DEALING WITH BIG DATA QUANTITIES

BIG DATA QUANTITIES?

We're talking several dozen to several 100 TB.

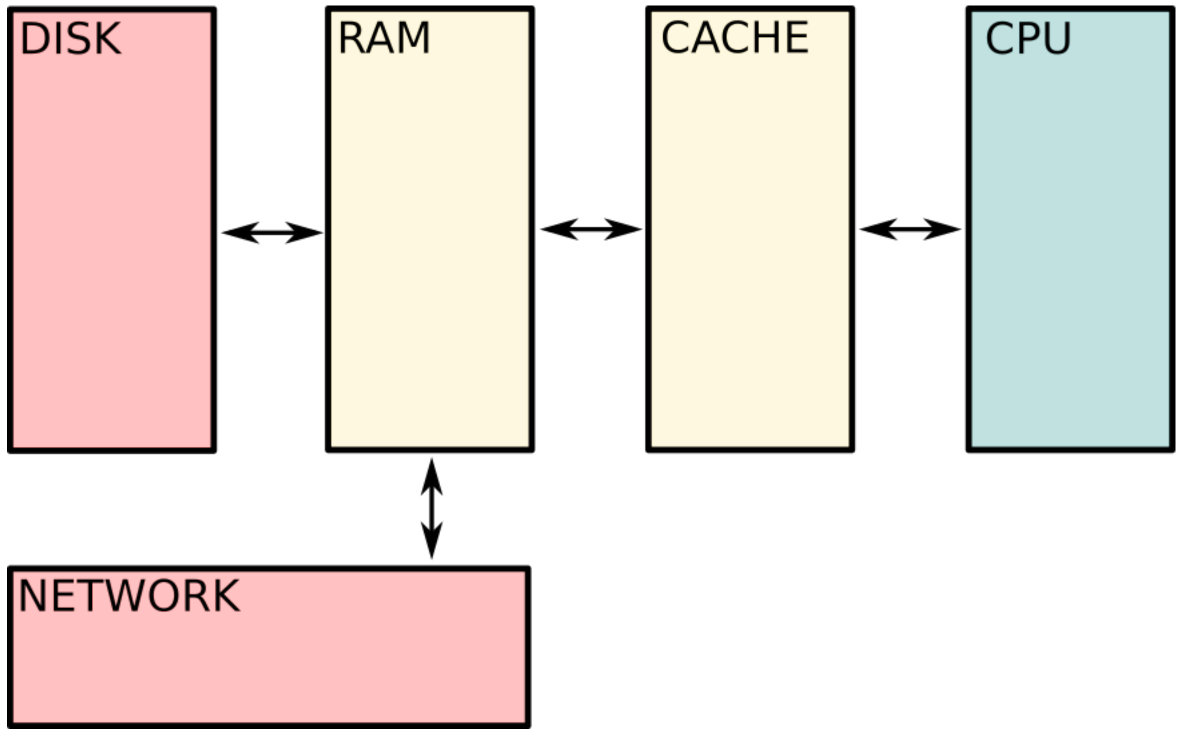
EXAMPLE: AWS INSTANCES FOR RENT

X1.32XLARGE (FEB. 2017)

- 128 CPUs
- 1 952 GB of RAM
- 2 x 1920 TB SSD
- approx. 130 NOK/hour

HOW DOES A COMPUTER WORK ANYWAY?

DATA FLOW IN YOUR COMPUTER



INTERESTING PROPERTIES

- **Latency**
  - How fast can data be accessed?
- **Bandwidth**
  - How much data per second can be transferred?
- **Size**
  - How much data can be stored?

These vary by *orders of magnitude*.

