

# Dataflow: Best of Times or Worst of Times?

**DFM'2019:  
Dataflow Model Workshop 2019**

Erik Altman



Research



# Talk Theme

It was the best of times, it was the worst of times.

*Charles Dickens, "A Tale of Two Cities"*



# Caveats

- It has been many years since I have devoted significant research effort to dataflow models
- Views here are of a fan looking from a distance with nostalgia and hope

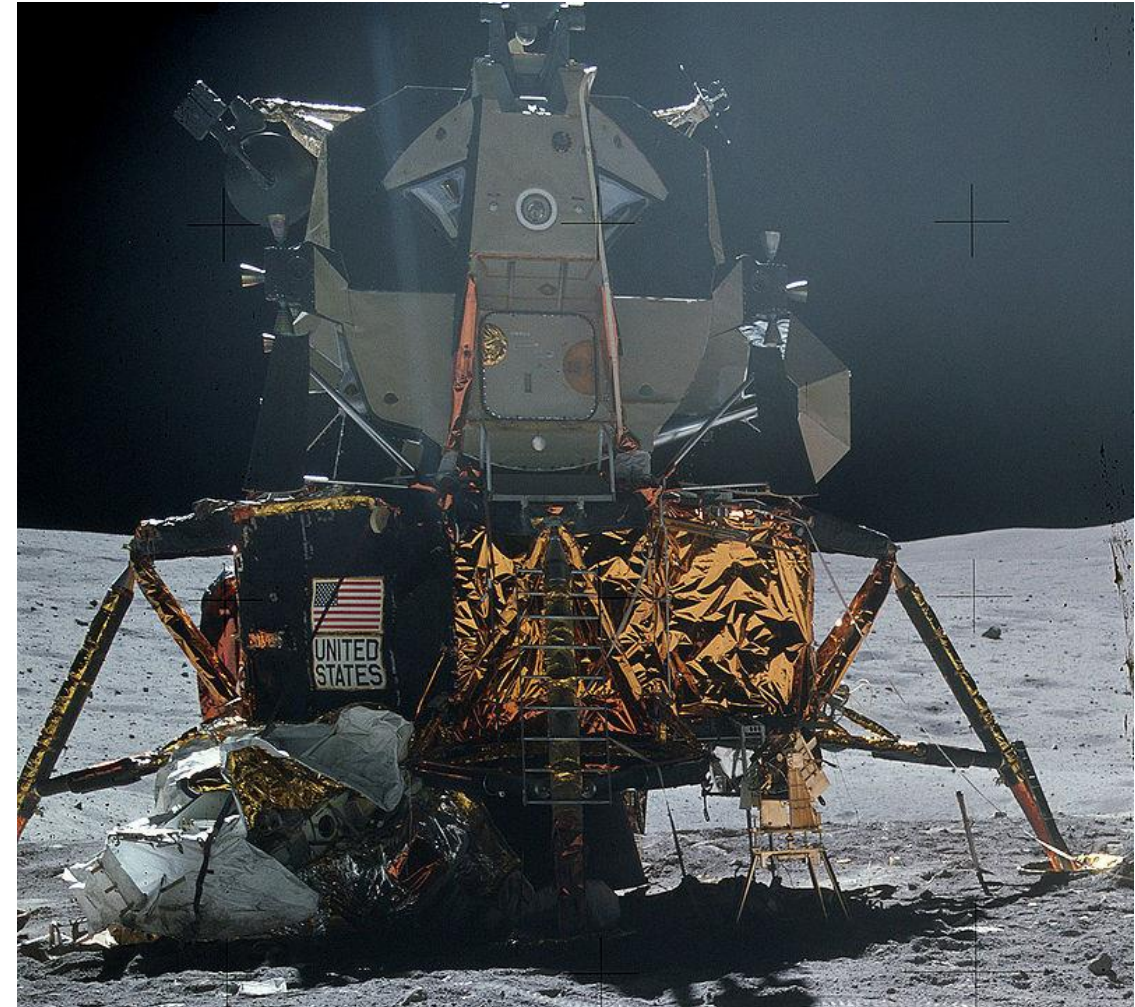


# Aside

**July 19, 2019**

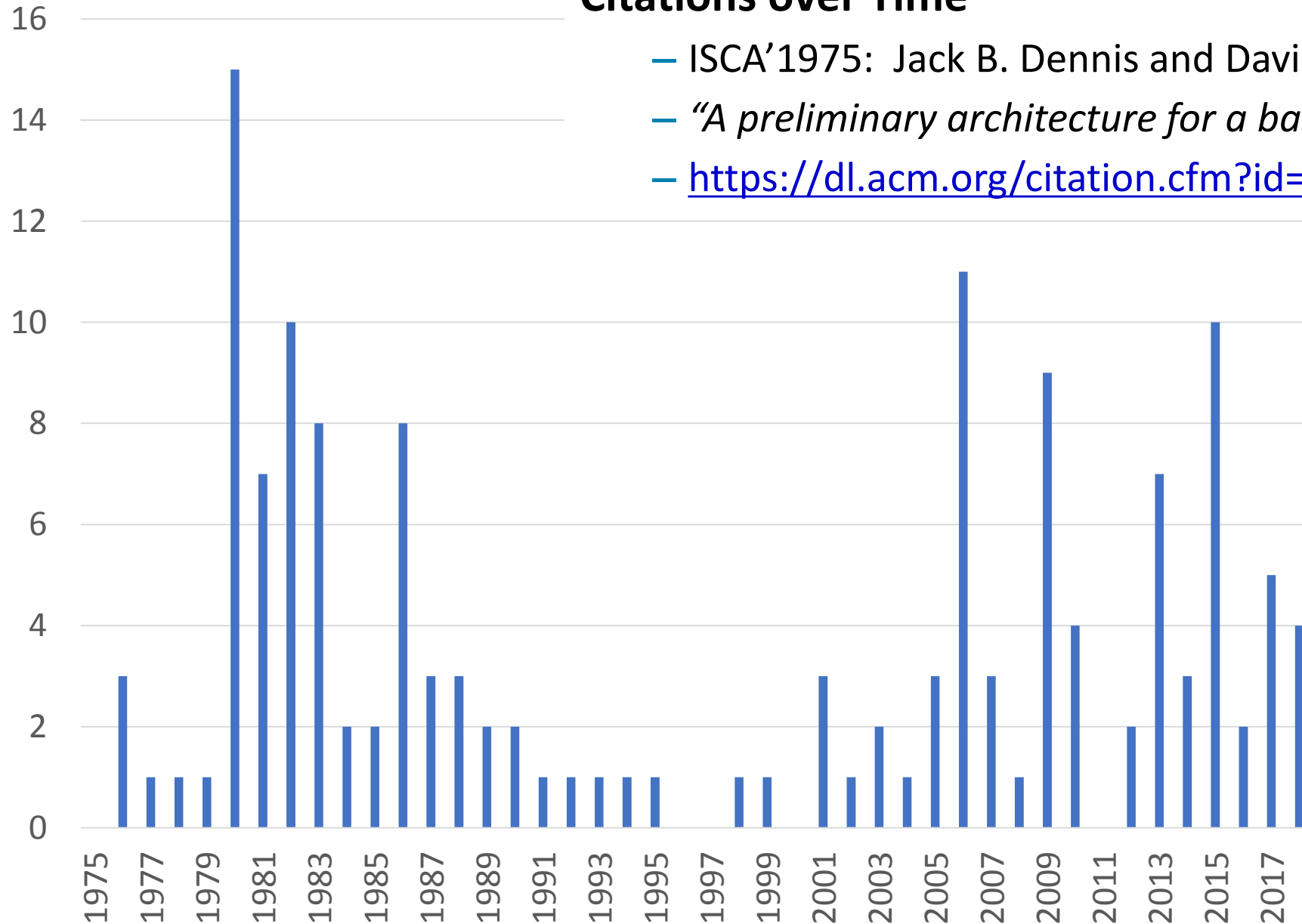
50 years less a day from the first moon landing

