COMPSCI 589
Lecture 12: Introduction to Data Parallel Computing

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Slides by Benjamin M. Marlin (marlin@cs.umass.edu).
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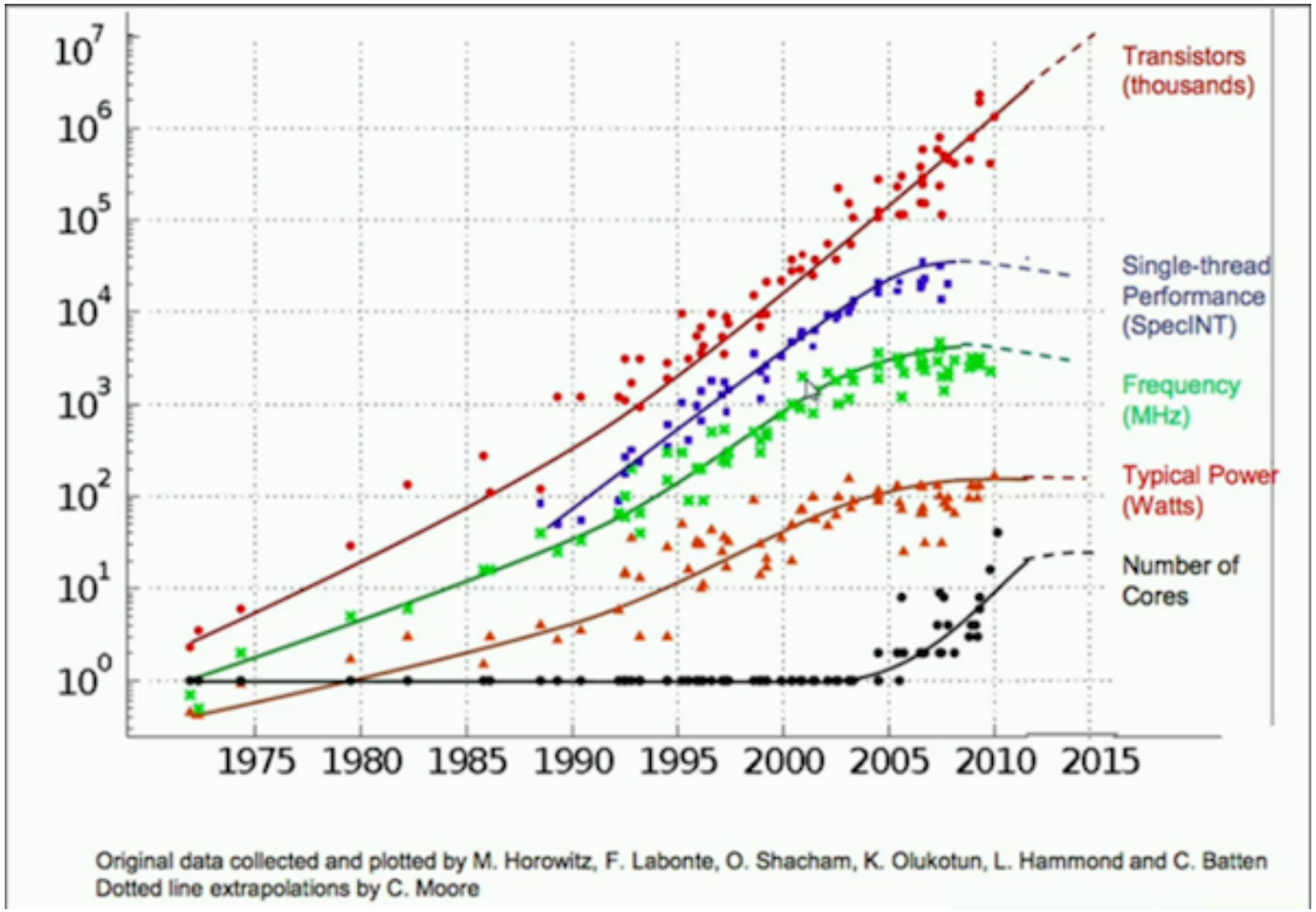
Outline

Moore's Law


10^7
10^6
10^5
10^4
10^3
10^2
10^1
10^0
1975 1980 1985 1990 1995 2000 2005 2010 2015
Transistors (thousands)
Single-thread Performance (SpecINT)
Frequency (MHz)
Typical Power (Watts)
Number of Cores
Original data collected and plotted by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond and C. Batten
Dotted line extrapolations by C. Moore

