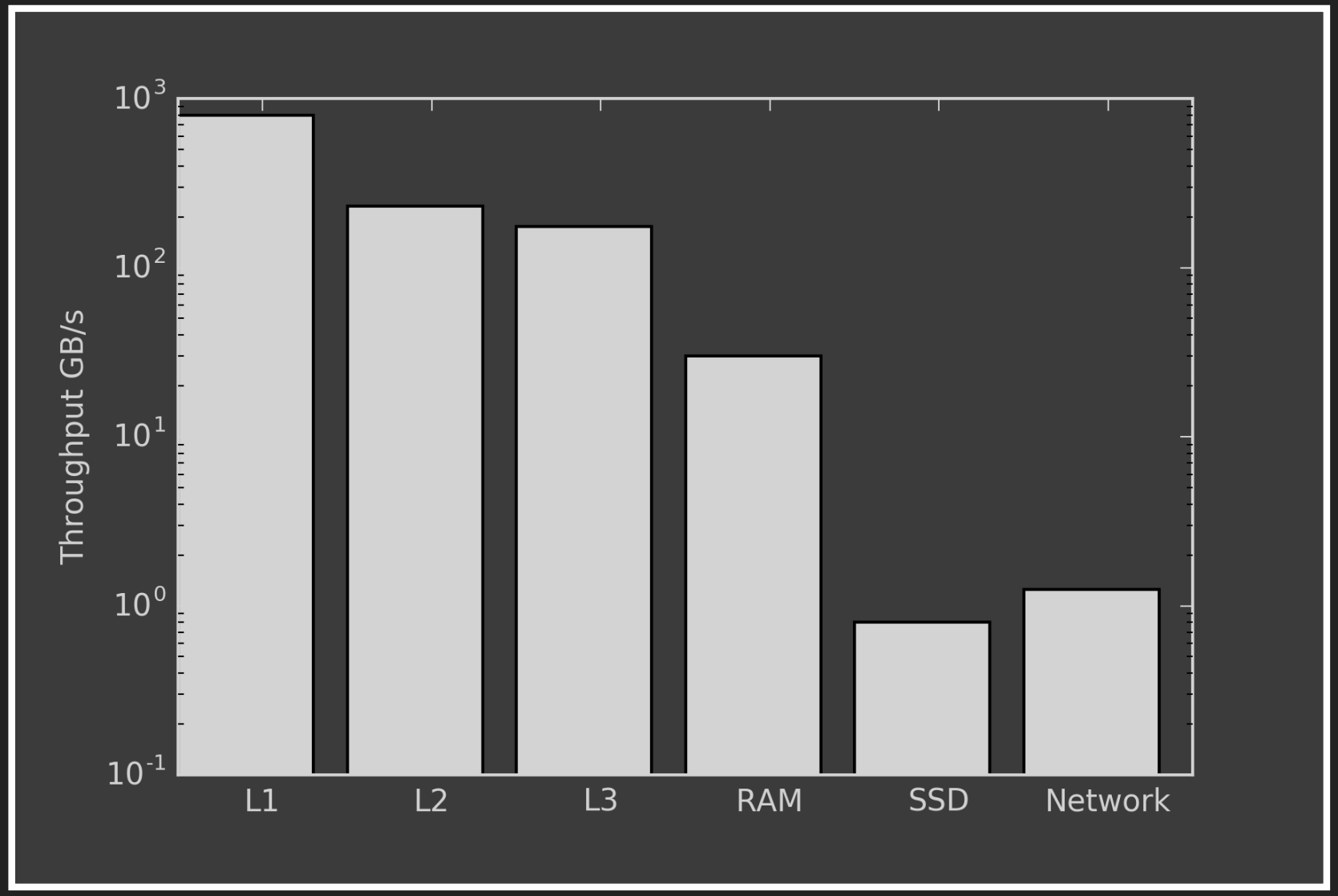
Problem: disks cannot be read in parallel... Solution: Use several disks.