*If we can put a person on the moon, can we make dataflow succeed?*

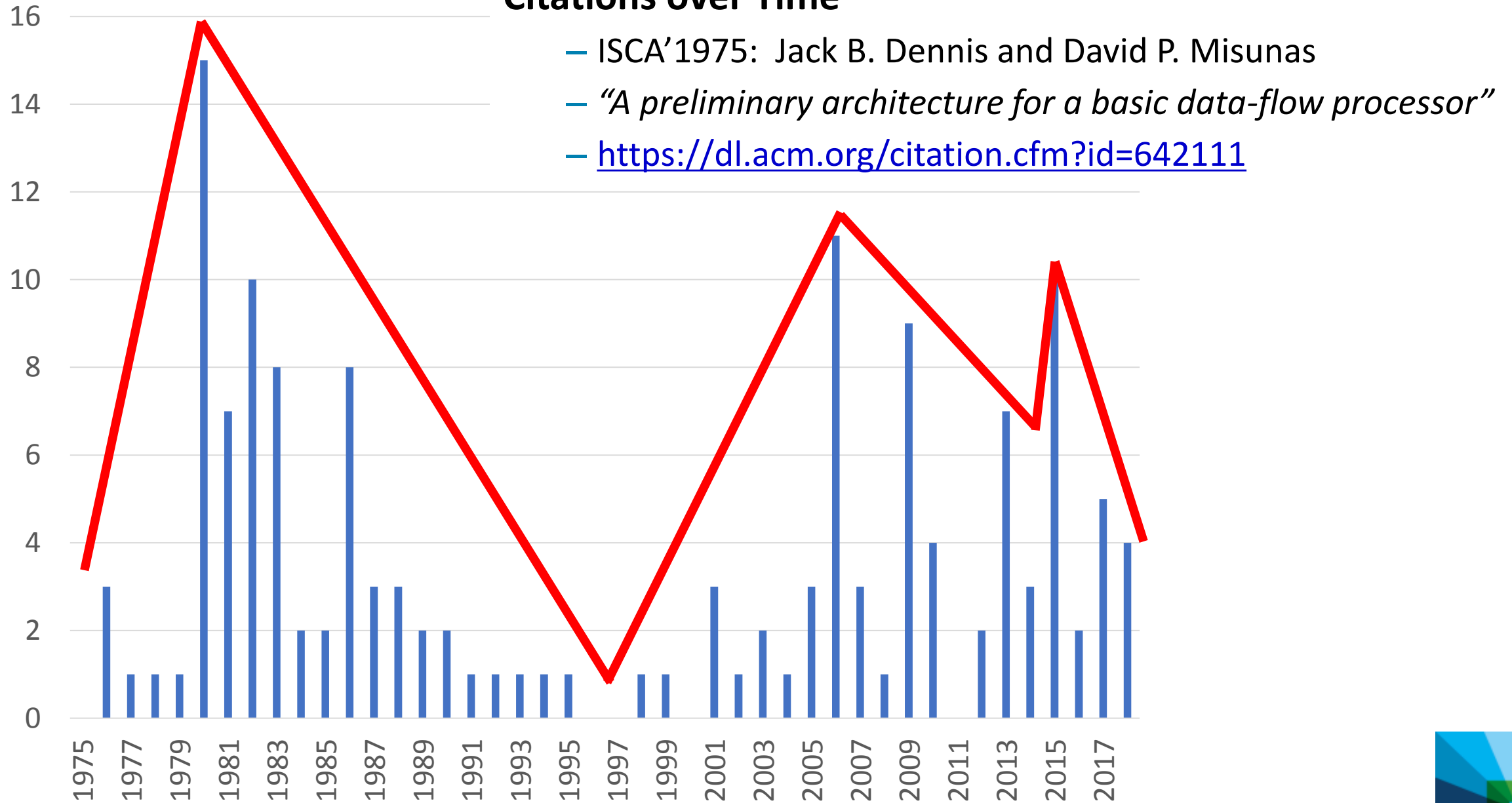


## Citations over Time

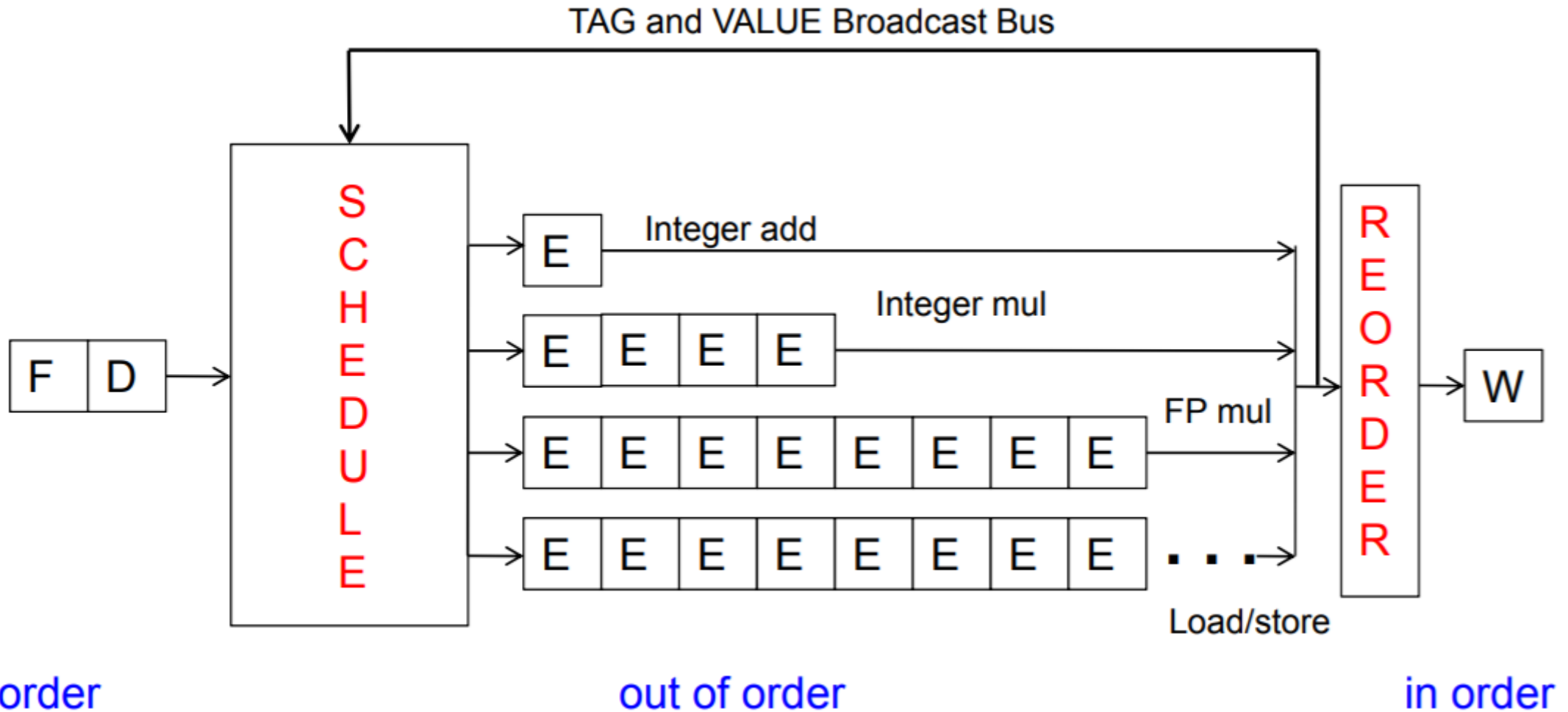
- ISCA'1975: Jack B. Dennis and David P. Misunas
- *"A preliminary architecture for a basic data-flow processor"*
- <https://dl.acm.org/citation.cfm?id=642111>



## Citations over Time



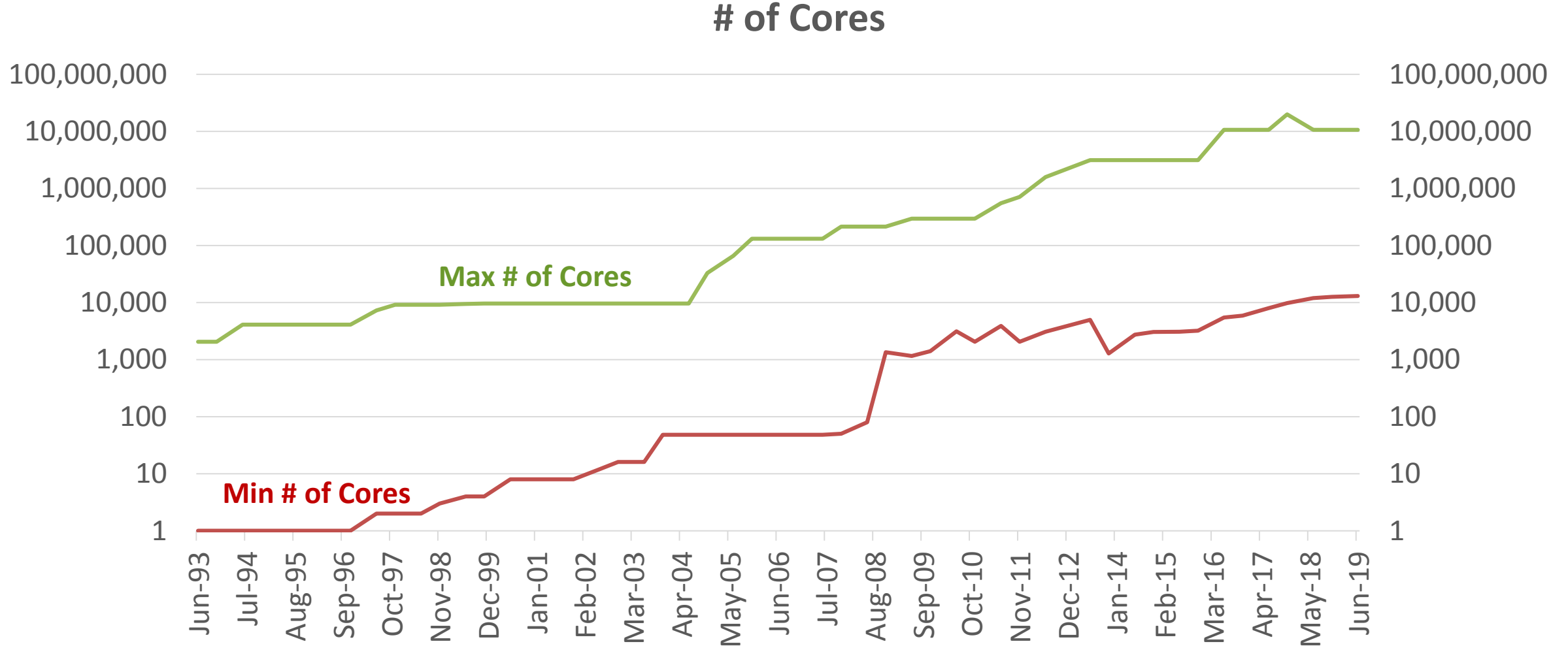
# Early Dataflow Success: Tomasulo / Reorder Buffers



Onur Mutlu

<https://www.archive.ece.cmu.edu/~ece740/f11/lib/exe/fetch.php?media=wiki:lectures:onur-740-fall11-lecture10-ooo-afterlecture.pdf>





*Why has dataflow not emerged as the dominant paradigm for Top500 workloads?*





# Successful Software Transitions

- **Spreadsheets:** Visicalc → Lotus 123 → Microsoft Excel
- **Word Processors:** Wang → Wordperfect → Word
- **Browsers:** Netscape / Mozilla → Internet Explorer → Chrome / Safari

# Language Popularity



May 2019	May 2018	Change	Programming Language	Ratings	Change
1	1		Java	16.0%	-0.38%
2	2		C	14.2%	+0.24%
3	3		C++	8.1%	+0.43%
4	4		Python	7.8%	+2.64%
5	6	↑	Visual Basic .NET	5.2%	+1.07%
6	5	↓	C#	4.0%	-0.42%
7	8	↑	Javascript	2.7%	-0.23%
8	9	↑	SQL	2.6%	+0.57%
9	7	↓	PHP	2.5%	-0.83%
10	13	↑	Assembly Language	1.8%	+0.82%
11	15	↑↑	Objective-C	1.6%	-0.69%
12	12		Delphi/Object Pascal	1.4%	+0.39%
13	18	↑↑	Perl	1.4%	-0.48%
14	16	↑	MATLAB	1.4%	-0.44%
15	10	↓↓	Ruby	1.3%	-0.16%

**C Flavors: 28%**

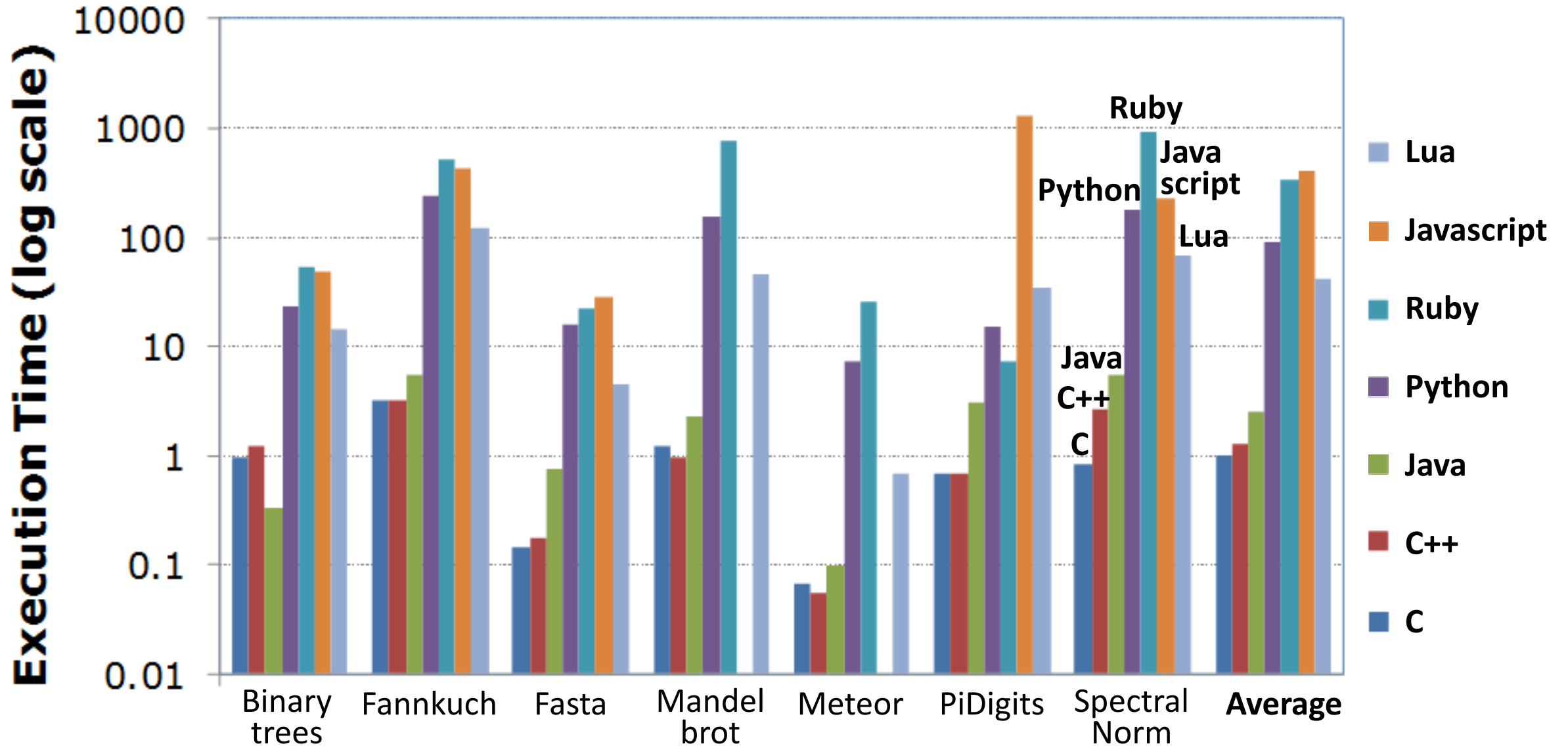
**Fortran #27: 0.5%**

**Lisp #32: 0.4%**

**Haskell #45: 0.2%**

*No major niche  
where dataflow  
dominates!*





# The Challenge of Parallelism

“When we start talking about **parallelism** and ease of use of truly parallel computers, we're talking about a problem that's **as hard as any that computer science has faced.**

