CS 649 Intro to Big Data: Tools and Methods
Fall Semester, 2022
Doc 2 Big Data Introduction
Jan 19, 2022

Big Data

Data sets that are so large or complex that traditional data processing applications are inadequate

Wikipedia

Big Data

Hulu

- Imports 20GB per second continuously

Celeste Project

- 55 terabytes of data processed in 15 minutes

Intel Ruler

32 TB SSD

Rack mounted

1PB in 1U

1 Rack holds 42 PB

Amazon AWS Snowball

80 Terabytes

Amazon AWS Snowmobile

100 Petabytes

Value	Metric	
1000	kB	kilobyte
1000^2	MB	megabyte
1000^3	GB	gigabyte
1000^4	TB	terabyte
1000^5	PB	**petabyte**
1000^6	EB	exabyte
1000^7	ZB	zettabyte
1000^8	YB	yottabyte

Big Data 3-5 V's

Volume

Large datasets

Clusters - Spark

Velocity

Real time or near-real time streams of data

Kafka

Variety

Different formats

Structured, Numeric, Unstructured, images, email, etc.

NoSQL

Cassandra

Variability

Data flows can be inconsistent

Veracity

Accuracy

Complexity

Scaling to Handle Large Data Sets

Scaling up (Vertically)

- Add more resources to single machine
- Memory, disk space, faster processor, etc
- Easier that scaling out but limited
- Amazon AWS has servers with 2 TB of memory

Scaling out (Horizontally)

- Using multiple machines/processors
- Adds complexity

Scaling Up & Amdahl's Law

$T(1)$ be the time it takes a sequential program to run
$T(N)$ be the time it takes a parallel version of the program to run on N processors.

Speedup using N processors

$$S(N) = T(1)/T(N)$$

Let p = % of program that can be parallelized

Amdahl's Law

$$S(N) = 1/(1 - p + p/N)$$

Amdahl's Law

Let p = % of program that can be parallelized

Amdahl's Law

$$S(N) = 1/(1 - p + p/N)$$

$p = 1$

$$S(N) = 1/(1 - 1 + 1/N) = 1/(1/N) = N$$

$p = 0$

$$S(N) = 1/(1 - 0 + 0/N) = 1$$

Amdahl's Law

Let p = % of program that can be parallelized

Amdahl's Law

$$S(N) = 1/(1 - p + p/N)$$

Given p = 0.5 how many processors does in make sense to use?

What does p have to be to get a speedup of

5 or greater using 10 processors?

10 or greater using 20 processors?

20 or greater using 40 processors?

50 or greater using 100 processors?

Issues

What types of problems can be solved using cluster of commodity computers?

- When are setup time and communication time too high?
- How many machines?

How to distribute data?

How to find the data?

What to do when machine fails?

How to distribute computation? Load balancing?

How to share computation?

- Send computation result from node A to node B
- How does node B wait? How long is B idle?