Limited number of disks inside one machine? Use several machines: distributed computing!

When one machine can no longer process or even store all the data, use distributed computing.

At what data size distributed computing starts to be useful? *Very dependent on the task, the data quality, and the data type*

e.g. Full Movielens dataset, 22m ratings, 240k users, 635Mb.



SCALING-OUT

Keywords: *distributed computing*

Scale-out means using many small machines.

Uses commodity hardware: cheap, common architecture i.e. processor + RAM + disk.

Problem: dealing with network computation adds software complexity.

Challenges:

- Scheduling: How to split the work across machines? Must consider network, data locality as moving data may be very expansive.
- Reliability: How to deal with failure? Commodity (cheap) hardware fails more often. At Google, 1-5% hard drive failure per year. 0.2% DIMM failure/year.
- Uneven performance of the machines: some nodes (*stragglers*) are slower than others.

PERFORMANCE MEASURES

How to evaluate the performance of a scaling? Let T_J be the time complexity of an algorithm using J processing elements.

$$\text{Efficiency} = \frac{T_1}{NT_N} \leq 1$$

Provides an indication of the effective utilization of all the processing units.

$$\text{Speedup} = \frac{T_1}{T_N} \leq N$$

Measures the benefits of using parallelism.

Strong scaling:

How to compute faster? Relevant when the task is CPU-bound.

Fixed problem size, increased number of processing elements.

In such case, speedup and efficiency can be used to measure the performance gain and tune the number of processing units.

Weak scaling:

How to compute using more data? Relevant when the task is I/O-bound.

Problem size (workload) assigned to each processing element stays constant. Additional processing elements are used to solve a larger total problem.

In this case, efficiency does not make sense, as we assume a constant workload.

TOOLS

In practice, softwares such as Spark or HadoopMR are in charge of these problems.

They are *distributed compute engines*, i.e. softwares that ease the development of distributed algorithms.

They run on clusters, managed by a resource manager, such as YARN or Mesos

In short, resource managers ensures that the different tasks running on the cluster do not try to use the same resources all at once.

HADOOP MAPREDUCE

Hadoop is older, more enterprise-grade codebase (e.g. security with Kerberos)

Good for data crunching (e.g. data cleaning, ETL: Extract, Transform, Load).

Problems: lots of disk I/O

For Machine Learning problems, this is a real problem as iterative algorithms need to access such as gradient values, parameters vector, etc. very often.

