The seven deadly sins of cloud computing research

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The seven deadly sins of cloud computing research

sin, n. – *common simplification or shortcut employed by researchers; may present threat to scientific integrity and practical applicability of research*

The seven deadly sins of **cloud computing** research

Large-scale data processing, cluster computing, scalable web application serving.

Not in focus:

Cloud storage, NoSQL databases, network protocols, cloud economics...

Disclaimer #1

We have committed many of these sins ourselves in our own work.

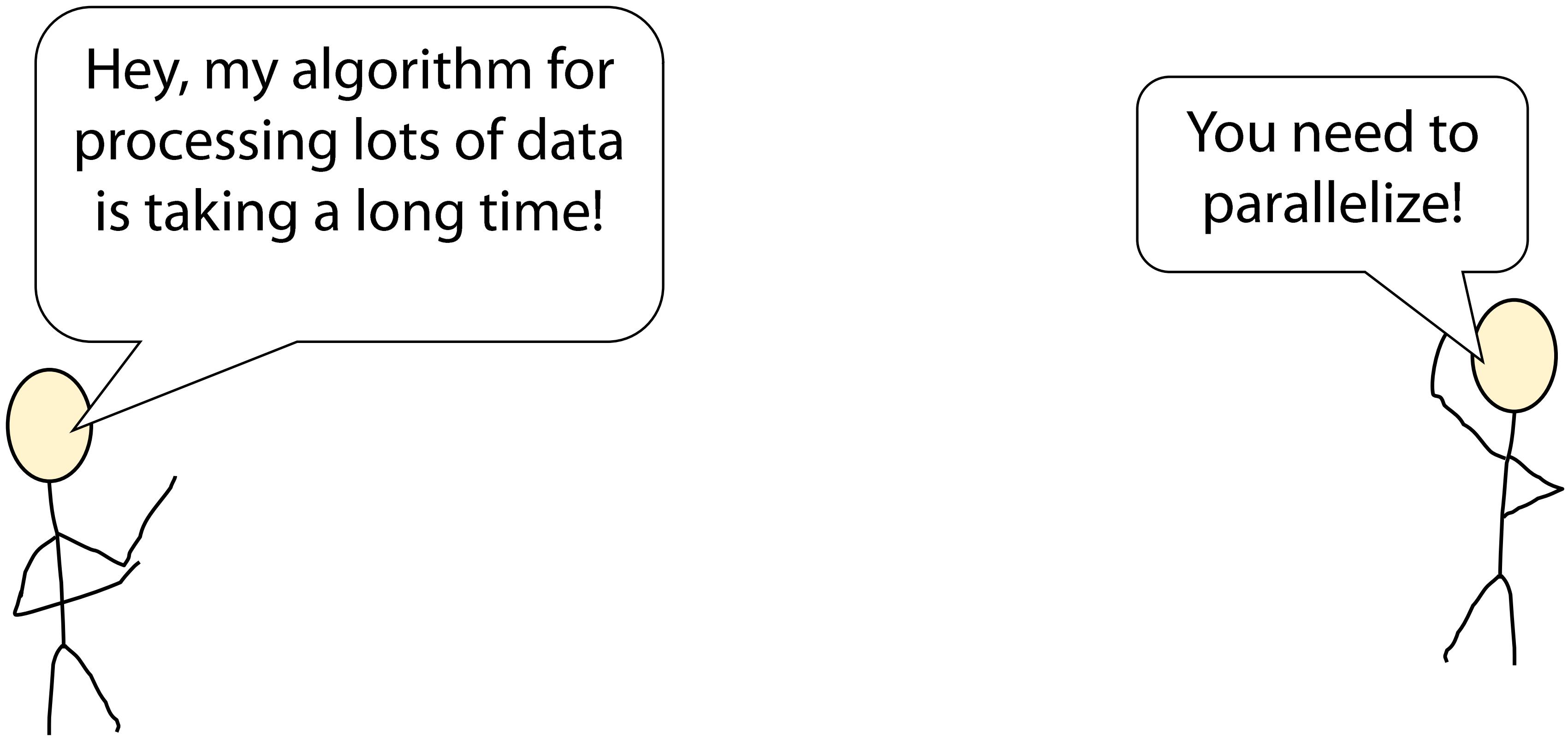
Disclaimer #2

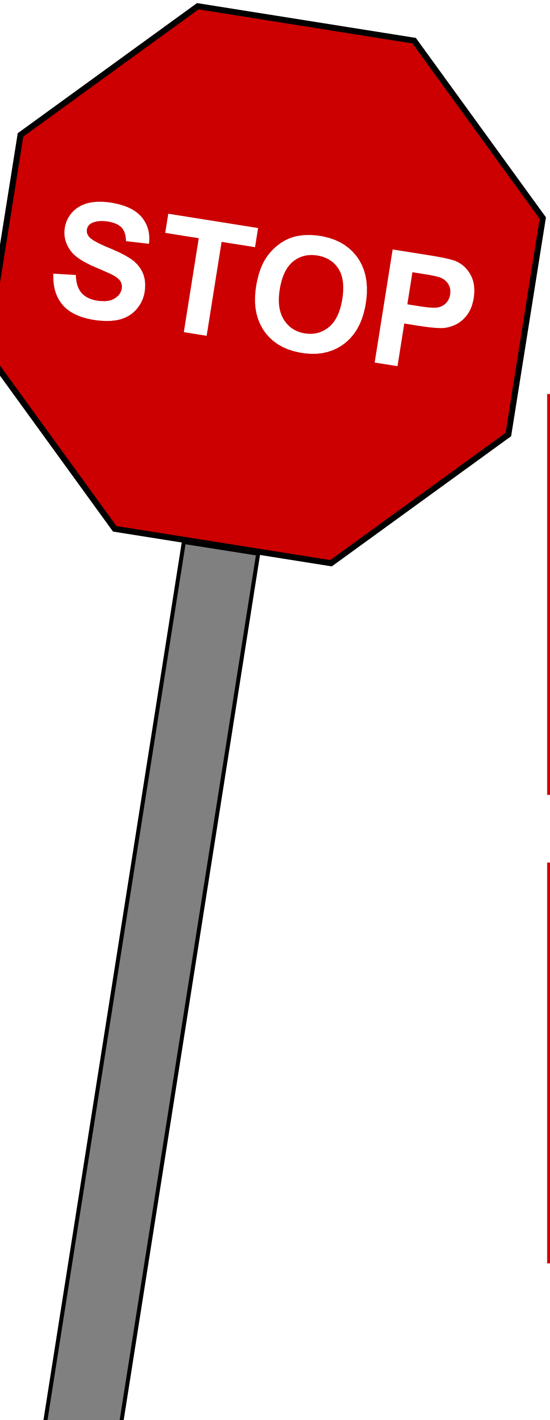
We are highlighting wide-spread issues here, not judging the value of specific research endeavours.

1

First sin:

Unnecessary distributed parallelism


Hey, my algorithm for processing lots of data is taking a long time!
You need to parallelize!



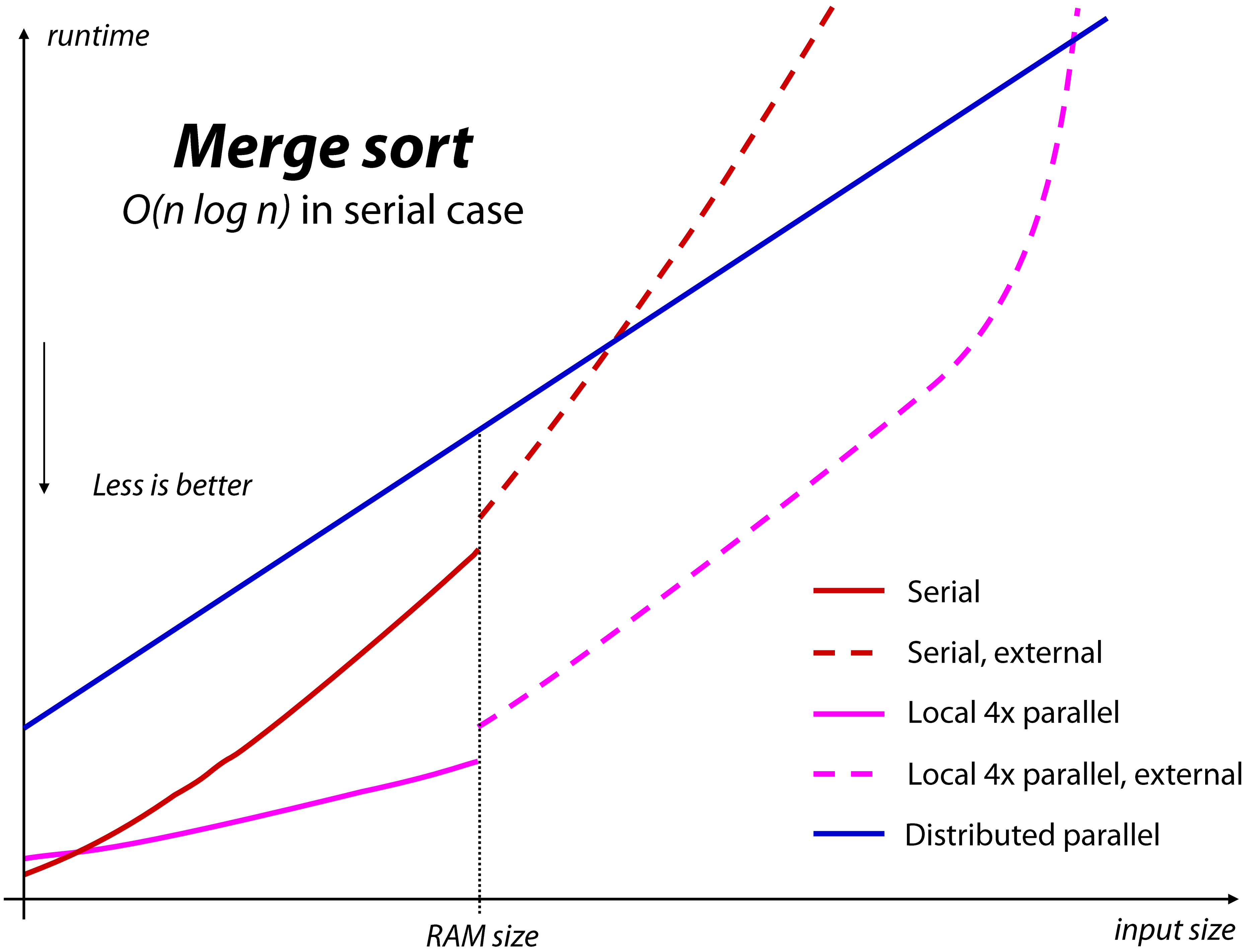
Really?

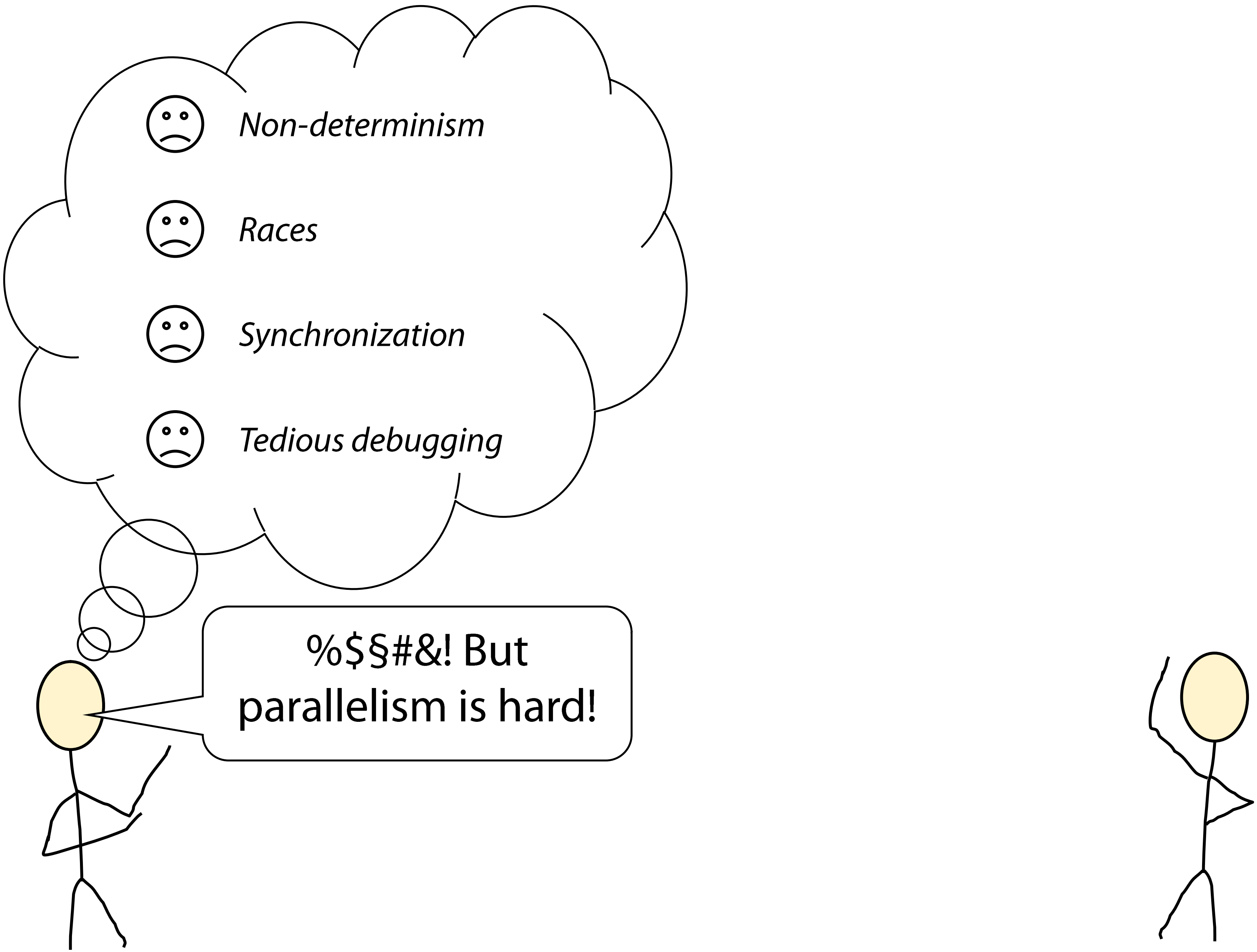
Parallelism is not free!