How to combine results

Performance tuning

Pleasingly Parallel

Compute Sum

2 -3 5 9 1 7 8 2 1 6

2 -3 5 9 1

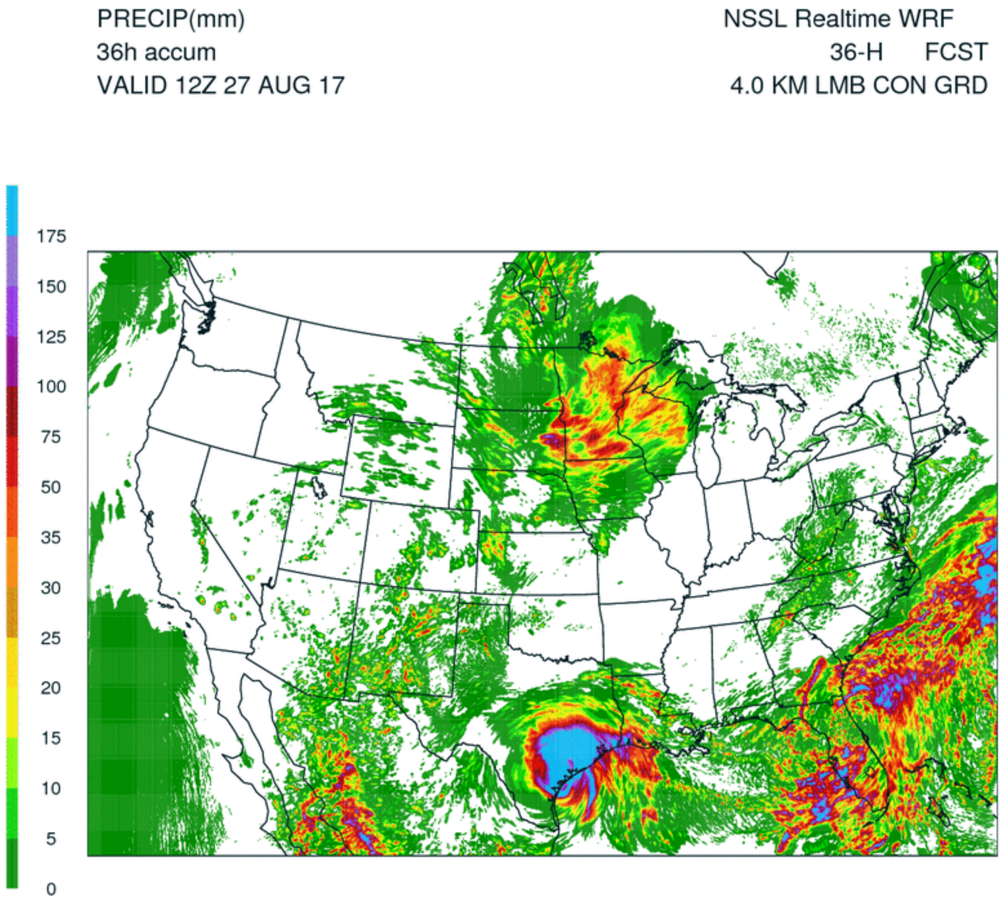
7 8 2 1 6

14

24

38

Weather Simulation



Create 4km grid

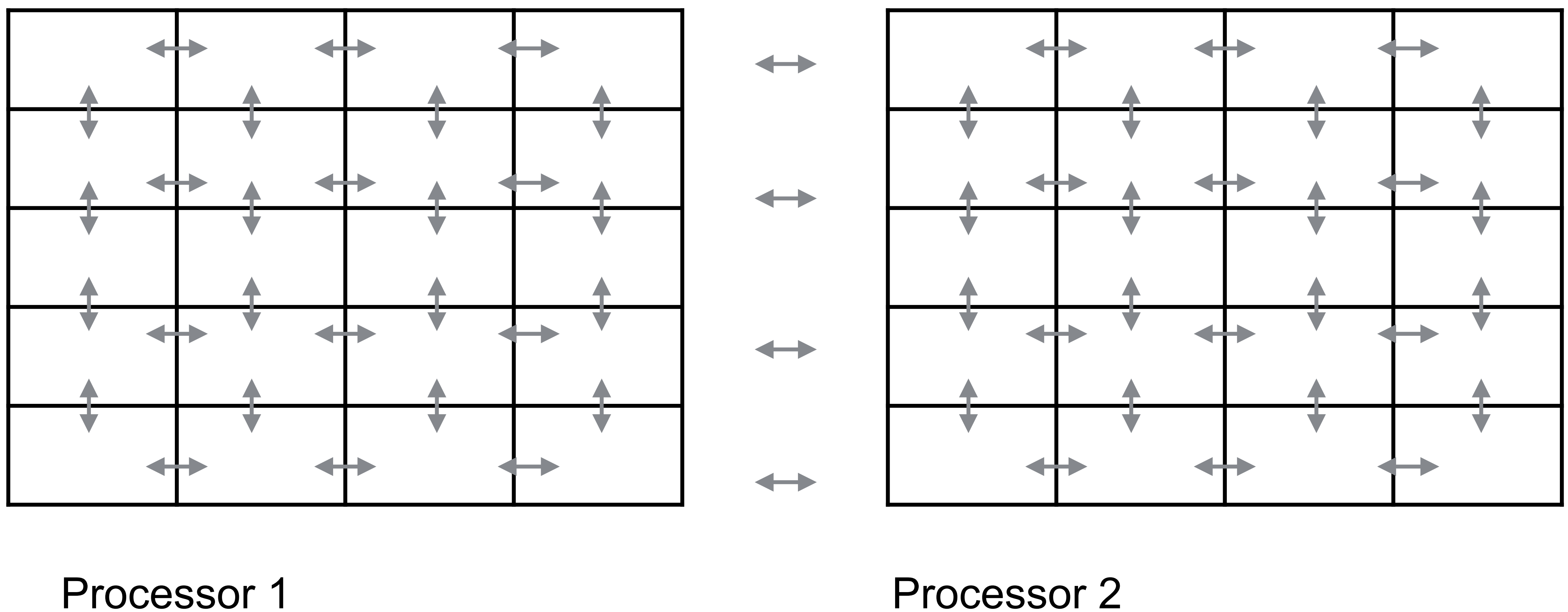
24 second time steps

35 vertical layers

Each time step

Compute effect of rain solar radiation in each square in grid

Propagate effect of change to neighboring grid cells and layers



Processor 1
Processor 2

How to Distribute Data & Computation

Automate as much as possible

Want to run code on different number of nodes at different times
- Code should be independent of number of nodes

Node B should not know about Node C
- Is there a node C?
- Which is node B? C?

