

Higher Level Programming on Parallel
Computers: Sweetening the Deal for
Programmers
(and Making Compilers Work Harder)

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University of Rochester, Nov 30, 2009



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“A New Kind of Science”

Stephen Wolfram

“Computing is as fundamental as the physical, life, and social sciences.”

Peter J. Denning and Paul S. Rosenbloom
Communications of the ACM, Sep 2009

“What our community should really aim for is the development of a curriculum that turns our subject into the fourth R—as in ‘rogramming—of our education systems.

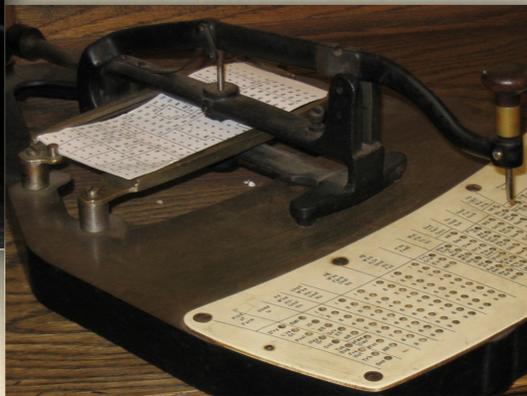
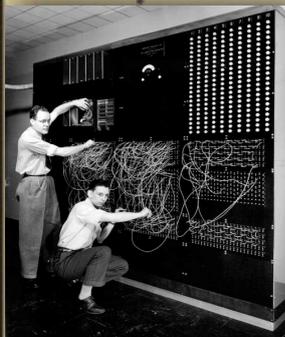
...

A form of mathematics can be used as a full-fledged programming language, just like Turing Machines.”

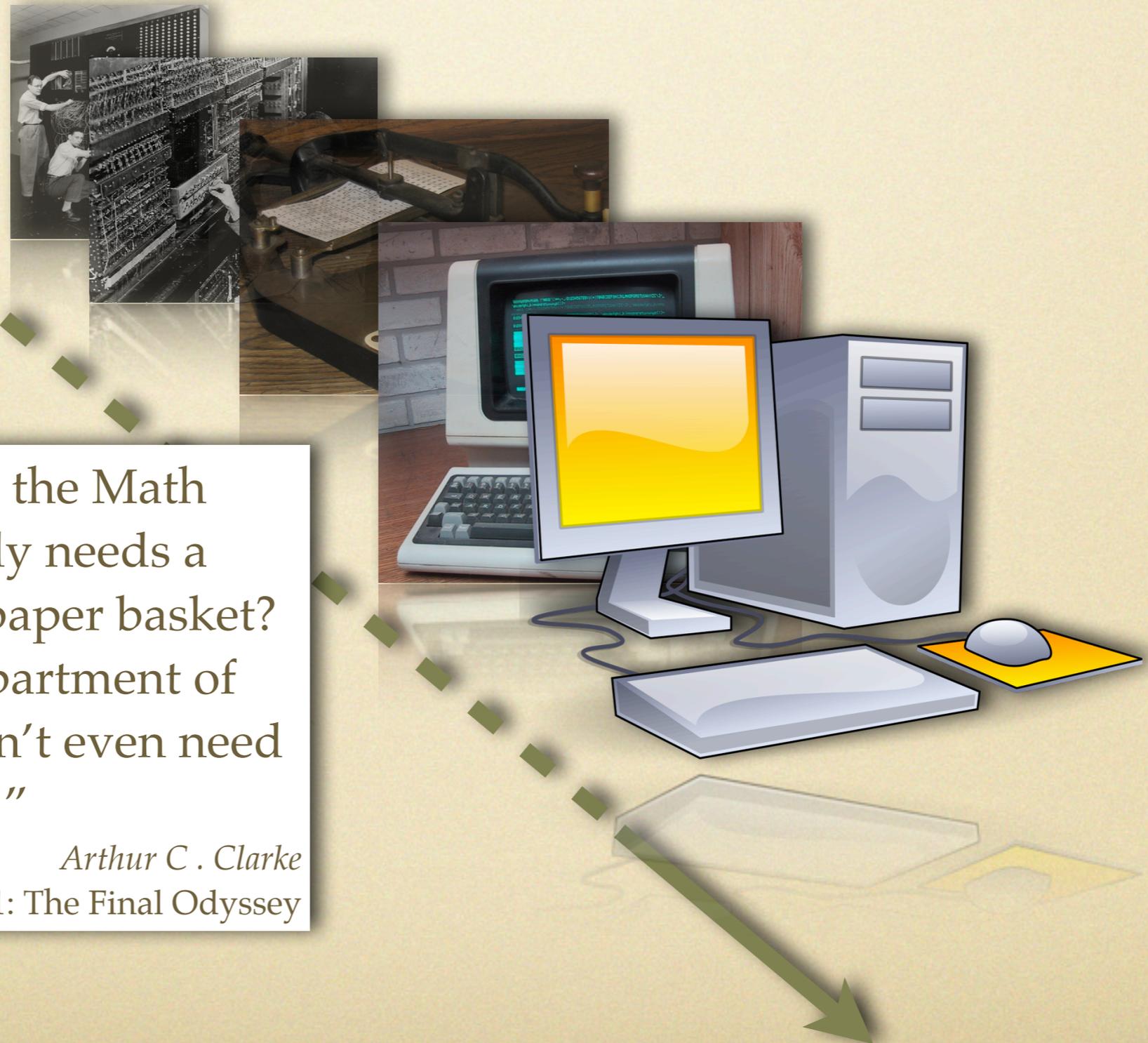
Matthias Felleisen and Shriram Krishnamurthy
Communications of the ACM, Jul 2009



Programming



Programming



“Why can't you be like the Math Department, which only needs a blackboard and wastepaper basket? Better still, like the Department of Philosophy. That doesn't even need a wastepaper basket ...”

Arthur C. Clarke
3001: The Final Odyssey

Computers are for Computing and ...

- Computers as general-purpose tools
 - communication, navigation, data collection, entertainment, etc.
- Computers as computing tools
 - problem solving
 - data processing and analysis



Overview

- **Motivation**
- Rethinking program analysis
- Rescuing parallel programmers
- Concluding remarks



Rethinking Program Analysis



Problem

- Nice programming languages
 - domain-specific
 - often dynamically typed and interpreted
- Poor performance
 - inefficient use of computing resources
 - inefficient use of energy



“It is a capital mistake to theorize before one has data. Insensibly one begins to twist facts to suit theories, instead of theories to suit facts.”

Sir Arthur Conon Doyle
A Scandal in Bohemia



Example 1: BLAS

$$A + A * B' + 2 * (A + B)' * A + (x + y) * x'$$

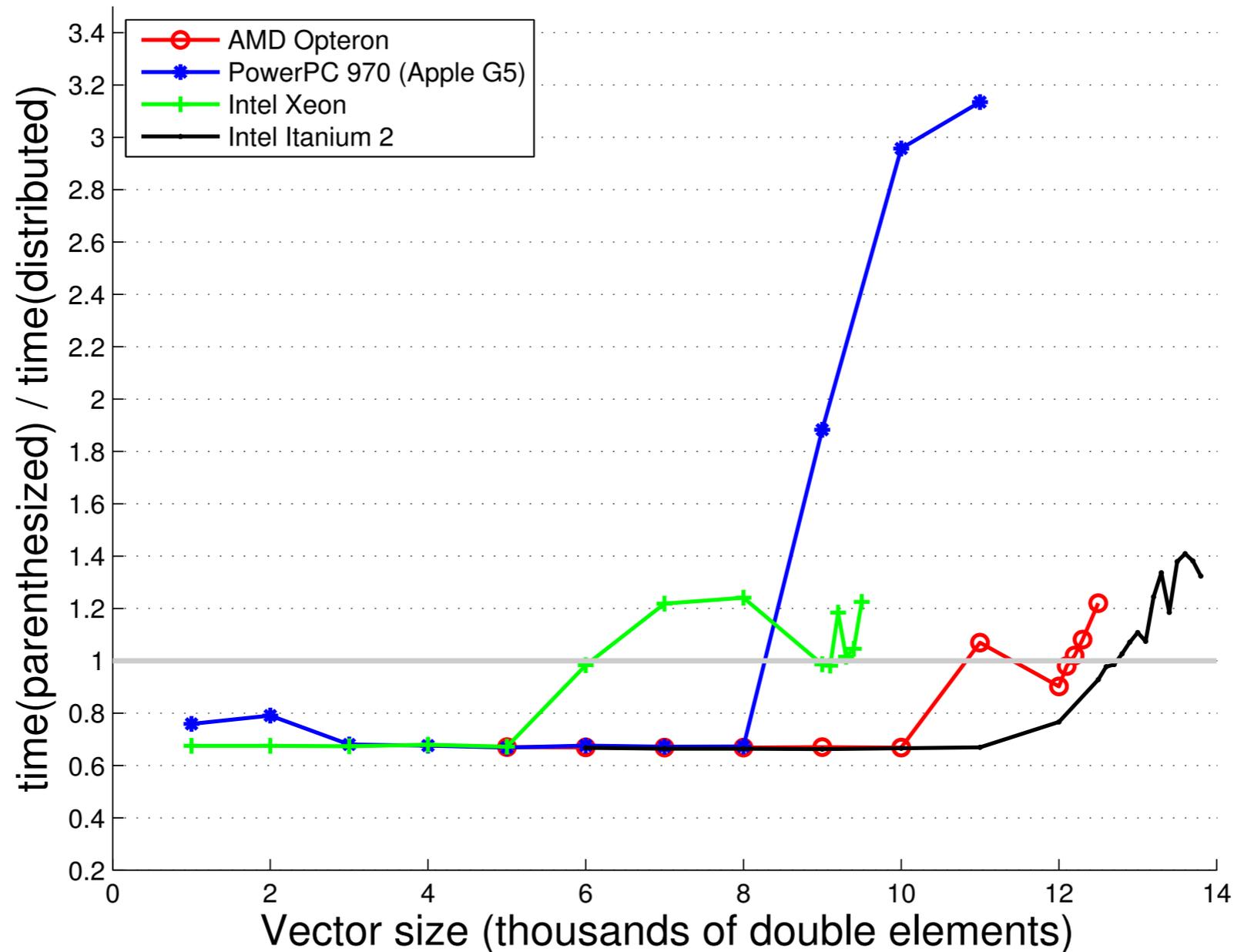
```
copy(A, tmp0);  
gemm(1, A, B, 1, tmp0);  
copy(A, tmp1);  
axpy(1, B, 1, tmp1);  
gemm(2, tmp1, A, 1, tmp0);  
copy(x, tmp1);  
axpy(1, y, 1, tmp1);  
ger(1, tmp1, x, tmp0);
```