**I would be panicked if I were in industry.”**

## **John Hennessy**

Turing Laureate

CS Professor and President Emeritus, Stanford

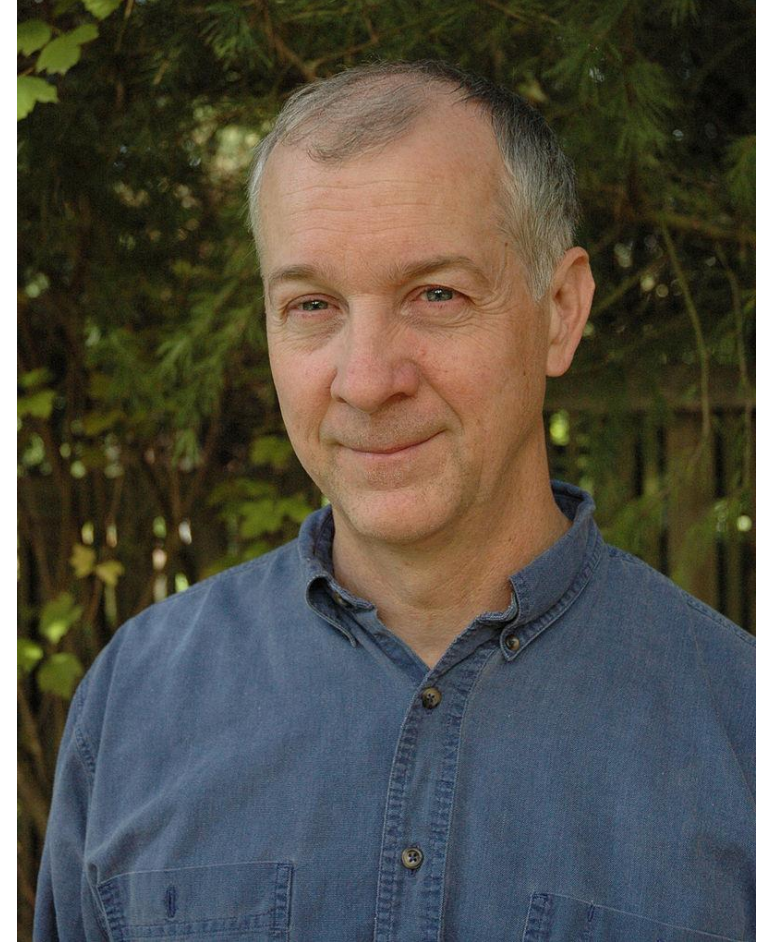
Author – Best-selling Computer Architecture textbook

Chair – Alphabet / Google



# Popularity is Essential

- **“He who makes the most silicon wins”**  
—Bob Colwell



# Killer Apps

- **Java:** JEE and WebSphere-like middleware
- **C:** Operating systems, Realtime, IoT
- **Python:** Deep Learning Frameworks
- **Fortran:** HPC
- **Lisp:** Symbolic AI
- **PCs:** Spreadsheets, Word Processing
- **Smartphones:** Texting, Pictures, Map Guidance, Social Networks, News
  
- *What is the dataflow killer app?*



# Who is the target audience for Dataflow?

- All programmers
- HPC programmers
- DSP programmers
- Data scientists
- Deep learning algorithm developers
- Other domains





# What tasks can dataflow make easier?

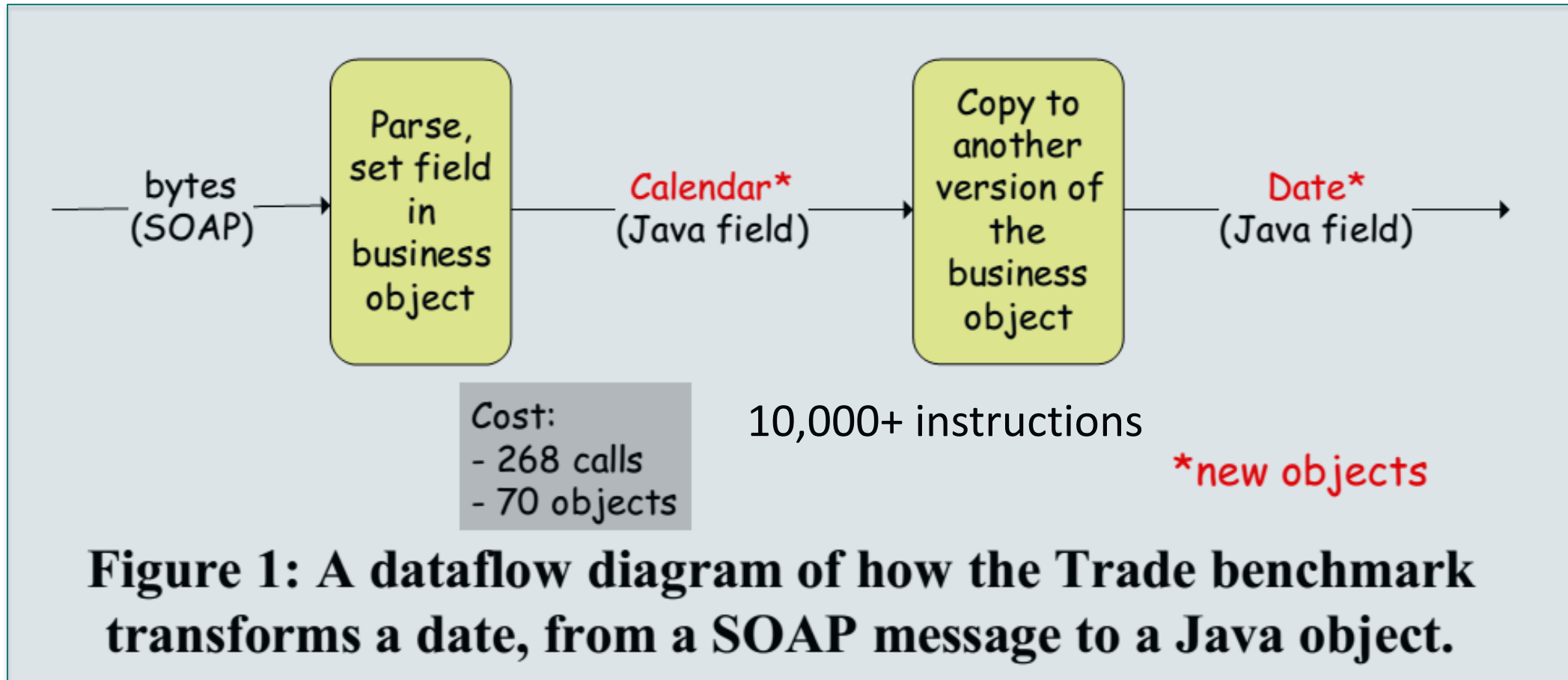
- **Exploiting parallelism**
- **Maintainability**
  - Explicit dependences



## The Diary of a Datum:

An Approach to Modeling Runtime Complexity in Framework-Based Applications

- [Nick Mitchell, Gary Sevitsky, Harini Srinivasan](#)
- Workshop on Library-Centric Software Design, San Diego, CA, 2005

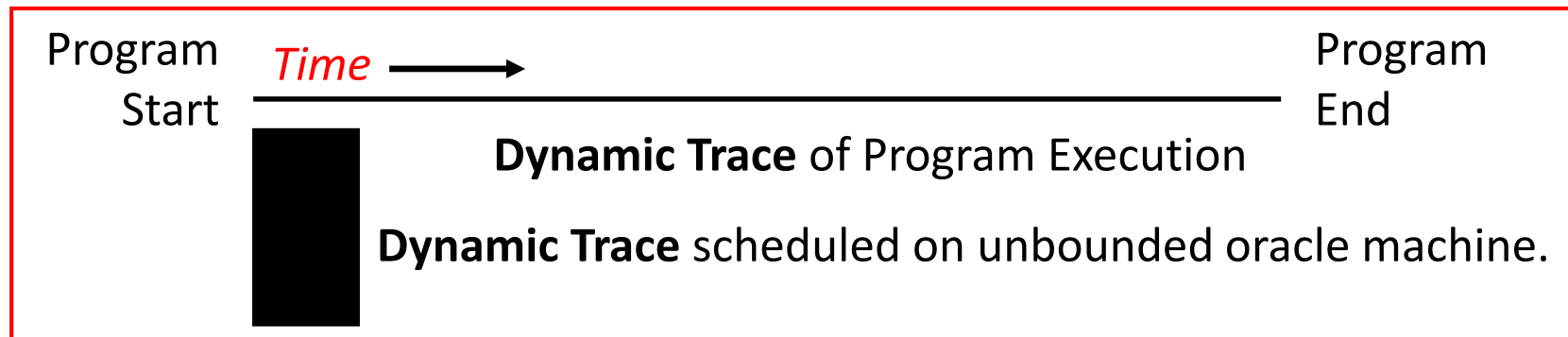




- Explicitly pass all state (cumbersome)
- Programmer mental models
- Handling overabundance of parallelism at peak
- Interoperation with other code
- Interaction with non-dataflow I/O
- Applicability to random code
- Memory Footprint
- **Wide separation of parallelism in code**
  - Not tractable for compilers or processors
- **Compiler analysis typically ignorant of semantic function**



- Many studies have found large amounts of parallelism, even in integer apps like SPECint:
  - 1970, Tjaden and Flynn
  - 1972, Riseman and Foster
  - 1981, Nicolau and Fisher
  - 1991, Wall
  - 1991, Butler et al
  - 1992, Austin and Sohi
  - 1992, Lam and Wilson
  - 1992, Theobald et al
  - 1993, Rauchwerger et al
  - 1998, Postiff et al
  - 1999, Ebcioğlu et al
- **Machine with unbounded resources and an oracle for branch prediction and memory disambiguation could execute *hundreds or thousands of instructions per cycle.***



## Natural Structure → Parallelism

- Any long running program, must have the following structure at some level:

```
while (end_cond_not_met) {  
    task_1 ();  
    task_2 ();  
    ...  
    task_n ();  
}
```

1. Tasks *1-n* are often largely independent of each other, or
2. Task *q* at iteration *i* is independent of task *q* at iteration *i+1*.



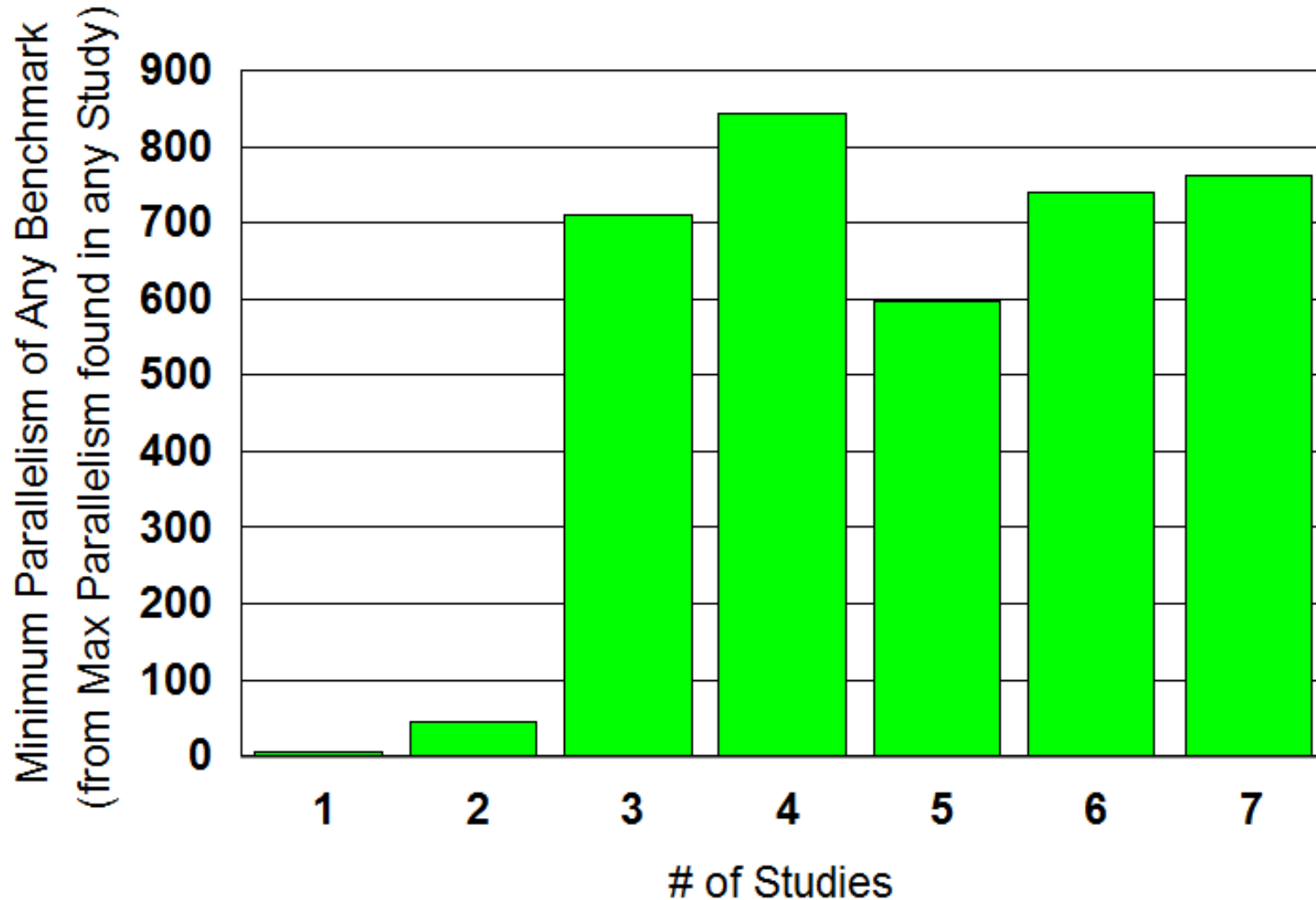
# Example

*LLVM* (mostly) compiles one function at a time.