It always adds overheads...

Diminishing returns

We can only scale to a limit...


runtime
Merge sort
O(n log n) in serial case
Less is better
Serial
Serial, external
Local 4x parallel
Local 4x parallel, external
Distributed parallel
RAM size
input size


Non-determinism
Races
Synchronization
Tedious debugging
%$§#&! But parallelism is hard!

Messrs. Dean & Ghemawat

INTRODUCE THEIR AMAZING

MAP-REDUCE

(U.S. Pat. 7,650,331)

Stop worrying about:

- Synchronization
- Data motion
- Parallel coordination
- Failures
- Communication

TODAY!

Fits all parallelization problems!

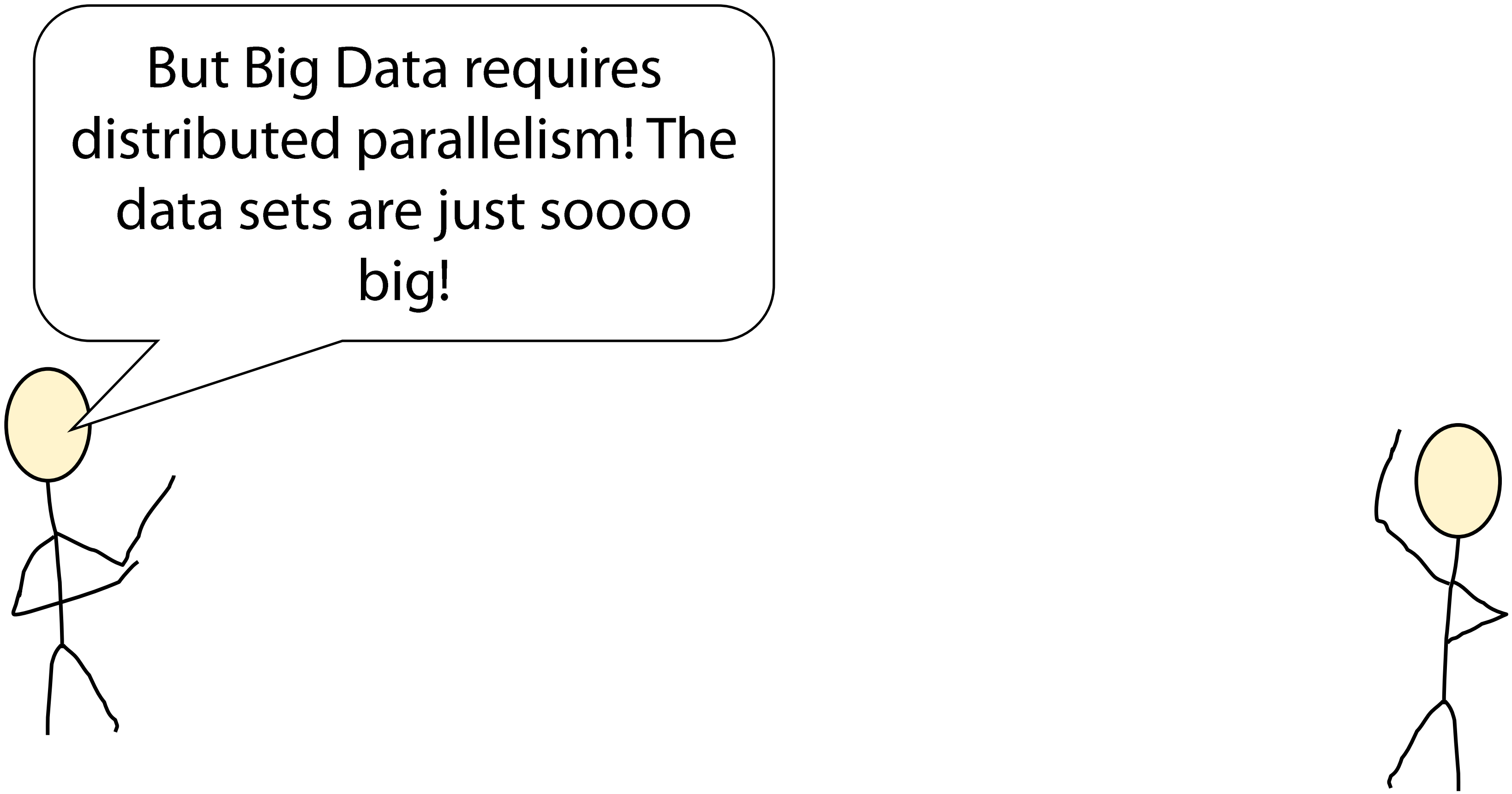
A little bit of history...

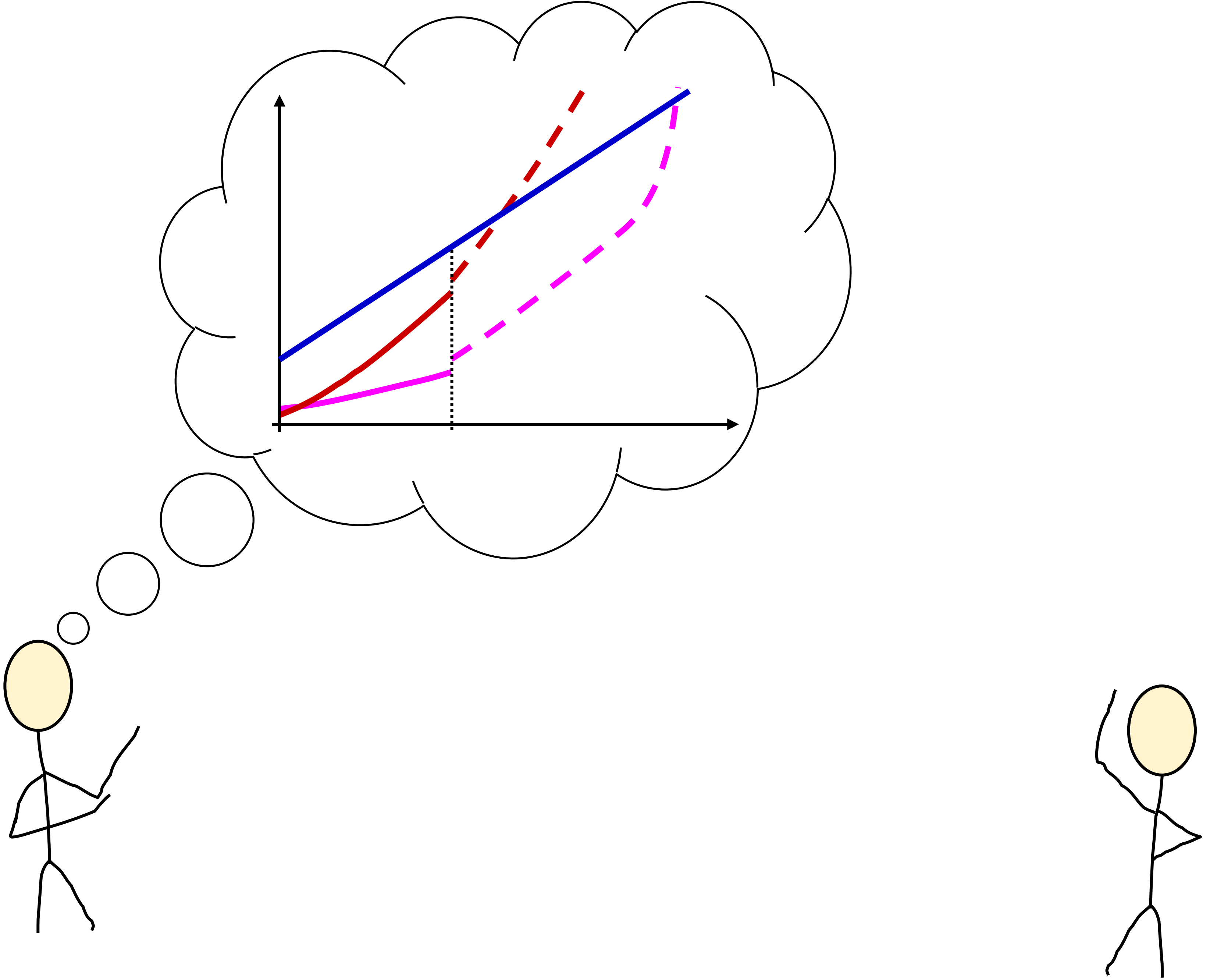
*"[…] **the input data is usually large** and the computations have to be distributed across **hundreds** or **thousands of machines** in order to finish in a reasonable amount of time."*

-- Dean et al., MapReduce paper, OSDI 2004

*"Each machine had **two 2GHz Intel Xeon processors** with Hyper-Threading enabled, **4GB of memory**, two 160GB IDE disks, and a gigabit Ethernet link."*

-- Dean et al., MapReduce paper, OSDI 2004


But Big Data requires distributed parallelism! The data sets are just soooo big!



Most “big data“ isn‘t that big...

Average input size observed in many production clusters is ~10–15 GB!

2

Second sin:

Assumption of performance homogeneity

“the cloud“ is not homogeneous!

Schad *et al.*, VLDB 2010 | Li *et al.*, IMC 2010

Barker *et al.*, MMSys 2010 | Wang *et al.*, INFOCOM´10

Later in HotCloud:

