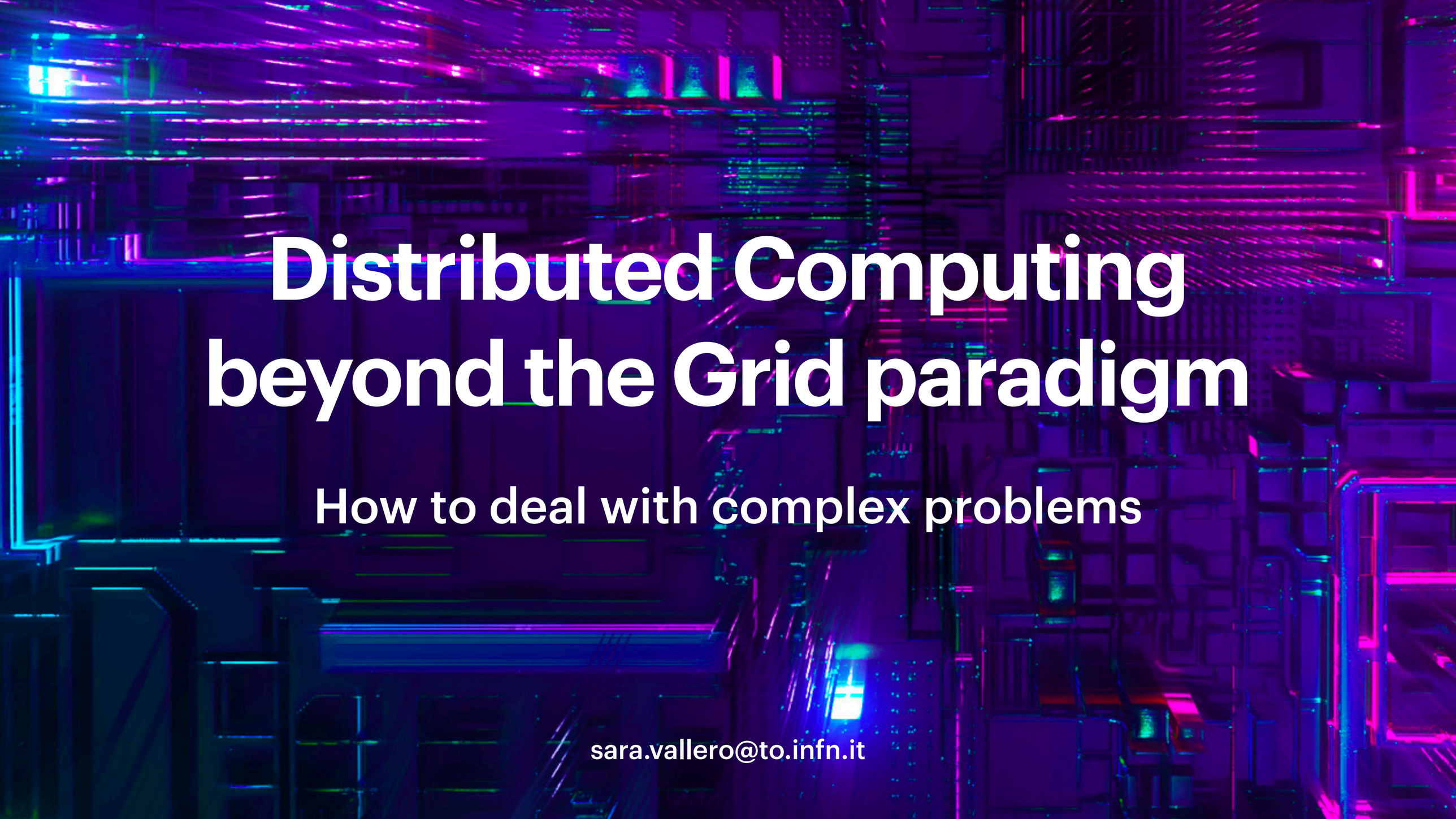

Distributed Computing beyond the Grid paradigm

How to deal with complex problems