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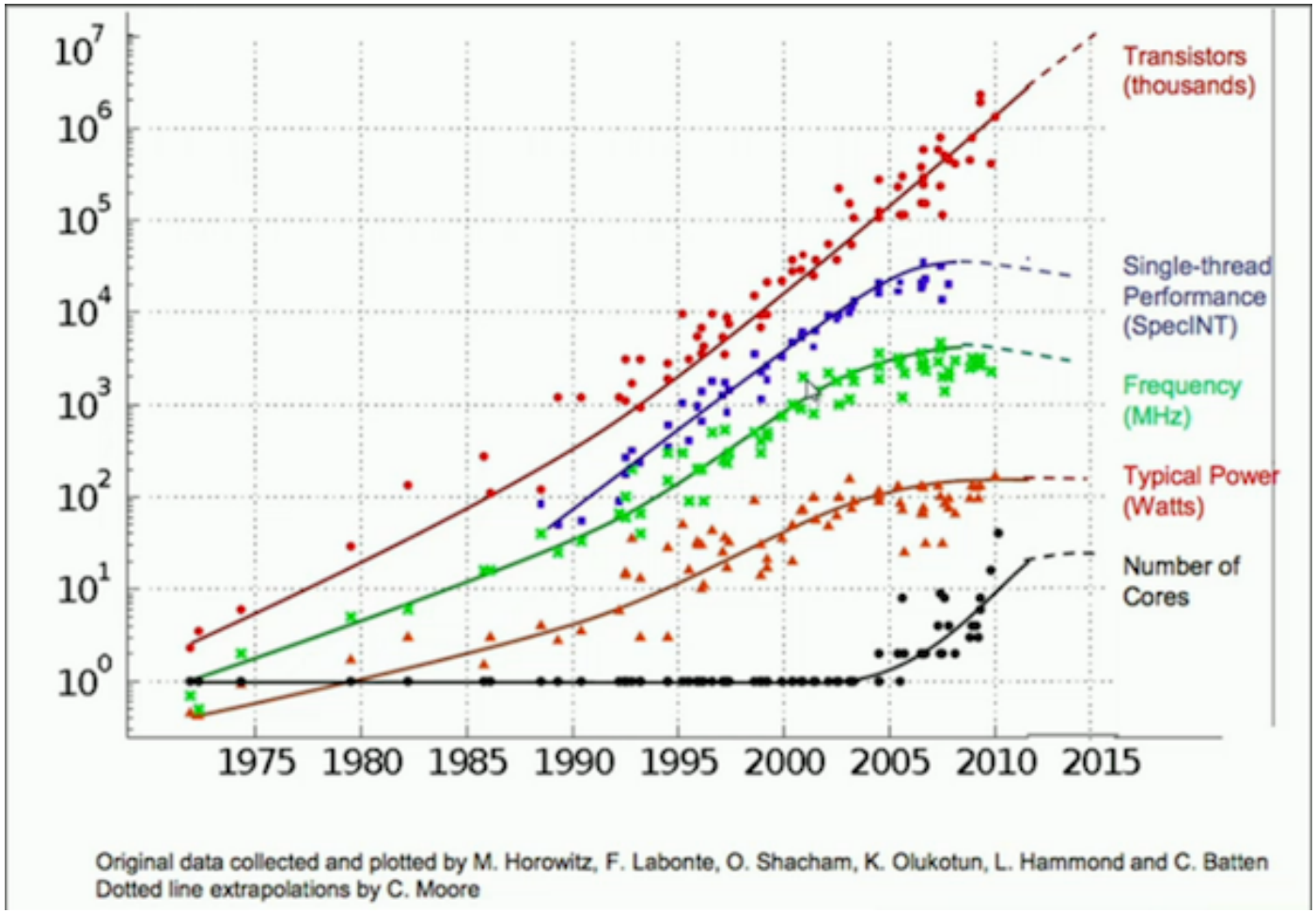