EC2 instance heterogeneity *[Ou et al.]*

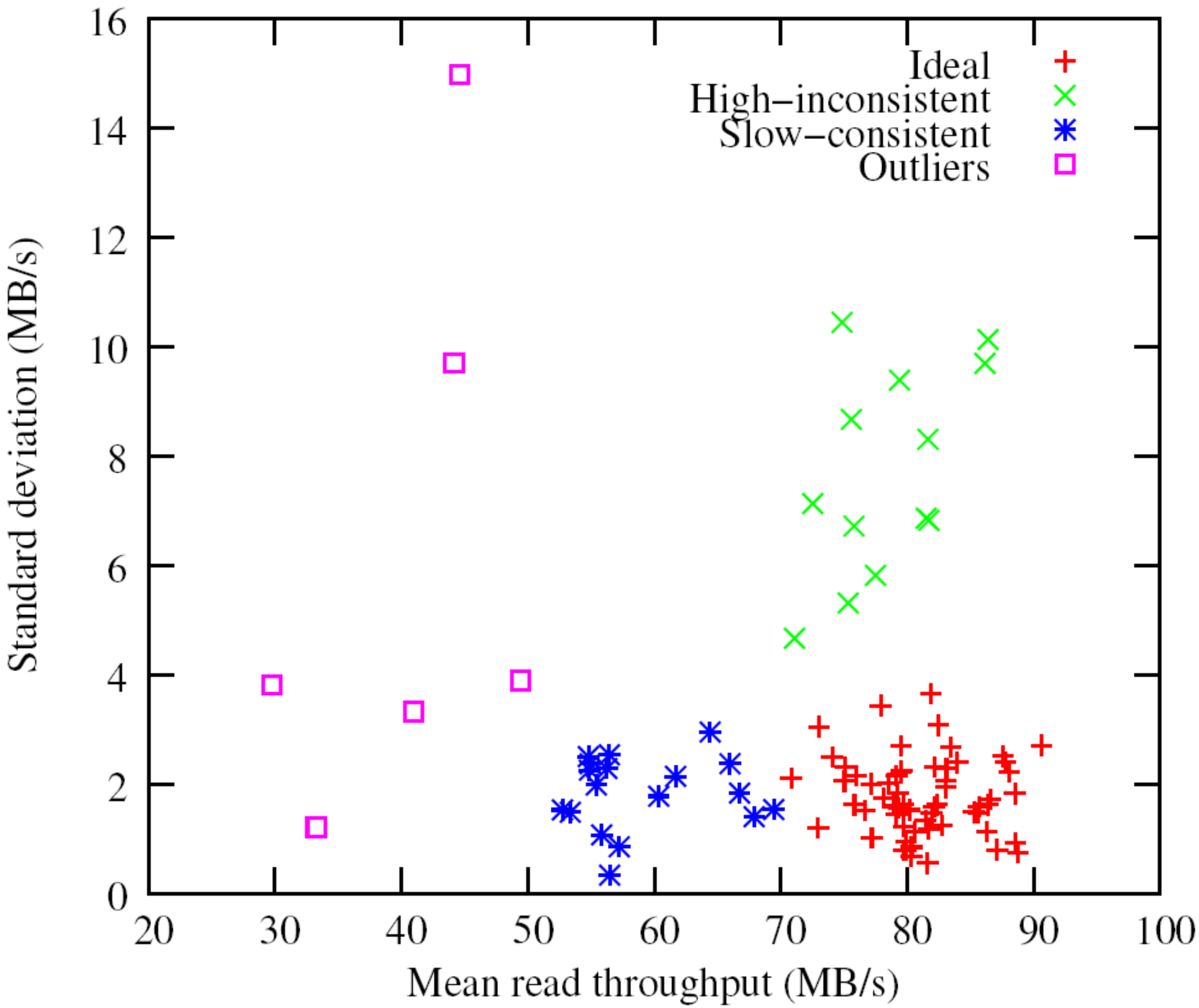
Variance hurts predictability *[Bortnikov et al.]*

Own results from 2010 follow...

... and by the way:

Neither are dedicated clusters!

EC2 performance variance

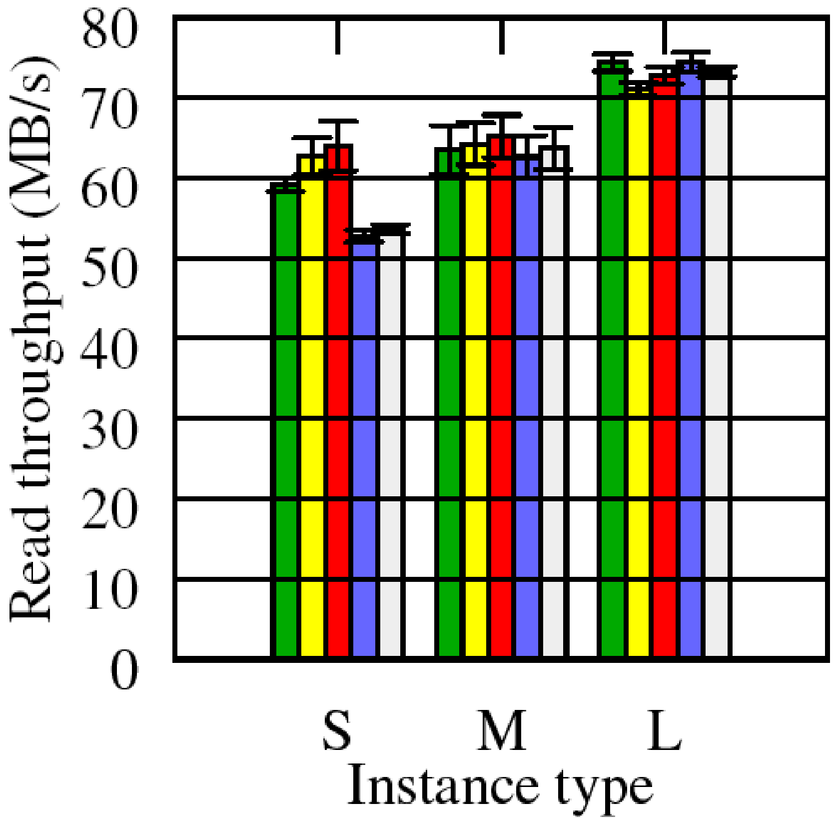


Disk read performance

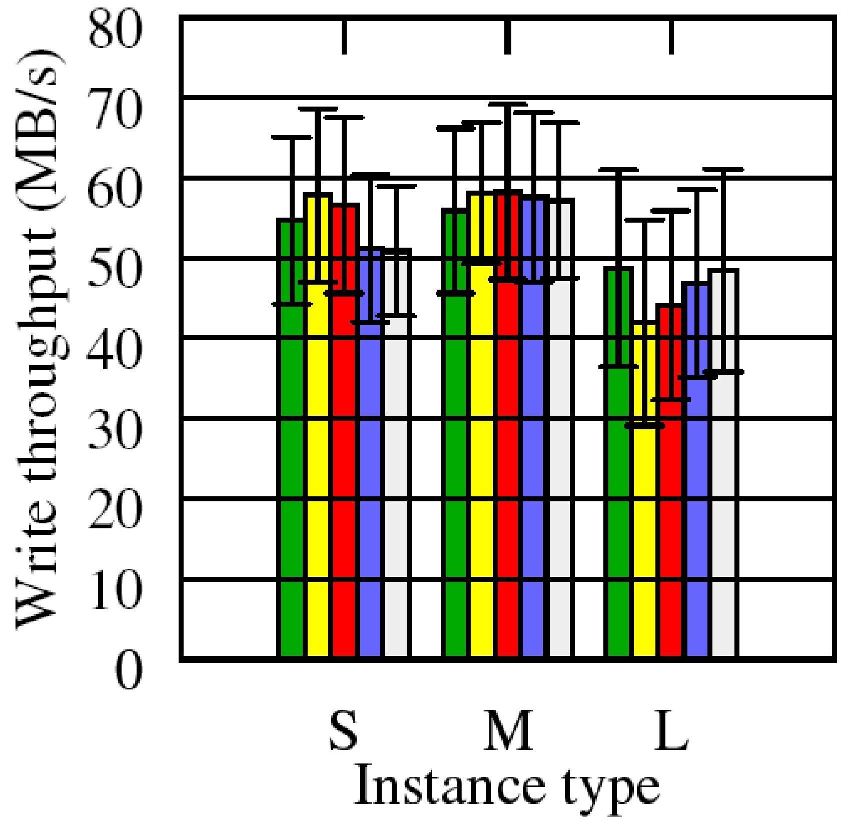
100 EC2 `m1.small` instances

Mean and standard deviation over 9 samples

EC2 performance variance



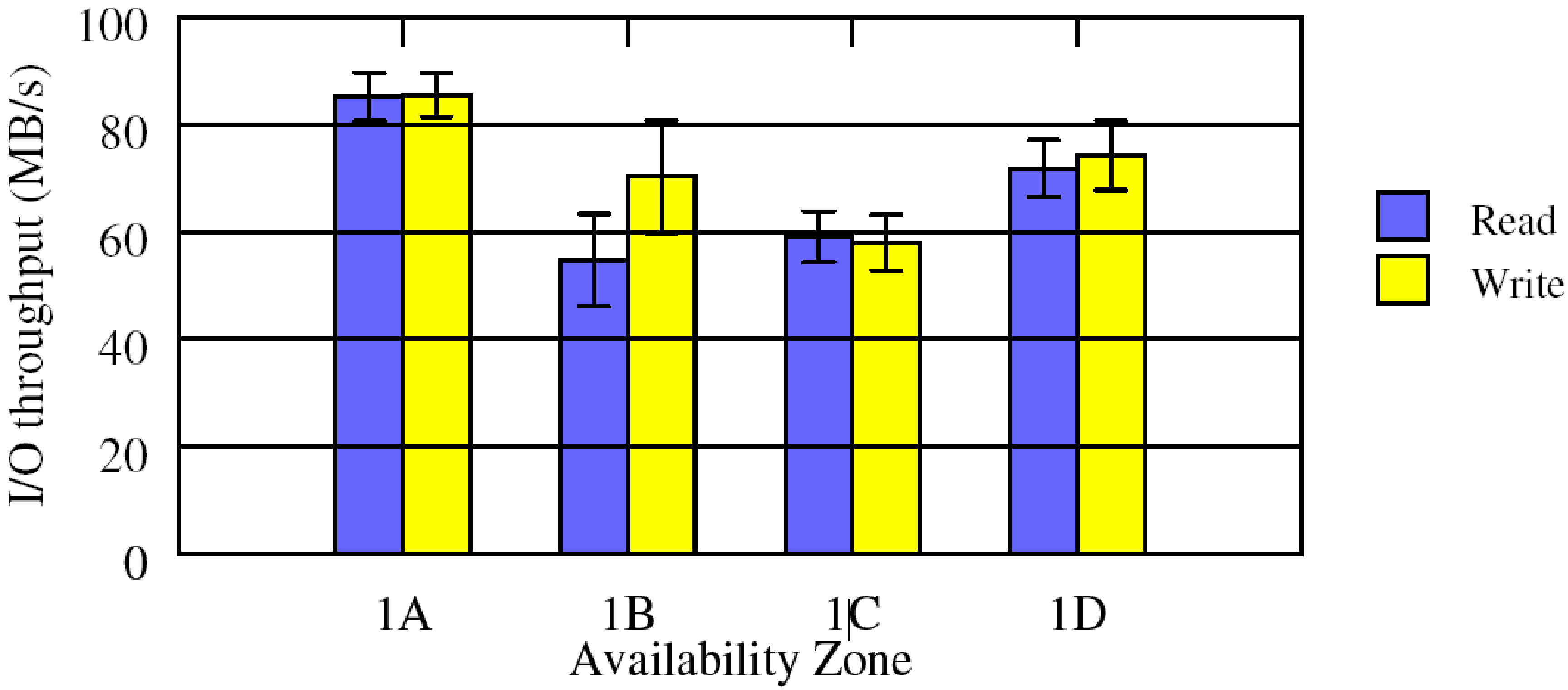
Disk read



Disk write

Colours:	different instances (randomly selected)
Values:	means over 4 runs of `bonnie++`
Error bars:	+/- 1σ (std. dev.) over 4 runs

EC2 performance variance



Values: means over 5 randomly selected instances
Error bars: +/- 1σ (std. dev.)

“The three R‘s“

Rigor

Describe and quantify performance variability

- Repeated runs (at least 5-10)
- Error bars and their meaning

Ensure the results are true across time and space

- Repeat runs at different times
- Different “hardware“ (instance types, if EC2)

Repeatability

Sufficient information to repeat the experiment

- Hardware config / instance type
- Communication fabric / topology
- Dataset(s)

“three R‘s“ due to Vitek et al., R3 – Repeatability, Reproducibility and Rigor, SIGPLAN Notices, 2012

Re

3

Third sin:

Picking the low-hanging fruit

Scarlett	20%	iMapReduce	5x
iHadoop	25%	Hyracks	16x
CIEL	50%	Hadoop++	20x
PACMan	50%	Spark	40x
HaLoop	85%	PrIter	50x
Mesos	2x	Incoop	80x
LATE scheduler	2x	CamDoop	180x
Sector/Sphere	2x	DVM	200x
Mantri	3x		

HOT → OFF THE PRESS!

Venkataraman et al.:	10x
Ananthanarayanan et al.:	47%

How hard is it to beat Hadoop?