Example

```
val data = readDataIntoArray(xxx)

var sum = 0

for (k <- 0 to data.length)
  sum += data(k)
```

```
val sum = data.reduce(_ + _)
```

Compiler issue

- Has to handle all possible loop contents
- Has to know where data is located

Library issue

- Handle one case
- No direct access to array index
- Library can distribute data

```
for (k <- 0 to data.length/2)
  sum += data(k) + data(data.length - k -1)
```

Parallelizing Python Code

- Hadoop
  - Map-reduce only
- Spark
  - Map-Reduce
  - Some
    - ML
    - Statistics
- Dask
  - Parallelize Panda, NumPy, Scikit-Learn
  - Low level parallelization

Latency numbers every programmer should know

```
L1 cache reference ......................... 0.5 ns
Branch mispredict ............................ 5 ns
L2 cache reference ........................... 7 ns
Mutex lock/unlock ........................... 25 ns
Main memory reference ...................... 100 ns
Compress 1K bytes with Zippy ............. 3,000 ns  =   3 µs
Send 2K bytes over 1 Gbps network ....... 20,000 ns  =  20 µs
SSD random read ........................ 150,000 ns  = 150 µs
Read 1 MB sequentially from memory ..... 250,000 ns  = 250 µs
Round trip within same datacenter ...... 500,000 ns  = 0.5 ms
Read 1 MB sequentially from SSD* ..... 1,000,000 ns  =   1 ms
Disk seek ........................... 10,000,000 ns  =  10 ms
Read 1 MB sequentially from disk .... 20,000,000 ns  =  20 ms
Send packet CA->Netherlands->CA .... 150,000,000 ns  = 150 ms
```

More at: http://highscalability.com/numbers-everyone-should-know

Multiple by 2 Billion

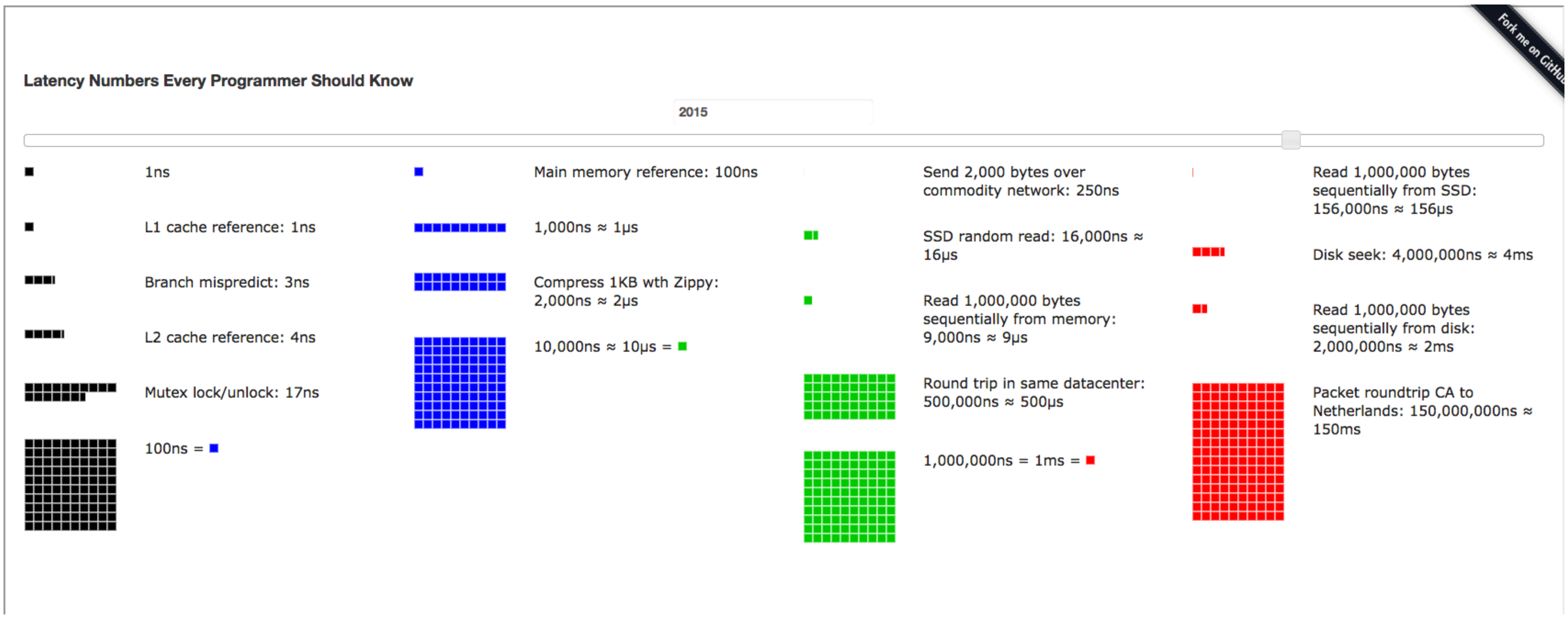
Scale to human time to see relative difference

```
L1 cache reference                       1 second

Branch mispredict                       10 second

L2 cache reference                      17 second

Main memory reference                   3.3 minutes

Round trip within same datacenter      11.6 days

Read 1 MB sequentially from SSD        23.2 days

Disk seek & read 1 MB from disk          2 years
```