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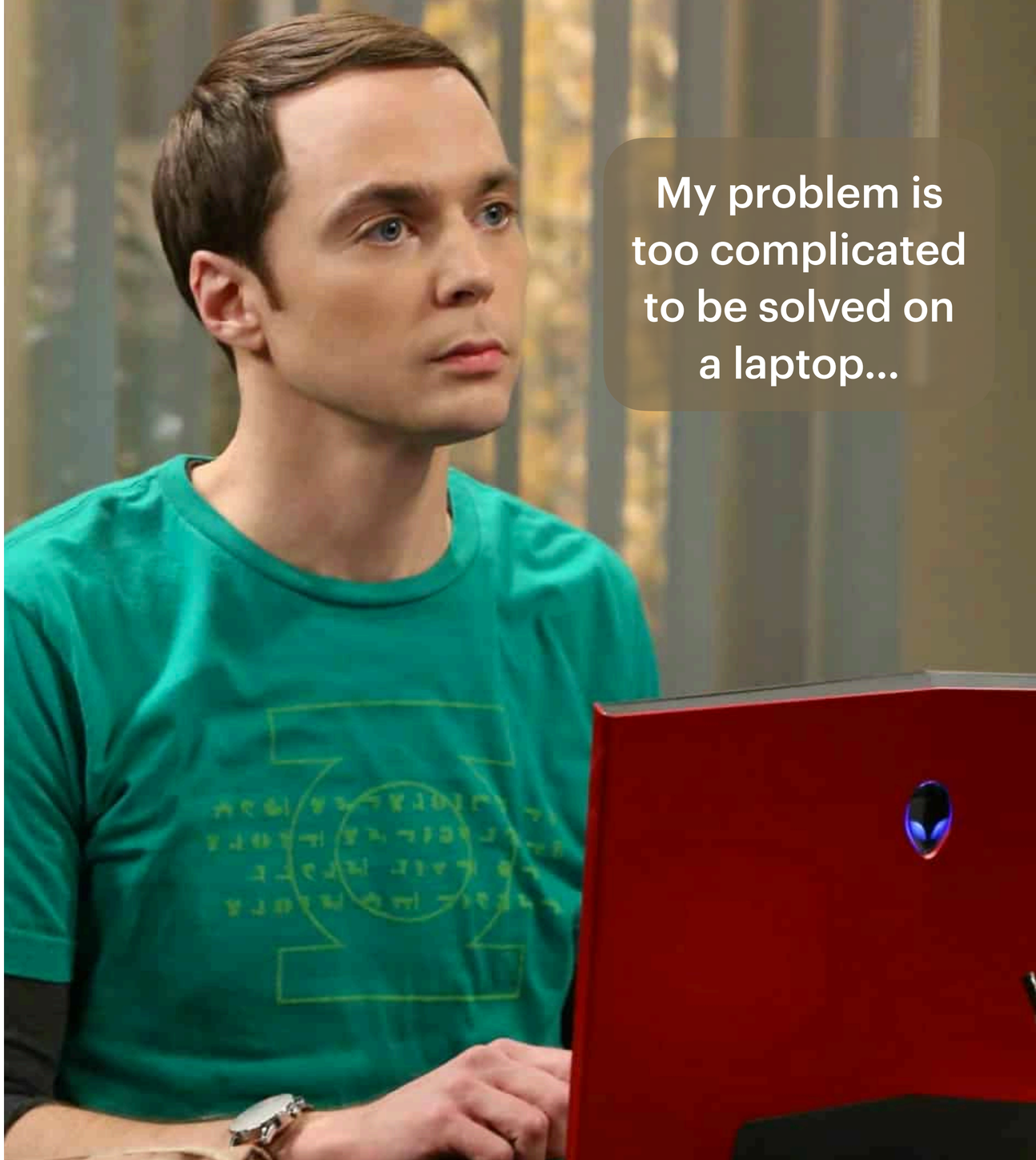
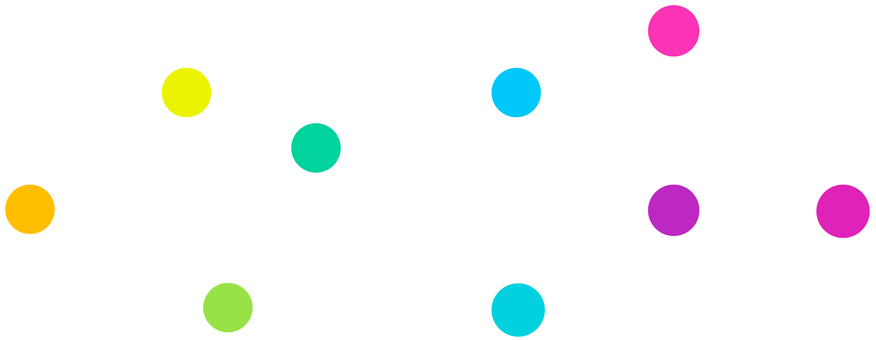
Distributed computing