- Compilation of each function is largely independent.
- A skilled programmer could parallelize *LLVM* to compile functions in parallel.
- *Better to perform this parallelization:*
  - *Automatically or with tools providing guidance.*
  - *For any program, not just *LLVM*.*



## Parallelism vs # of Studies

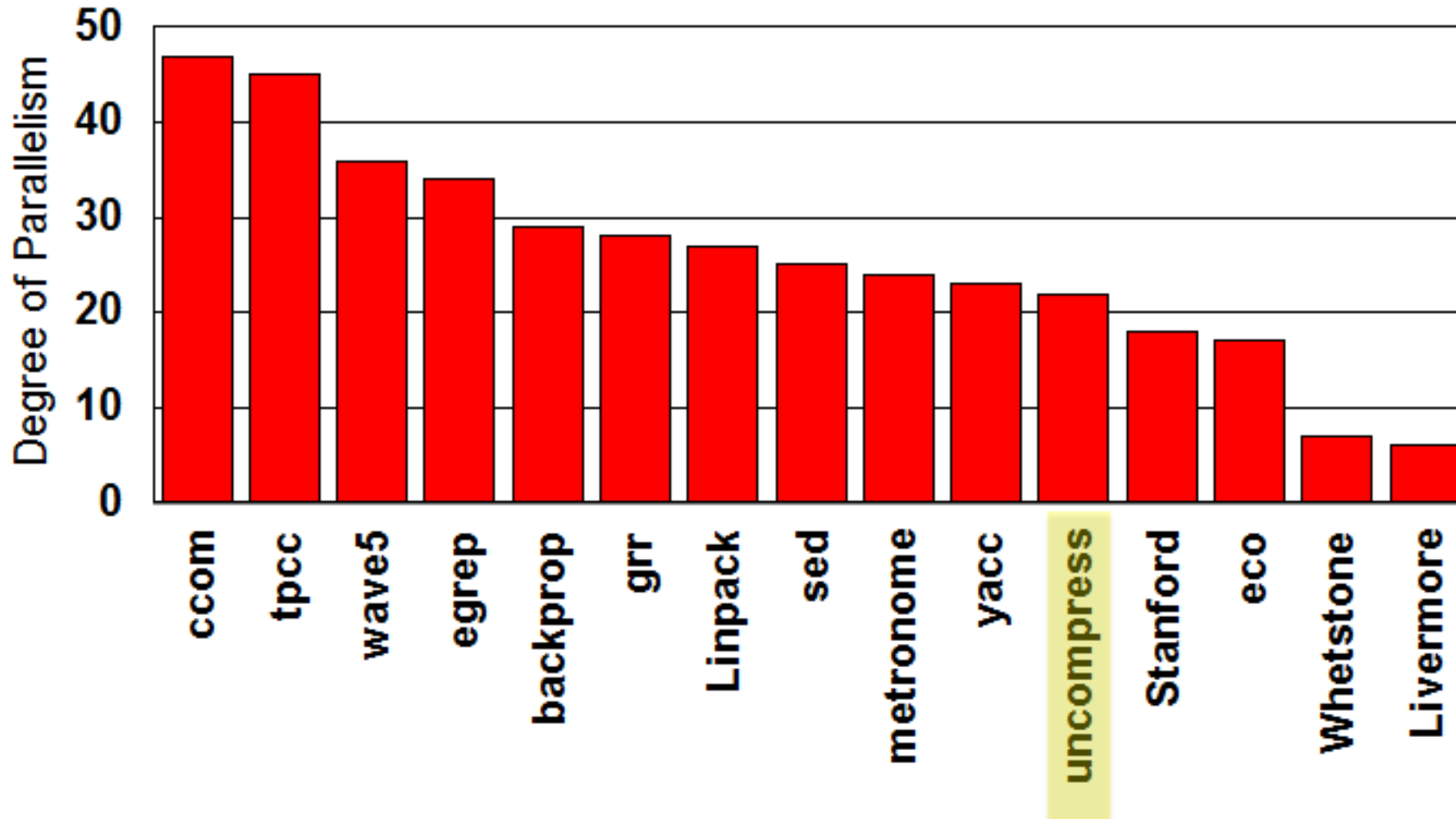


When good techniques from many researchers are applied:

→ Almost all apps appear to have more than 500-way parallelism.



## 5 < Parallelism < 50 (Highest Parallelism in Any Study)

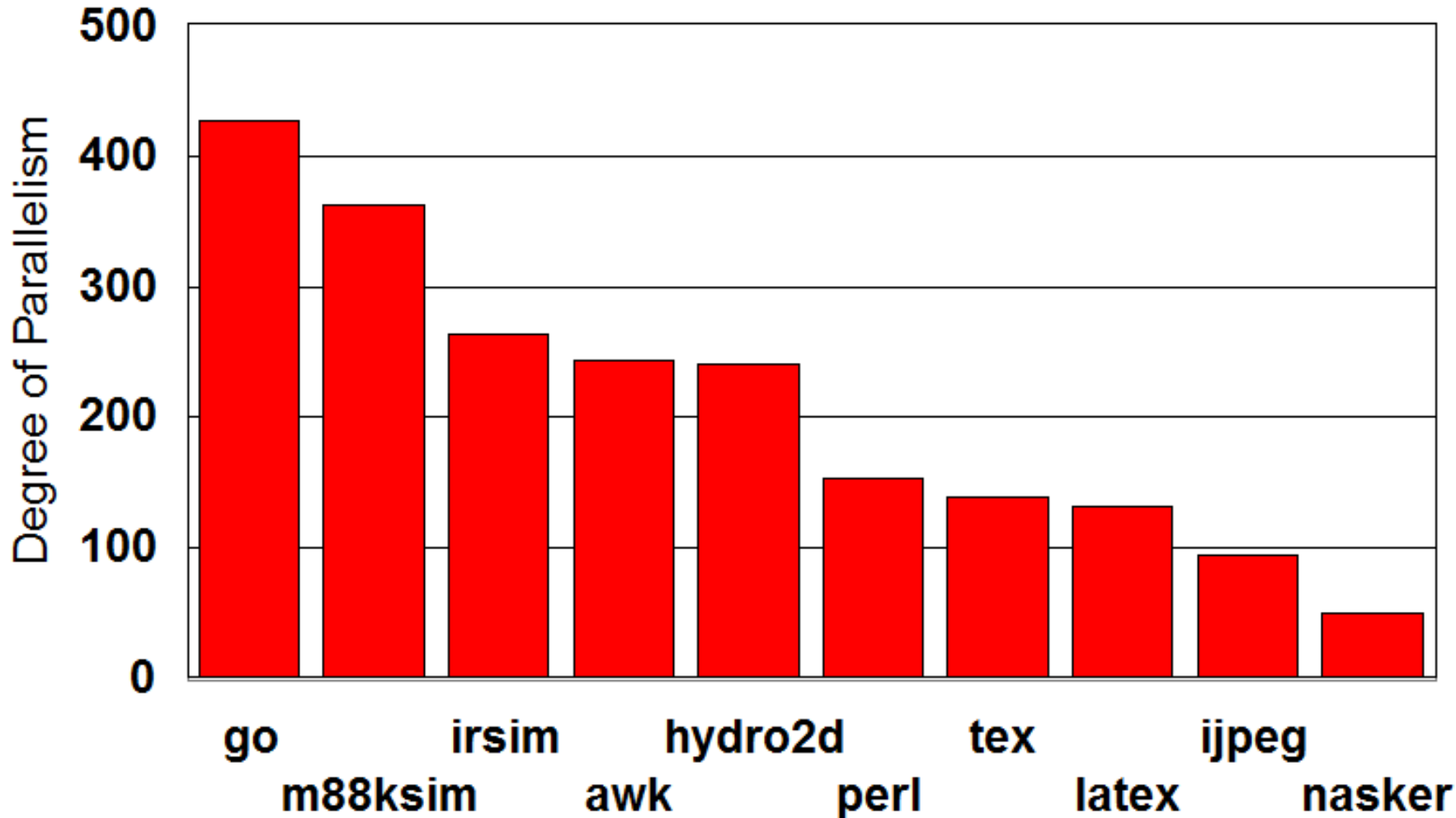


“Low” Parallelism only in limited apps .

These estimates are probably far too low.



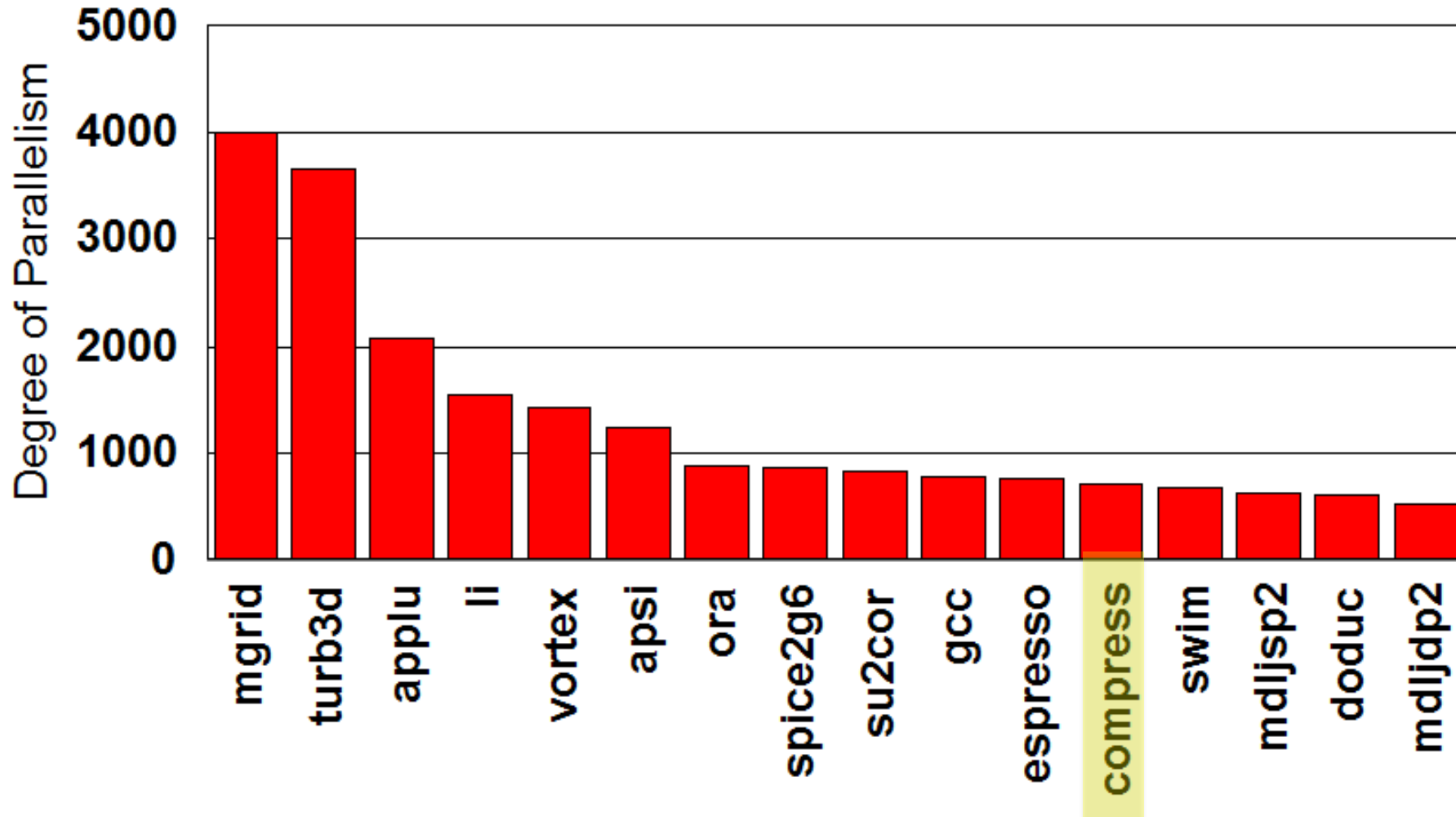
## 50 < Parallelism < 500 (Highest Parallelism in Any Study)



High degree of parallelism  
in wide variety of apps.