LATENCIES

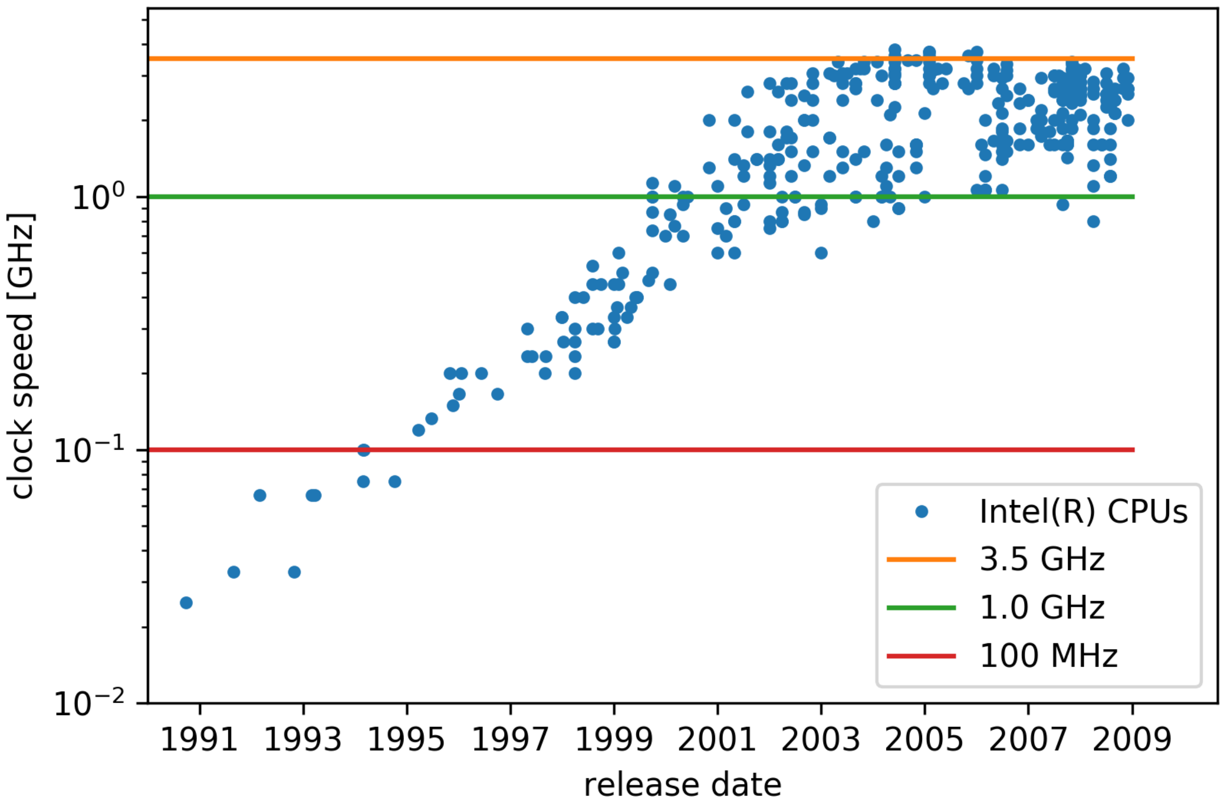
Time	Event	Equivalent
1ns	L1 cahce ref.	Human blink (150ms).
3ns	Branch mispr.	Light travels around the world twice.
4ns	L2 cache ref.	Arrow travels 50m (0.6s).
100ns	RAM ref.	Usain Bolt runs 150m (15s).
2μs	Zip 1KB	Make a coffe (5 min).
16μs	SSD read	Watch 2 episodes of Seinfeld (40m).
500μs	Net DC<->DC	Watch all LOtR movies twice (20h).
3ms	Disk seek.	Watch all James Bond movies twice (5d).
150ms	Net CA<->NL	Take STK-INF4000 twice (8.5 months).

SIZES AND BANDWIDTHS (HASWELL MOBILE)