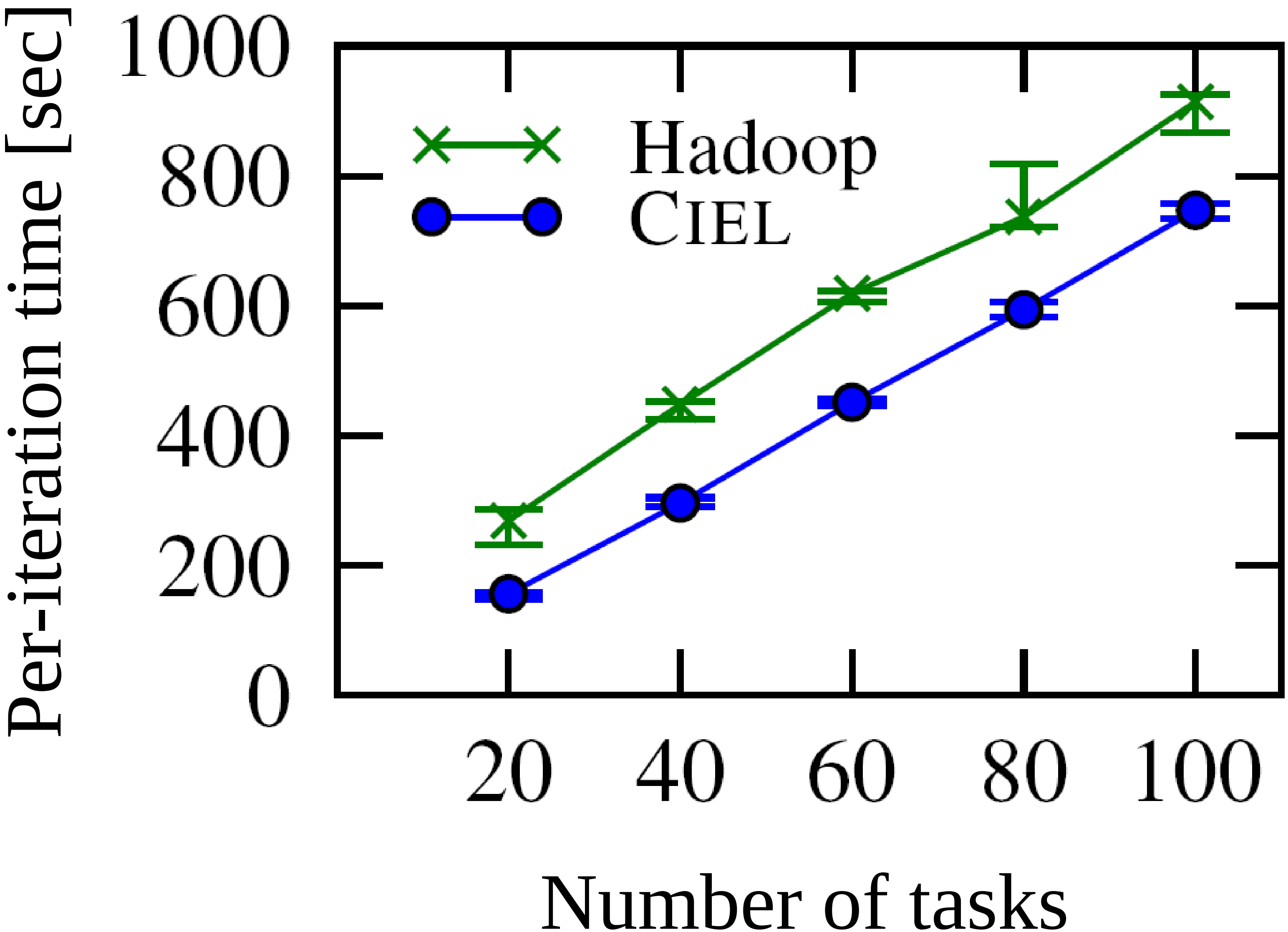
It depends!

Do all these optimizations compose?

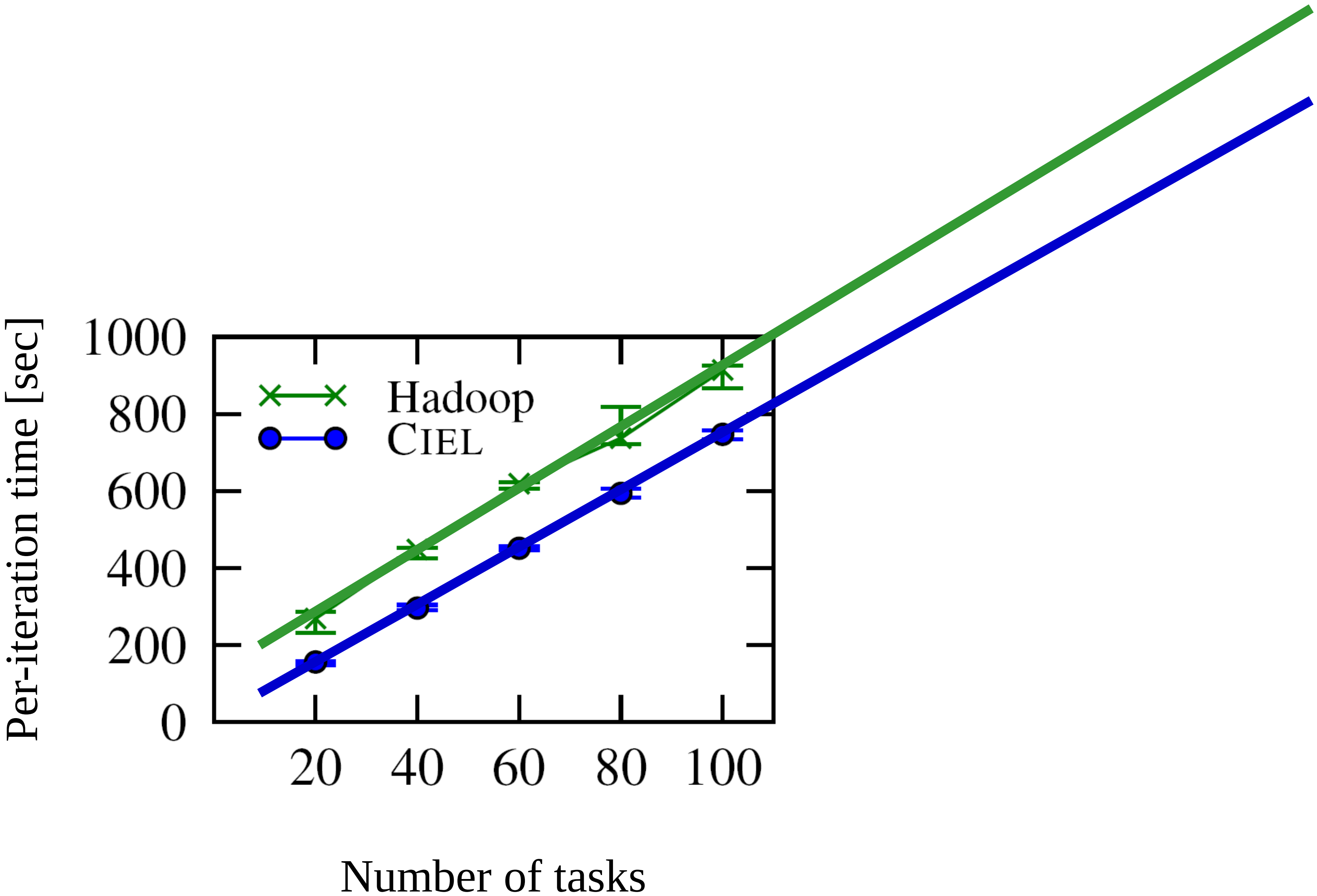
Of course not!

Categories of optimizations

1. *in-memory (RAM) caching*
2. *memoization of results*
3. *exploitation of data locality*
4. *domain-specific algorithms*
5. *load vs. job runtime trade-off*

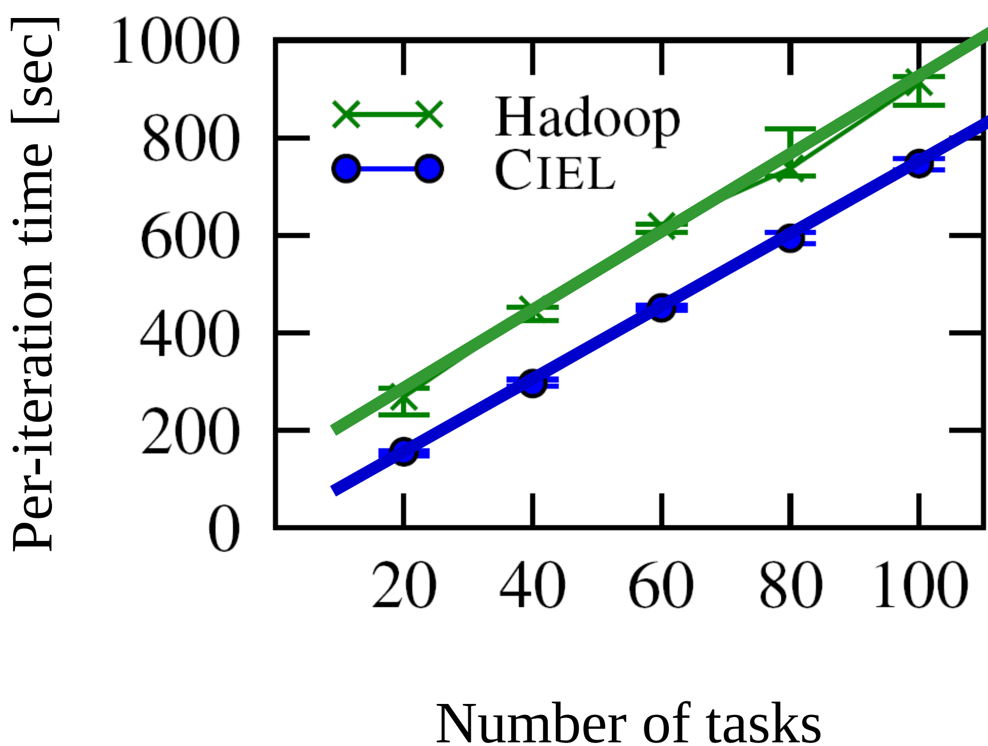


Per-iteration time [sec]
1000
800
600
400
200
0
20
40
60
80
100
Number of tasks
Hadoop
CIEL

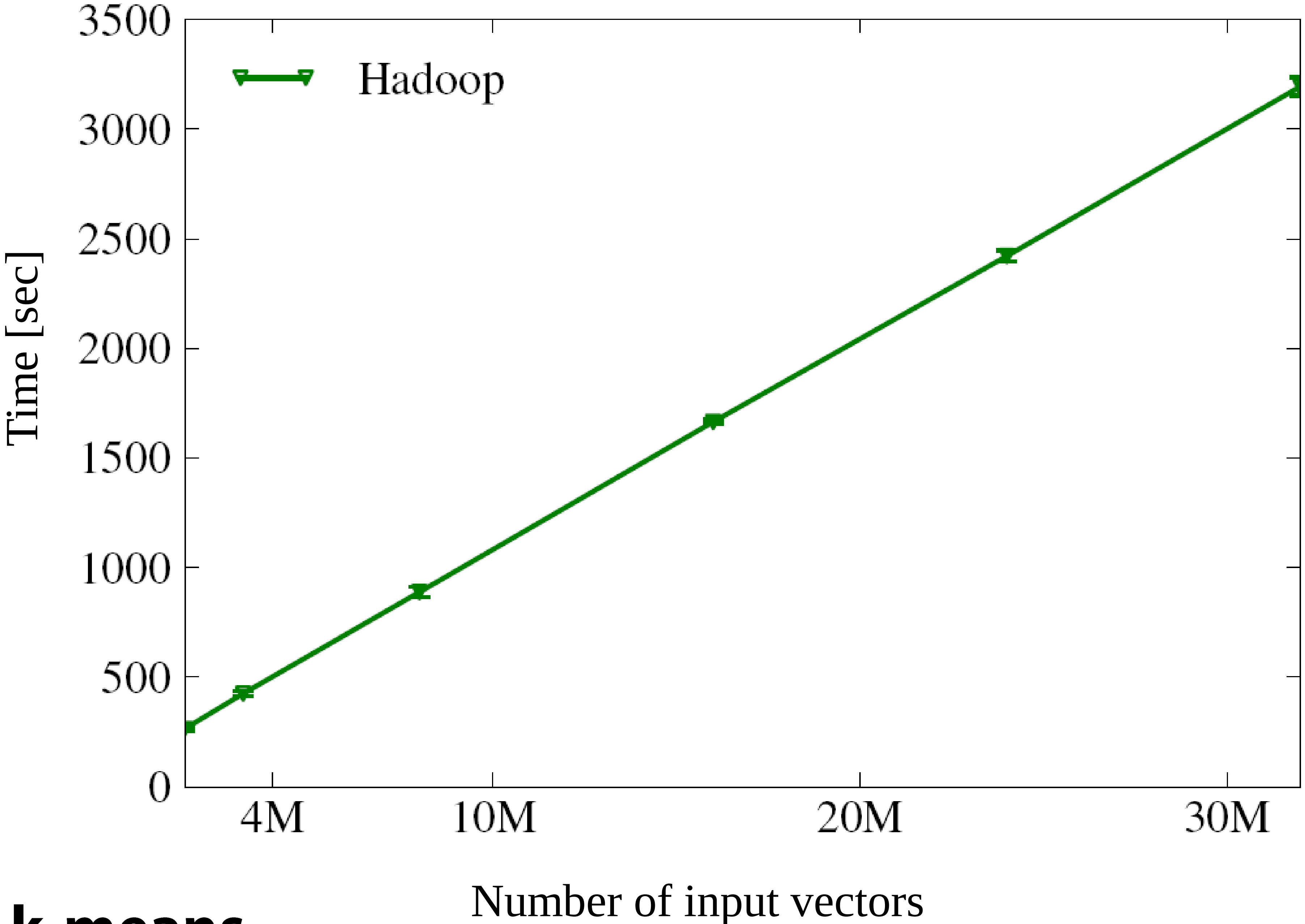


Per-iteration time [sec]
1000
800
600
400
200
0
20
40
60
80
100
Hadoop
CIEL
Number of tasks