$$A + A * B' + 2 * A' * A + 2 * B' * A + x * x' + y * x'$$

```
gemm(1, A, B, 1, tmp0);  
ger(1, x, x, tmp0);  
ger(1, y, x, tmp0);  
gemm(2, A, A, 1, tmp0);  
gemm(2, B, A, 1, tmp0);
```

Example 1: BLAS

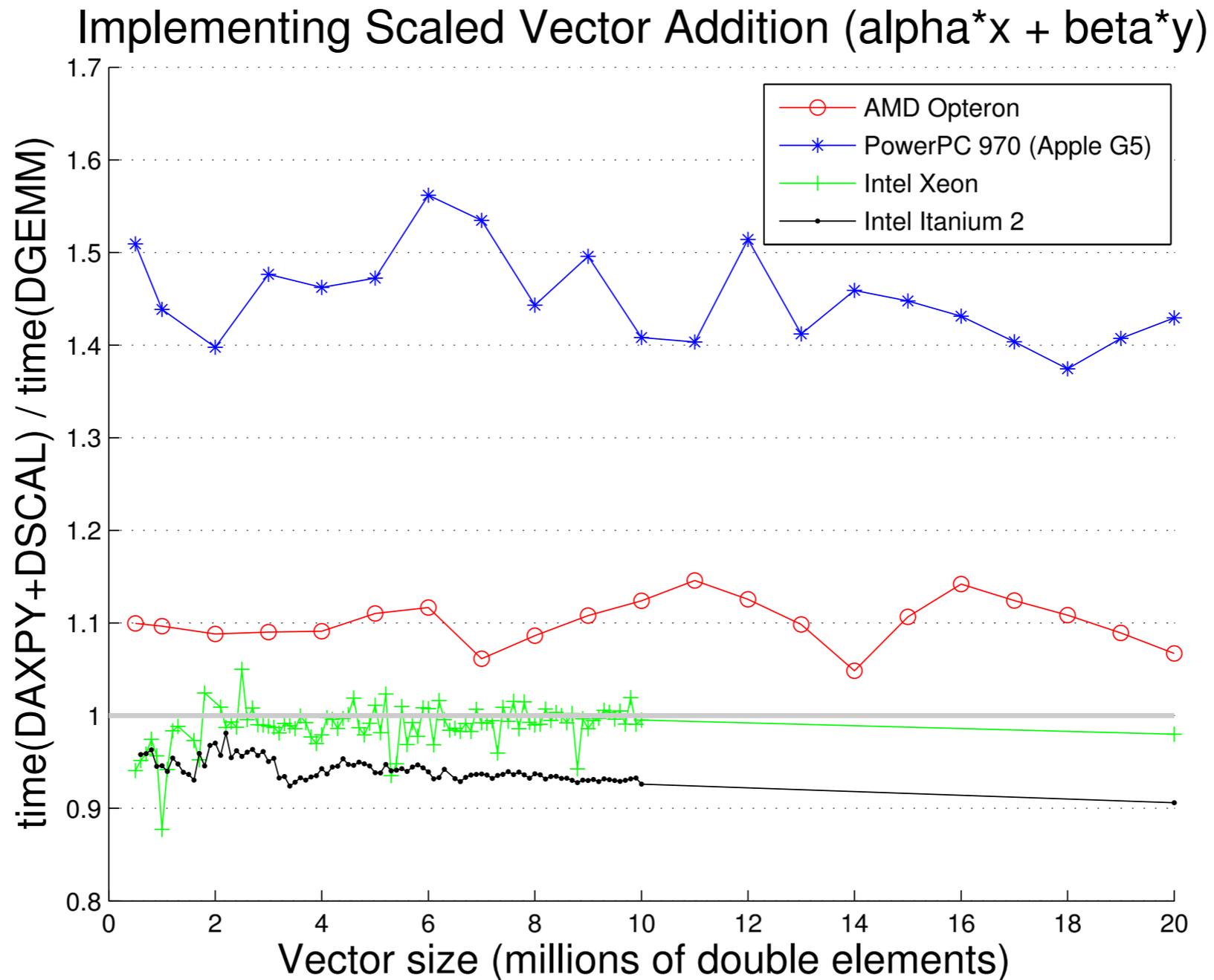
Implementing A Big Expression



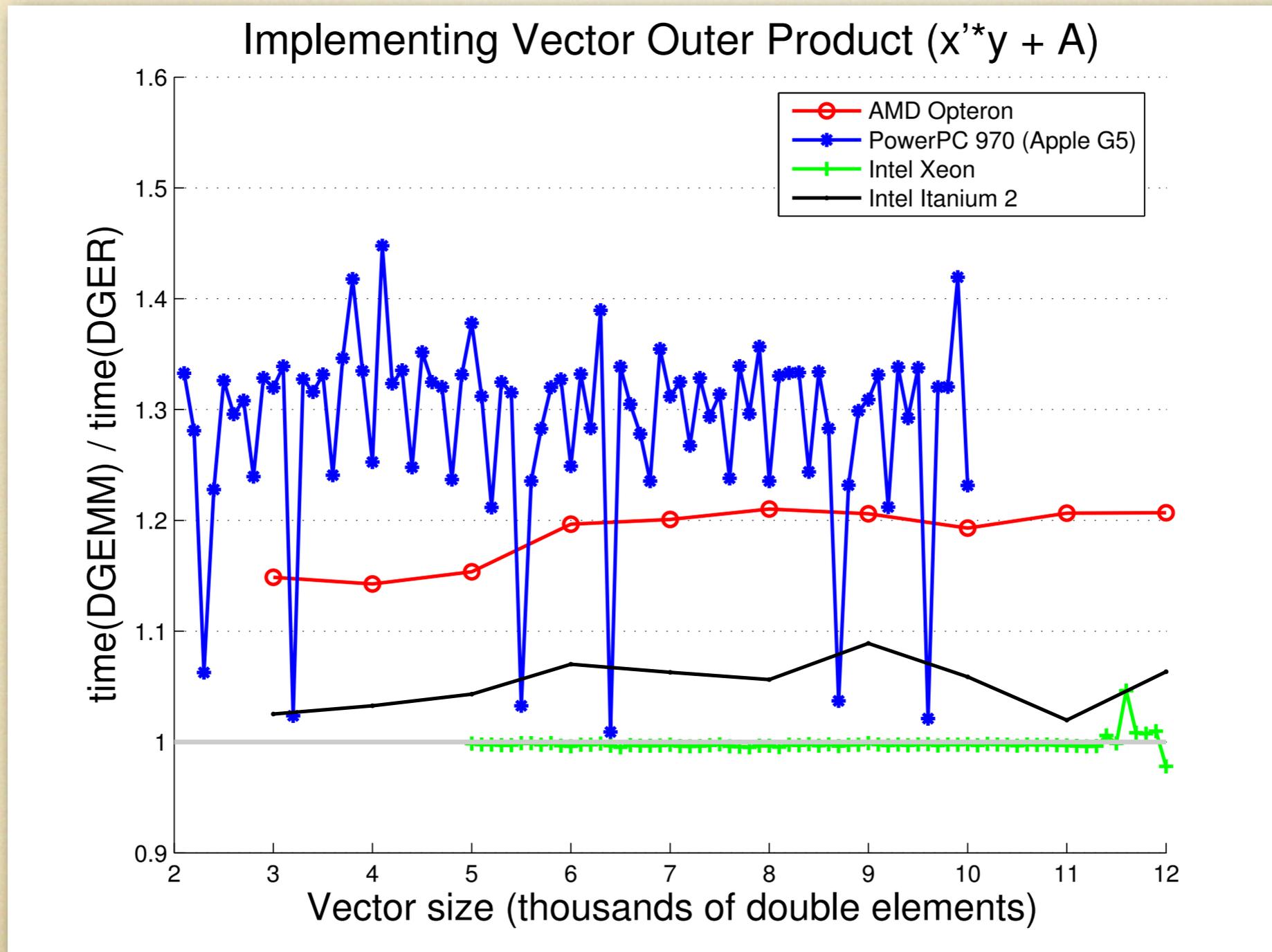
Lessons

- Minimize buffer copies
- Combine as many simple operations as possible into a single BLAS call
- Work on data-flow graph
 - simple algorithm within basic blocks
 - expanded to work globally (intra-procedurally)