- The problem is really computing intensive
- **Choose the right software stack:**
  I need do **distribute the calculation** (vs. distributing the data, although often you need a combination of the two)
- **Choose the right infrastructure:**
  should I use a **High Performance Computing (HPC)** platform or a **High Throughput Computing (HTC)** one?



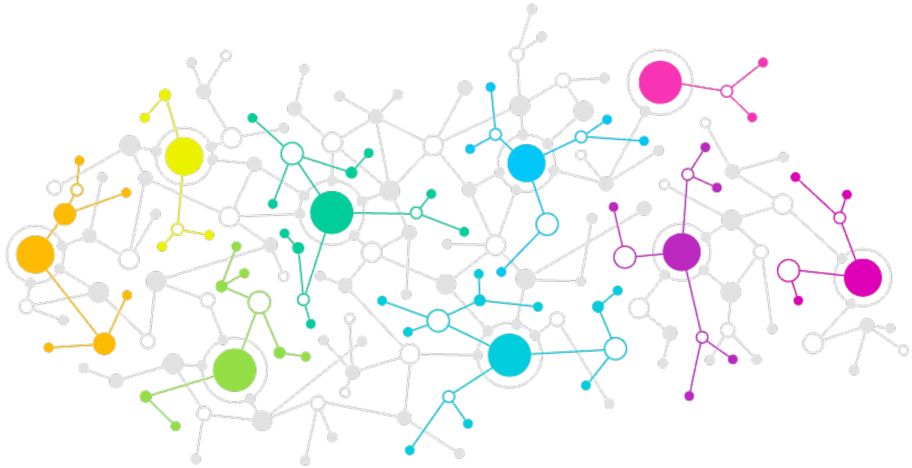
Split the task in many smaller pieces

Embarrassingly parallel



Sub-tasks are independent

Challenging

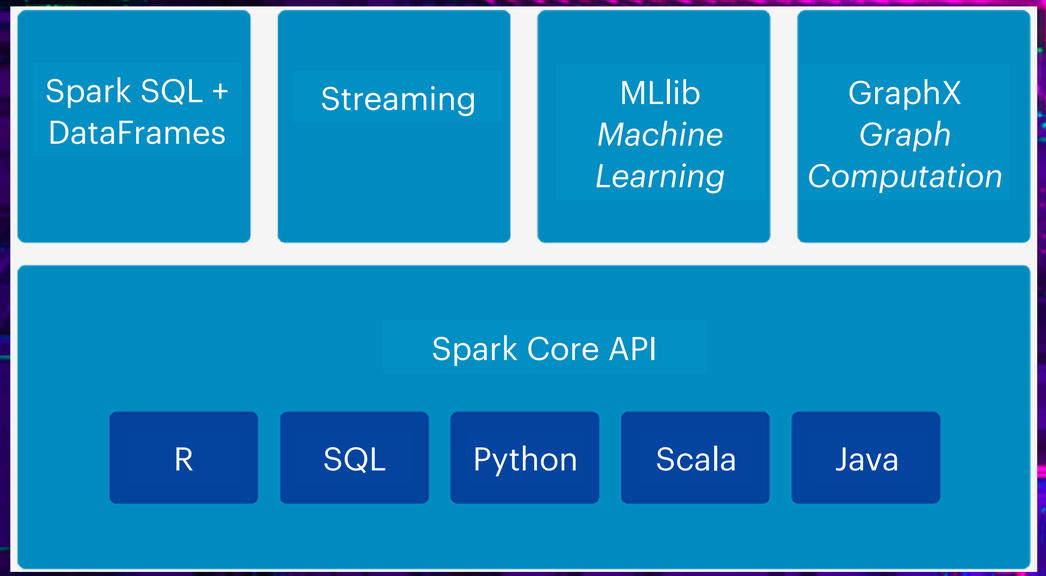


Sub-tasks need to communicate and synchronise

Apache Spark

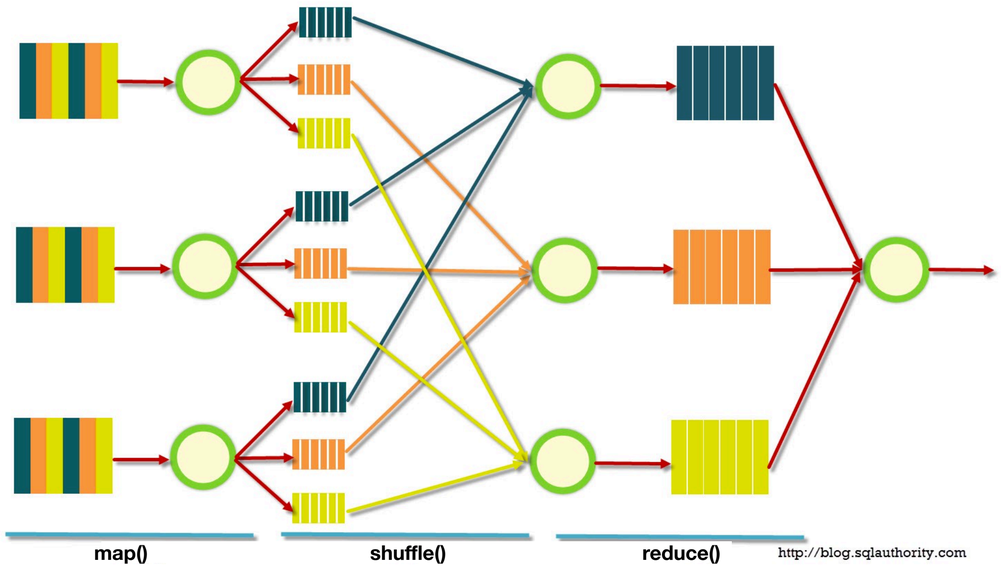
- A large-scale distributed **general-purpose cluster-computing framework**.
- It provides an interface for programming entire clusters with **implicit data parallelism and fault tolerance**.
- Core data processing engine + specific libraries
- These libraries can be combined in modern **data pipelines** (i.e. analytics and machine learning workloads)
- Jobs perform **multiple operations consecutively, in memory,** only spilling to disk when required
- The Spark project was born (Berkley 2009) as an improvement of the Hadoop MapReduce framework.

Let's start with choosing the appropriate software



- **PIPELINE:** combine very different techniques and processes into a single, coherent whole
- **SQL:** domain-specific language used in programming and designed for managing data held in a relational database management system (RDBMS), or for stream processing in a relational data stream management system (RDSMS)

The MapReduce paradigm



See also: https://www.reddit.com/r/ProgrammerHumor/comments/55ompo/map_filter_reduce_explained_with_emojis/

```
function map(String name, String block):
  // name: block name
  // block: block contents
  for each color c in block:
    emit (c, 1)
```

```
function reduce(String color, Iterator partialCounts):
  // color: a color
  // partialCounts: a list of aggregated partial counts
  sum = 0
  for each pc in partialCounts:
    sum += pc
  emit (color, sum)
```

map: each node applies the map function to the local data

shuffle: nodes redistribute data based on the output keys (produced by the map function), such that all data belonging to one key is located on the same node