"CIEL is faster than Hadoop [by 160s per iteration]"

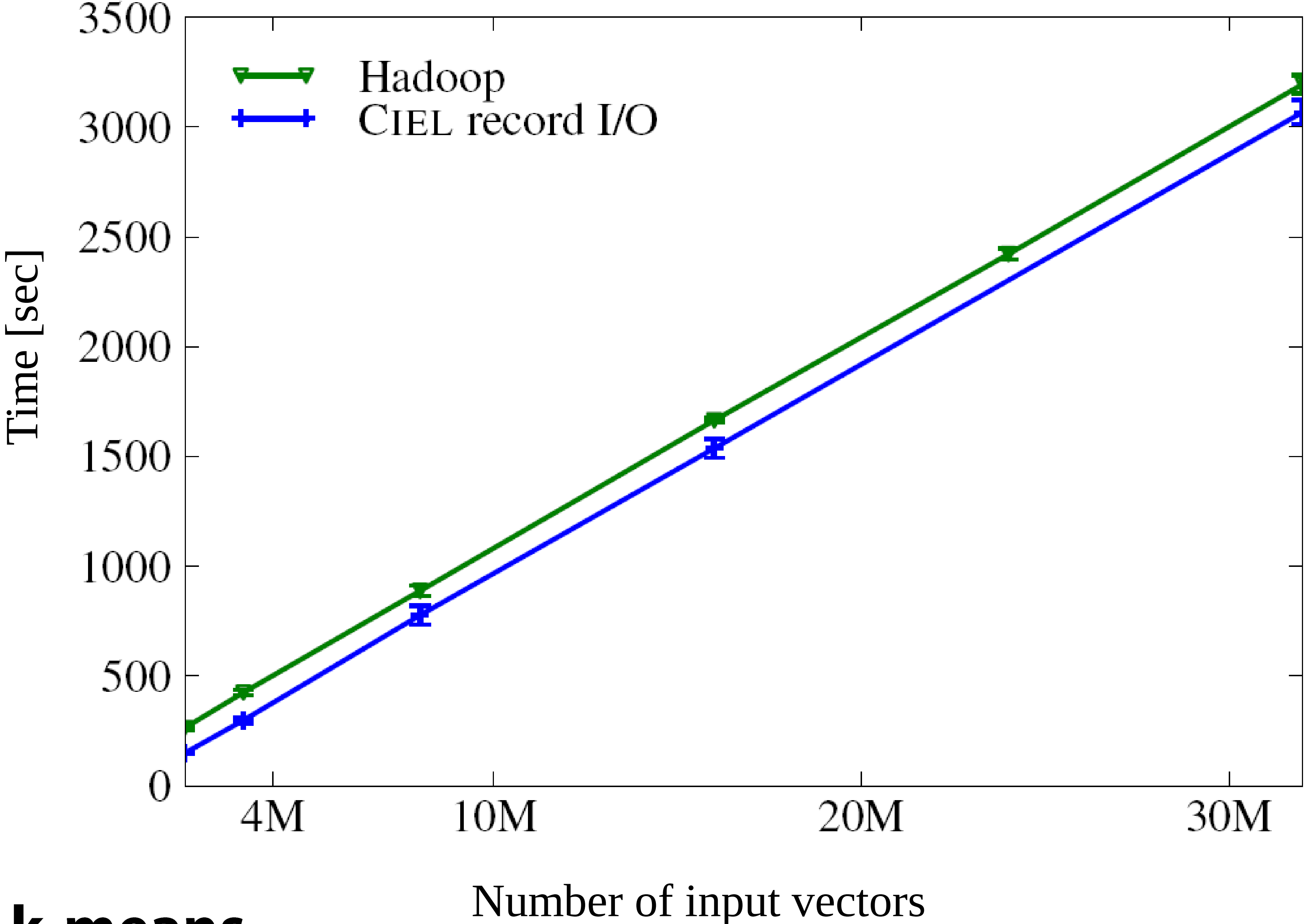


"CIEL has less constant overhead than Hadoop and scales similarly well."



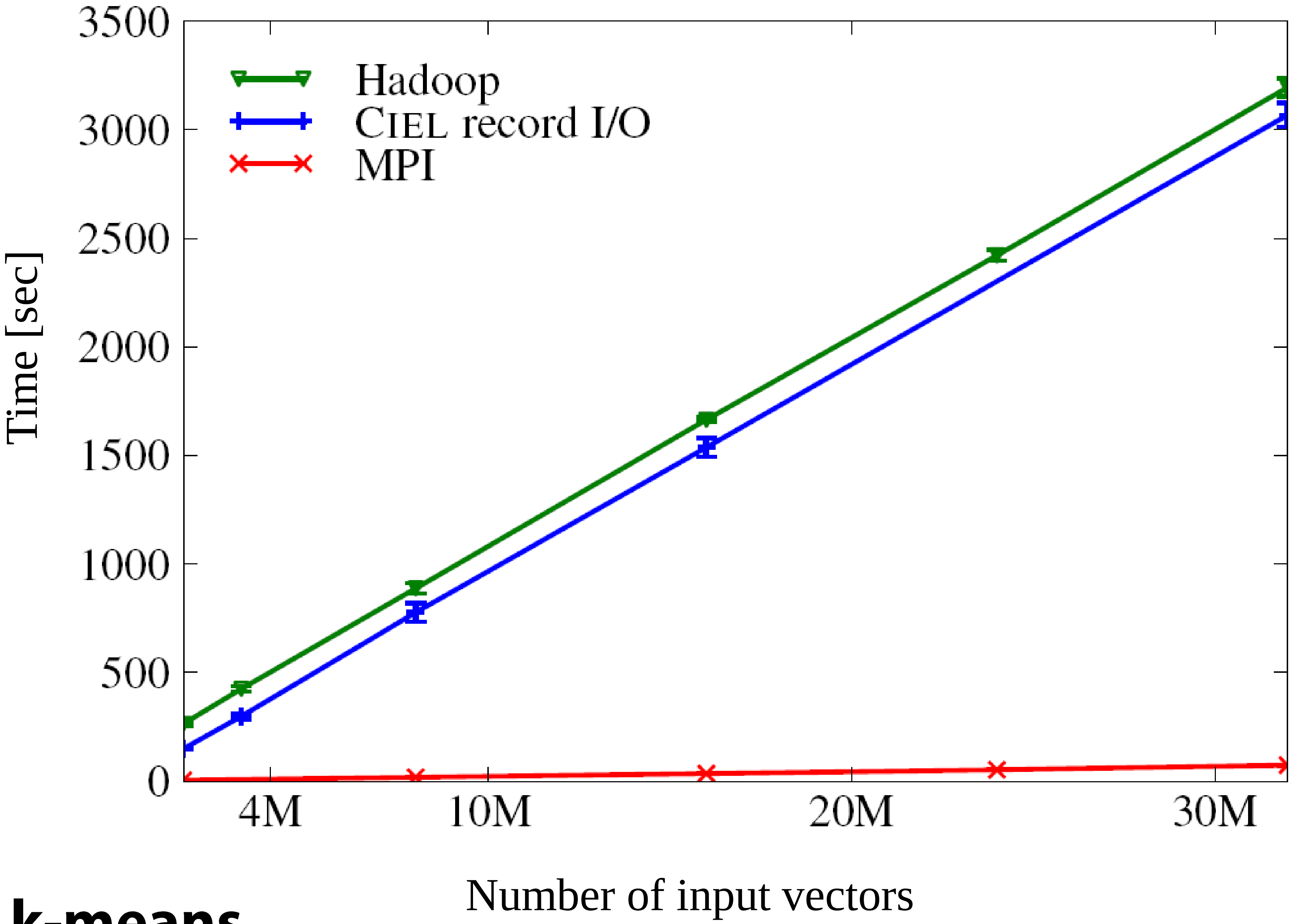
Hadoop
Time [sec]
3500
3000
2500
2000
1500
1000
500
0
4M
10M
20M
30M
Number of input vectors

k-means

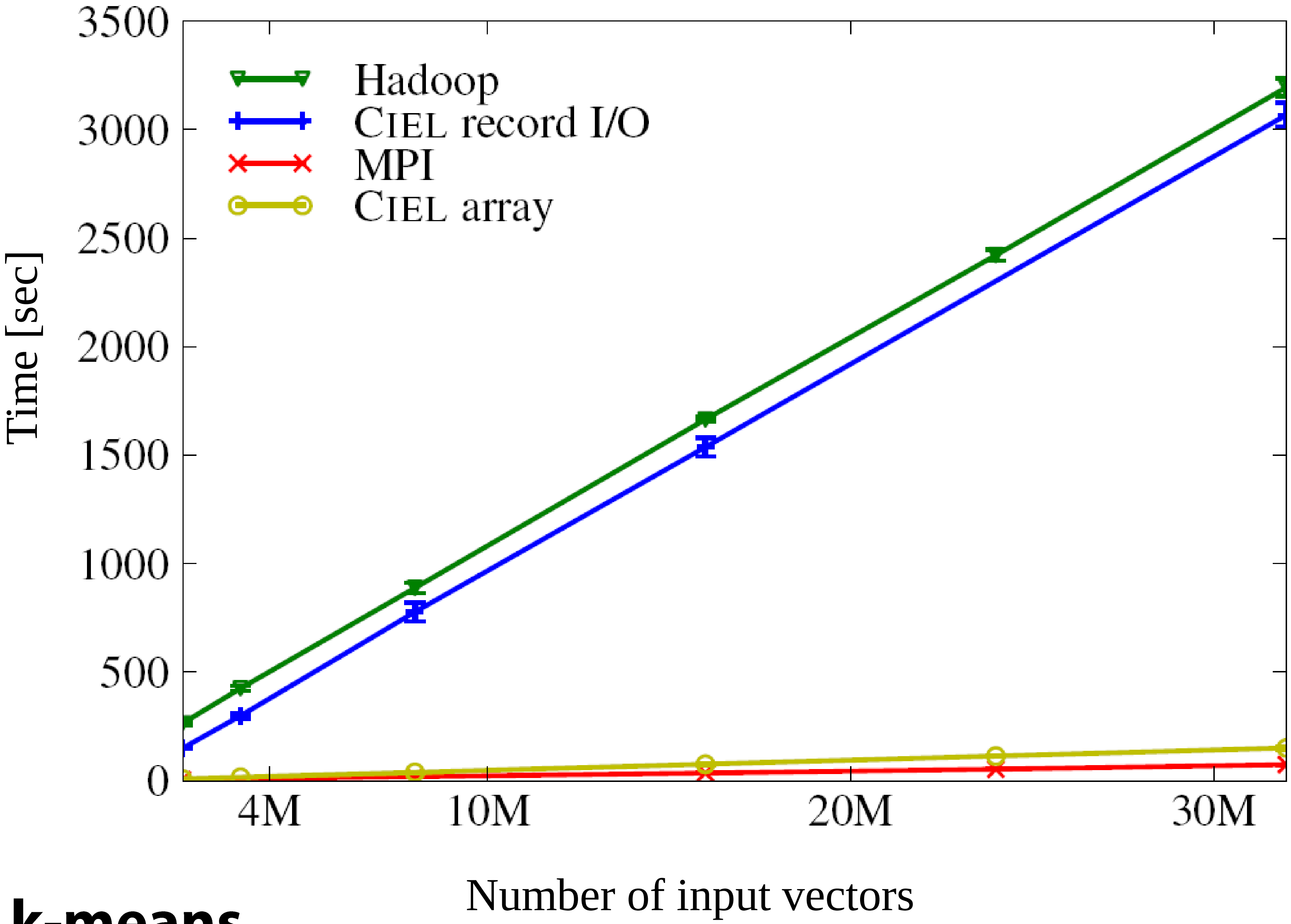


3500
3000
2500
2000
1500
1000
500
0
Time [sec]
Hadoop
CIEL record I/O
4M
10M
20M
30M
Number of input vectors