## 500 < Parallelism < 5000 (Highest Parallelism in any Study)

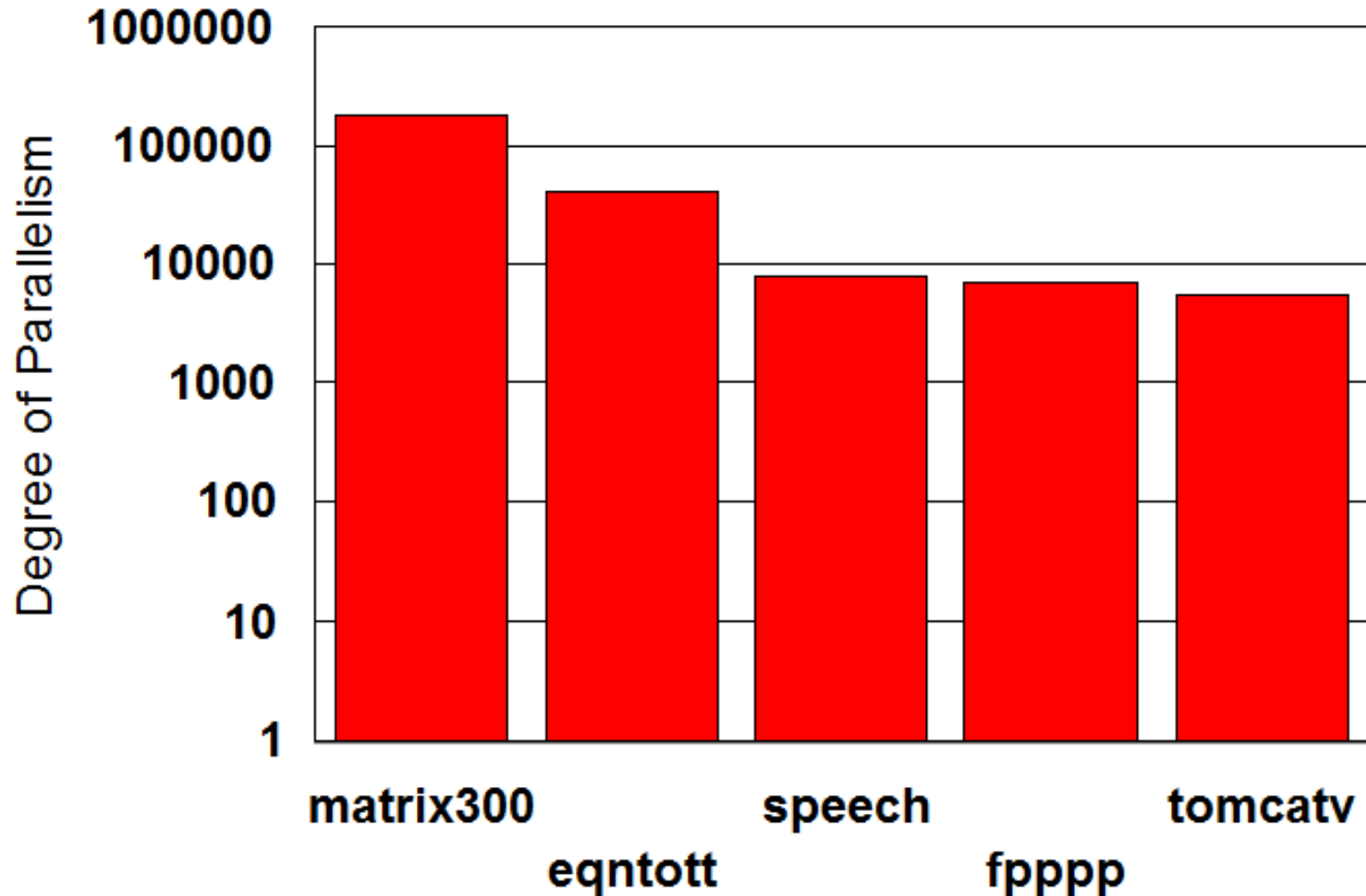


Parallelism > 500 even  
for irregular integer apps:

**li, gcc, compress**



## Parallelism > 5000 (Highest Parallelism in any Study)



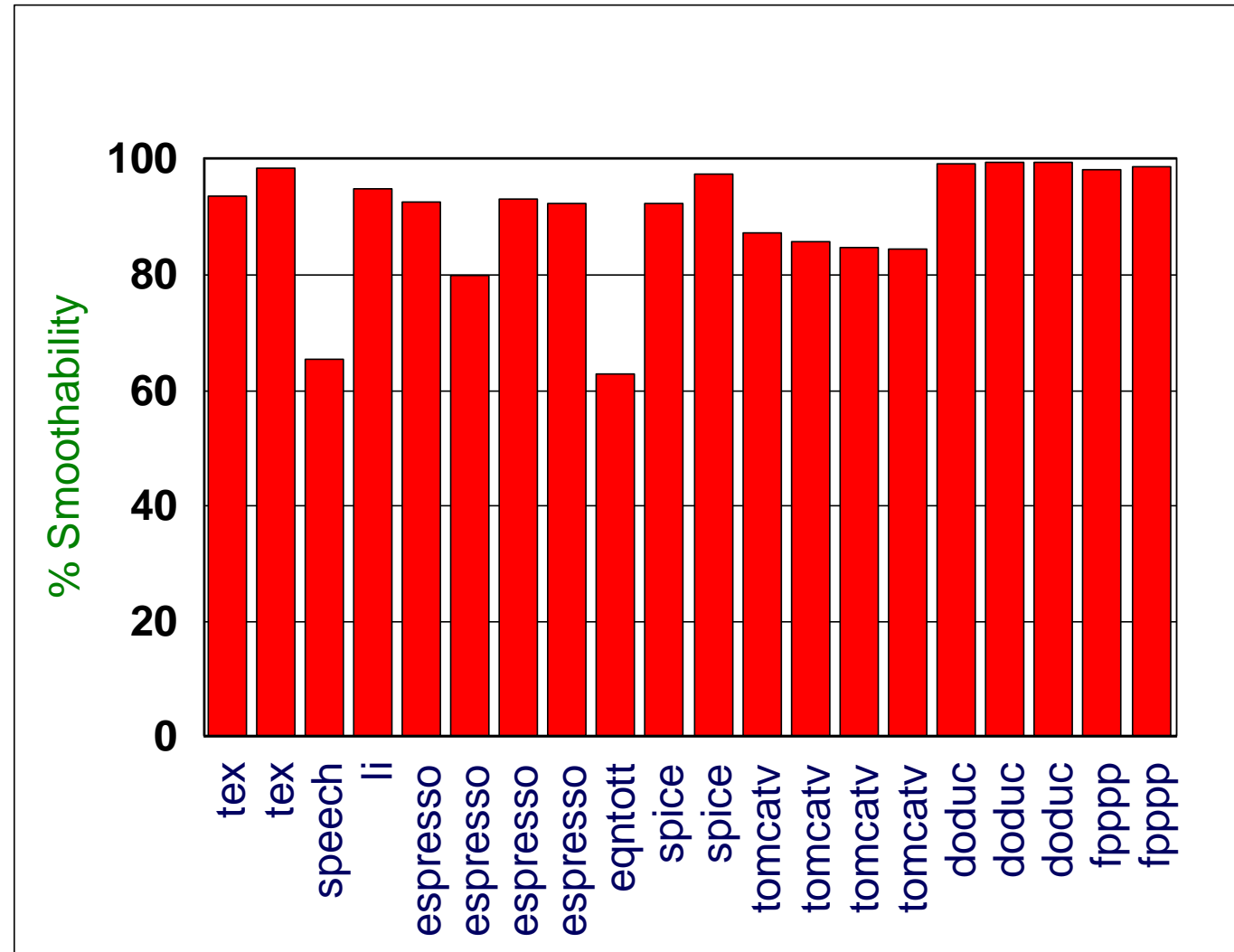
Highest Parallelism in Numerical Applications:

*5,800 - 188,000 IPC*



# Oracle Parallelism: Smoothability

- Does high parallelism require unbounded hardware:
  - Can all the parallelism be effectively smoothed out onto finite hardware?
  - And still run in almost as short a time?



Theobald, Gao, Hendren  
Micro 1992

# Some Efforts to Exploit Coarser-Grain Parallelism

- **Wisconsin:** **MultiScalar**
- **UIUC, CMU, Stanford:** **Speculative Multithreading**
- **UPC:** **Kilo Processors**
- **Cornell:** **Cherry**
- **Princeton:** **DSWP, Commutativity**
  
- **<Many>:** ***Transactional Memory***

**+ *Many Others***





# Exploiting Coarse-Grained Single-Thread Parallelism

**Q:** Why have we not already exploited this task level parallelism in a single thread?

**A:** It is widely separated – independent compute often millions of instructions apart.

– **Too hard** for a compiler:

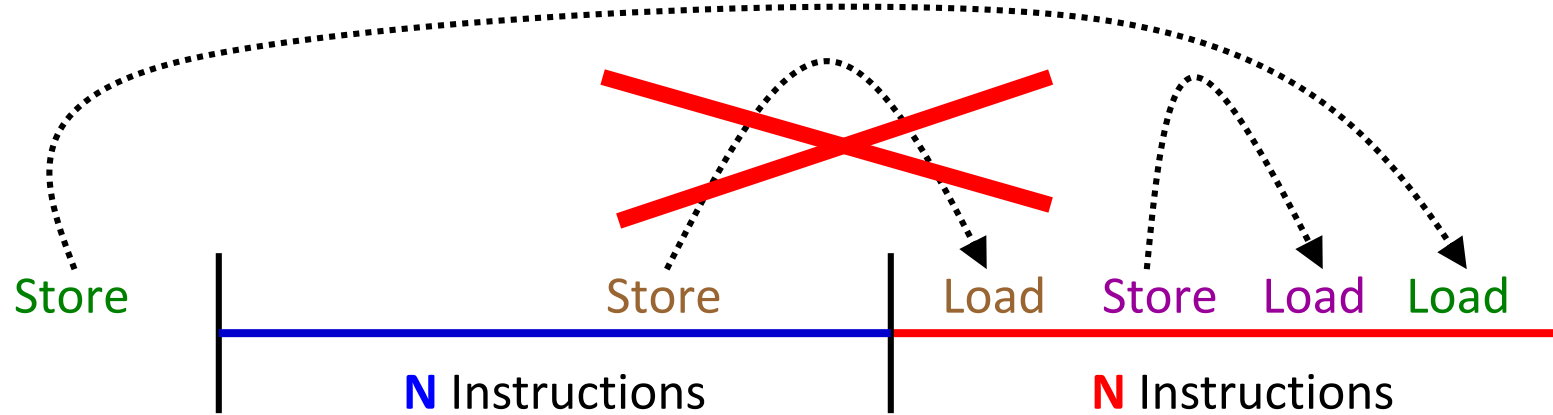
- To generate threads from arbitrary code.
- To determine all memory aliases.
- To know full call graph:
  - Indirect method calls
  - Dynamically linked libraries

– **Too big** for the largest *instruction window / reorder buffer*.