reduce: nodes process each group of output data, per key, in parallel

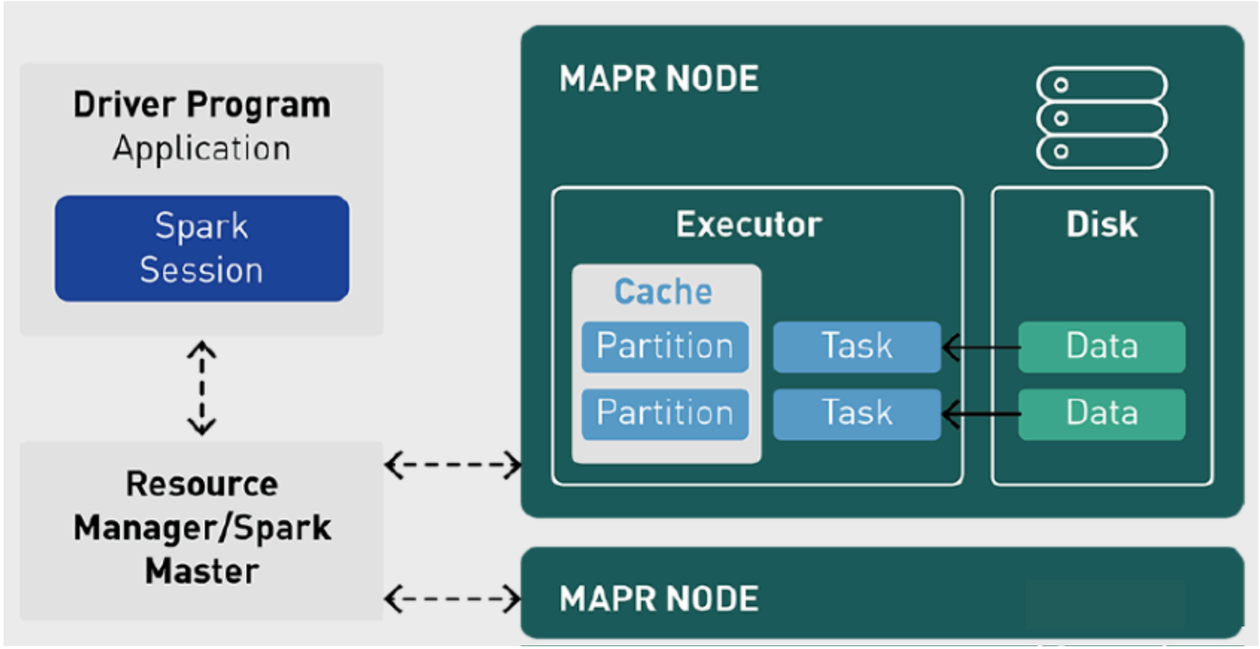
Caveats:

- Map Reduce ok for Big Data analytics
- Not ok for iterative processes (Machine Learning)
- Data not in memory

Spark vs. MapReduce

Spark:

- runs multi-threaded lightweight tasks inside of JVM (Java Virtual Machine) processes, providing fast job startup and **parallel multi-core CPU utilisation**
- **caches data in memory** across multiple parallel operations, making it especially fast for parallel processing of distributed data with **iterative algorithms**



Data structures

DataFrame:

- a 2-dimensional labeled data structure with columns of potentially different types (like a spreadsheet or a table)
- a very convenient Python implementation is Pandas
- it's a **local data structure**

```
In [74]: iris = pd.read_csv('data/iris.data')

In [75]: iris.head()
Out[75]:
   SepalLength  SepalWidth  PetalLength  PetalWidth         Name
0          5.1         3.5          1.4         0.2  Iris-setosa
1          4.9         3.0          1.4         0.2  Iris-setosa
2          4.7         3.2          1.3         0.2  Iris-setosa
3          4.6         3.1          1.5         0.2  Iris-setosa
4          5.0         3.6          1.4         0.2  Iris-setosa
```

Spark Resilient Distributed Dataset (RDD):

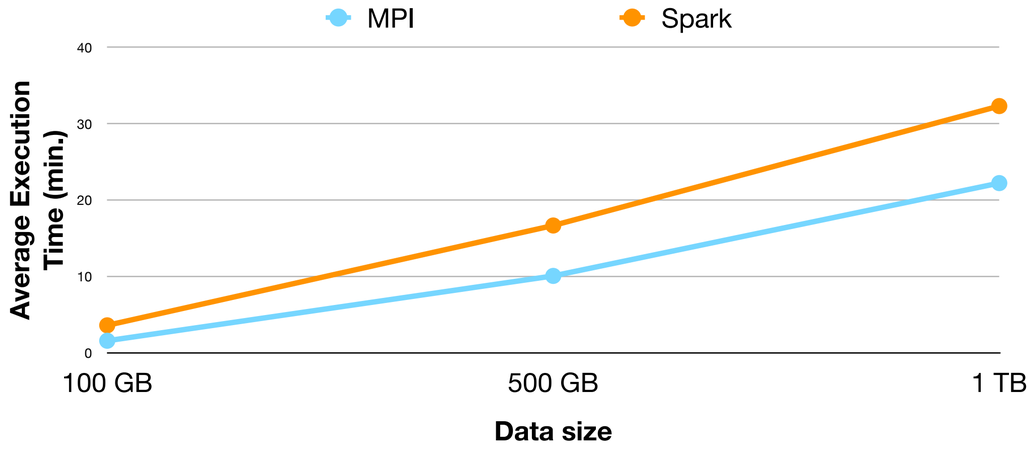
- a read-only collection of objects (data) partitioned across a set of machines that can be re-built if a partition is lost
- it'a a **memory abstraction**
- can be built from:
  - parallelising an existing collection in your driver program
  - referencing a dataset in an external storage system