k-means

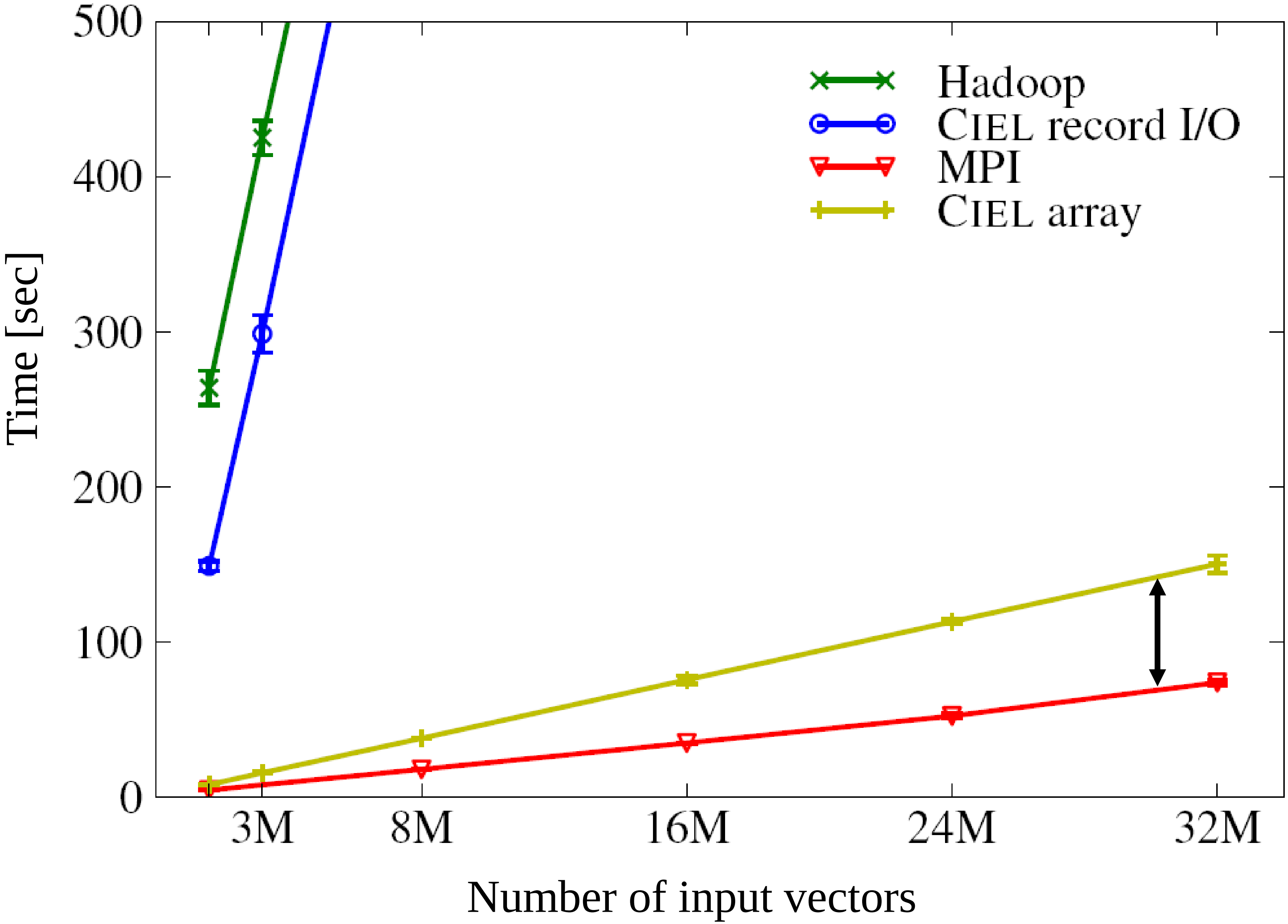

3500
3000
2500
2000
1500
1000
500
0
Time [sec]
Hadoop
CIEL record I/O
MPI
4M
10M
20M
30M
Number of input vectors

k-means

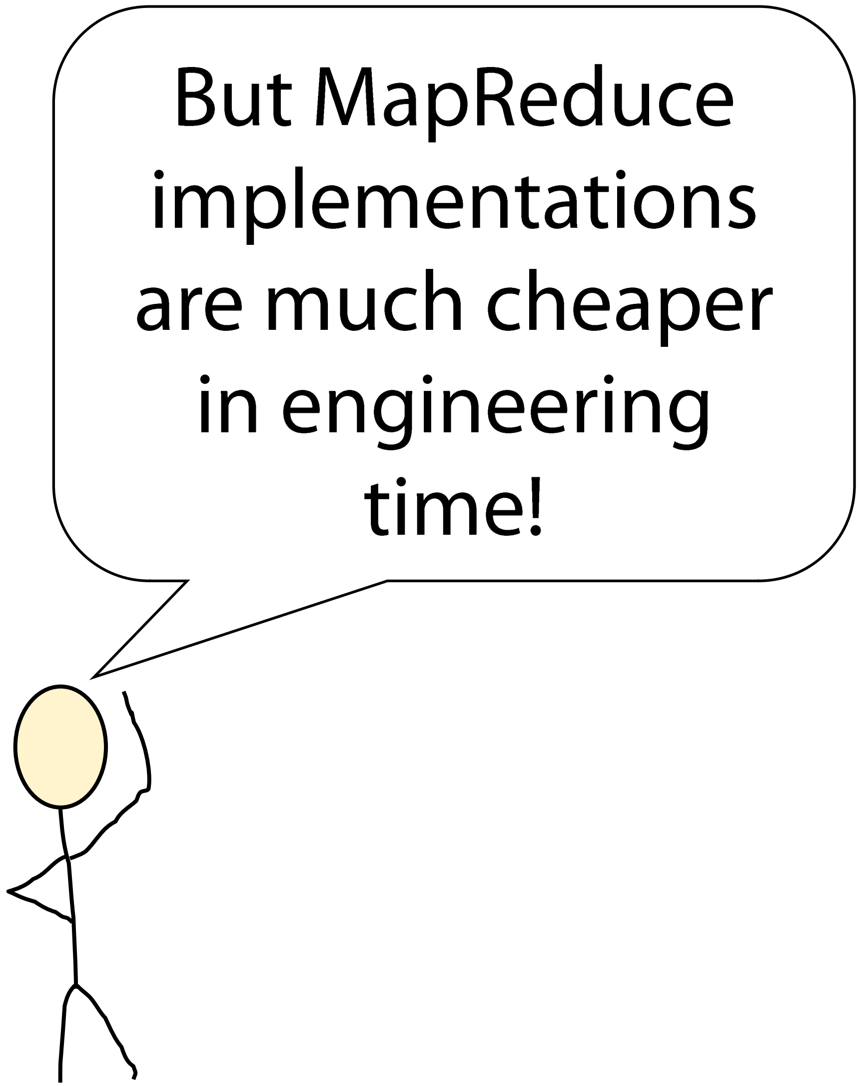


Hadoop
CIEL record I/O
MPI
CIEL array
3500
3000
2500
2000
1500
1000
500
0
Time [sec]
4M
10M
20M
30M
Number of input vectors

k-means



Hadoop
CIEL record I/O
MPI
CIEL array
500
400
300
200
100
0
Time [sec]
3M
8M
16M
24M
32M
Number of input vectors



Quantify the performance sacrificed.

Actually, we may be okay…

Lots of new, domain-specific research systems improve on MapReduce.

Evaluate against the best-of-breed, not Hadoop/MapReduce!

Publish your code, if at all possible!

Here endeth the sermon ☺

(but there are four more sins!)

1. Unnecessary (distributed) parallelism
2. Assumption of resource homogeneity
3. Picking the low-hanging fruit
4. Forcing the abstraction
5. Unrepresentative clusters/workloads
6. Assumption of perfect elasticity
7. Ignorance towards fault tolerance

Now is the time to confess!

(or to shoot the messenger ☺)

FURTHER SINS

[these were not part of the HotCloud 2012 presentation, but included in other versions of this talk]

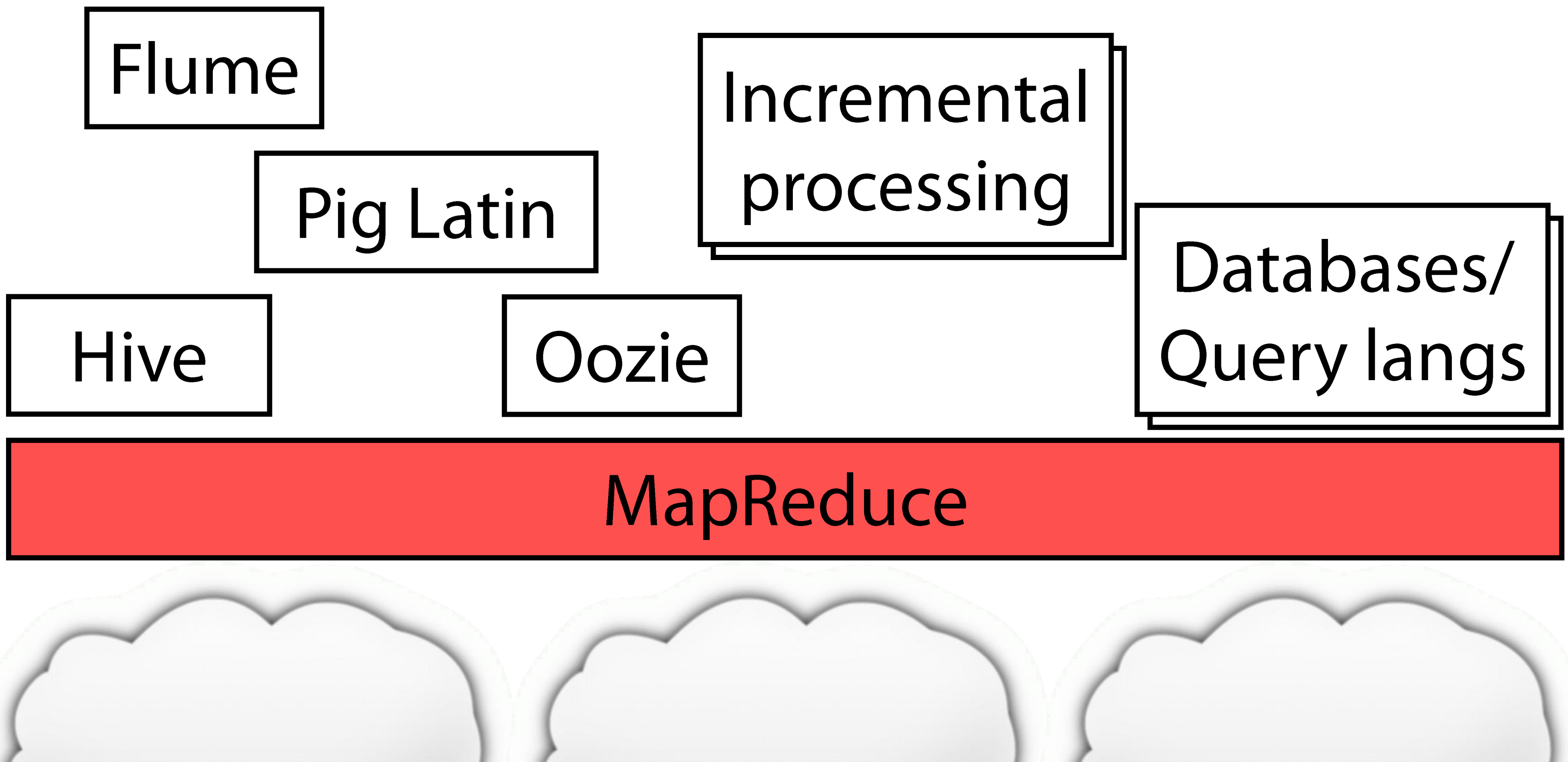
4

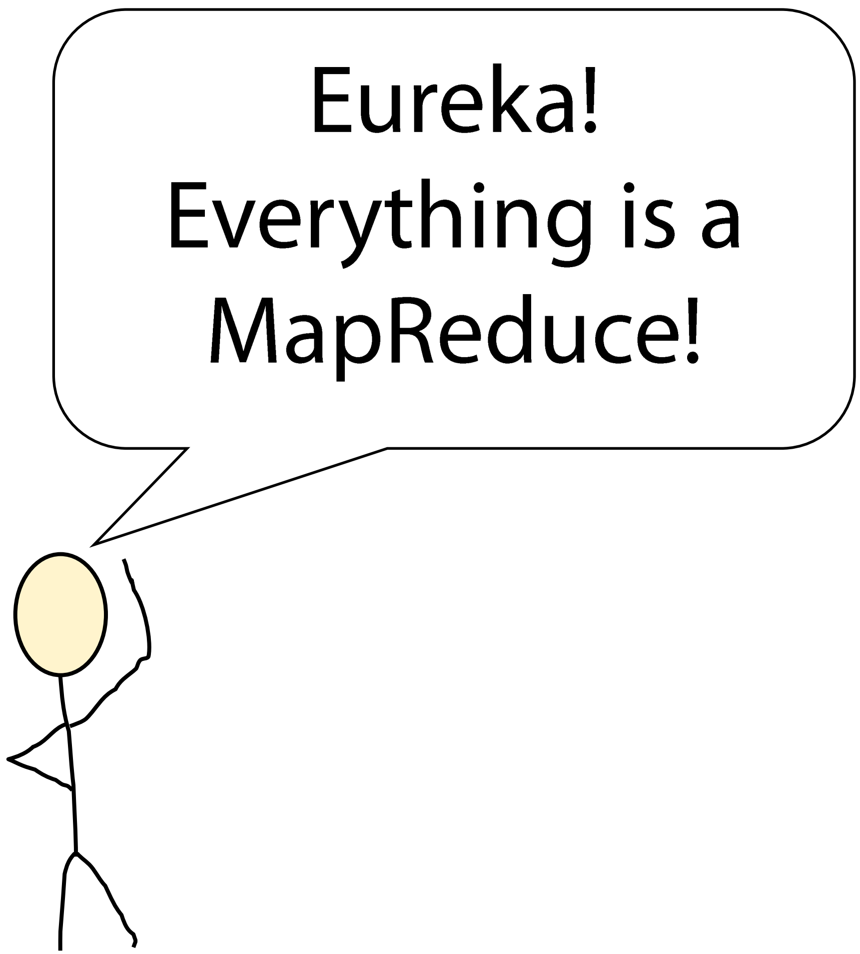
Fourth sin:

Forcing the abstraction

"Java MapReduce [... is] the assembly language of Apache Hadoop"

-- Cloudera executive, Stanford EE380 class





... really?!