SPARK

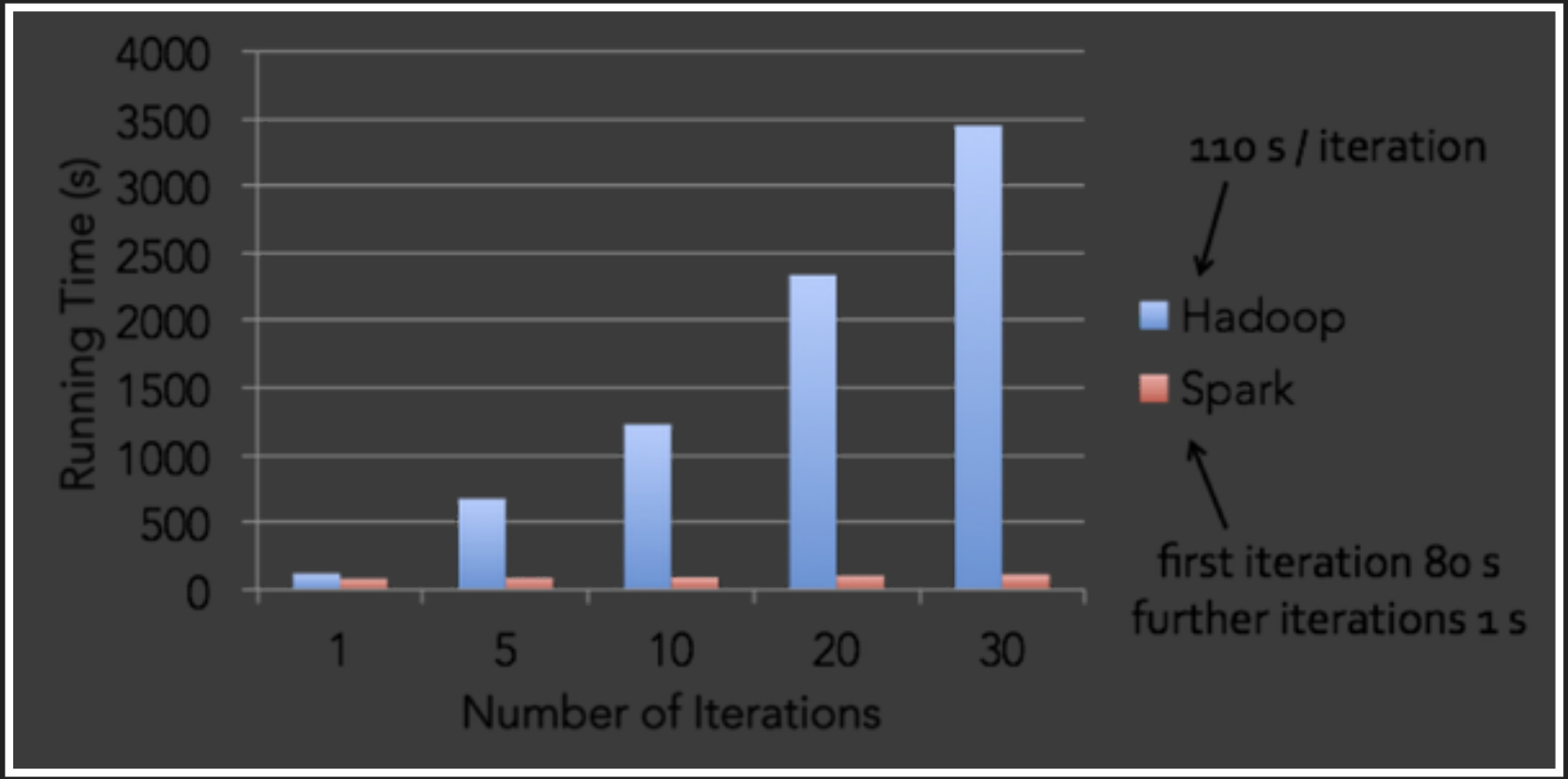
HadoopMR is designed for acyclic data flow models while Spark handles cyclic (e.g. iterative) data flows.

Advantage of Spark over HadoopMR ?