Spark vs. MPI

What is the best way to solve this?

Definitely MPI (for computing intensive workloads)

- Message Passing Interface (MPI) is a specification
- It defines a message passing model to facilitate the transport of data between distributed processing elements
- Specific implementations, i.e. OpenMPI or MPICH
- Very low latency and injection rate for short messages and high bandwidth (HPC's favorite)



DATA INTESIVE WORKLOADS

Why Spark then...

- Because it provides a common runtime for big data processing
- Availability and fault tolerance
- To be preferred O(1TB) ⟶ I/O access delays start to affect MPI
- Supports real-time data streaming

What about scalability?

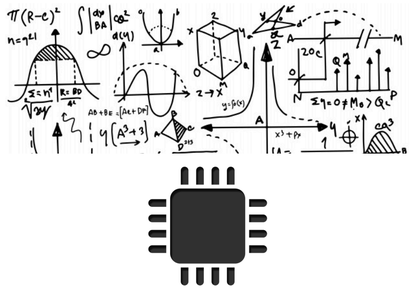
Scalability is the property of a system to deliver greater computational power when the amount of resources is increased.

Follow-up: https://www.researchgate.net/publication/228367369_Reevaluating_Amdahl's_law_and_Gustafson's_law

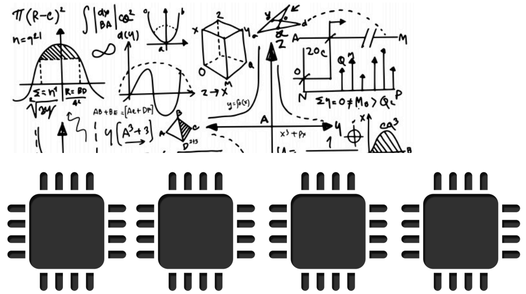
Strong scaling

Fixed problem size

t_1



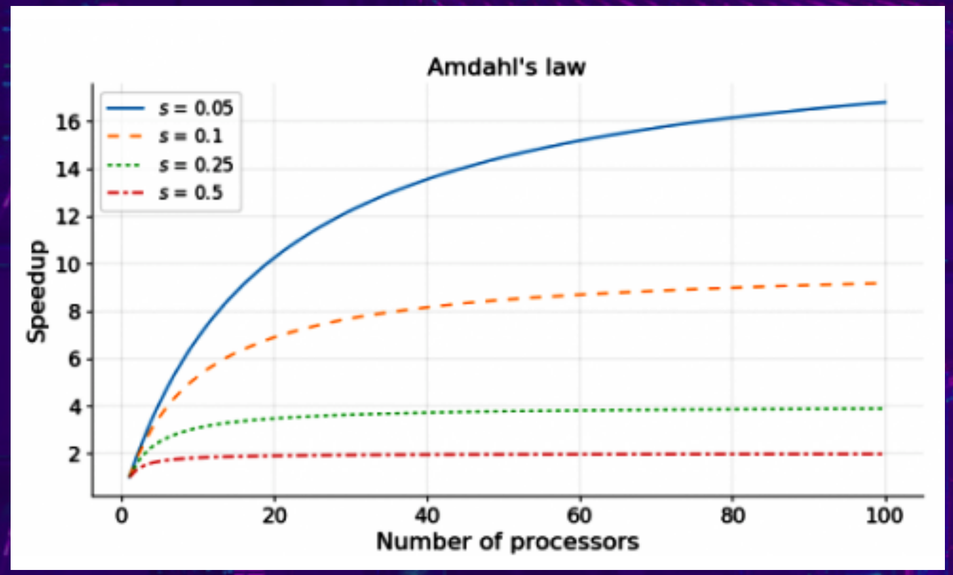