Assembly languages...

... have small, fine-grained, fast, composable instructions.

MapReduce was designed for...

... long-running, large, coarse-grained, massively parallel workloads!

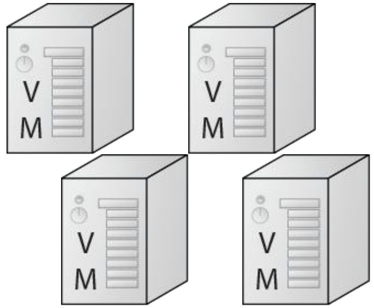
5

Fifth sin:

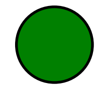
Use of unrepresentative workloads and clusters

The three cluster types

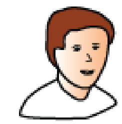
1



(usually) virtual



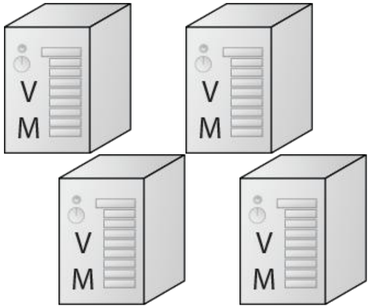
single-purpose,
single-job



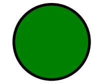
single-user

The three cluster types

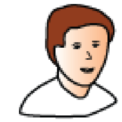
1



(usually) virtual



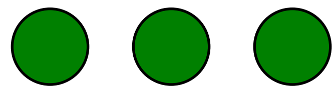
single-purpose,
single-job



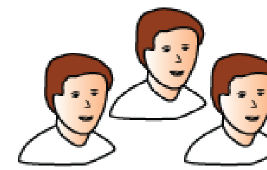
single-user

2

physical/virtual

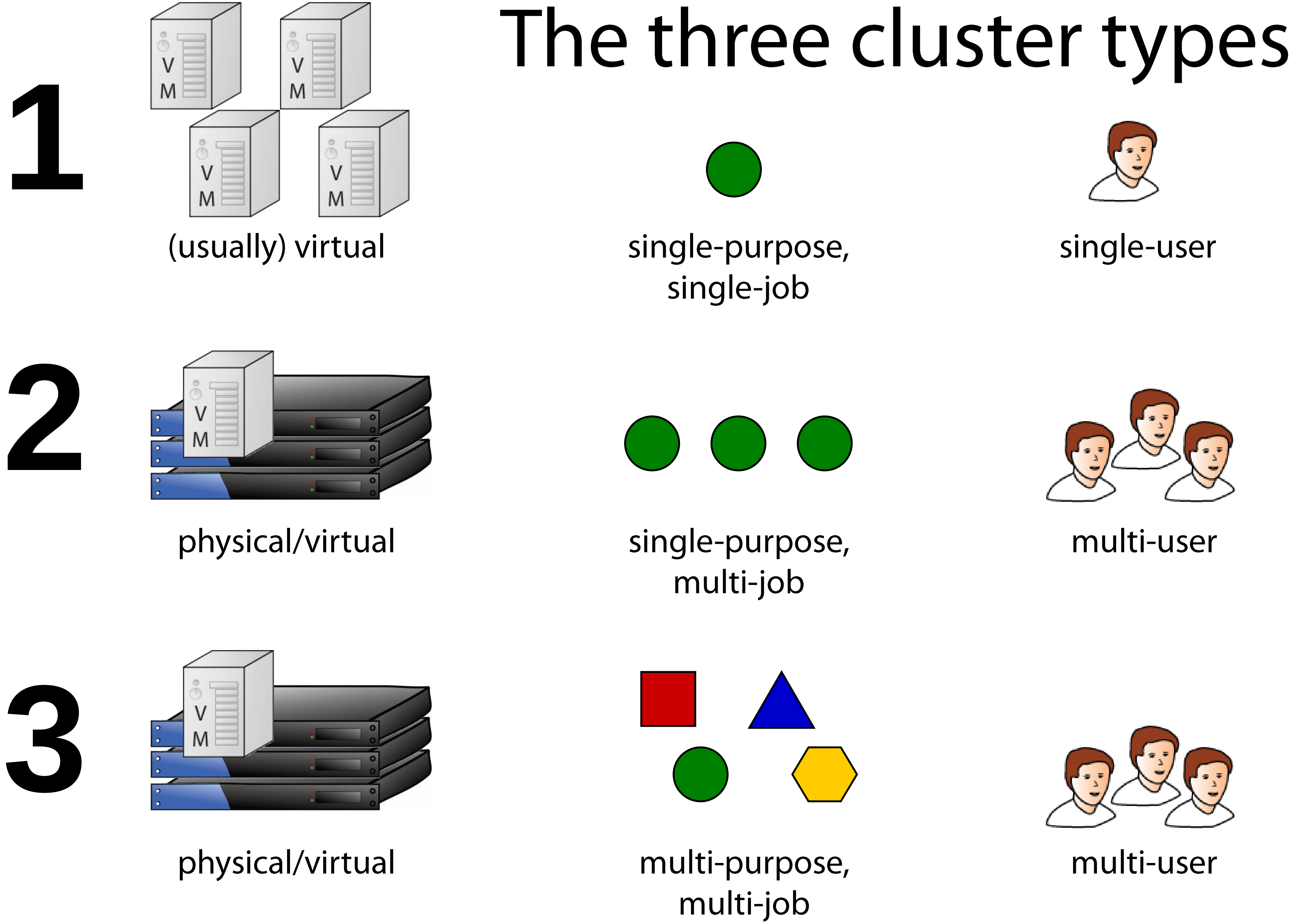


single-purpose,
multi-job



multi-user

The three cluster types



The three cluster types

1

(usually) virtual

single-purpose,
single-job

single-user

2

physical/v

Often used by academics…

… but not representative of type 3!

So don't imply it is!

3

physical/virtual

multi-purpose,
multi-job

multi-user

We need “cluster mix“ benchmarks!

Starting points:

Hadoop GridMix

Google Trace

Berkeley SPIM

6

Sixth sin:

Assumption of perfect elasticity

[…] using 1000 servers for one hour costs no more than using one server for 1000 hours.

-- Armbrust et al., Above the clouds: A Berkeley View of Cloud Computing, 2009

[C]ompanies ***with large batch-oriented tasks*** *can get results* ***as quickly as their programs can scale****, since using 1000 servers for one hour costs no more than using one server for 1000 hours.*

-- Armbrust et al., Above the clouds: A Berkeley View of Cloud Computing, 2009

Scalability and resources are finite in reality!

- *Unexpected bottlenecks*
- *Scheduling load*
- *Communication structure*
- *Increased likelihood of failures*

7

Seventh sin:

Ignoring fault tolerance

Fault tolerance is a 1^{st} class feature in MapReduce...

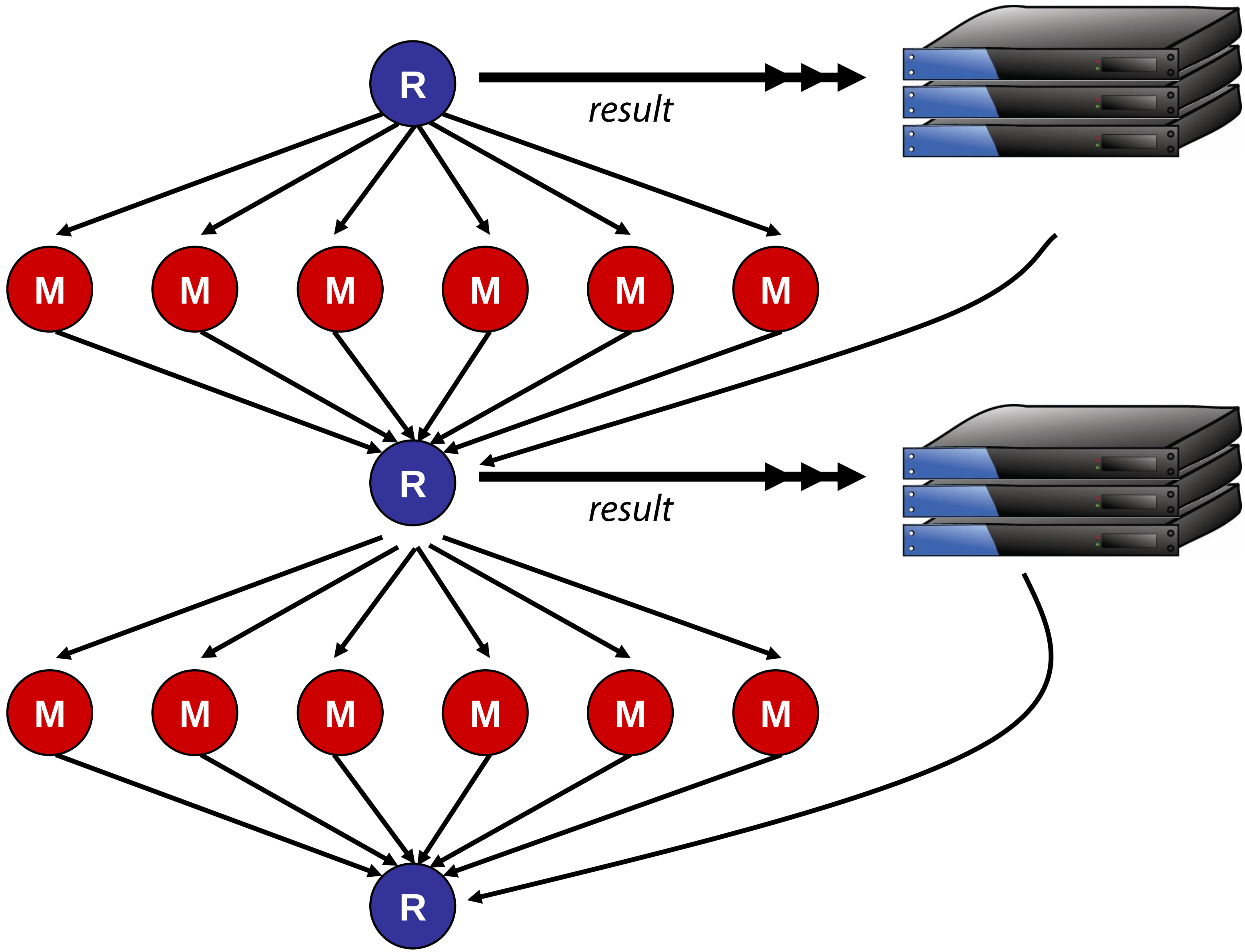
[…] we provide a fault-tolerant implementation that scales to thousands of processors. In contrast, most [existing] parallel processing systems […] leave the details of handling machine failures to the programmer.