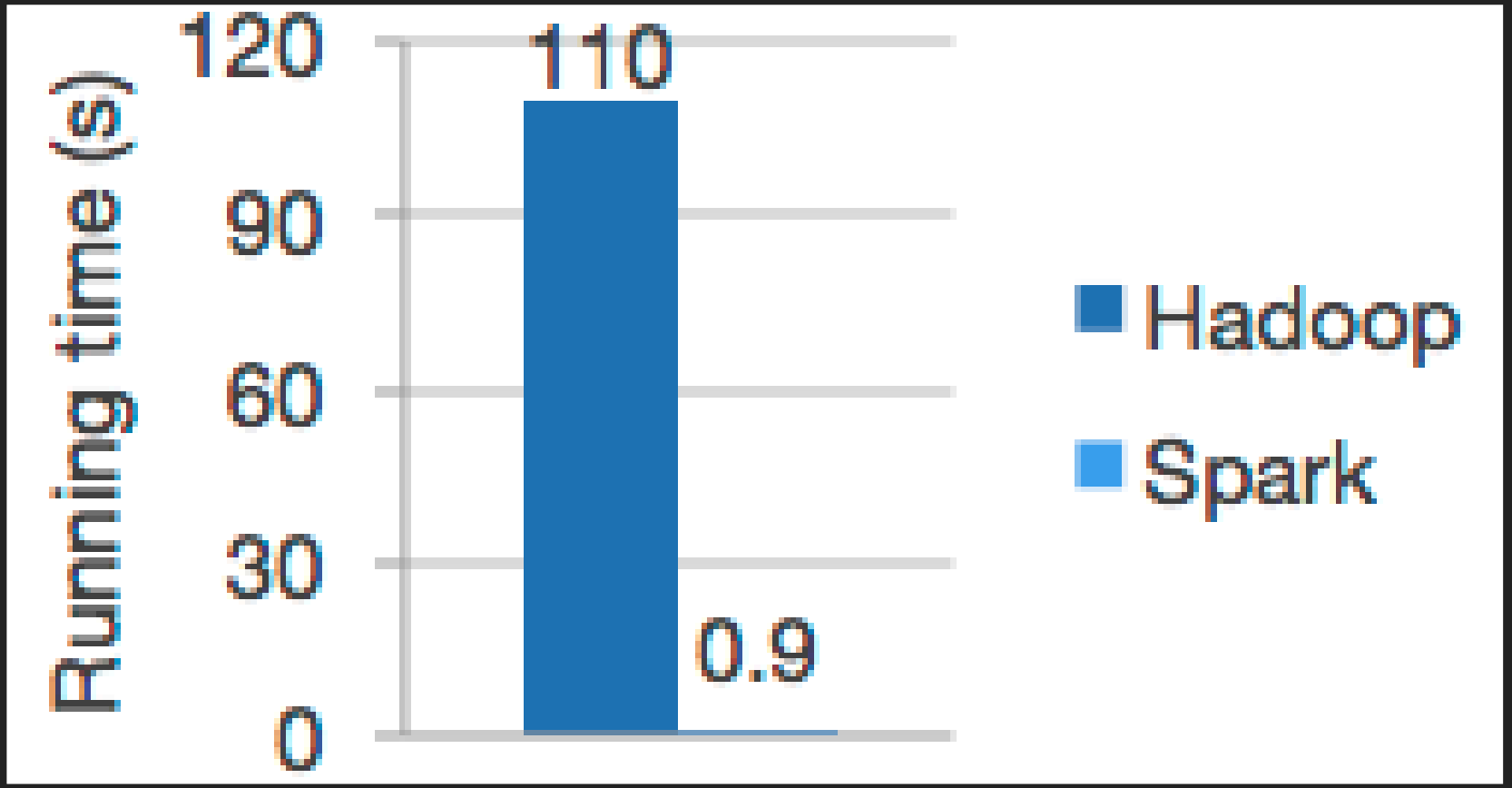
- Use RAM, i.e. fast iterative computations
- lower overhead for starting jobs
- simple & expressive (scala, python + interactive shell)
- higher level libraries (SparkSQL, SparkStreaming, MLlib, GraphX)

Requires servers with more CPU and more memory (more expensive), but still quite cheap compared to HPC.