t_N



Speedup (ideal) = $t_1 / t_N = N$

Amdhal's law

Speedup = $t_1/t_N = 1/(s+p/N)$

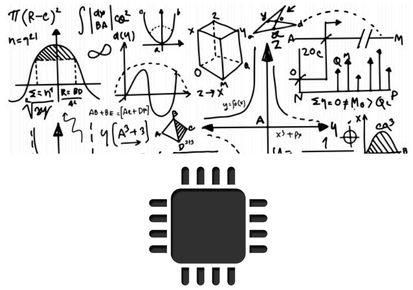


s = fraction of execution time spent in serial part
p = fraction of execution time spent in parallel part
N = number of processors

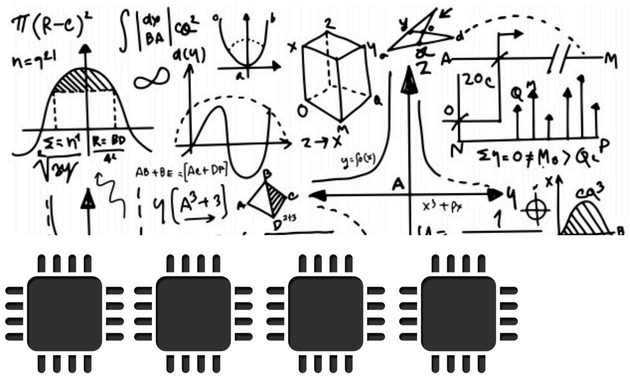
Weak scaling

Increasing problem size

t_1



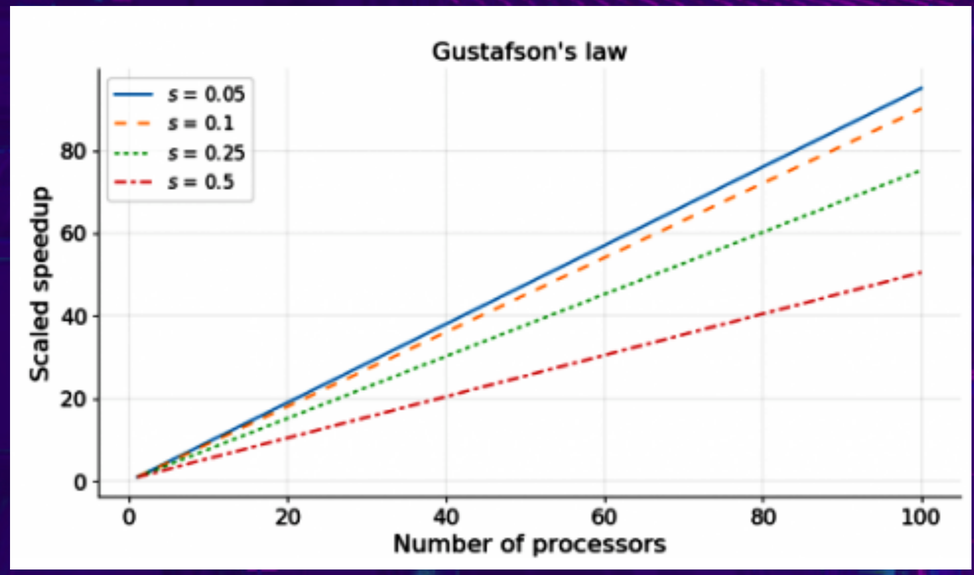
t_N



Scaled Speedup (ideal) = $t_1 / t_N = N$

Gustafson's law

Scaled Speedup = $t_1/t_N = s + p\,N$



s = fraction of execution time spent in serial part
p = fraction of execution time spent in parallel part
N = number of processors

To take home

- Understand your problem's features: is it embarrassingly parallel or not?
- Choose the right cluster framework:
  - MPI for computing intensive tasks
  - Spark for data intensive tasks
- Understand the scaling behaviour: more cores does not always mean shorter execution times

What about the Grid?

Geographically distributed facility for High Throughput Computing.

Can accomodate embarrassingly parallel jobs.