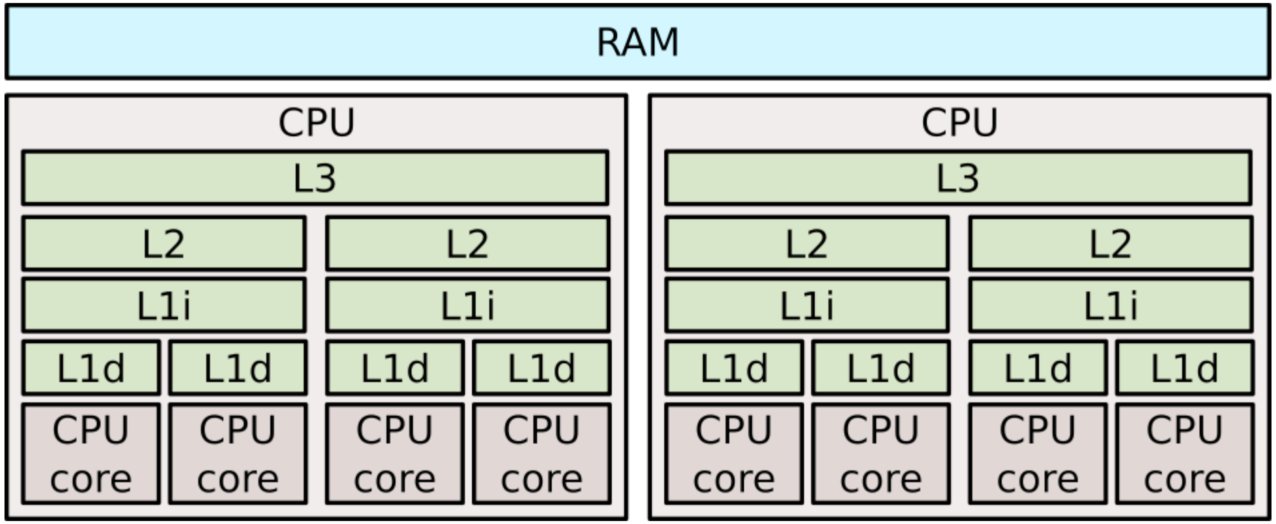
Medium	Size	Bandwidth
Level 1 Cache	128 KiB	700 GiB/s
Level 2 Cache	1 MiB	200 GiB/s
Level 3 Cache	6 MiB	100 GiB/s
RAM	16 GiB	10 GiB/s
SSD	500 GiB	600 MB/s
Ethernet		13 MB/s
Wifi		1.4 MB/s

WHY NOT USE A SINGLE CPU?

CPU CLOCK SPEEDS



THE UGLY TRUTH



PARALLELIZE THE WORK

- Multiprocessing / Threading
  - Operate with multiple CPUs/cores on same memory.
- Cluster computing (i.e. Cray, Blue Gene)
  - Have multiple machines work on the same problem.
  - Communicate via network (slow).
  - Usually used for scientific simulations (fluid dynamic, quantum chromodynamics)
    - Tend to be communication intensive.
- Low-cost commodity hardware clusters.
  - Things break easily.
  - Communication not as efficient.
  - Cheap.

MULTIPROCESSING

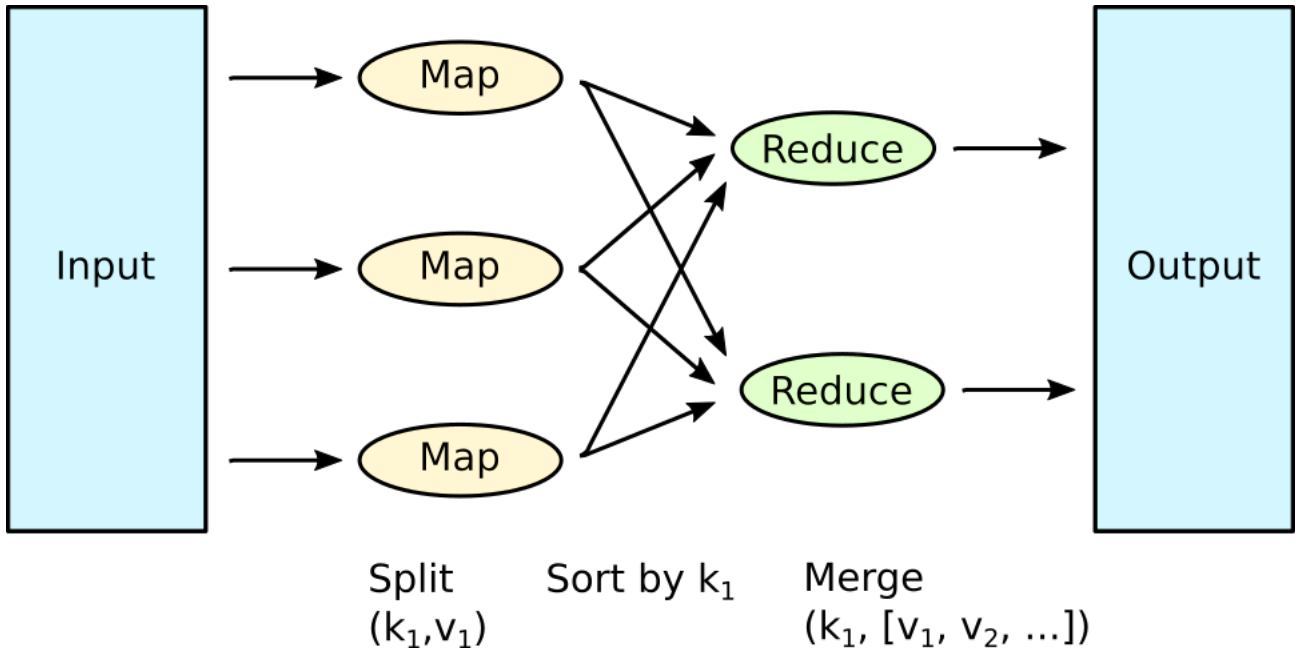
- Needs synchronization between threads.
- Needs coordination of memory accesses.
- Done automatically in some `numpy` backends.
    - And hence in `scikit-learn`.
- Manually: `multiprocessing`.
    - Will keep track of synchronization/coordination for you.