Example 1: BLAS

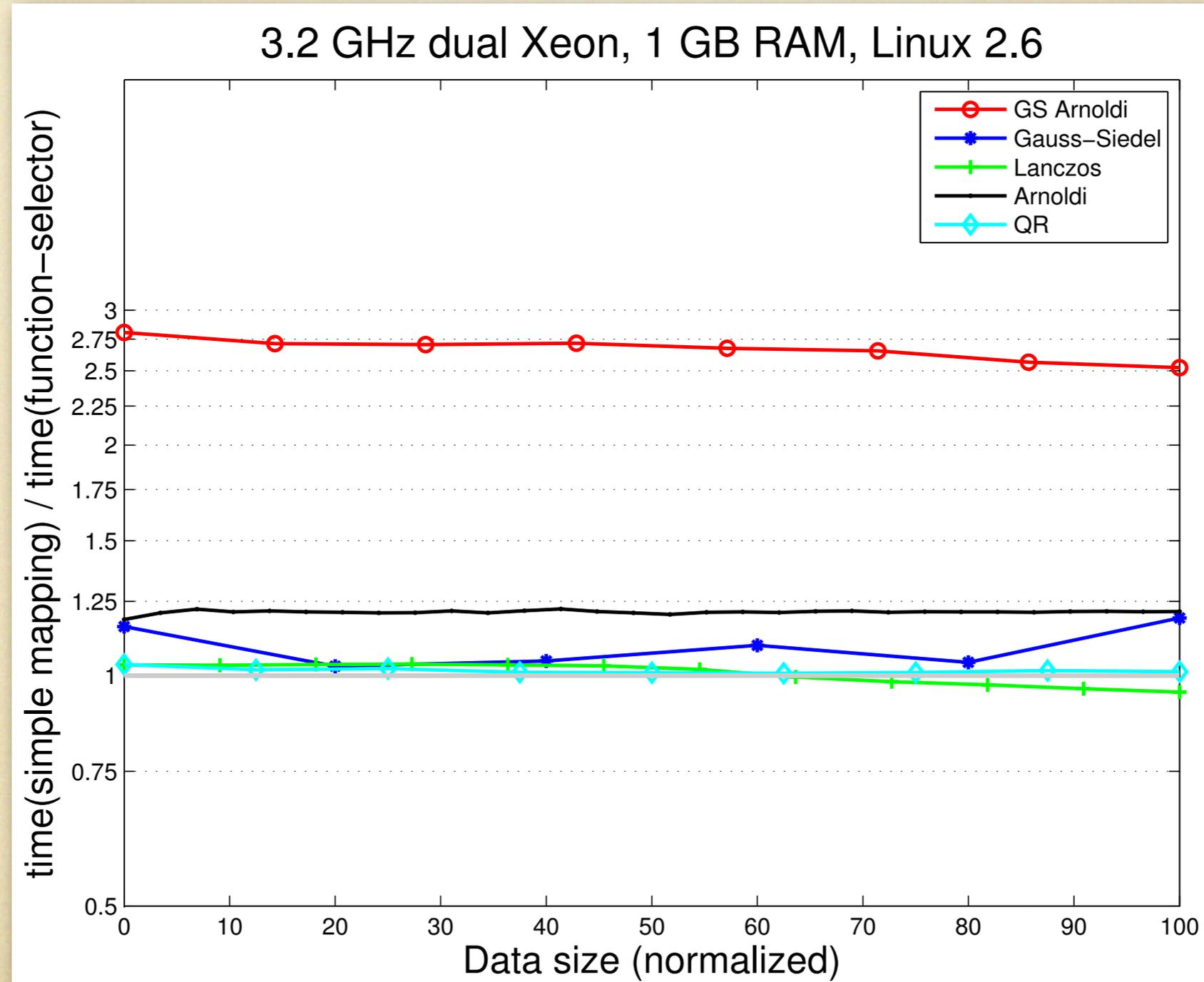


Example 1: BLAS



Results

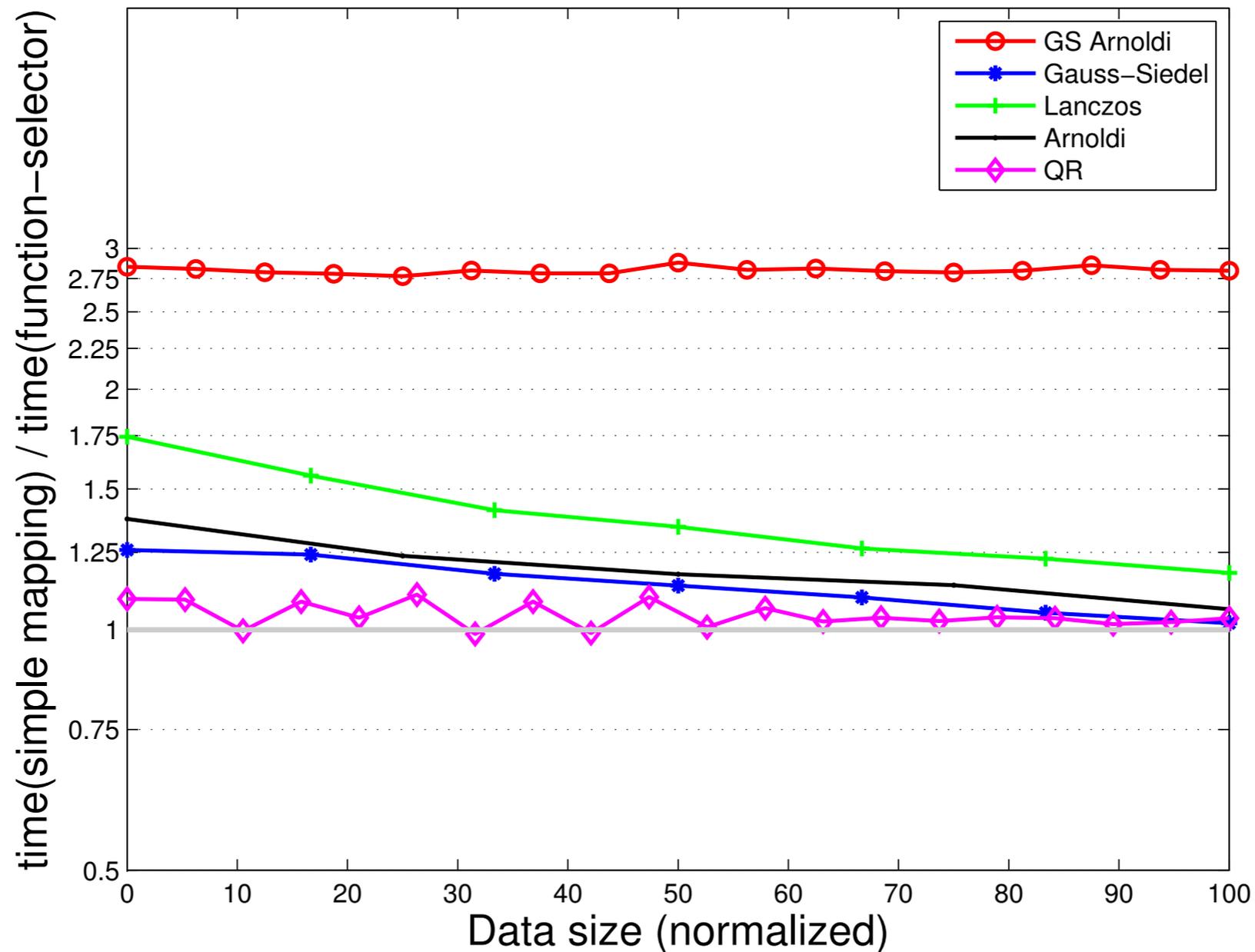
POHLL (IPDPS) 2007, McFarlin and Chauhan