Times slower than L1

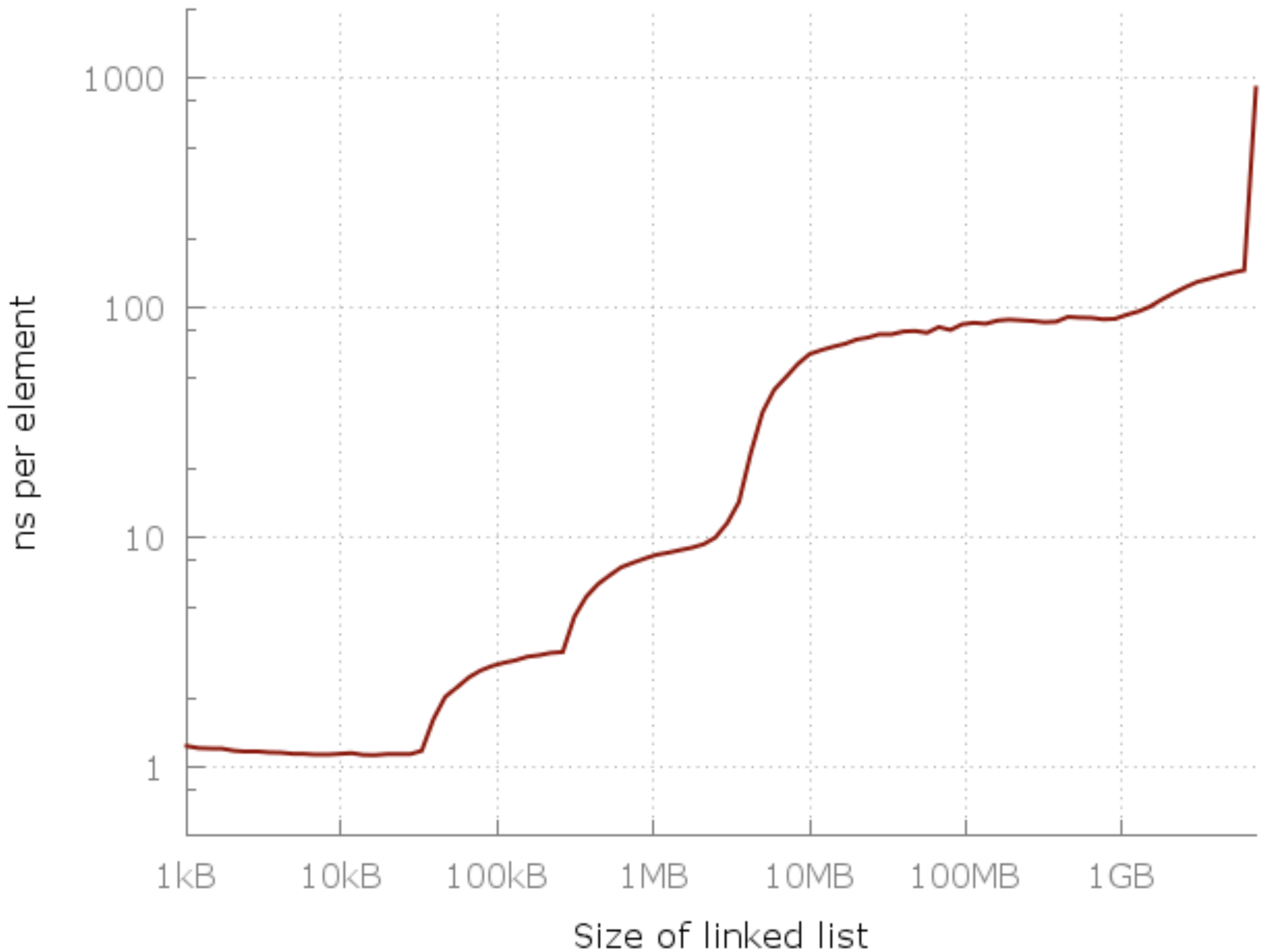
	Times slower
L1 cache reference	1x
Branch mispredict	10x
L2 cache reference	17x
Main memory reference	200x
Round trip within same datacenter	1,000,000x
Read 1 MB sequentially from SSD	2,000,000x
Disk seek & read 1 MB from disk	60,000,000x