– **Too hard** to predict branches:

- **90%** chance of reaching of following correct path for a million ins  
→ **99.9999+%** individual branch prediction accuracy.

# Memory Parallel Regions

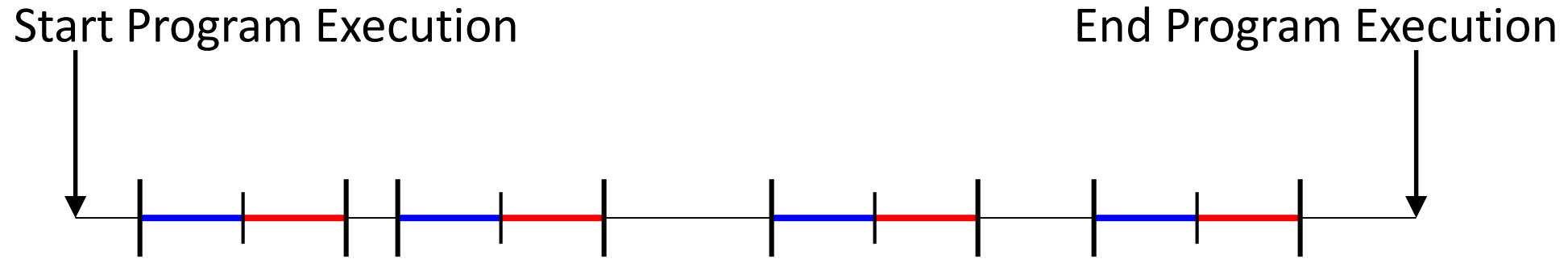


Find regions of **N** instructions that are independent of stores performed in the previous **N**-instruction region.

➔ Execute **Blue** and **Red** Regions in Parallel



# Covering Execution with Memory Parallel Regions

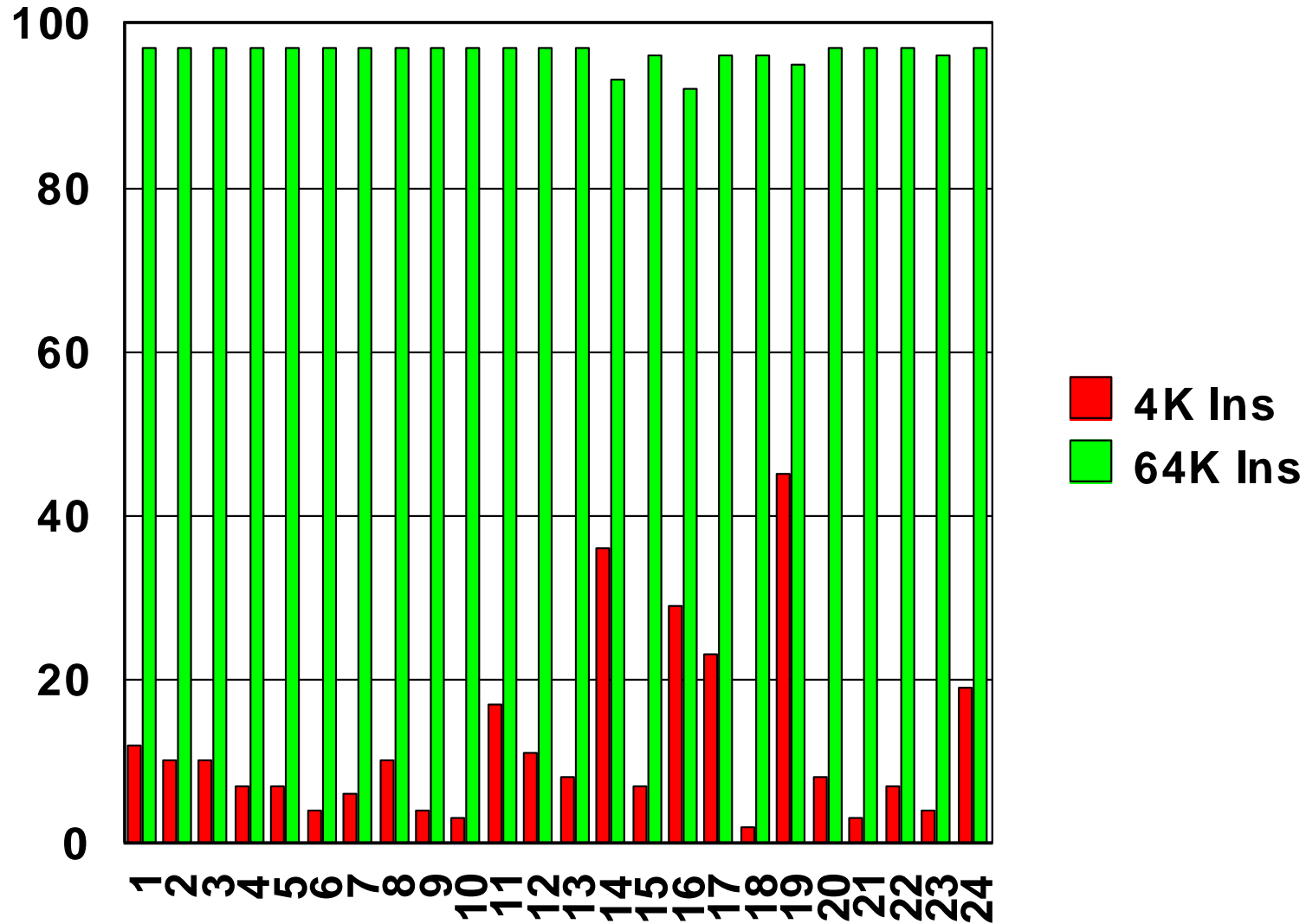


For a given **N**, how much of execution is covered by independent region pairs?

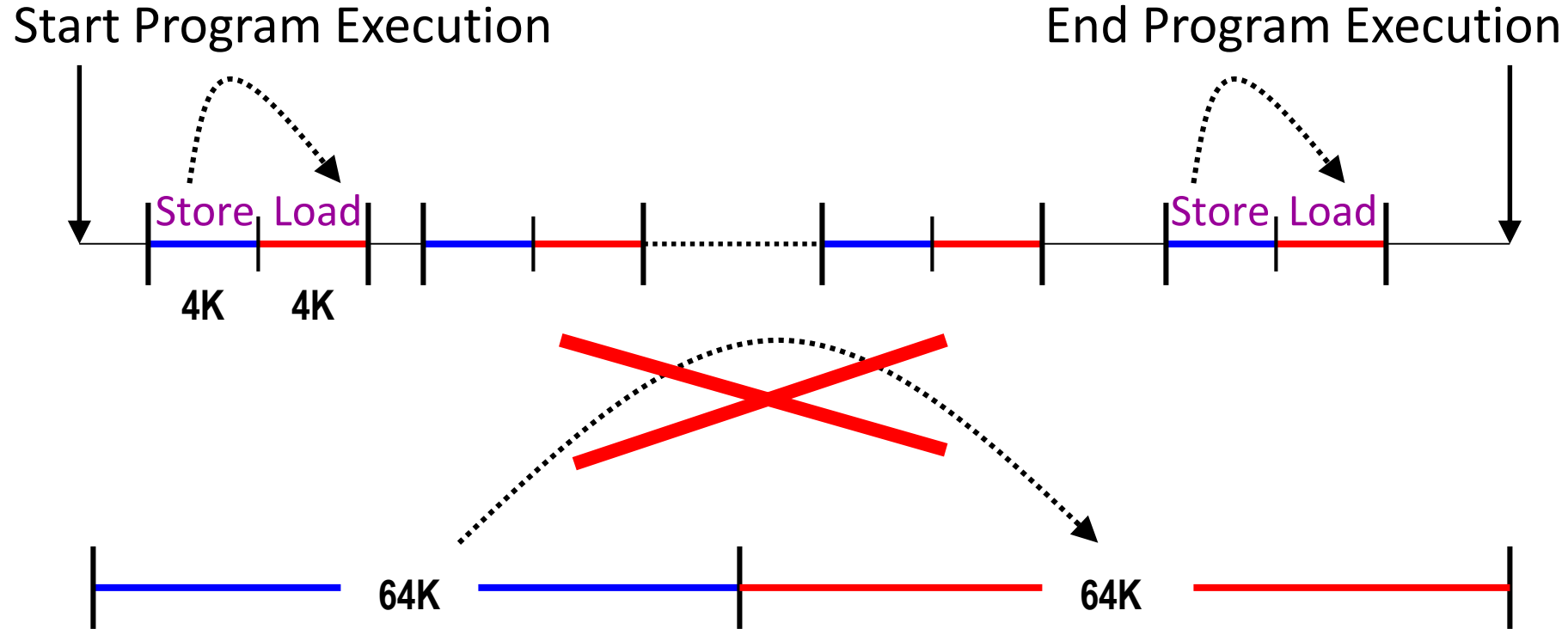


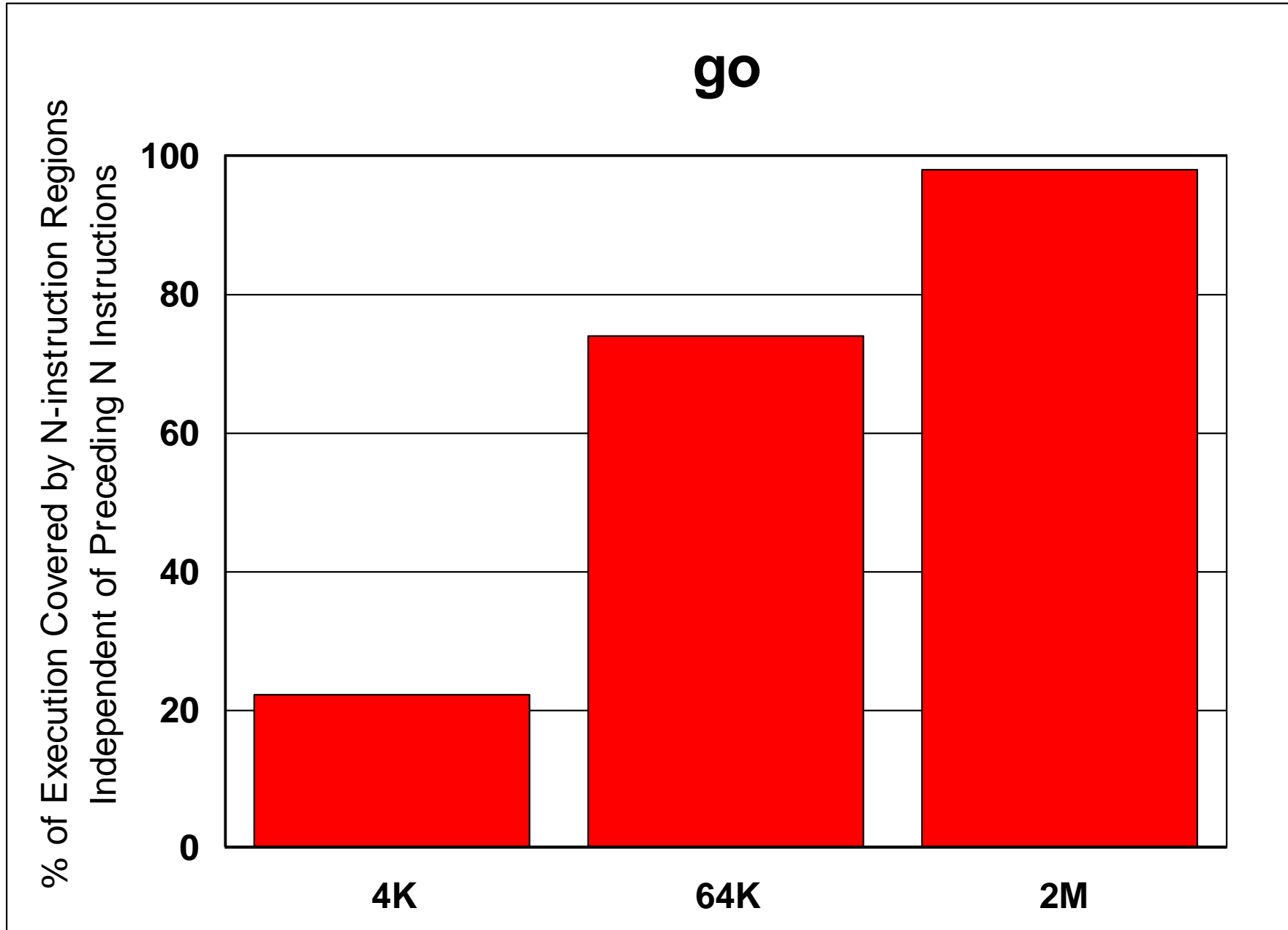
# Livermore Loops

% of Execution Covered by N-instruction Regions Independent of Preceding N Instructions