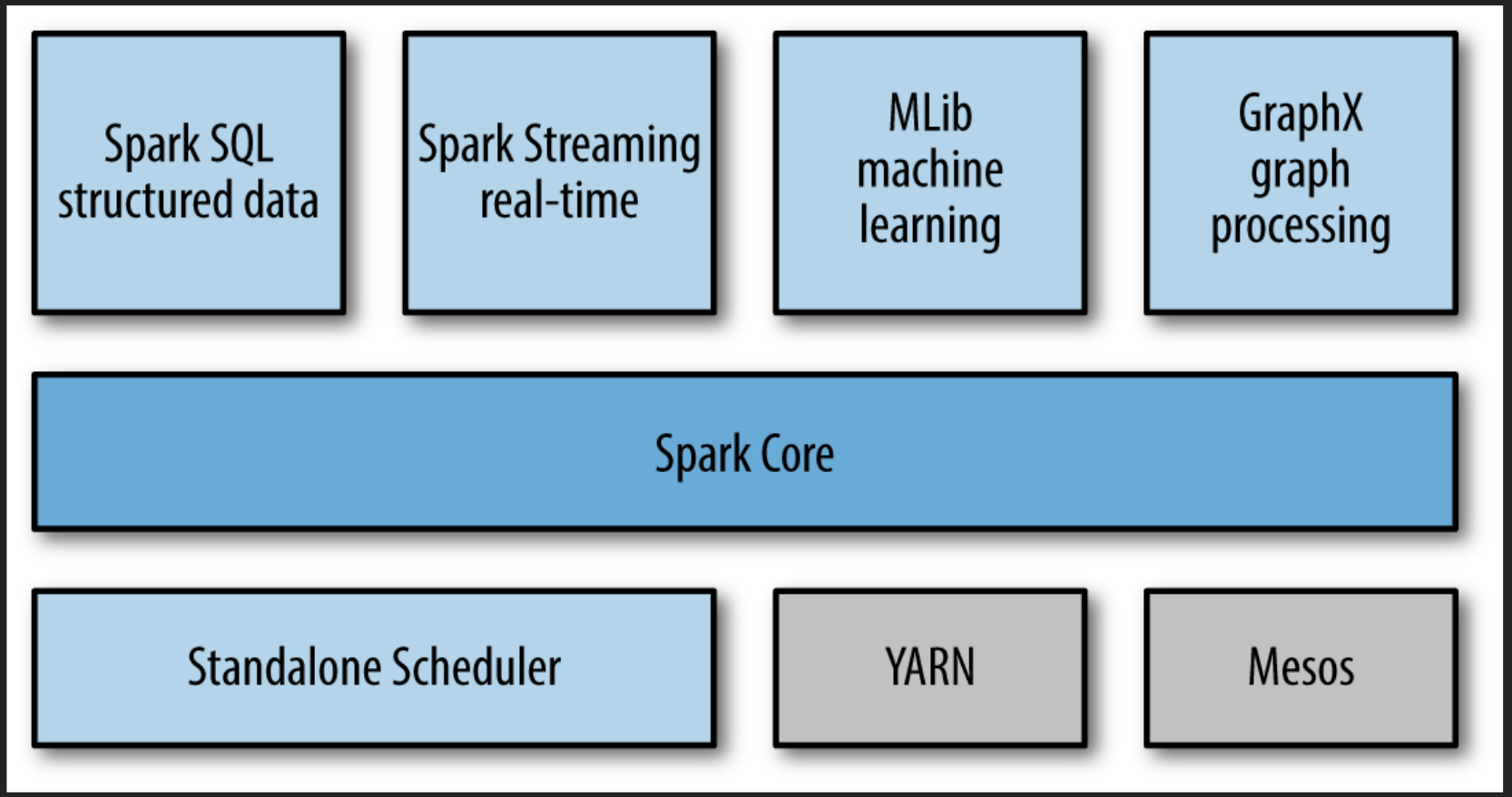
ITERATION SPEED COMPARISON



LOGISTIC REGRESSION SPEED COMPARISON



SPARK STACK


Spark SQL
structured data
Spark Streaming
real-time
MLib
machine
learning
GraphX
graph
processing
Spark Core
Standalone Scheduler
YARN
Mesos

MACHINE LEARNING

Most of the time, doing machine learning is roughly trying to minimize a function.

Iterative algorithms: EM algorithms, gradient descents, etc.

Distribution is hard: Try to minimize the number of communication rounds.