Results

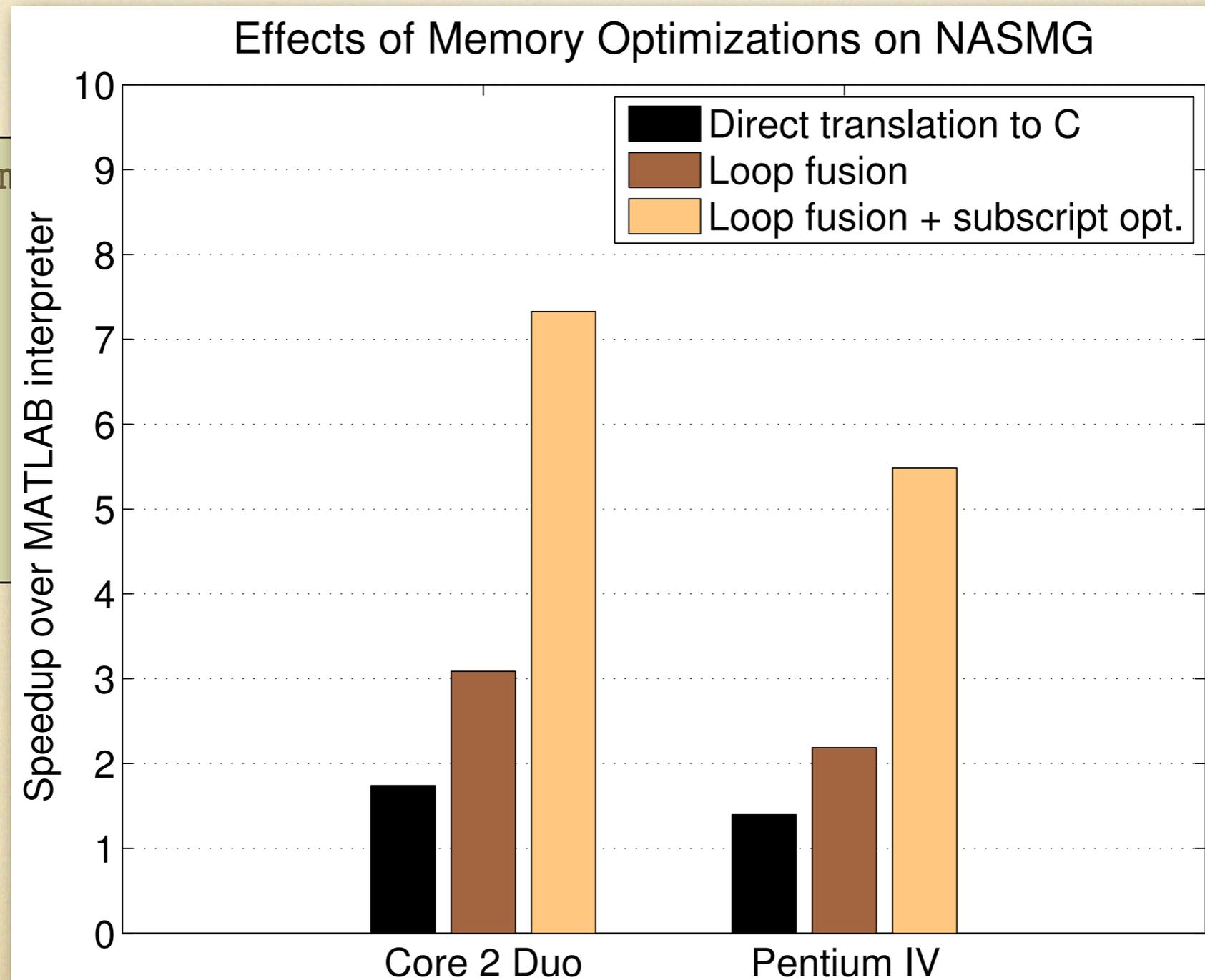
POHLL (IPDPS) 2007, McFarlin and Chauhan

1.5 GHz dual Intel Itanium 2, 4GB RAM, Linux 2.6



Example 2: Subscripts

HiPC 2009, Shei, Chauhan, and Shaw



Enabling Technology

HiPC 2009, Shei, Chauhan, and Shaw

- Type Inference
 - infer base types, and array sizes
- Leverage MATLAB / Octave interpreter
 - “concretely interpreted partial evaluation” to combine type inference and constant propagation+folding
 - type transfer functions encoded within MATLAB
- Potential for spectacular improvements
 - 100x on biology code (electron μ -scope image-proc.)
 - 1.5x on math code (ODE solver)



Type Inference Through Concrete Interpretation

```
x = 10.5;  
y = [1, 2; 3, 4];  
y = x * y + a;
```

Example Code



```
x$1 = 10.5;  
y$1 = [1, 2; 3, 4];  
t$1 = x$1 * y$1;  
y$2 = t$1 + a$1;
```

After SSA & flattening

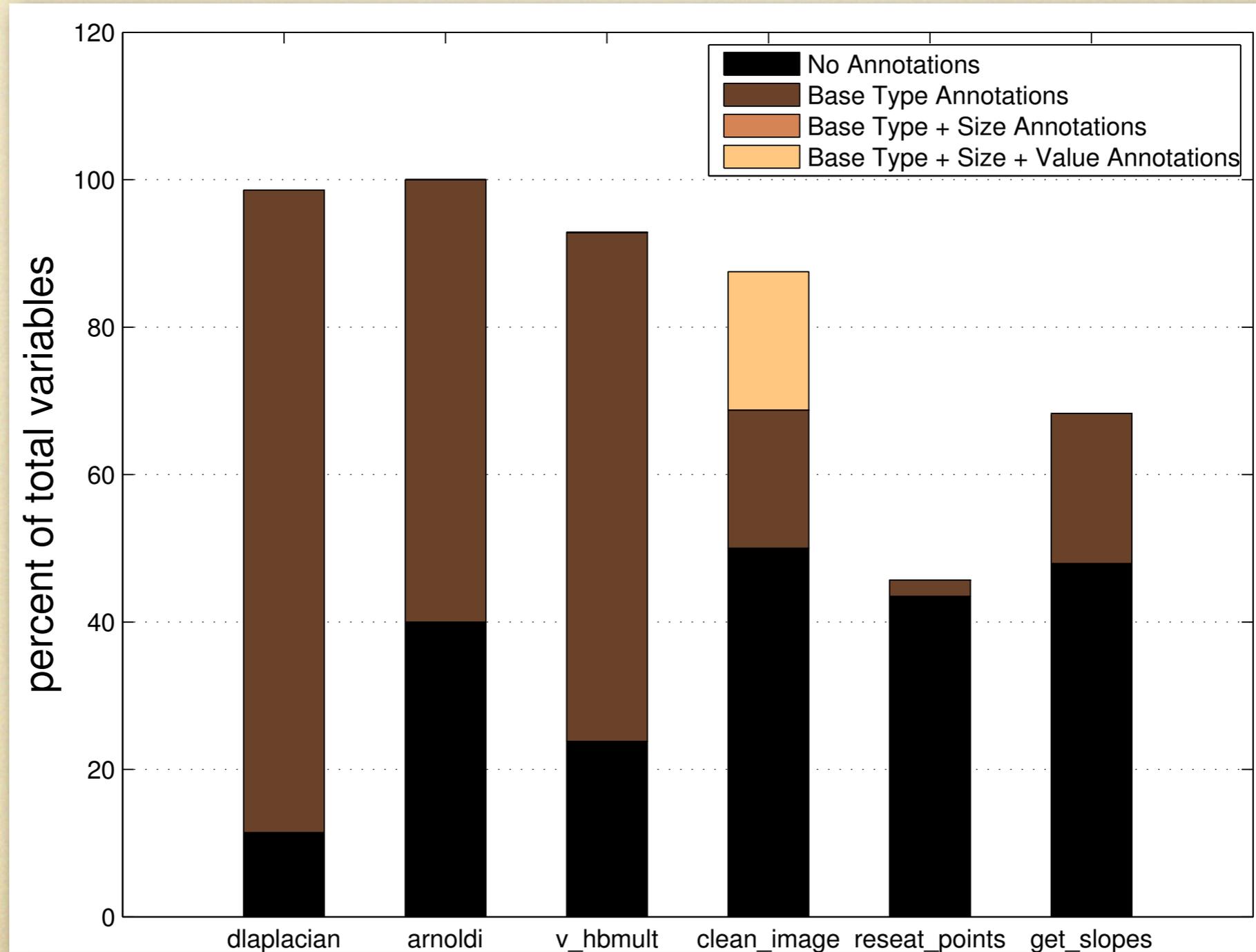
```
BT_x$1 = 'd';  
x$1 = 10.5;  
BT_y$1 = BXF_vertcat( ...  
    BXF_horzcat('i', 'i'), ...  
    BXF_horzcat('i', 'i') ...  
);  
y$1 = [1, 2; 3, 4];  
BT_t$1 = ...  
    BXF_product(BT_x$1, BT_y$1);  
t$1 = x$1 * y$1;  
BT_y$2 = ...  
    BXF_sum(BT_t$1, BT_a$1);  
y$2 = t$1 + a$1;
```