https://people.eecs.berkeley.edu/~rcs/research/interactive_latency.html



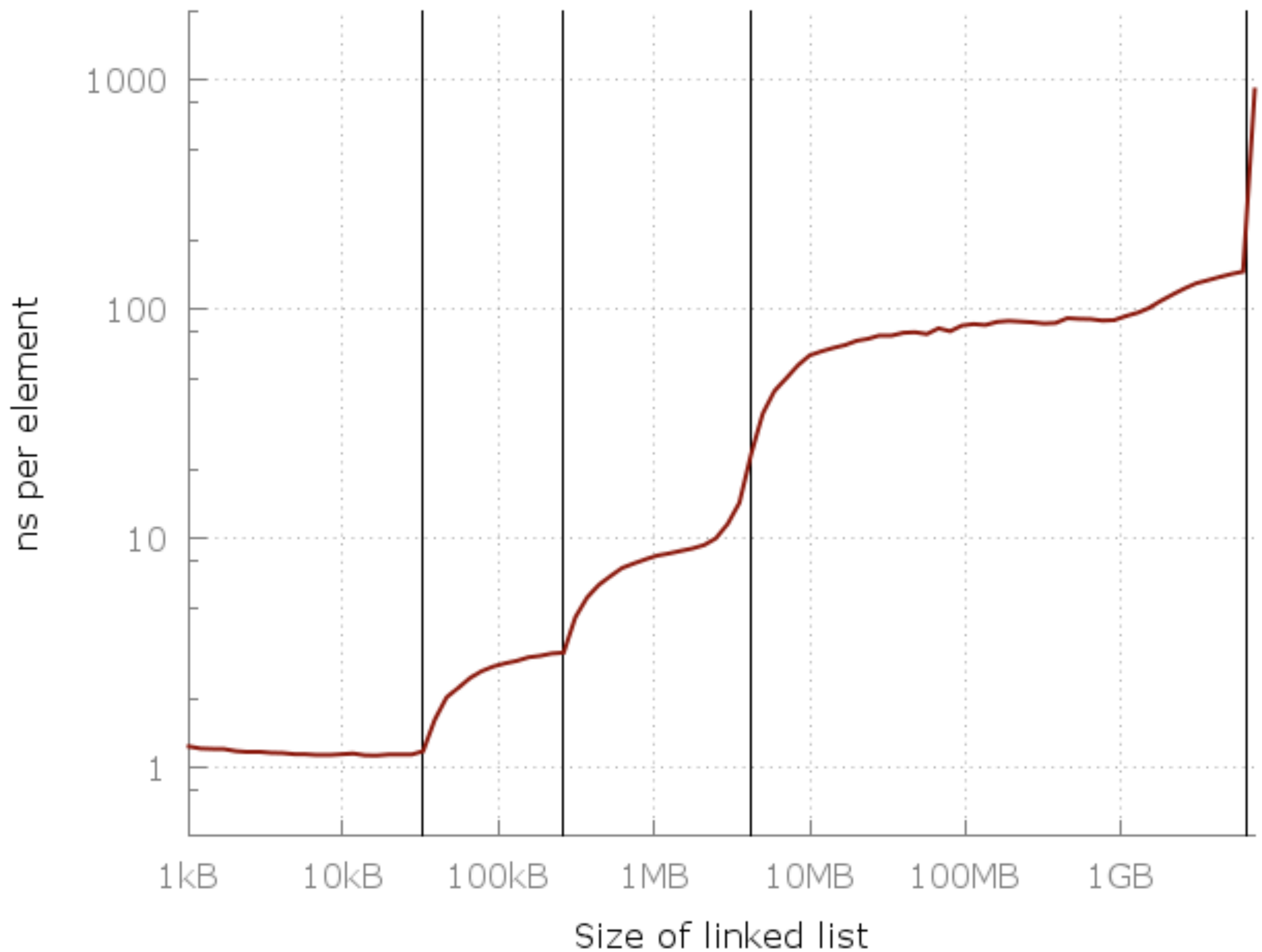
Myth of Ram Access Being O(1)