Less communication has a cost: slower convergence, sometime bad precision (i.e. $1e^{-5})

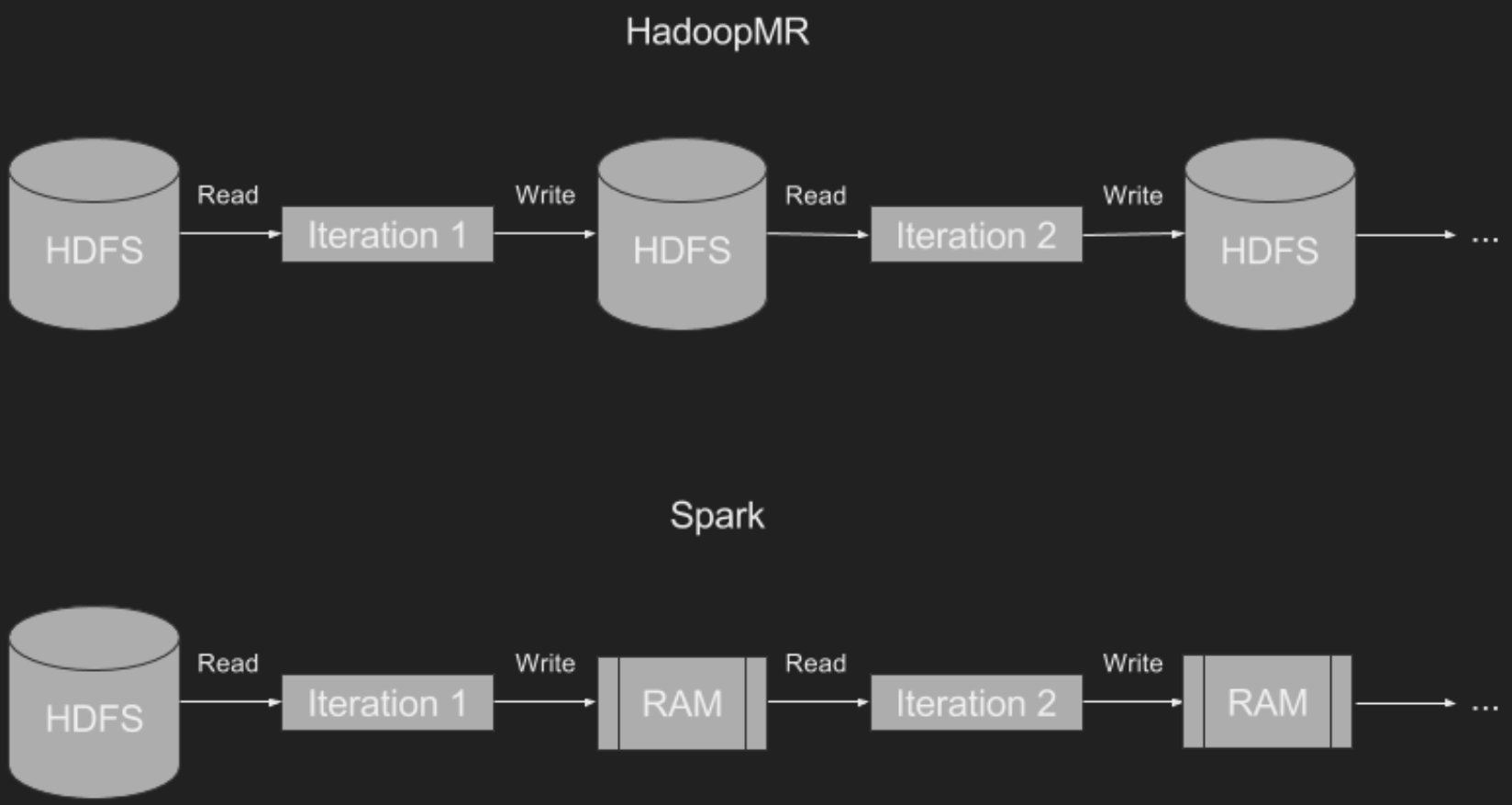
MACHINE LEARNING

Begin the optimization with a low communication algorithm, then use a batch algorithm.