With type disambiguation code

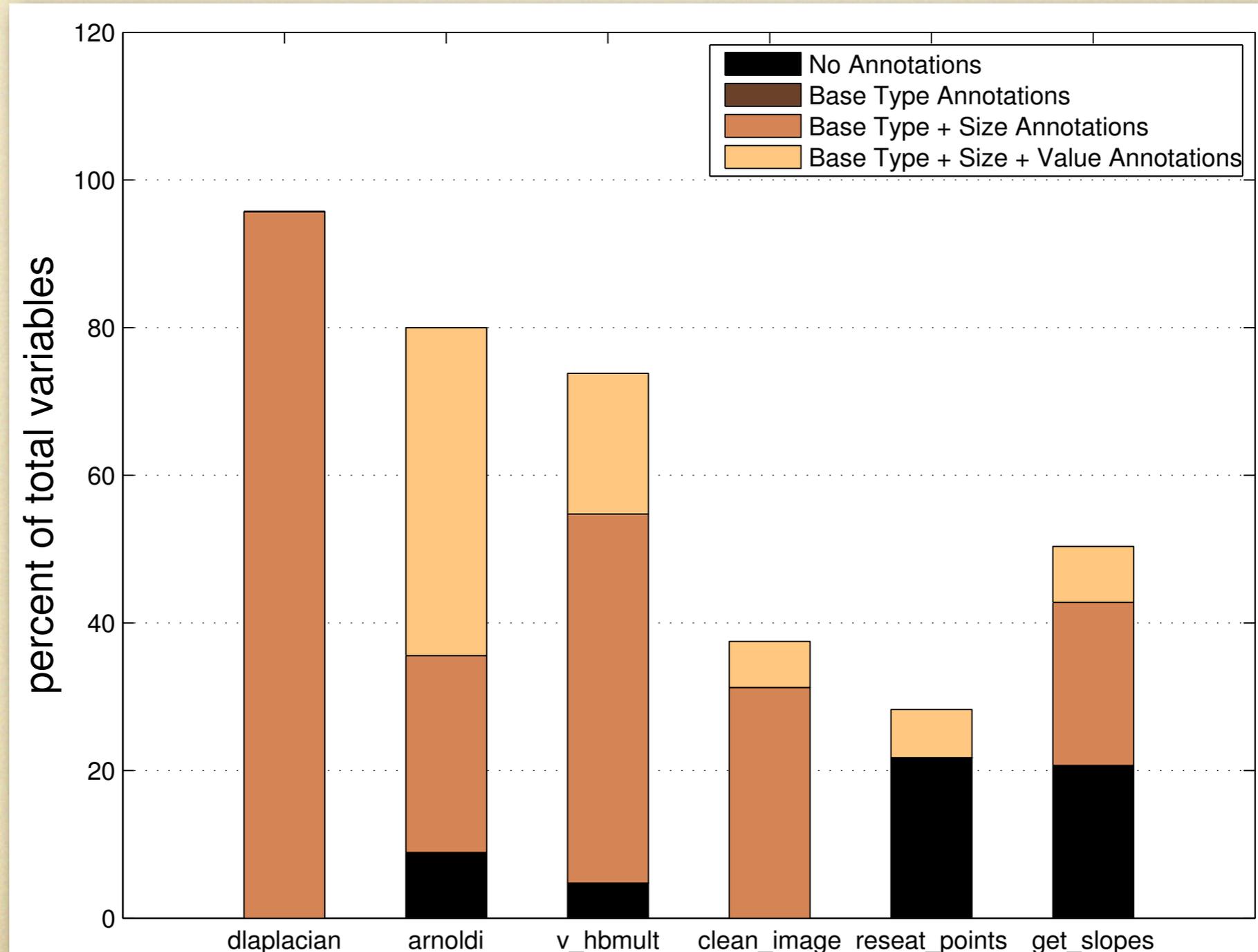
```
x$1 = 10.5;  
y$1 = [1, 2; 3, 4];  
t$1 = x$1 * y$1;  
BT_y$2 = ...  
    BXF_sum(BT_t$1, BT_a$1);  
y$2 = t$1 + a$1;
```

After partial evaluation

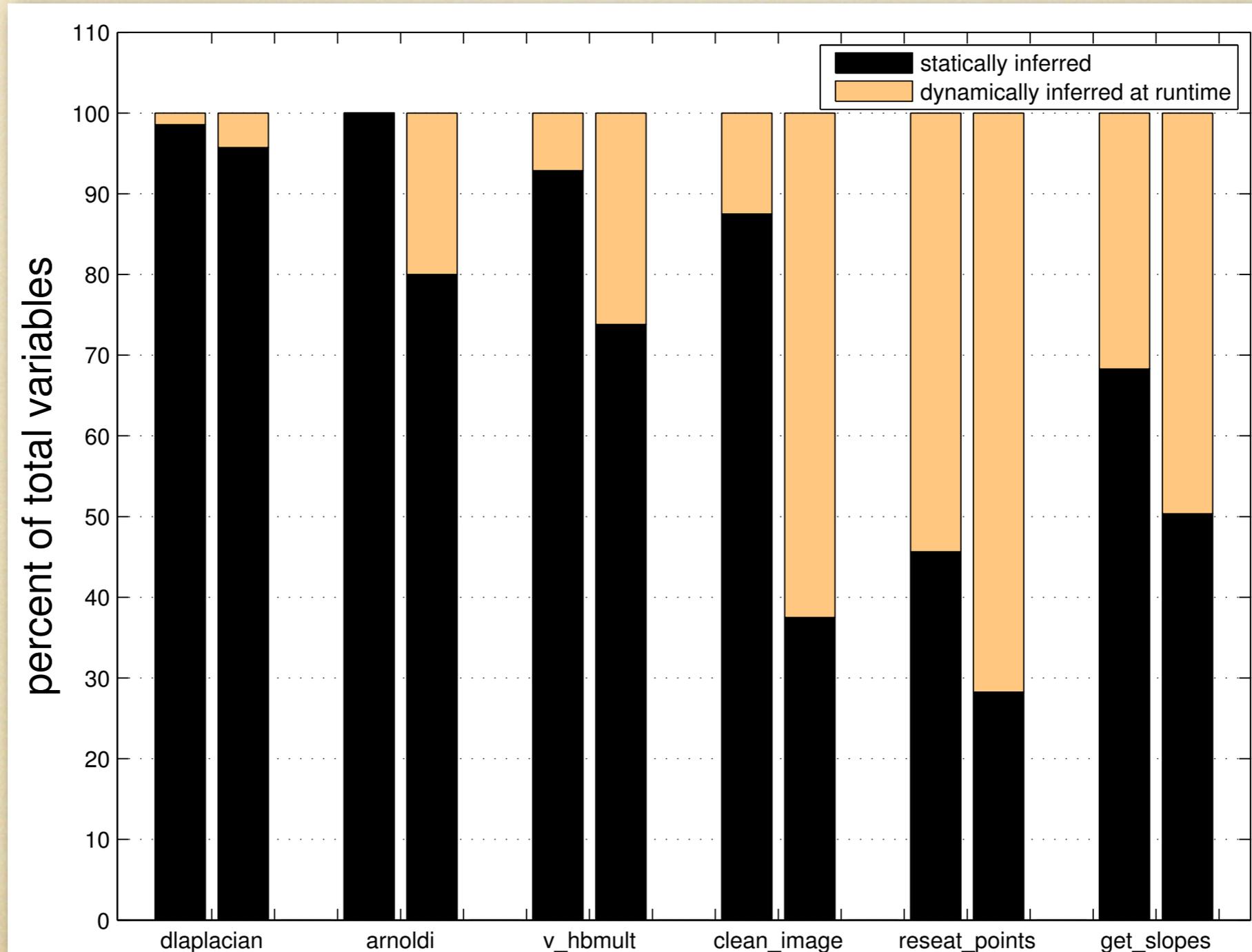
Inferring Base Types



Inferring Array Sizes



Static vs Dynamic Inference



Observations

- Memory seems to play a key role in performance of high-level dynamically type languages (studied MATLAB and Ruby)
- Lack of general-purpose analytical models to guide the compiler toward generating programs with better memory locality
 - need inter-procedural methods
 - need a way to incorporate separately-compiled libraries

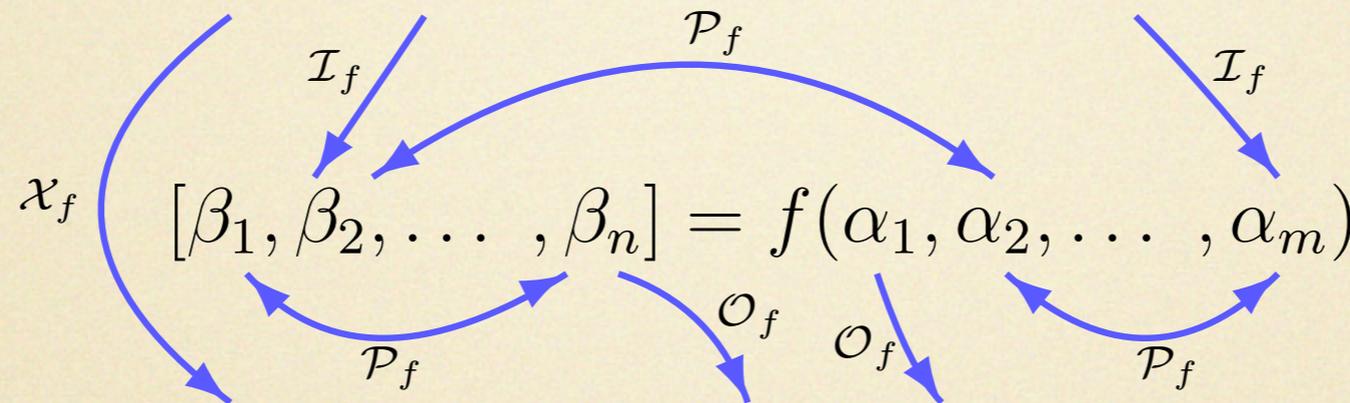
Static Reuse Distances

```
x = a + b;  
c = a + d[i]*100;  
y = x * 10;
```

Static Reuse Distance = 6 (a, b, c, d, i, 100)

Definition: A reference point, p , is the unique syntactic reference that is either an lvalue or an rvalue. When the point is inside a loop nest a superscripted reference point p^i refers to the dynamic instance of p at the iteration vector \underline{i} .

SRD Across Function Calls



P : set of all possible reference points in a program

A : domain of alias functions such that an alias function $a(p_1, p_2)$ returns true iff p_1 and p_2 overlap in their memory references

Z : set of integers

$$\mathcal{X}_f : A \rightarrow Z$$

$\mathcal{X}_f(a)$ is the volume of data accessed within f .

$$\mathcal{I}_f : P \times A \rightarrow Z$$

$\mathcal{I}_f(p, a)$ is the volume of data accessed within f before the first access to ρ .

$$\mathcal{O}_f : P \times A \rightarrow Z$$

$\mathcal{O}_f(p, a)$ is the volume of data accessed within f after the last access to ρ .

$$\mathcal{P}_f : P \times P \times A \rightarrow Z$$

$\mathcal{P}_f(p_1, p_2, a)$ is the volume of data accessed between the last use of ρ_1 and the first use of ρ_2 within f . It is 0 if $a(\rho_1, \rho_2)$ is true.