http://goo.gl/JwtF5v



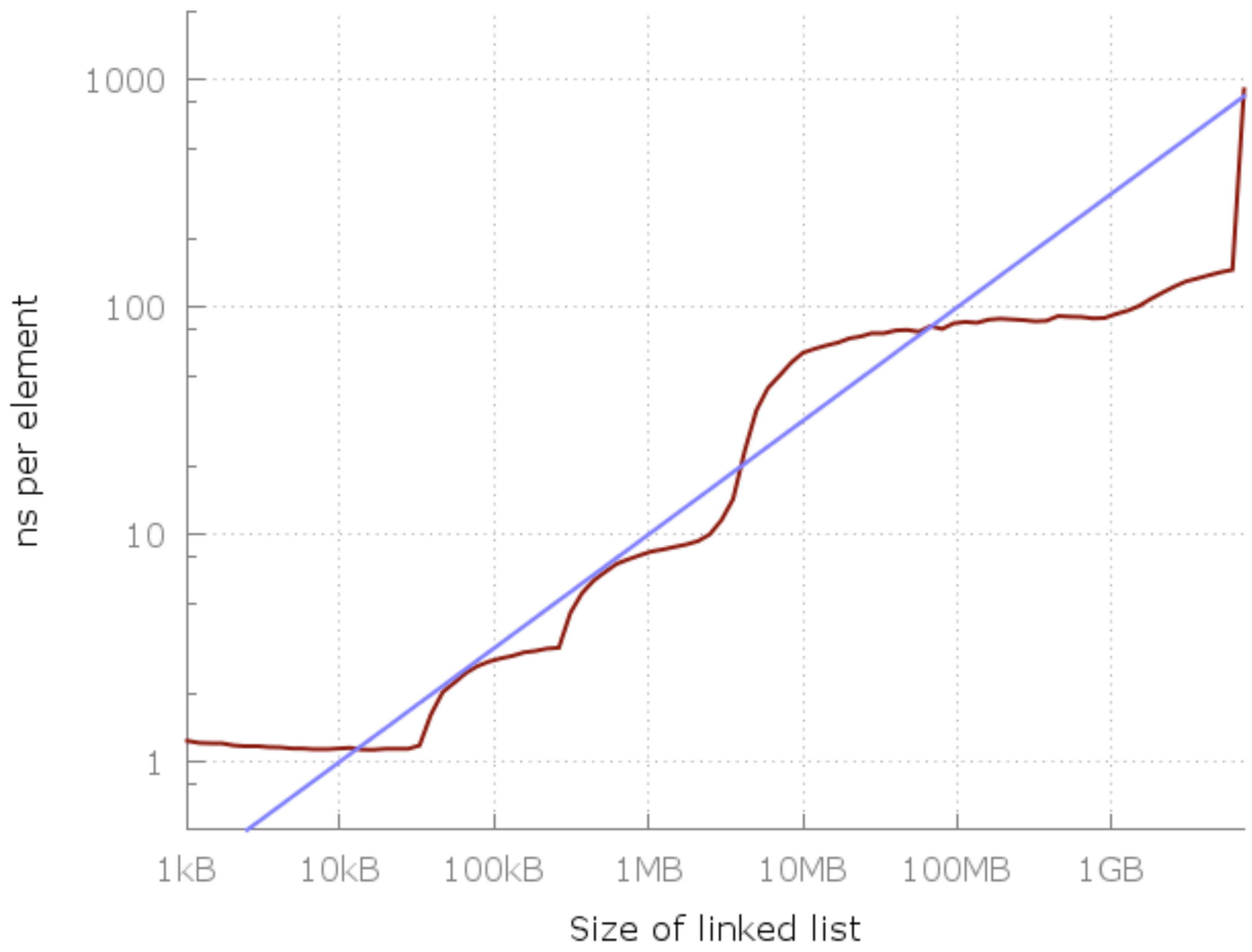
Myth of Ram Access Being O(1)

Lines - L1=32kiB,
L2=256kiB,
L3=4MB and
6 GiB of free RAM



Myth of Ram Access Being O(1)

Blue Line = O(√N)



History

		1GB Ram
1990		$103,880
1995 - Java 1.0	Haskell (92)	$30,875
2000 - Java 3		$1,107
2001 -	Scala started	
2002 - Nutch (Hadoop) started		
2004 - Google MapReduce paper	Scala v1	
2005 -	F#	$189
2006 - Hadoop split from Nutch	Scala v2	
2007 -	Clojure	
2009 - Spark started		
2010	Scala on Tiobe index	$12
2012 - Hadoop 1.0		
2014 - Spark 1.0		
2015		$4

Hadoop

Hadoop Distributed File System (HDSF)