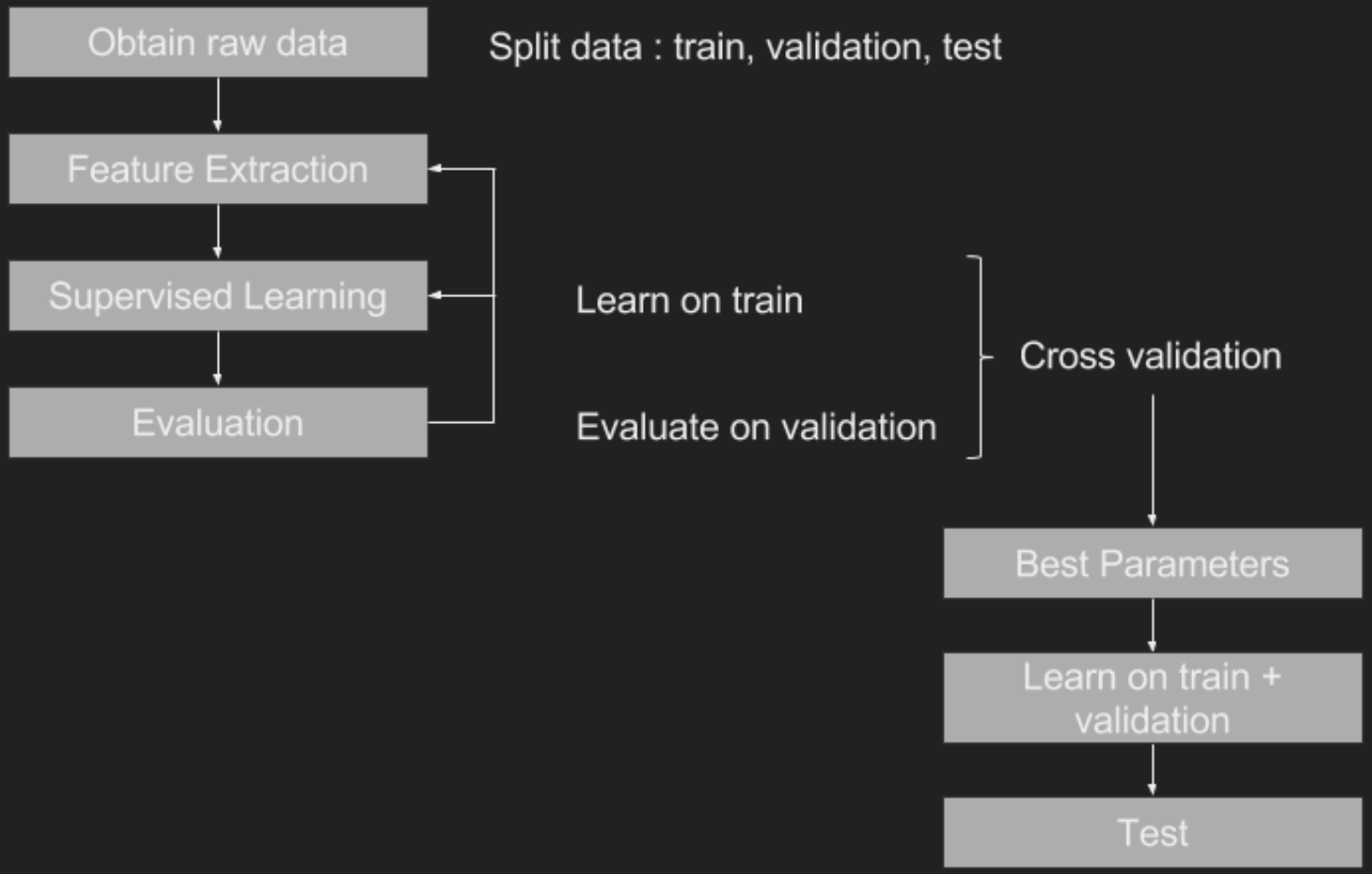
At some point each iteration require a pass on the whole dataset and a communication round.

In all case: you want to use RAM when using iterative algorithms

ITERATIVE JOBS



BASIC SUPERVISED LEARNING PIPELINE




THANKS!
ANY QUESTION?
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