SRD For Regions of Code

$$\mathcal{X}_f : A \rightarrow Z$$

$\mathcal{X}_f(a)$ is the volume of data accessed within f .

$$\mathcal{I}_f : P \times A \rightarrow Z$$

$\mathcal{I}_f(p, a)$ is the volume of data accessed within f before the first access to ρ .

$$\mathcal{O}_f : P \times A \rightarrow Z$$

$\mathcal{O}_f(p, a)$ is the volume of data accessed within f after the last access to ρ .

$$\mathcal{P}_f : P \times P \times A \rightarrow Z$$

$\mathcal{P}_f(p_1, p_2, a)$ is the volume of data accessed between the last use of ρ_1 and the first use of ρ_2 within f . It is 0 if $a(\rho_1, \rho_2)$ is true.

$$\mathcal{X}_c : A \rightarrow Z$$

$\mathcal{X}_c(a)$ is the volume of data accessed within c .

$$\mathcal{I}_c : P \times A \rightarrow Z$$

$\mathcal{I}_c(p, a)$ is the volume of data accessed within c before the first execution of p .

$$\mathcal{O}_c : P \times A \rightarrow Z$$

$\mathcal{O}_c(p, a)$ is the volume of data accessed within c after the last execution of p .

Algorithm to Compute \mathcal{I}_c

```
1 Algorithm: COMPUTE  $\mathcal{I}_c$ 
2 Input: code region  $c$ ; reference point  $p$ ; alias
   function  $a$  that is valid over  $c$ 
3 Output:  $\mathcal{I}_c(p, a)$ 


---


4 if  $c = [c_1; c_2]$  then
5   if  $p \in [c_1]$  then
6     return  $\mathcal{I}_{c_1}(p, a)$ 
7   else
8     return  $\mathcal{X}_{c_1}(a) + \mathcal{I}_{c_2}(p, a)$ 
9 else if  $c = [\text{if } e \text{ then } c_1 \text{ else } c_2]$  then
10  if  $p = [e]$  then
11    return 0
12  else if  $p \in [c_1]$  then
13    return  $|e| + \mathcal{I}_{c_1}(p, a)$ 
14  else
15    return  $|e| + \mathcal{I}_{c_2}(p, a)$ 
16 else if  $c = [\text{for } i = L : S : U \text{ begin } c_1 \text{ end}]$  then
17  if  $p \in [\text{for } i = L : S : U]$  then
18    return 0
19  else
20     $\bar{k} \leftarrow$  first iteration vector in which  $p$  is reached
21     $\bar{k}' \leftarrow$  largest iteration vector smaller than  $\bar{k}$ 
22     $r \leftarrow \sum_{p_1, p_2 \in c_1} |p_1 \xrightarrow{c} p_2|, p_1 \xrightarrow{c} p_2 \in \text{polytope}(c, \bar{k}')$ 
23    /*  $\xrightarrow{c}$  denotes loop carried dependence */
24    return  $\sum_{\bar{i} < \bar{k}} \mathcal{X}_{c_1}^{\bar{i}}(a) + \mathcal{I}_{c_1}^{\bar{k}}(p, a) - r$ 
25 else
26   return ERROR
```



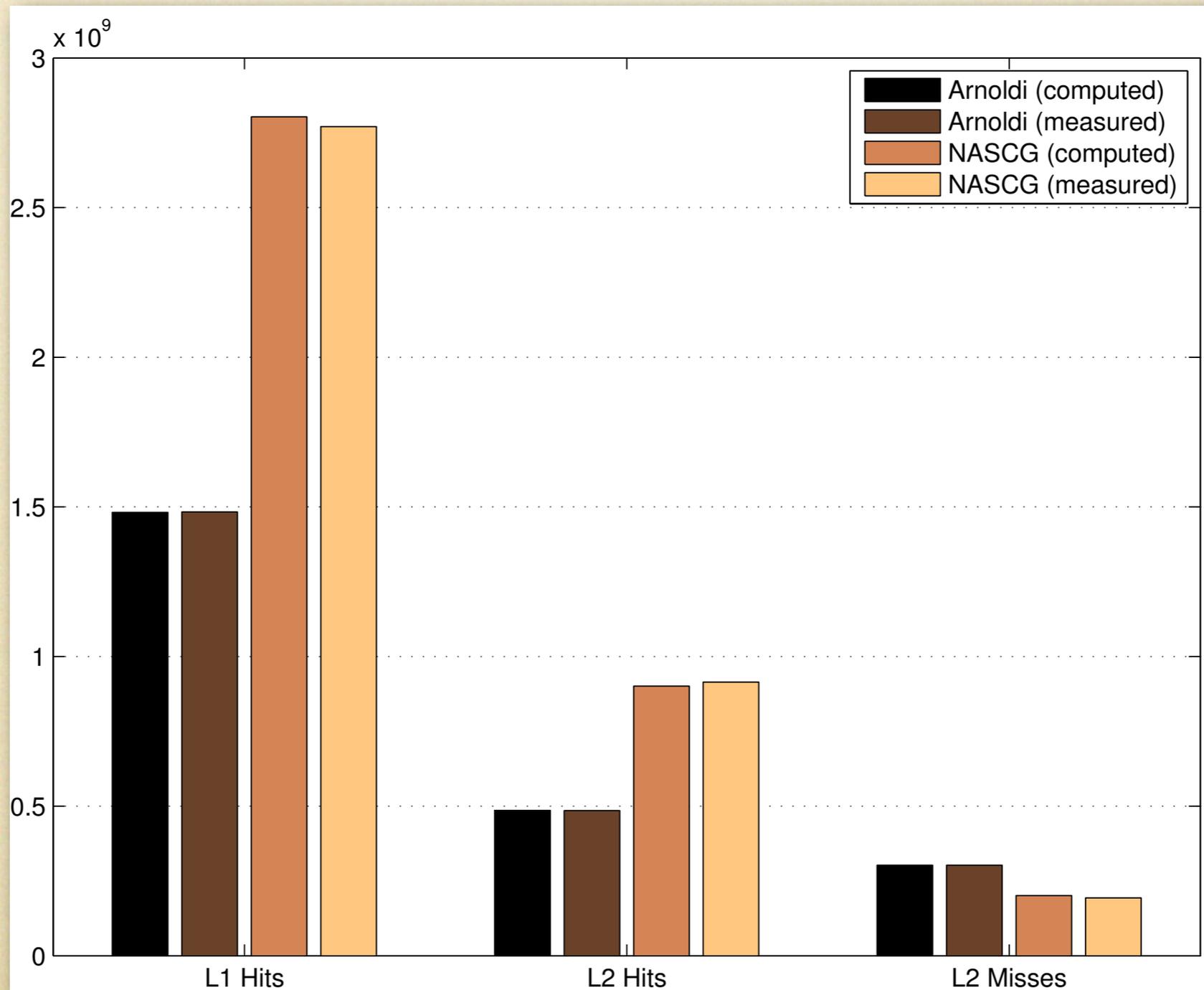
Algorithm to Compute X_c

```
1 Algorithm: COMPUTE  $\mathcal{X}_c$ 
2 Input: code region  $c$ ; alias function  $a$  that is valid
           over  $c$ ; probability weights,  $\pi$ , on CFG edges
3 Output:  $\mathcal{X}_c(a)$ 

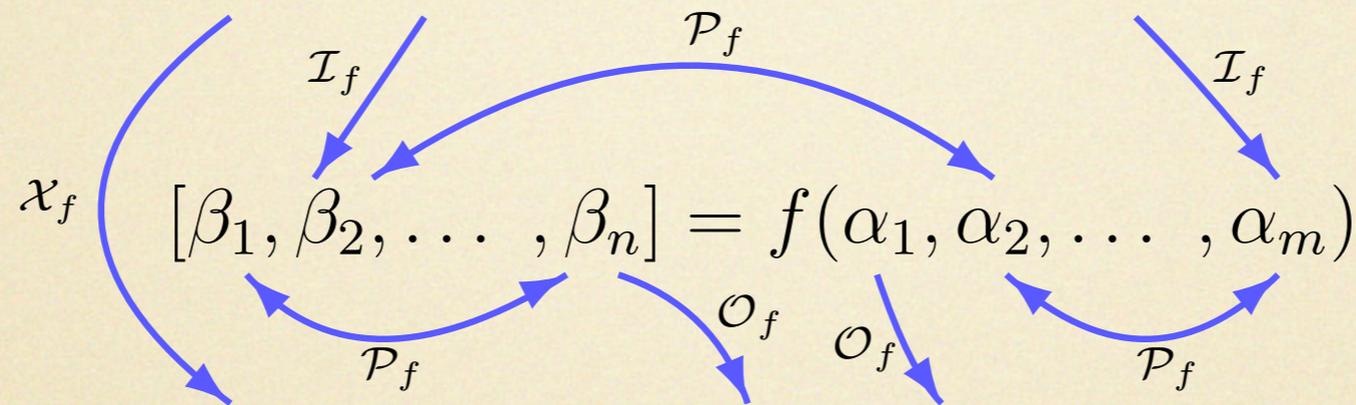

---


4 if  $c = \boxed{c_1; c_2}$  then
5   return  $\mathcal{X}_{c_1}(a) + \mathcal{X}_{c_2}(a)$ 
6 else if  $c = \boxed{\text{if } e \text{ then } c_1 \text{ else } c_2}$  then
7   return  $|e| + \pi(\text{true}) \times \mathcal{X}_{c_1}(a) + \pi(\text{false}) \times \mathcal{X}_{c_2}(a)$ 
8 else if  $c = \boxed{\text{for } i = L : S : U \text{ begin } c_1 \text{ end}}$  then
9    $\bar{n} \leftarrow$  iteration vector for the last iteration
10   $r = \sum_{p_1, p_2 \in c_1} |p_1 \xrightarrow{c} p_2|$ ,  $p_1 \xrightarrow{c} p_2 \in \text{polytope}(c, \bar{n})$ 
    /*  $\xrightarrow{c}$  denotes loop carried dependence */
11  return  $\sum_{\bar{i} \leq \bar{n}} \mathcal{X}_{c_1}^{\bar{i}}(a) - r$ 
12 else
13  ERROR
```