CLUSTER COMPUTING

- In the data science world: MapReduce.
- In other fields: MPI.

We won't talk about MPI here.

MAPREDUCE


Input
Map
Map
Map
Reduce
Reduce
Output
Split
(k_1,v_1)
Sort by k_1
Merge
(k_1, [v_1, v_2, ...])

MAPREDUCE

- Ingredients
  - **Mapper**: A touring machine μ accepting a key-value pair (k, v) and produces a *list* of key-value pairs $(\kappa_1, \nu_1), \ldots, (\kappa_n, \nu_n)$.
  - **Reducer**: A touring machine ρ, accepting a key k and a list of values $(v_1, \ldots, v_n)$ and producing as output the same key k and a new list of values $(\nu_1, \ldots, \nu_m)$.
- Algorithm
  - For a list of input pairs $(k_i, v_i), \ldots, (k_N, v_N)$ apply the mapper μ to all of them.
  - For each given output key k, collect the list of values $(v_{k,1}, \ldots, v_{k,N_k})$ produced by μ.
  - Apply a reducer to each of those in parallel.
- The algorithm can be iterated of many pairs of mappers and reducers.

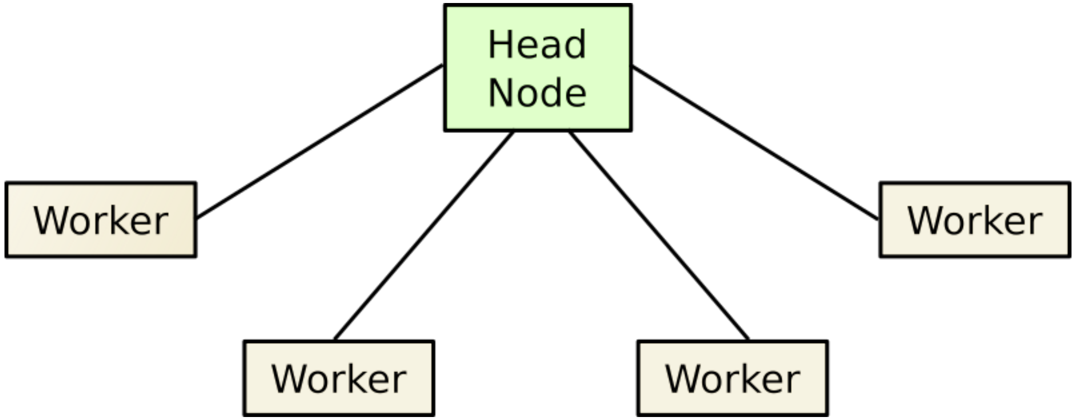
REDUCE

- Often reduce is required to be *associative*, so reduce inputs can be shuffled through the cluster. Schematically:

$$\rho(k, [v_{k,1}, \ldots, v_{k,n}]) = \rho \{k, \rho(k, [v_{k,1}, \ldots, v_{k,s}]) \oplus \rho(k, [v_{k,s+1}, \ldots, v_{k,n}])\}$$

- Reduce calls can then be executed in parallel.

A MAPREDUCE CLUSTER



WHAT'S THE FUSS?

Google managed to sort 1 *petabyte* of data ...

... in **hours** ...

... in **2011**!

IMPLEMENTATION

- Practical implementations take care of
  - Parallelization
  - Communication
  - Data distribution
  - Data collection
  - Node failure
- Most used/known implementation
  - Apache Hadoop
    - Comes with `hdfs`, a *distributed file system*.

APACHE SPARK

- In-memory MapReduce.
- Data processing.
- Machine learning.
- Streaming.
- Used to sort 100TB in 23 minutes.
  - Using 207 machines on EC2 (2014).
- Used to sort 100TB for $1.44/terabyte (2016).