Map Reduce

Hadoop MapReduce vs Spark

Spark - 10 to 100 time faster

- Hadoop stores data on disk
- Spark keeps as much data in memory as possible

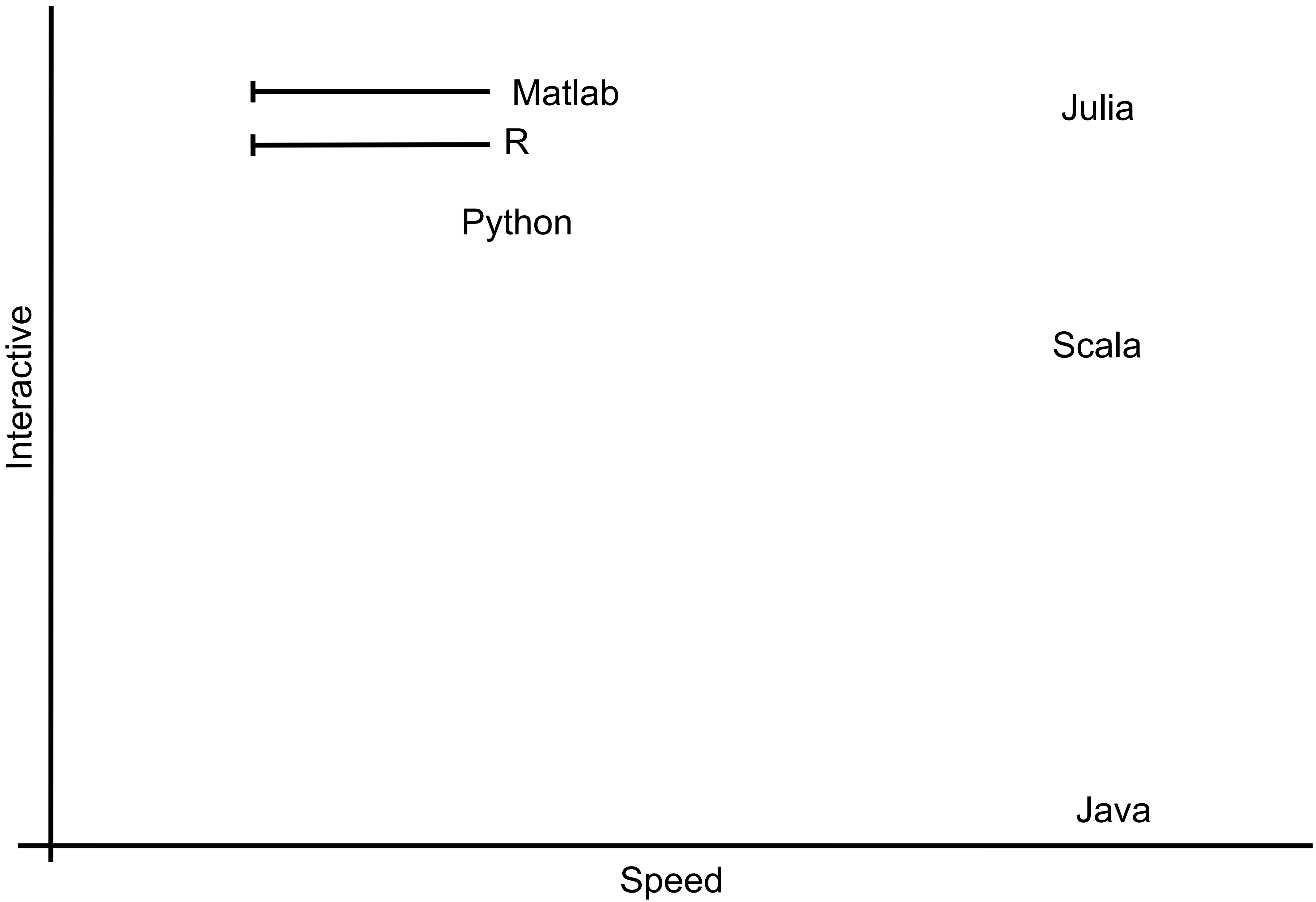
Spark

- Has much more functionality
- Uses most functional programming
- Hadoop only uses Map & Reduce