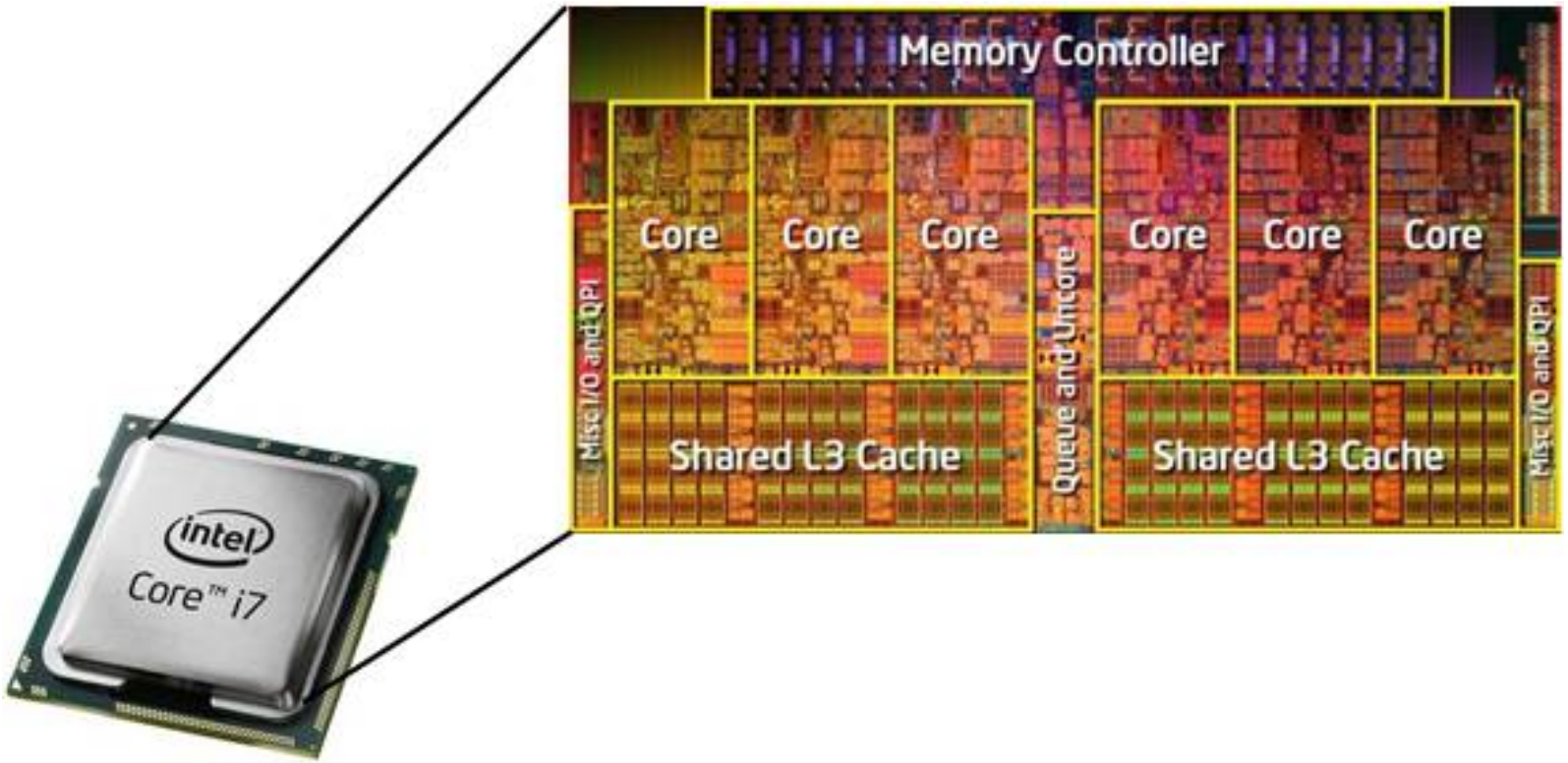
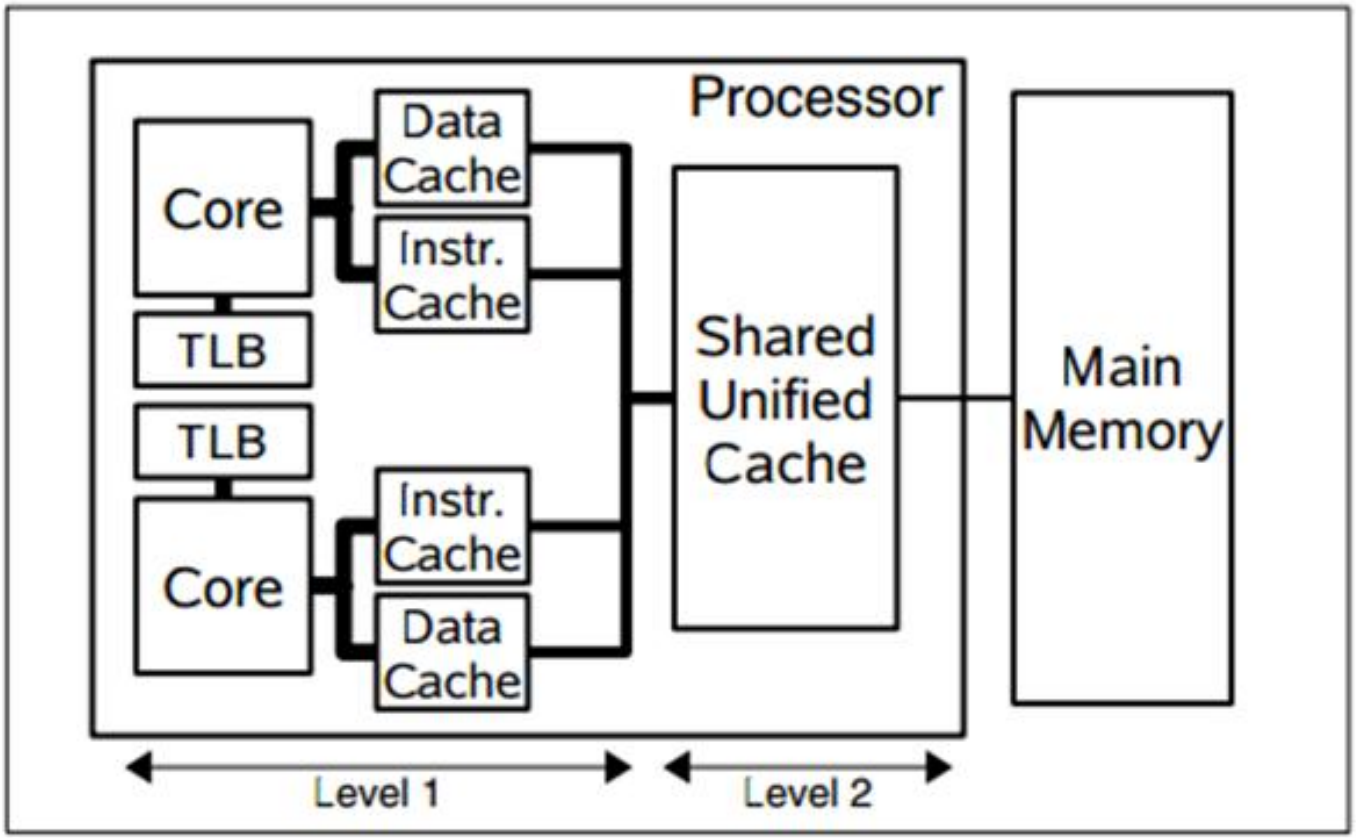