-- Dean et al., MapReduce paper, OSDI 2004

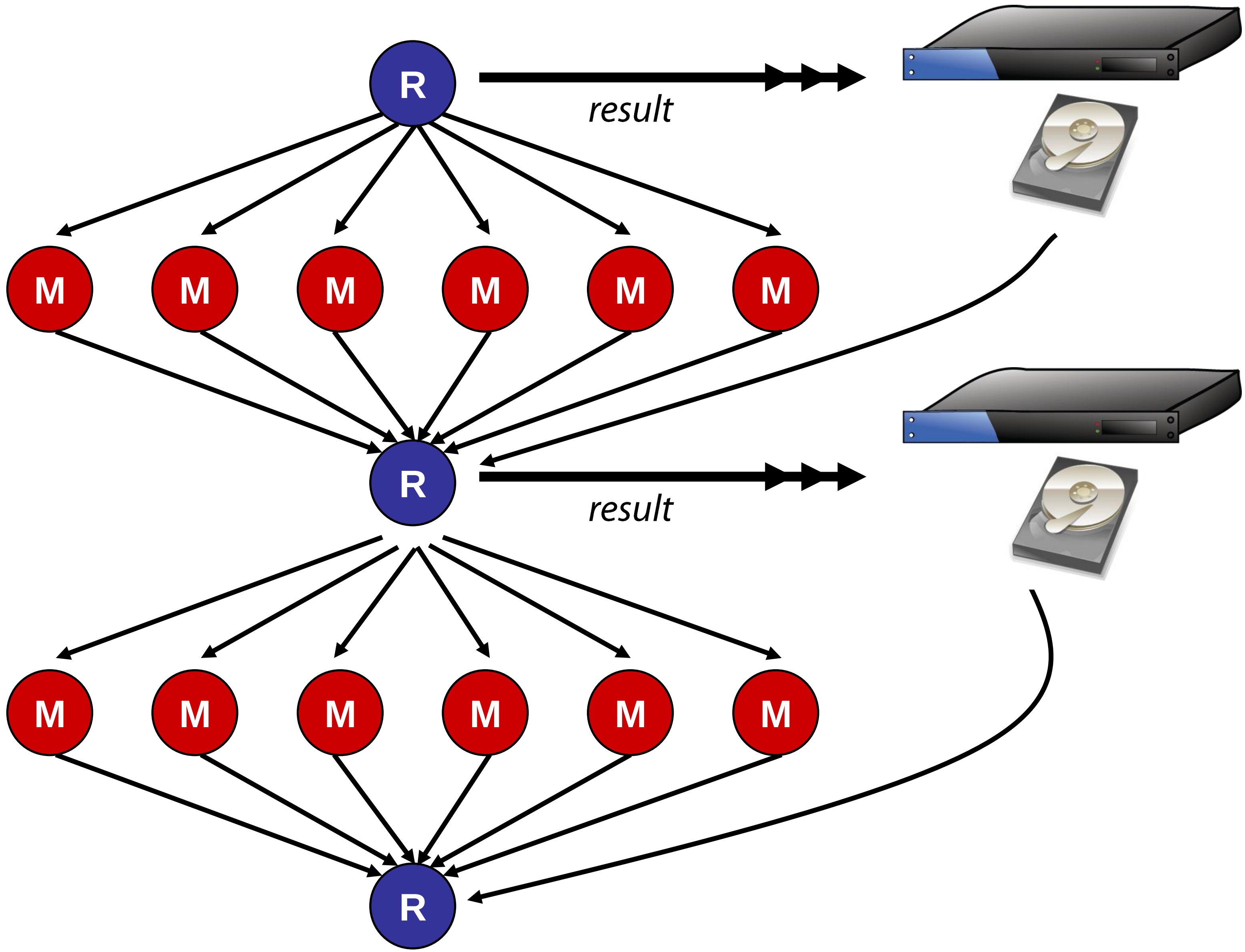
... but it is often treated as second class!

- *Rarely evaluated comprehensively*
- *In-memory caching often not fault tolerant*
- *Tricky with iterative processing on top of MapReduce*

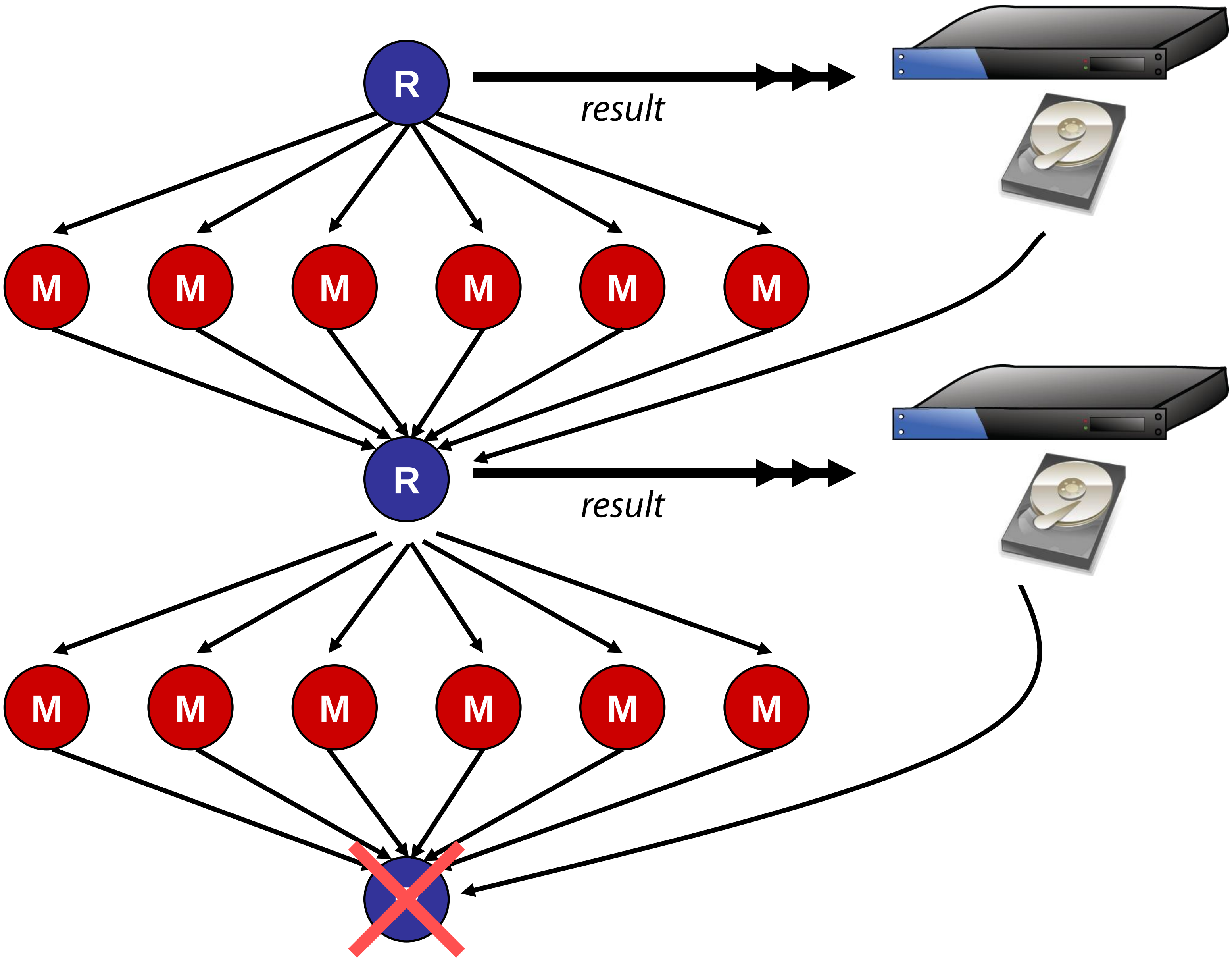
Iterative MapReduce example



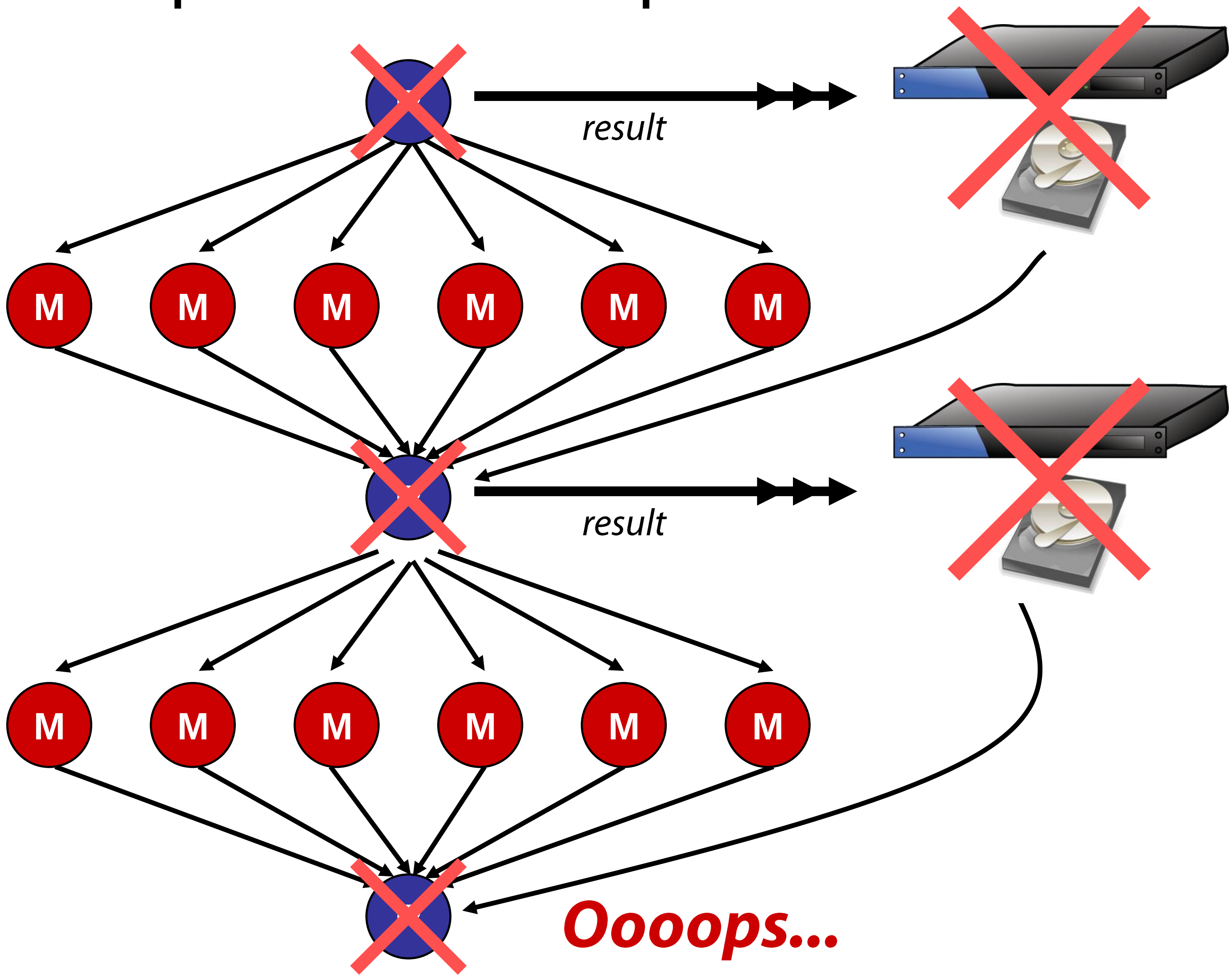
Iterative MapReduce example



Iterative MapReduce example



Iterative MapReduce example



Why do we sin?

Sometimes because we lack data & infrastructure!

➔ **Industry, please help us!**

- *Workload traces*
- *Statements of real-world problems*
- *Access to hardware*

Sometimes because we are lazy or working last-minute for a deadline...

➔ **Reviewers and shepherds can enforce standards (or we agree not to sin! ☺)**

How can we repent?

We agree to avoid the sins and heed the "three R"

- ➔ **Consciously design experiments**
- ➔ **Justify when sins are unavoidable or irrelevant**
- ➔ **Listen to reviewers & shepherds**

Allow sins to be exposed

- ➔ **Make source code available**
- ➔ **Support reproduction/validation efforts**

1

- *Compare serial to parallel implementation*
- *Derive maximum parallel speedup*
- *Justify going distributed*

2

- *Repeated runs!*
- *Indicate performance variance*
- *Clearly state parameters*
- *EC2: ideally, multiple clusters, multiple times of day*

3

- *Do not use speedup-over-Hadoop as headline result!*
- *Compare to relevant optimized alternatives*
- *Or quantify speedup over serial (1 worker)*
- *Release your source code, so others can build upon it!*

4

- *Decide if MapReduce is the correct abstraction*
- *If not, but cheaper, quantify loss in performance*

5

- *Consider different job types, priorities and preemption!*
- *Benchmark cluster “job mixes“*

6

- *Clearly qualify the elasticity assumptions made*
- *Note (potential) scalability bottlenecks*

7

- *Clearly state fault tolerance requirements*
- *Clearly state characteristics and techniques used*
- *Evaluate them!*

1. Unnecessary (distributed) parallelism
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