Spark

- Easier to use
- REPL

Two Language Problem



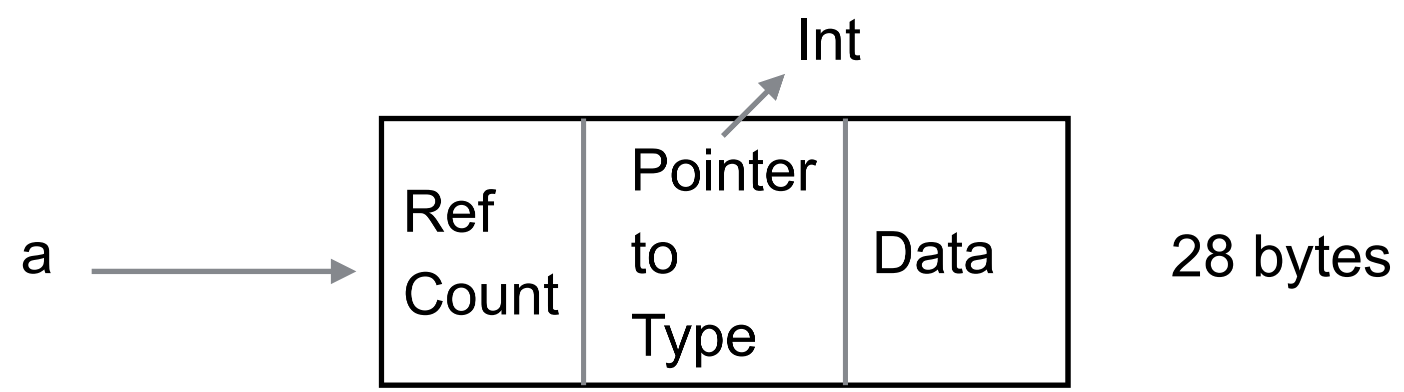
Two Language Problem - Addition

c = a + b

Python

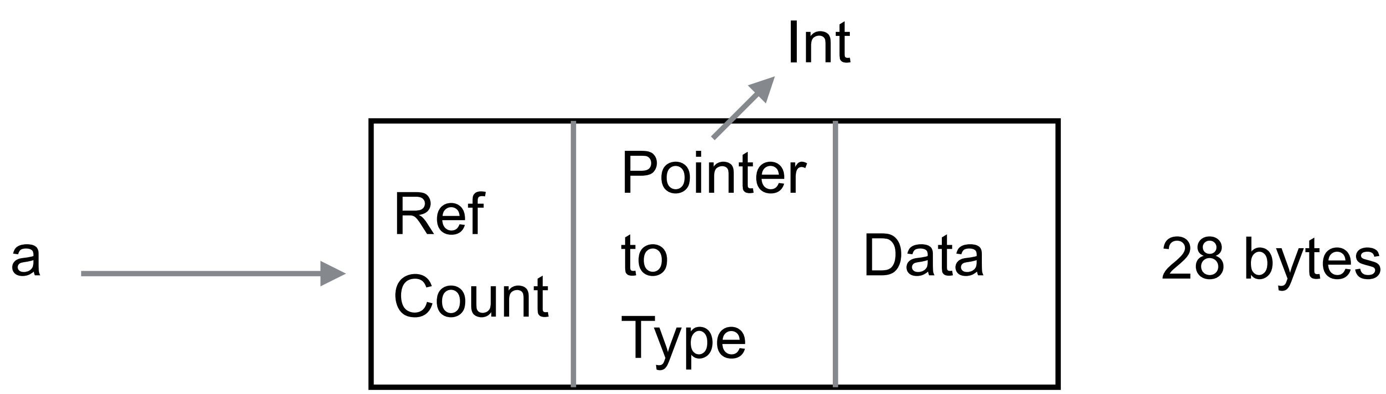
a = "cat"
a = 5

Python stores type information



Two Language Problem - Addition

c = a + b

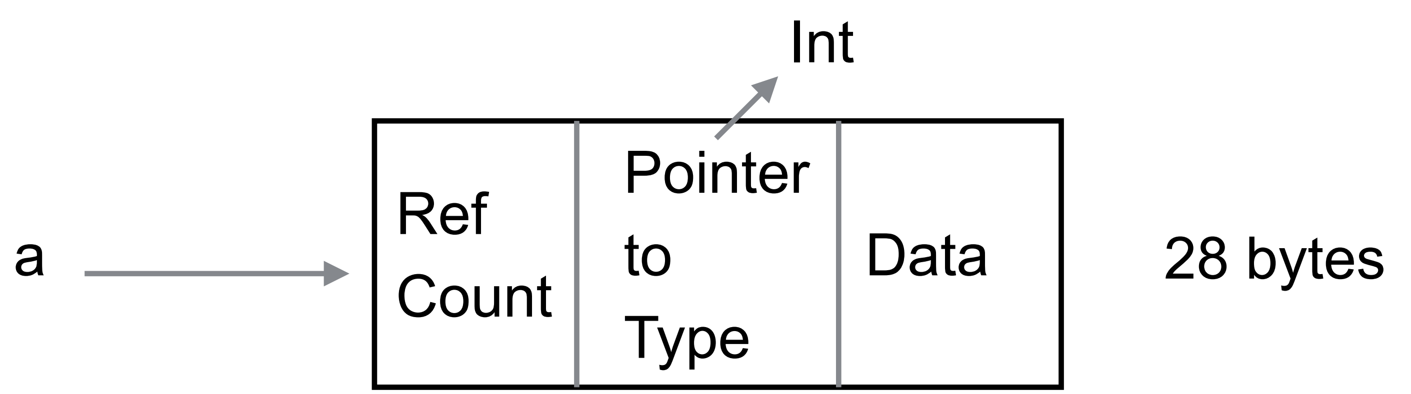


Problem 1 Large size fewer L1 & L2 hits

L1 cache reference	1x
Branch mispredict	10x
L2 cache reference	17x
Main memory reference	200x

Two Language Problem - Addition

c = a + b



Problem 2 To add a and b need to know type

To get type information for a

Two pointer access

1 addition

Problem 3 Need comparison & branch to perform addition

How Python Solves 2 Language Problem

NumPy

- Write data structures & algorithms in C
- Call them using Python

Works fine as longs as existing structures & algorithms are all you need