Machine Learning's free ride ended in about 2005.

Multi-Core CPUs



Multi-Core CPU Memory Architecture



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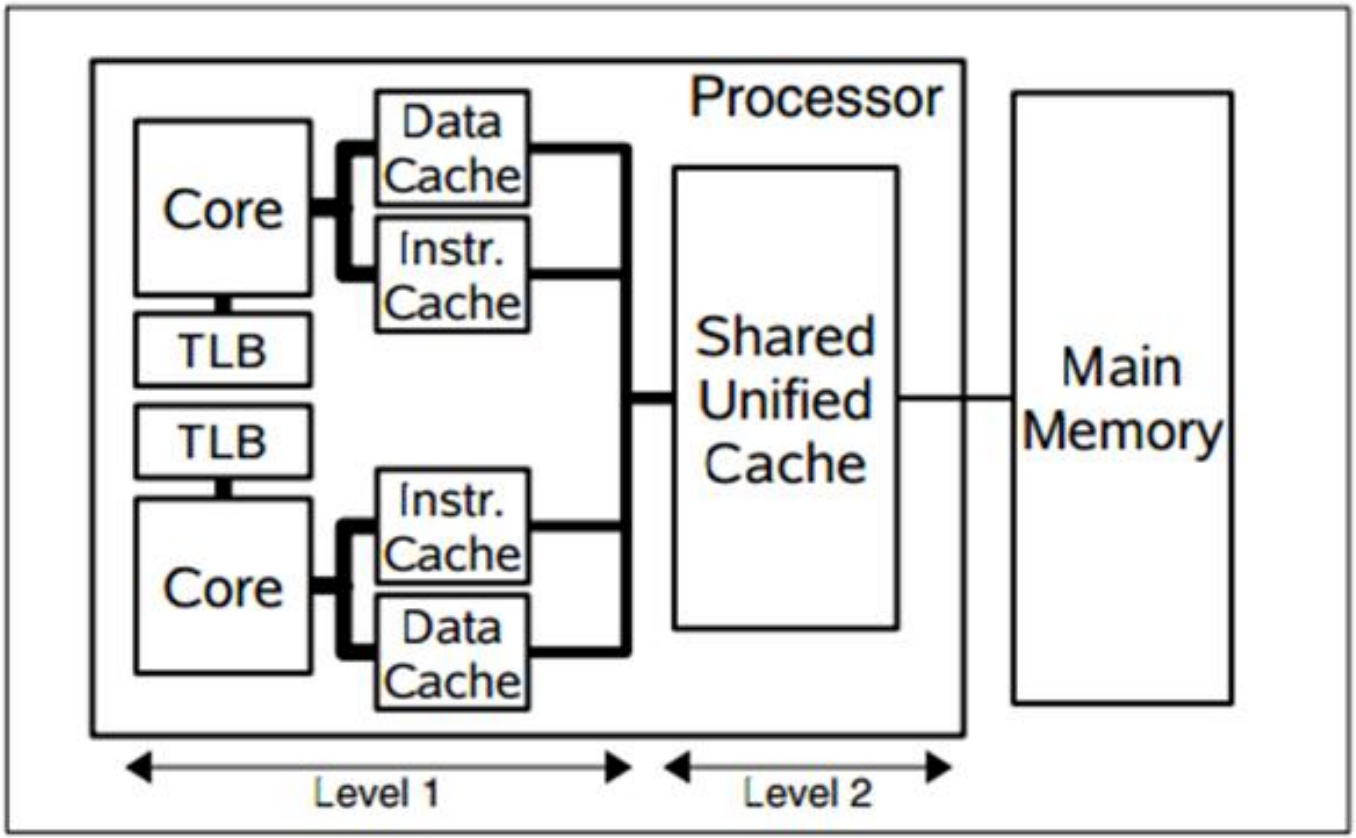
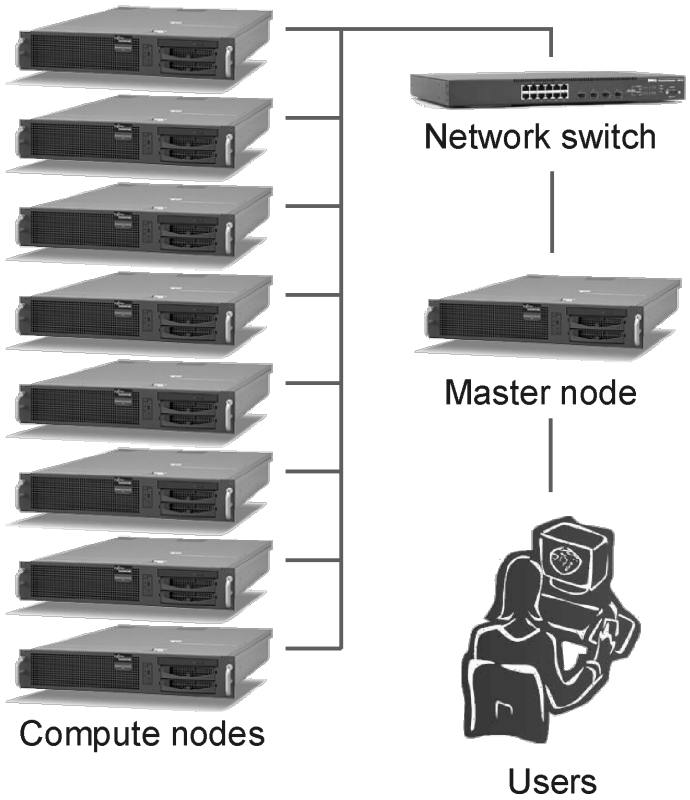


Question: What if one multi-core CPU isn't enough?

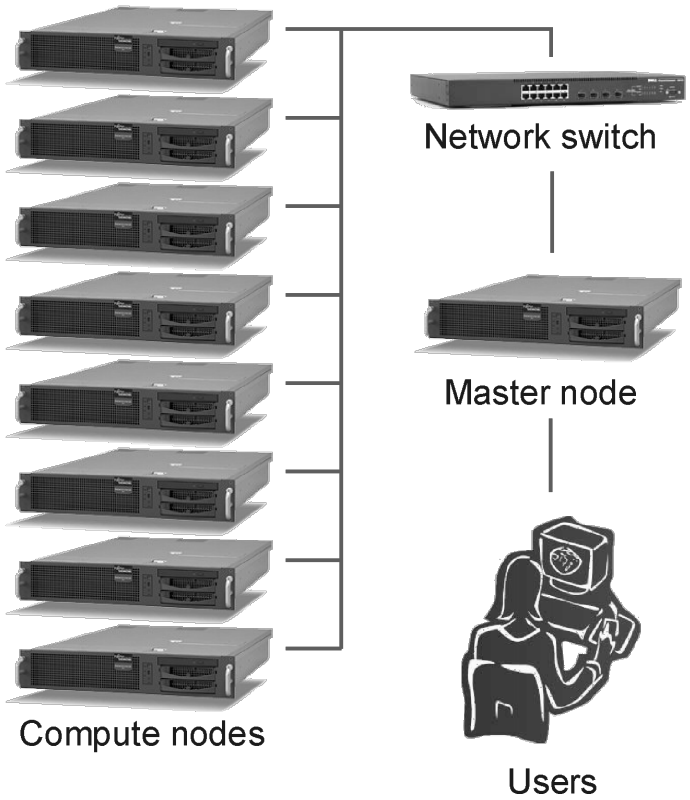
Distributed Computer (Cluster)

Facebook custom-built server rack.