Accuracy



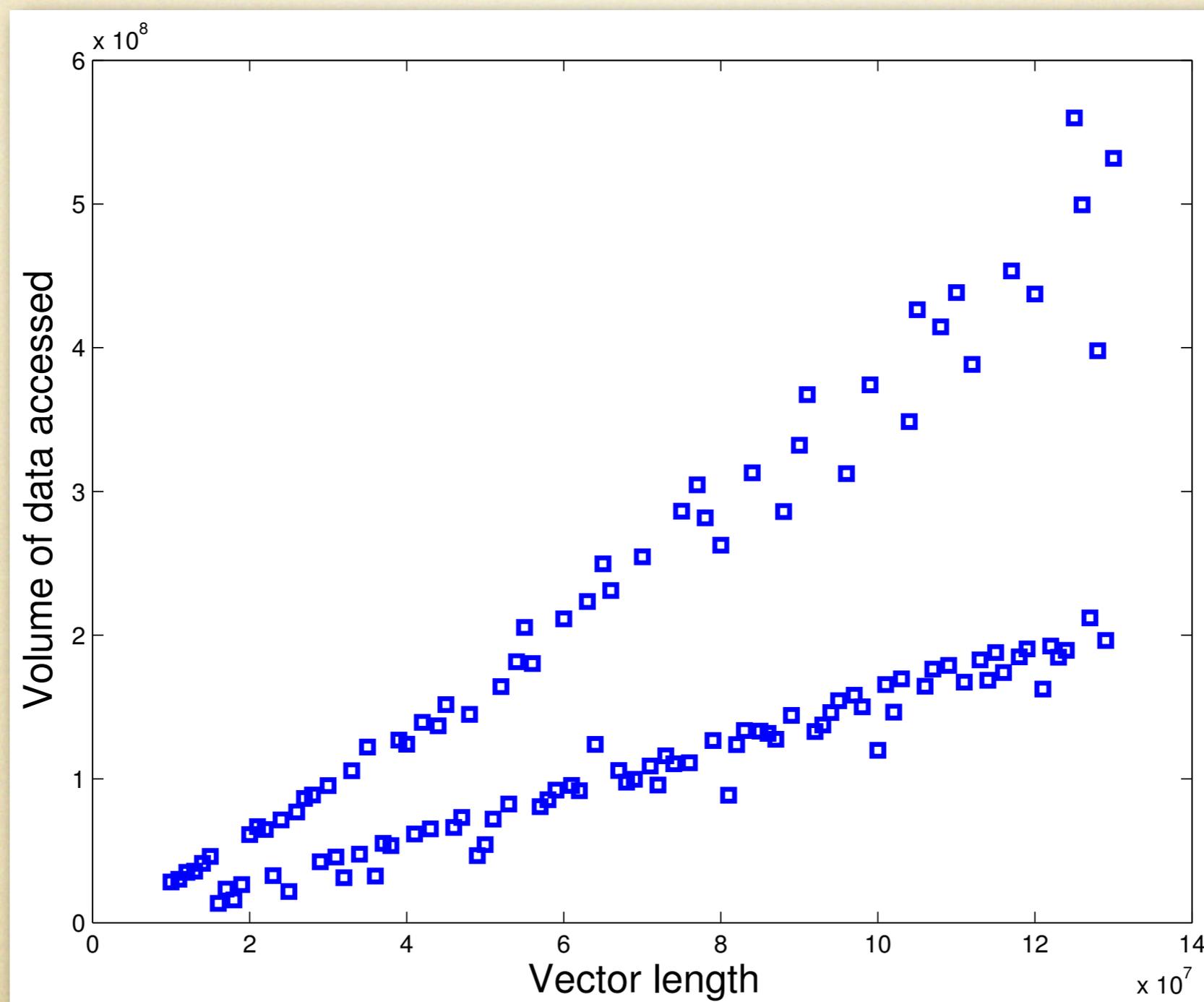
Empirical Data for Library Functions



$\mathcal{X}_f \approx$ L2 cache misses

$\mathcal{I}_f \approx \mathcal{O}_f \approx \mathcal{X}_f$

Challenges Remain: FFT

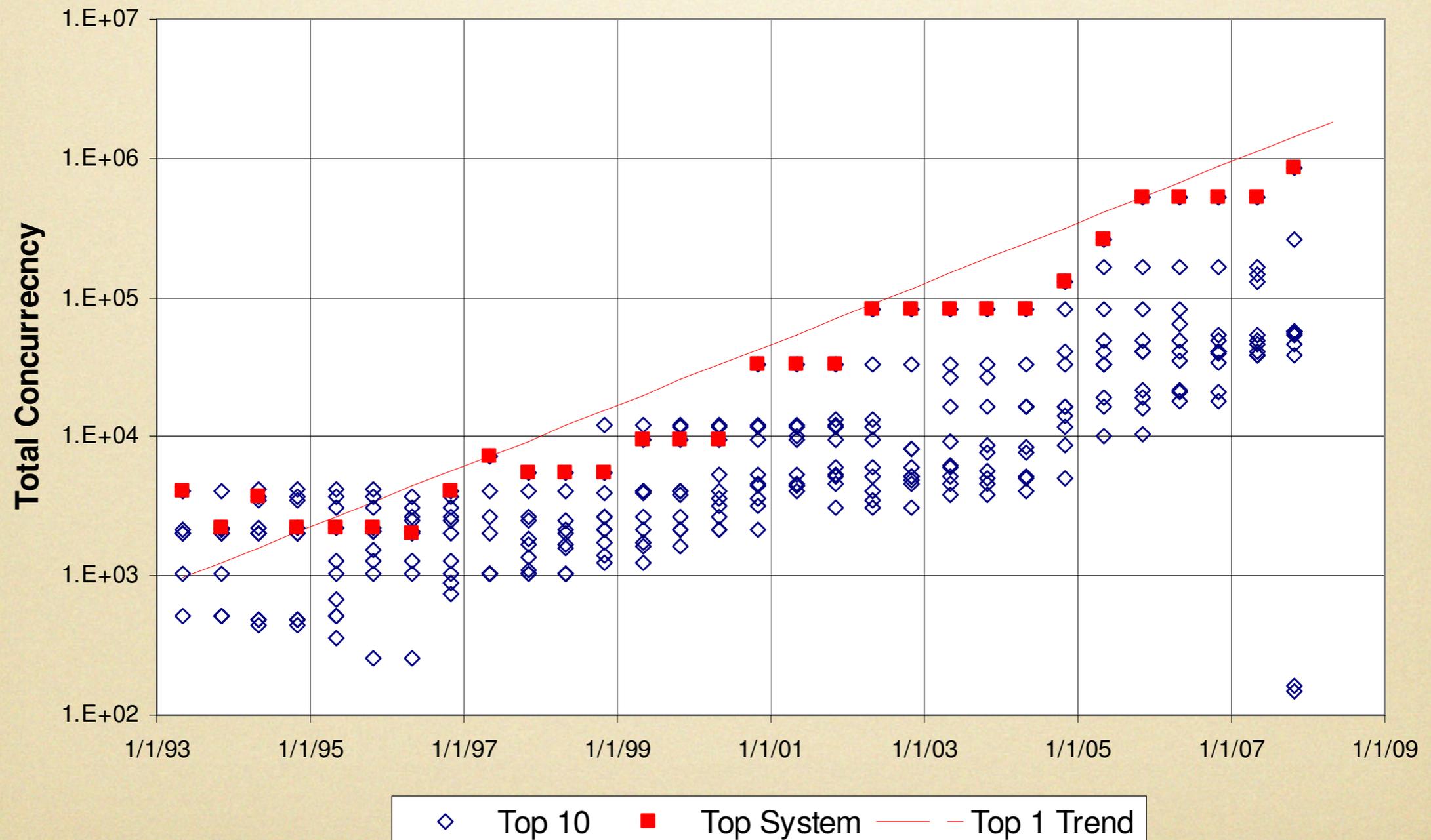


Rescuing Parallel Programmers

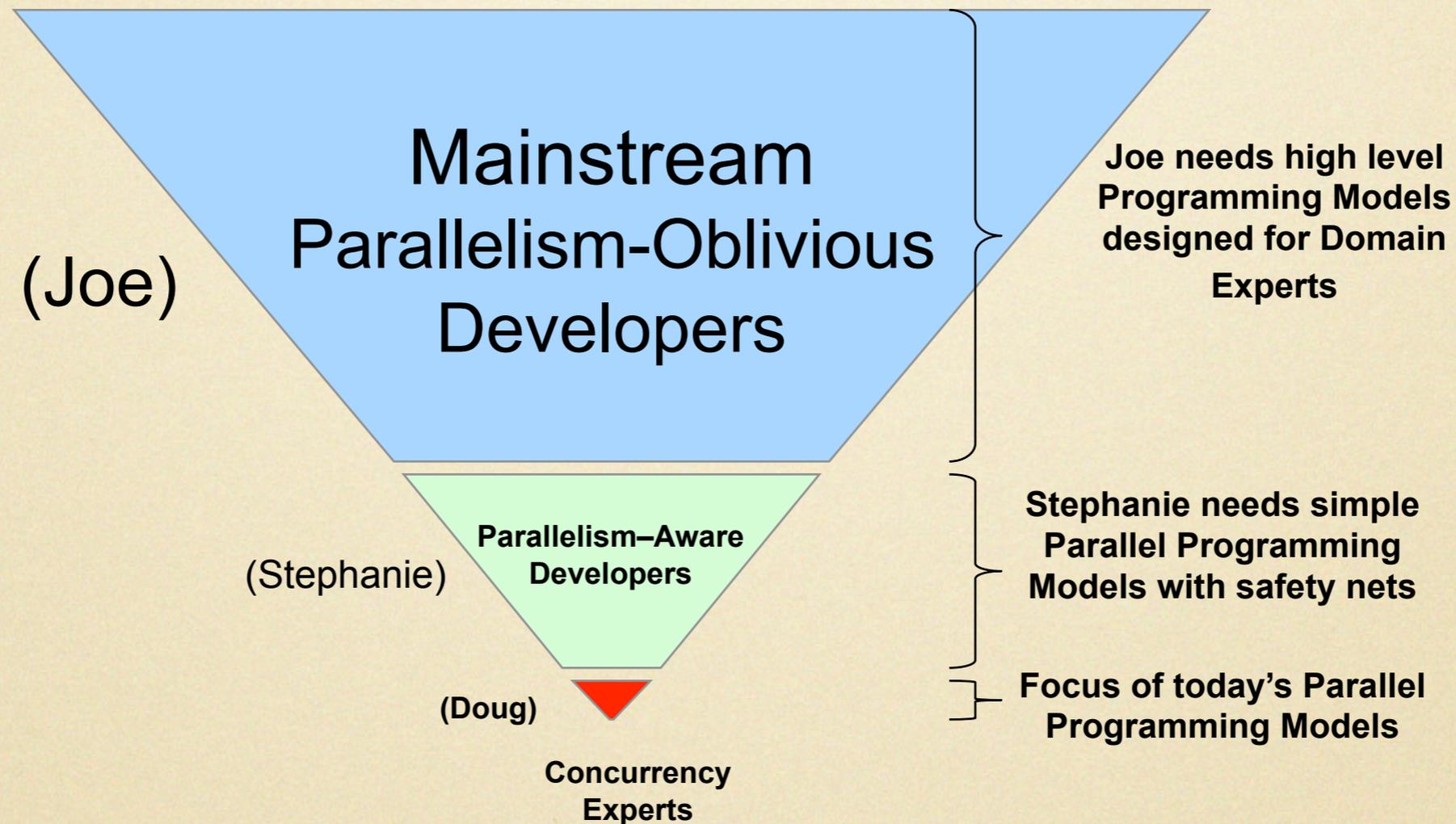


Concurrency Trends

(ExaScale Computing Study, Peter Kogge et al.)



Types of (Parallel) Programmers



Courtesy: Vivek Sarkar, Rice University



Parallelism Oblivious Users

- Programming languages-driven
 - implicit parallelism, compiler support
- OS-driven
 - innovative solutions to leverage extra cores
- Architecture-driven
 - ILP, hyper-threading

Observations for Parallelism-Aware and Expert Users

- Completely automatic parallelization has had limited success
- Writing parallel programs is hard; optimizing and maintaining them is harder!
- Compilation technology has worked well in communication optimization

Declarative Parallel Programming

- Let users write parallel programs
- Let compilers optimize parallel programs
- Separate computation and communication specification, using a domain-specific language to specify communication