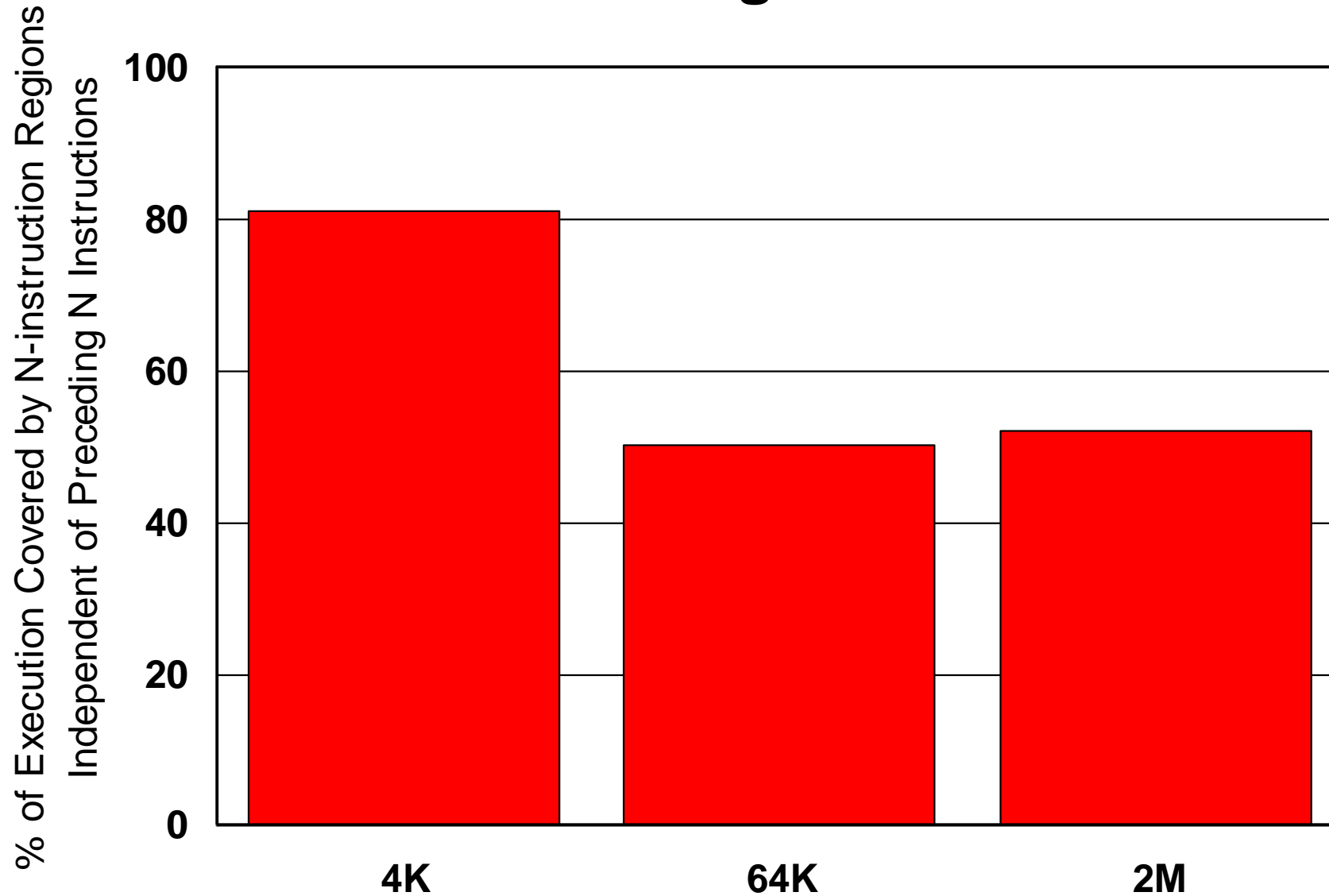


# Dependences in 4K vs 64K





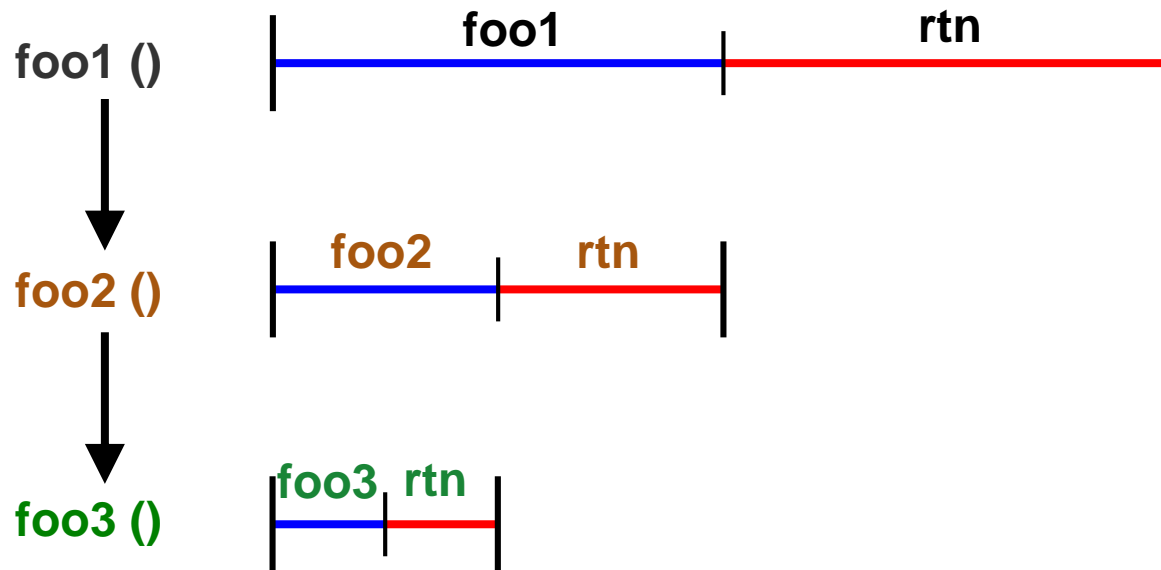
## Stanford Integer Benchmarks





# Exploiting Memory Parallel Regions

1. **Find** long running functions.
2. **Determine** subset of those functions where code at the **return point** is independent of the results produced by the function.



*Combination of hardware capabilities and software tools may be most effective.*



- Explicitly pass all state (cumbersome)
- Programmer mental models
- Handling overabundance of parallelism at peak
- Interoperation with other code
- Interaction with non-dataflow I/O
- Applicability to random code
- Memory Footprint
- Wide separation of parallelism in code
  - Not tractable for compilers or processors
- **Compiler analysis typically ignorant of semantic function**



# DSLs – Domain Specific Languages

## Example – PLDI'2018:

*Spatial:*

*A Language and Compiler for Application Accelerators*

- D Koeplinger, M Feldman, R Prabhakar, Y Zhang, S Hadjis, R Fiszal, T Zhao, L Nardi, A Pedram, C Kozyrakis, K Olukotun

Good, but compiler still does not know that this code implements **merge\_sort**

- Global optimizations easy to miss
- No opportunity to substitute another type of sort

```
1 def Merge_Sort(offchip: DRAM[Int], offset: Int) {
2   val N = 1024 // Static size of chunk to sort
3   Accel {
4     val data = SRAM[Int](N)
5     data load offchip(offset::N+offset)
6
7     FSM(1){m => m < N}{ m =>
8       Foreach(0 until N by 2*m){ i =>
9         val lower = FIFO[Int](N/2).reset()
10        val upper = FIFO[Int](N/2).reset()
11        val from = i
12        val end = min(i + 2*m - 1, N) + 1
13
14        // Split data into lower and upper FIFOs
15        Foreach(from until i + m){ x =>
16          lower.enq(data(x))
17        }
18        Foreach(i + m until end){ y =>
19          upper.enq(data(y))
20        }
21
22        // Merge of the two FIFOs back into data
23        Foreach(from until end){ k =>
24          val low = lower.peek() // Garbage if empty
25          val high = upper.peek() // Garbage if empty
26          data(k) = {
27            if (lower.empty) { upper.deq() }
28            else if (upper.empty) { lower.deq() }
29            else if (low < high) { lower.deq() }
30            else { upper.deq() }
31          }
32        }
33      }{ m => 2*m /* Next state logic */ }
34
35    offchip(offset::offset+N) store data
36  }
37 }
```

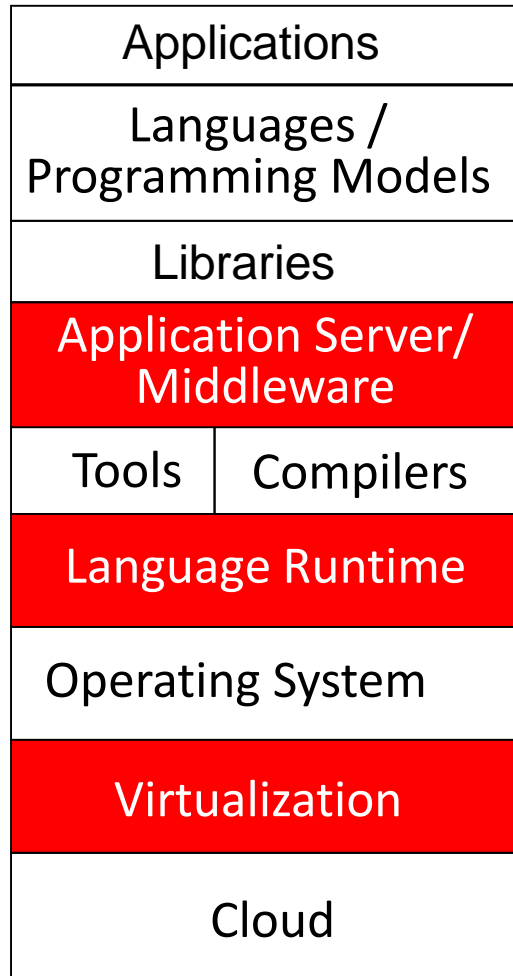
# Higher-Level Data Types and Algorithms as First-Class Objects

- Example: Repeated Insertion to a List, with sort immediately after each insertion
  - **List-insert / Sort**
  - **List-insert / Sort**
  - **List-insert / Sort**
  
- But knowing the semantics of List, Insert, and Sort allows optimization
  - **List-insert**
  - **List-insert**
  - **List-insert**
  - **Sort**
  
- Many higher-level constructs could be represented to compiler:
  - **Lists, trees, graphs, heaps, stacks, etc**
  - **Dates and times**
  - **Images**
  - ...



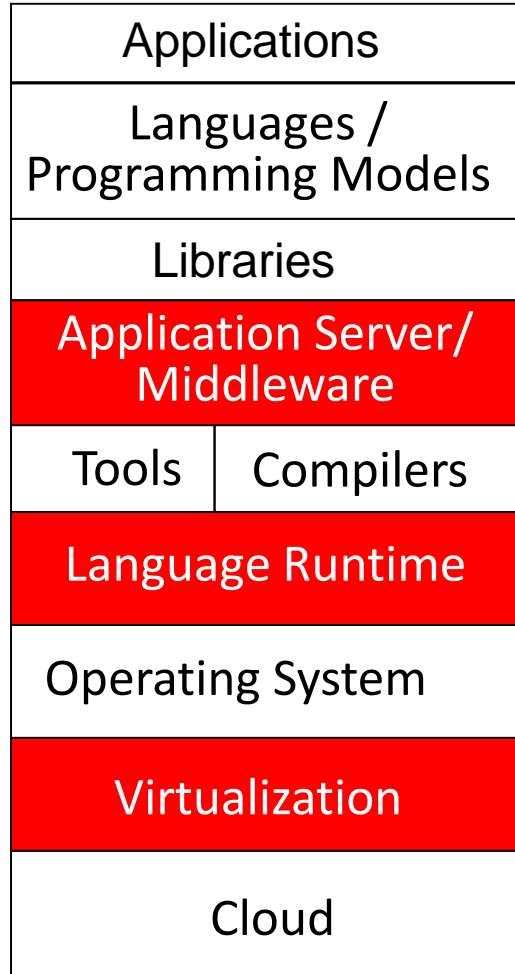
# But What if Rewriting Large Amounts of Code is not an Option?