Distributed Computer (Cluster) Architecture

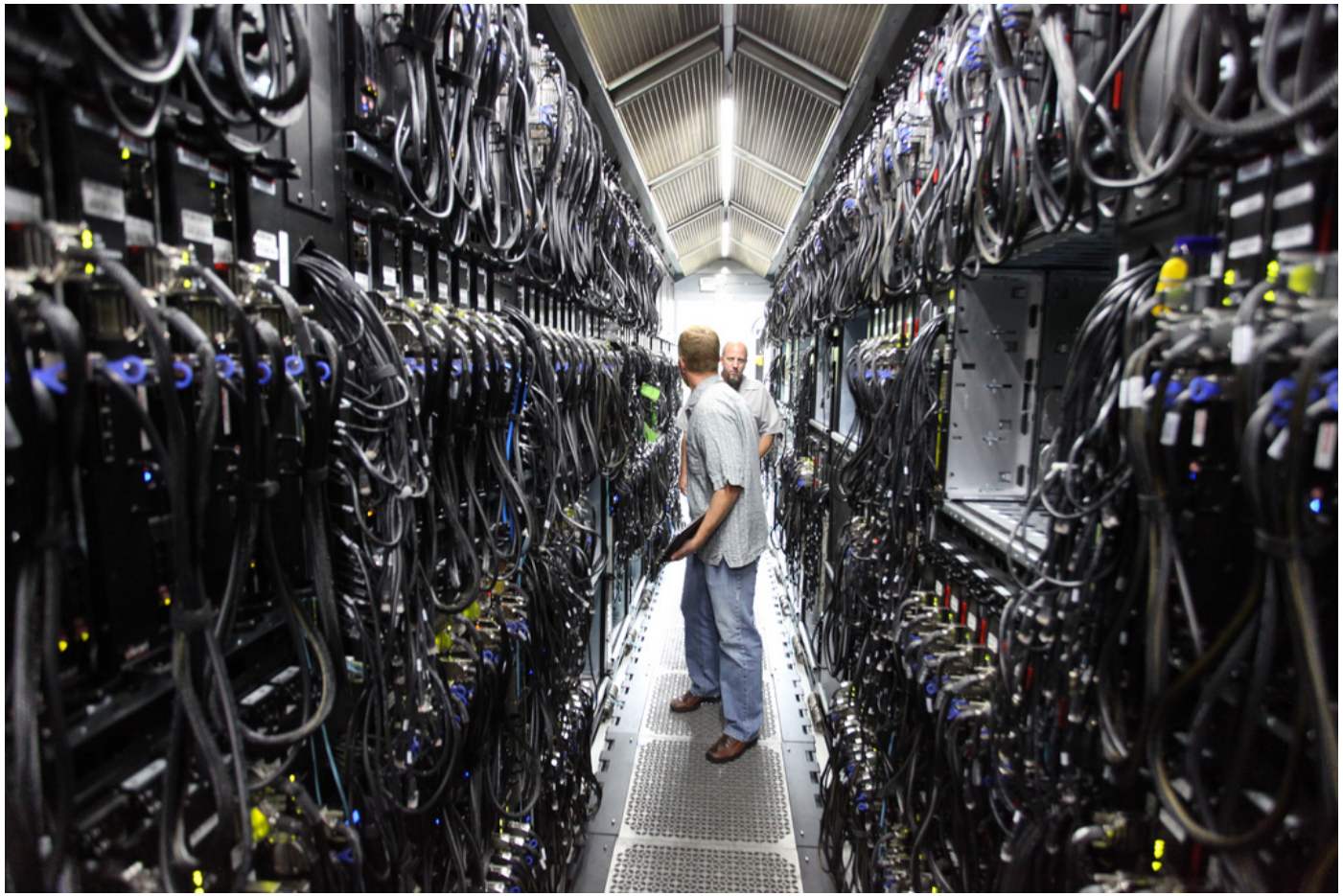


Distributed Computer (Cluster) Architecture



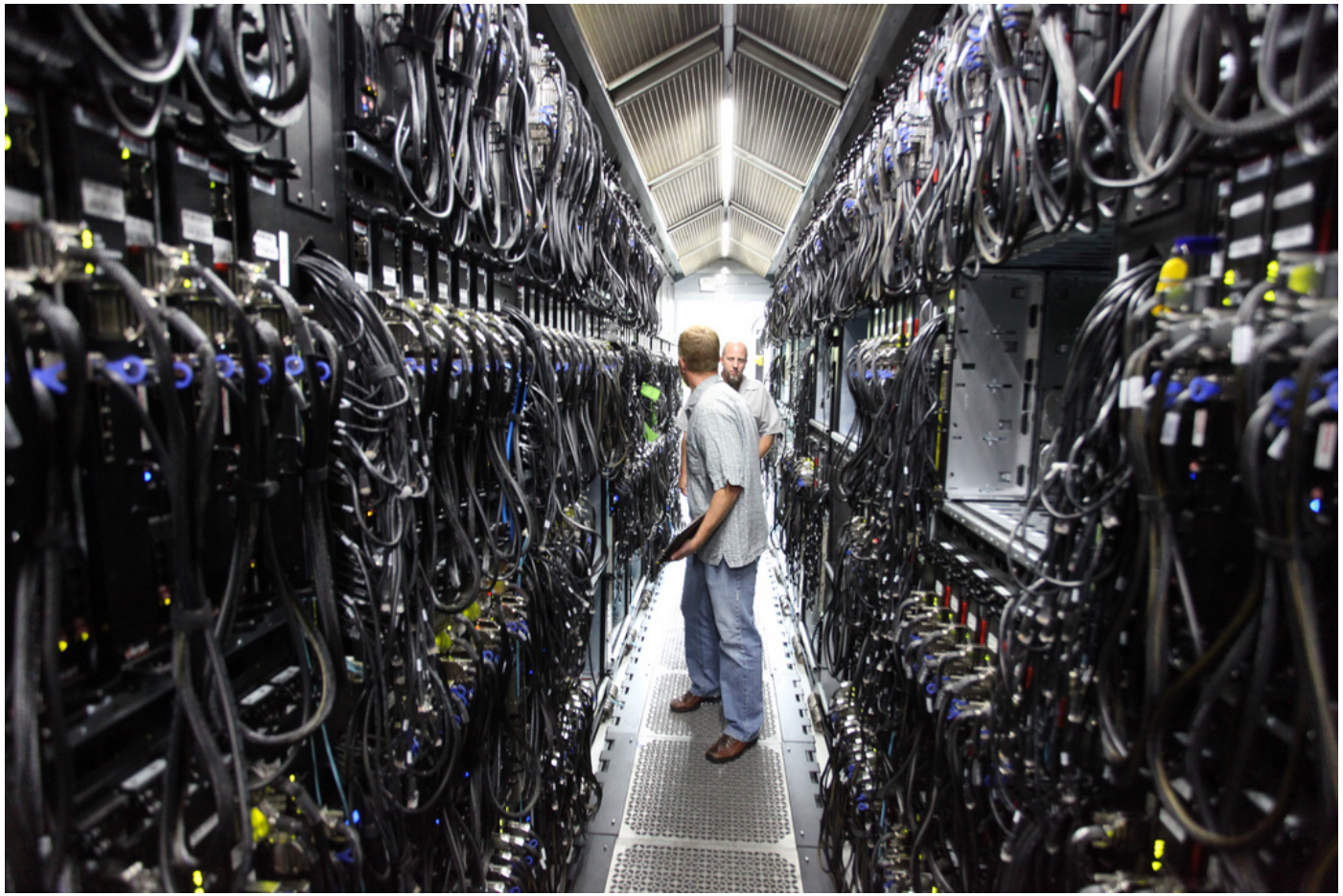
Question: What if a one-rack cluster isn't enough?

Server Container



Server container used by Bing Search.

Server Container



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Question: What if a one-container cluster isn't enough?

Container Hanger

Container hanger at Google data center.

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Question: What if you don't want to manage a compute center?

Cloud Computing

Infrastructure as a service (IAAS) + Hardware Virtualization

`http://aws.amazon.com/ec2/pricing/`

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Types of Parallelism

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- **Distributed Computing:** Running multiple processes on different machines that are networked together. High communication overhead. High scalability. Typical of cluster setting.

Types of Parallel Computing Tasks

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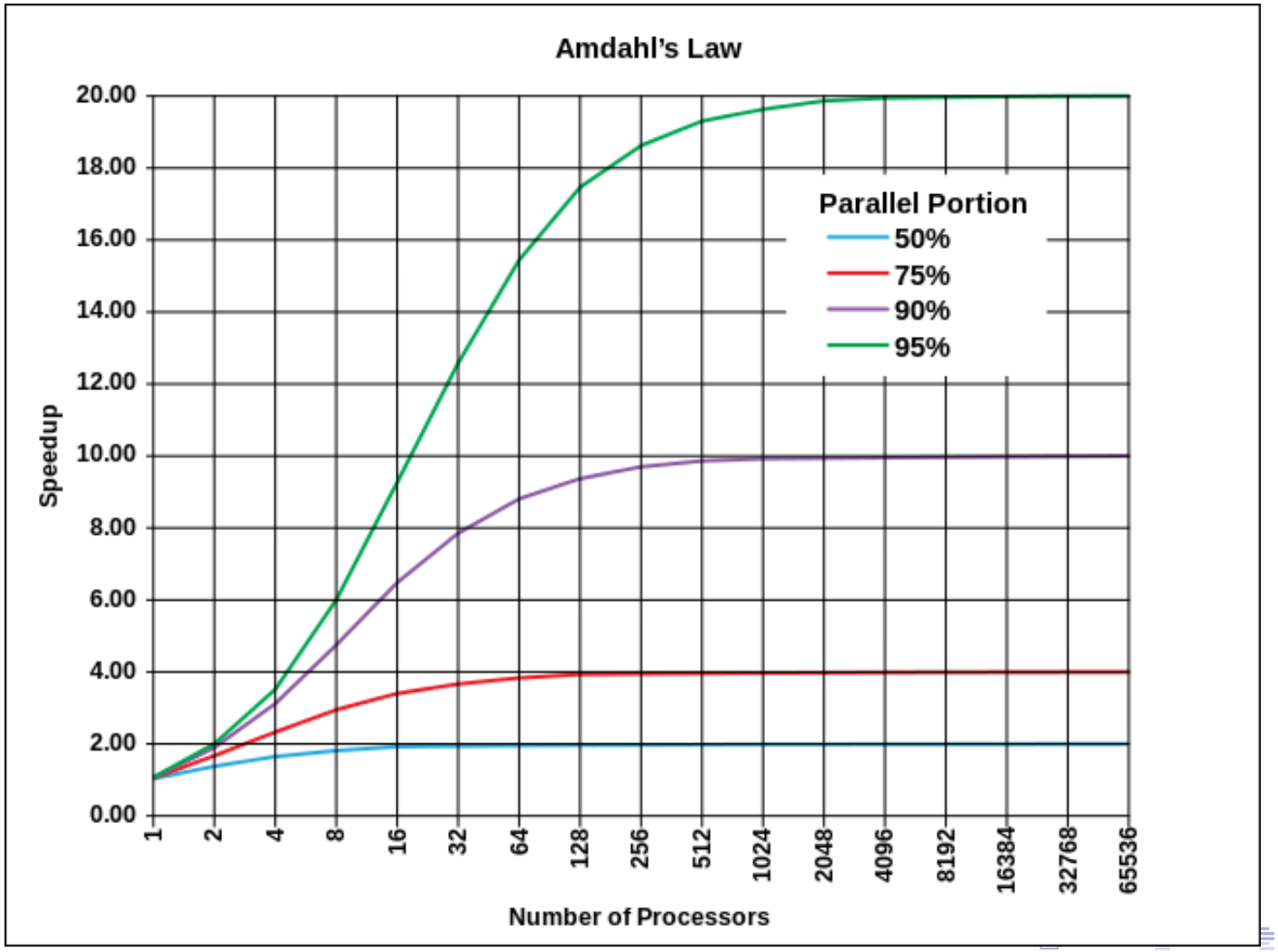
- In the limit as P goes to infinity, this ratio converges to $1/\alpha$.