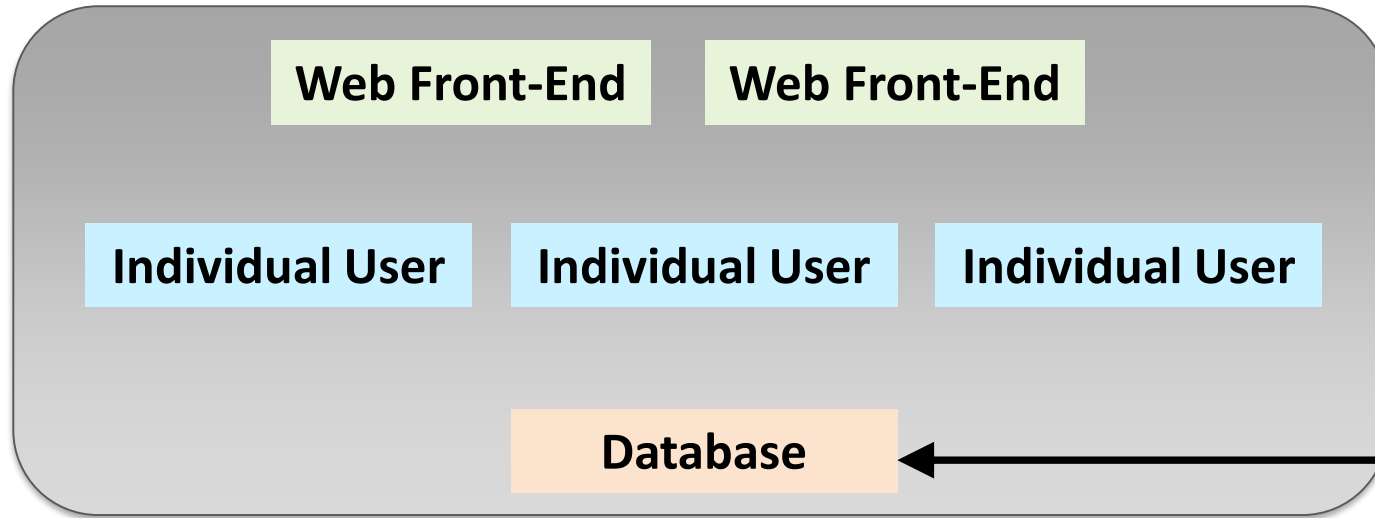
- To address complexity we created runtime stack
  - *Layer below provides abstraction to layer above*
- Widely successful
  - Hides most details of each layer
  - Enables componentization
    - Ability to change components at layer → Incentive for improvement
- Limitations
  - More layers accrue over time (e.g. *JVM, App server, hypervisor*)
    - 1 level of indirection → Brilliance
    - N levels → ???
  - Thin interfaces between layers promote
    - Lack of synergy
    - Duplicate functionality
      - *AppServer, JVM, OS, Virtualization, HW* have thread abstraction





← Here





*Only point of sequential code  
– isolated and minimized*

**CASE 1:** Single Enterprise in Cloud handling many individual users.

- Separate, Isolated VMs
- Processes / Containers

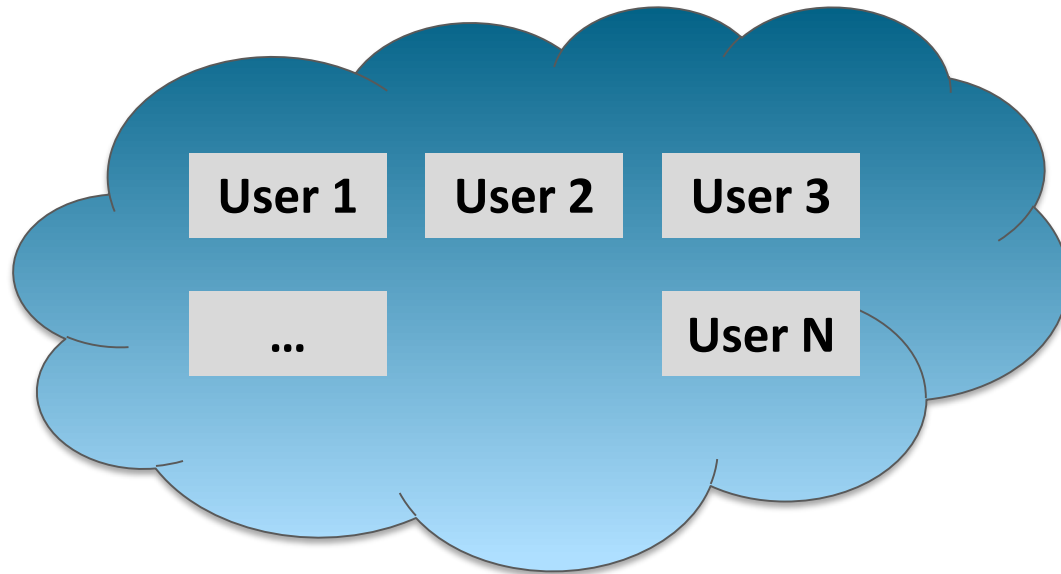
## Result – Dataflow:

- Scaleout Model with seamless scale-up and scale-down as degree of parallelism varies
- Arbitrary number of independent program counters
- Varying use of processors as parallelism varies
- Isolated Data





## CASE 2: Broad Set of Enterprises in Cloud



Each user can be dataflow within themselves

- *As in previous slide*

**User** = Broad set of services and tasks controlled by one entity

### Result – Dataflow:

- Lots of program counters
- Lots of processors
- No global state across users
- Run as data / input becomes available

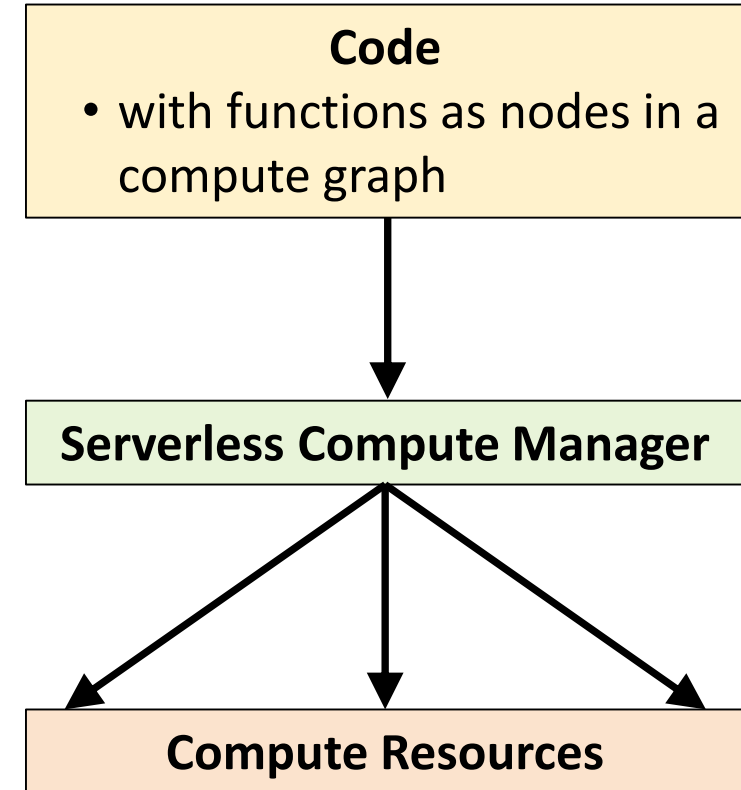


## CASE 3: Serverless Computing as Dataflow

- Amazon Lambda
- Google Cloud Platform – Functions
- Microsoft Azure
- IBM Cloud Functions
- Openwhisk
- Kubeless
- ...

### Result – Dataflow:

- Run as data / input becomes available
- Lots of program counters
- Lots of processors
- No global state across users



*Is cloud an unappreciated commercial success for dataflow and extreme scale?*



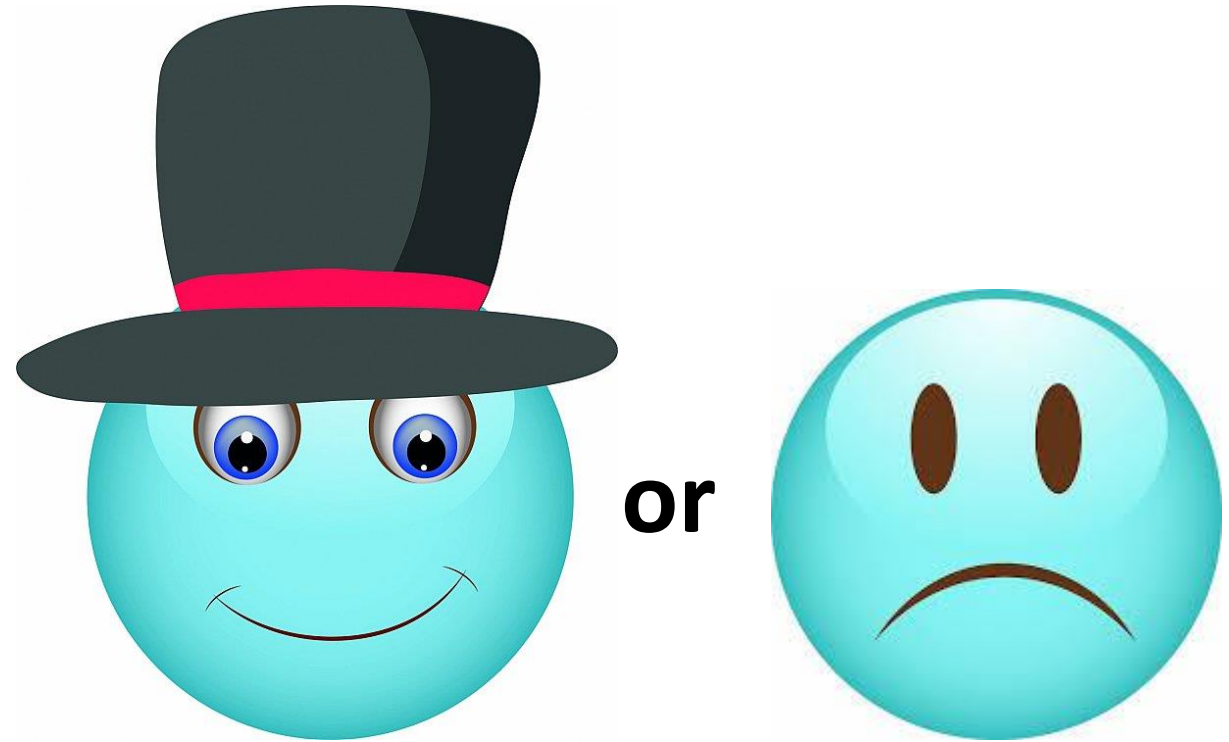
## Lessons: Dataflow and Cloud

- **There has long been debate about the proper granularity to express dataflow ops**
- **Cloud shows one case where coarse-grain allows a massive dataflow approach to succeed commercially and attract a vast set of users**
  - As programmers
  - As users of the end-result
- **What lessons from cloud can be applied elsewhere in dataflow?**
  - Need easy-to-use frameworks
  - Need massive independent parallel threads on which to run
  - Need massive hardware processing resources
  - Need coordination by centralized mechanisms to be too complex to implement



# Dataflow and Security

- **Good**
  - No pointers
  - No buffer over-run issues
- **Bad**
  - Side channels like Spectre and Meltdown seem open
- **Indifferent**
  - Phishing and Spear-phishing
  - Dumpster diving



# Conclusions

## ■ Worst of Times

- No commercial takeoff of traditional dataflow despite unprecedented compute resources, new computing paradigms, more programmers than ever, more languages than ever

## ■ Best of Times

- Major tenets of dataflow have been embraced commercially in cloud at extreme scale
- They are succeeding

## ■ Next Steps

- What do we learn from those successes?
- How do we amplify them?
- What other fields are ripe?