Amdahl's Law


Amdahl's Law
Speedup
20.00
18.00
16.00
14.00
12.00
10.00
8.00
6.00
4.00
2.00
0.00
Parallel Portion
50%
75%
90%
95%
1
2
4
8
16
32
64
128
256
512
1024
2048
4096
8192
16384
32768
65536
Number of Processors

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- Writing correct multi-threaded code is highly non-trivial. Since the order of execution of code in threads is basically random, detecting and replicating bugs is extremely difficult.
- A key problem in PL is automatically compiling a single-threaded imperative program into a multi-threaded program. No such general purpose compiler exists today.

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- Functional programming eliminates all of these problems by prohibiting mutable state variables and building computations only by nesting function evaluations.
- There is no explicit looping, only recursion. The component functions are required to always return the same output when run on the same input.

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lambda x,y:  x+y
```

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$$f(g(x), h(x), i(x), j(k(x), l(x)))$$

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- It turns out that a small number of such easily parallelizable functional programming primitives are sufficient for creating data-parallel implementations of machine learning algorithms.

Data Parallel Computing: Map

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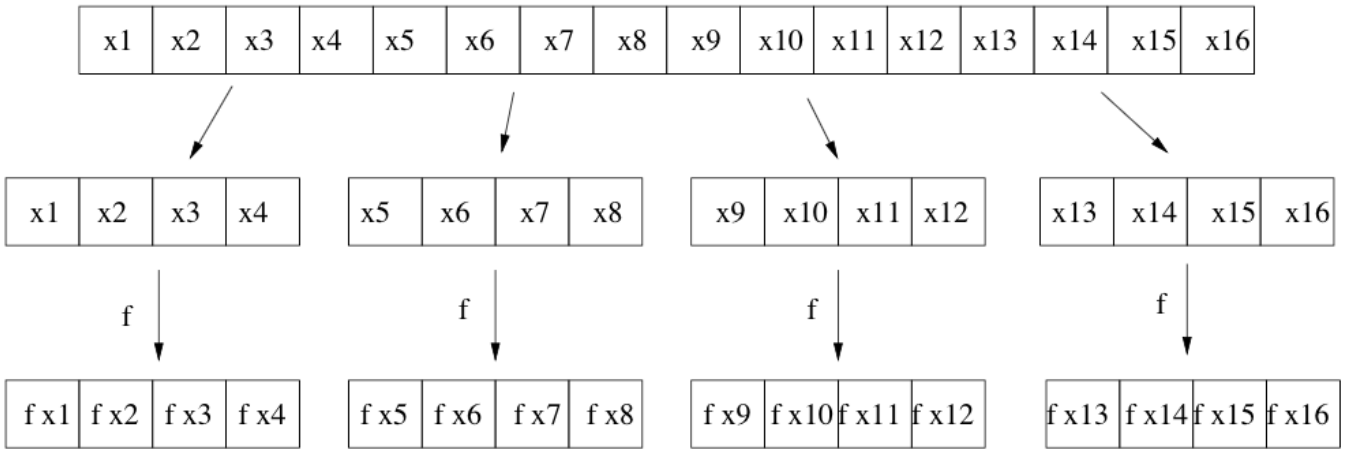

Data Parallel Computing: Reduce

- **Reduce:** Applies the function g to the first two elements of the array x recursively until the input contains a single value, which it then returns.

$$Reduce(g,x) = \begin{cases} Reduce(g,[g(x_1,x_2),x_3,\ldots,x_n]) & \ldots n > 1 \\ x_1 & \text{Otherwise} \end{cases}$$

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- **Question:** Can we parallelize this computation?

Data Parallel Computing: Reduce

- If the function is associative, this computation can be parallelized using a balanced binary tree.

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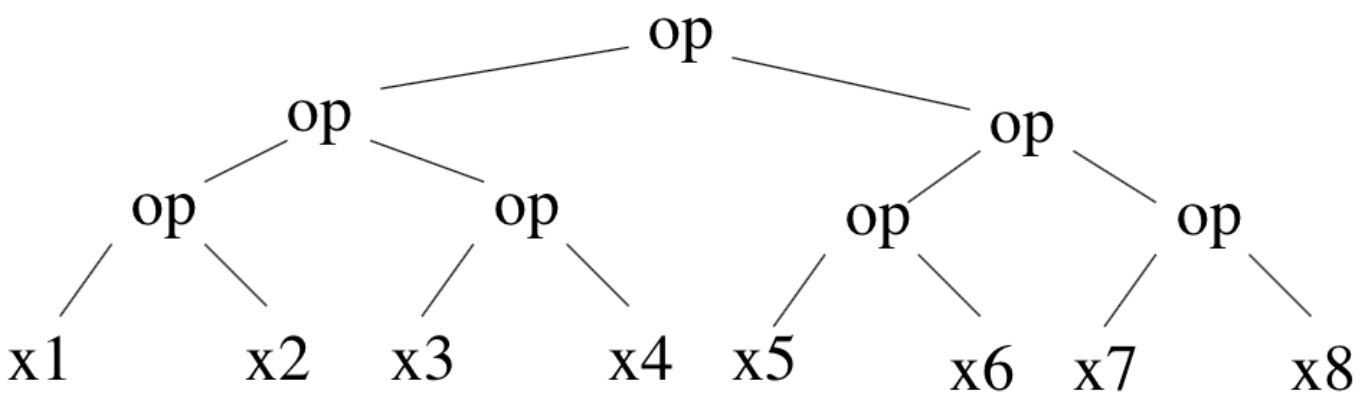

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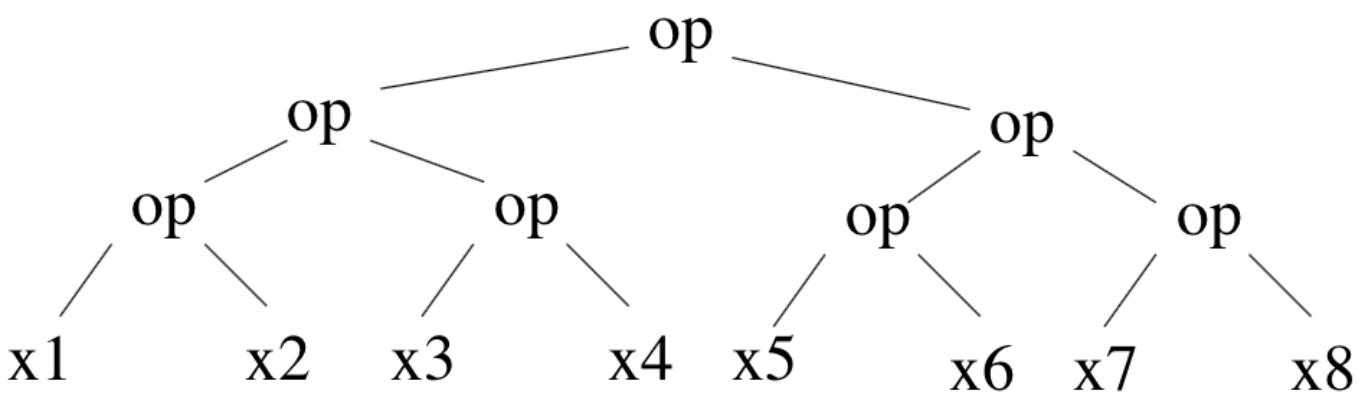

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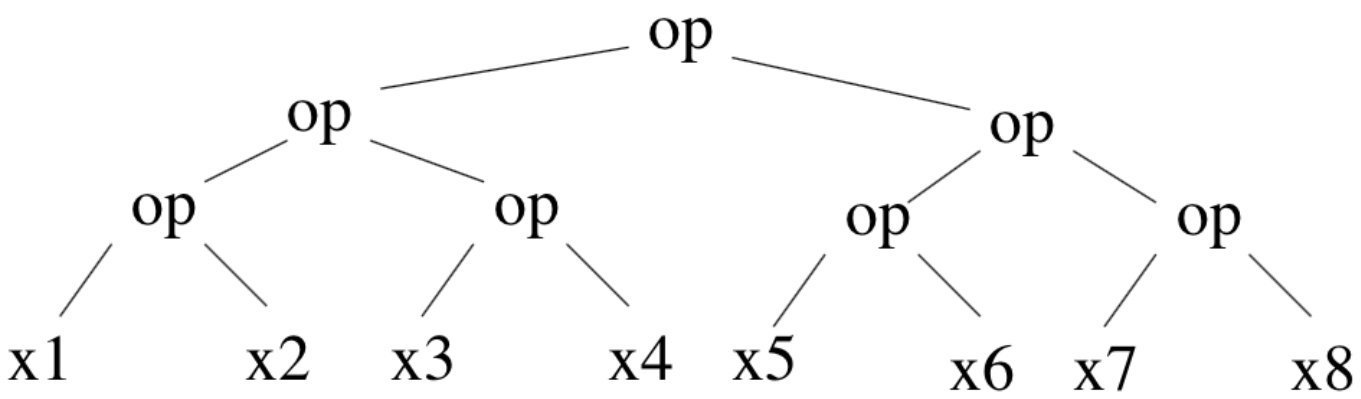

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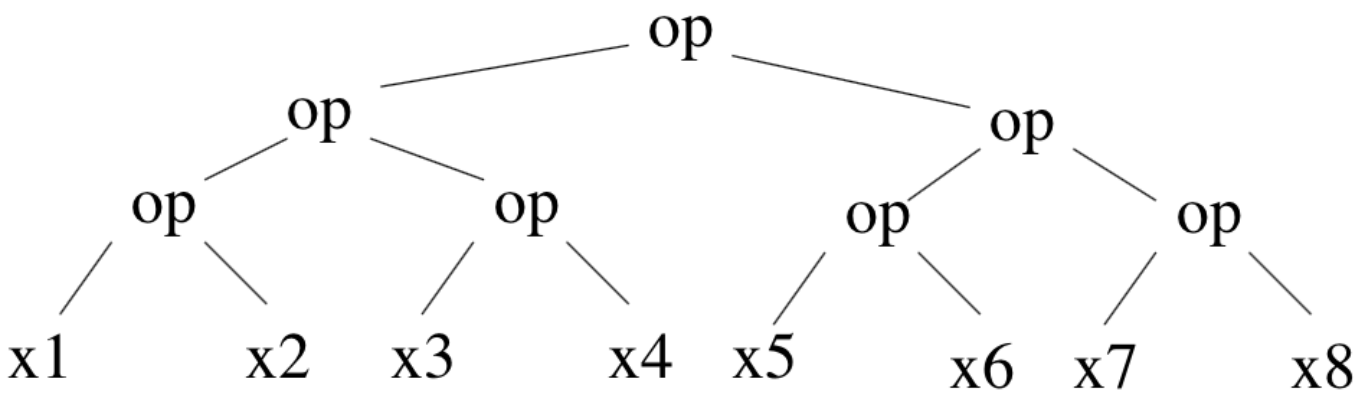

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  $Reduce(+, [13, 35]) = 48$