- Key insight: most parallel applications have predictable (but not necessarily static) communication patterns



Declarative Specification of Communication

ICPP 2009, Hoefler et al.

```
@collective cshift (A)
{
  foreach processor i
  {
    A@i := A@(i+1)
  }
}
```

Compiler converts collectives to MPI calls and optimizes communication by coalescing and overlapping with computation

```
@collective stencil (A, B)
{
  foreach processor i in Mesh2D
  {
    B@i := 0.25*(A@i.N + A@i.S + A@i.W + A@i.E)
  }
}
```

Concluding Remarks

- Computing is a core technique in an increasing number of fields
 - programming is no longer restricted to scientists and engineers
 - conventional programming models are inadequate
- Parallelism is no longer restricted to scientific and engineering applications
 - need to address the needs of different types of users and applications
- Traditional program analysis is inadequate on modern machines

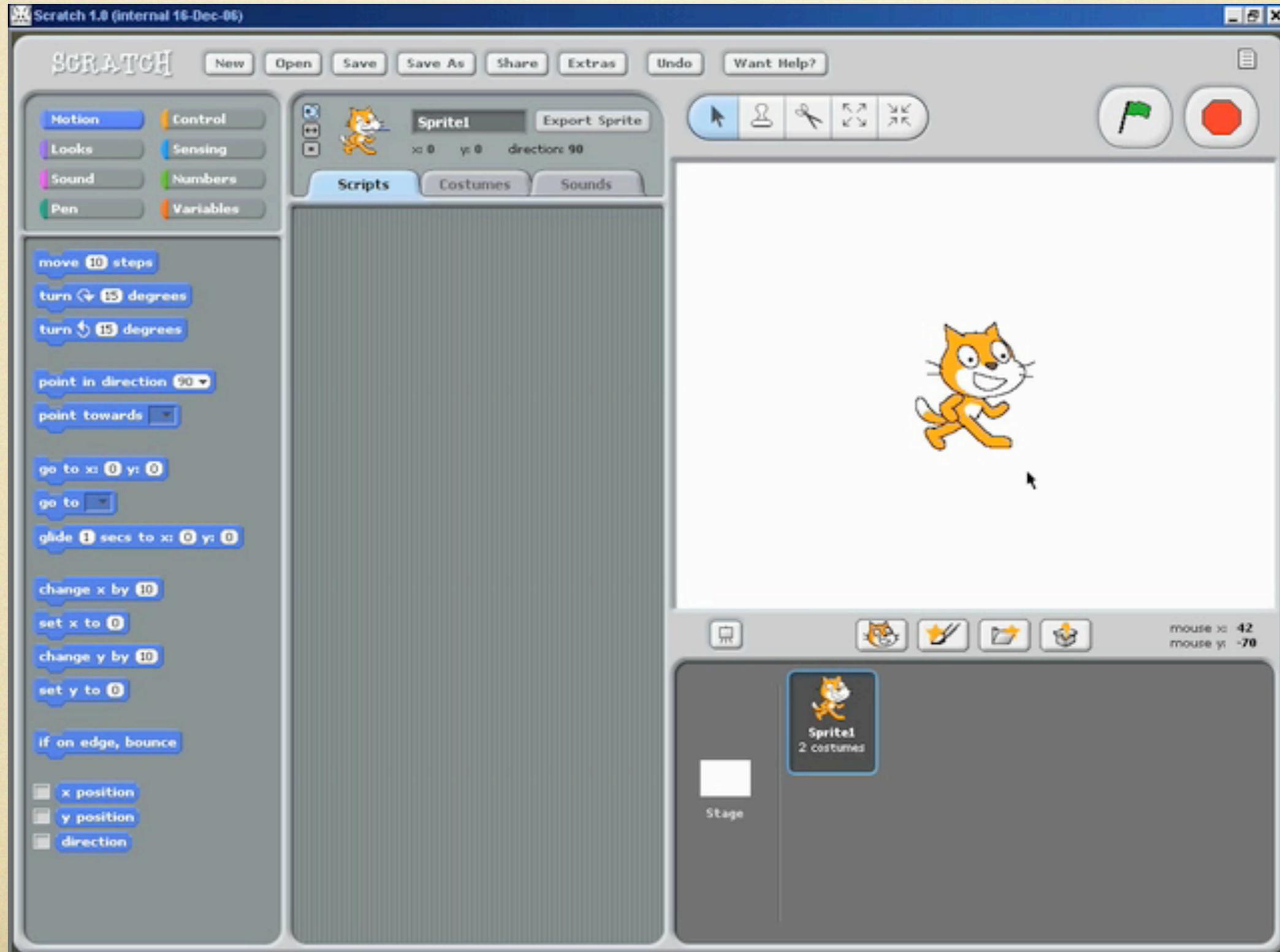
Other Interests

- High-level Languages
 - Ruby
- Heterogeneous parallel computing
- Large memory-footprint applications
- Automatic parallelization



Scratch

<http://scratch.mit.edu/>



<http://www.cs.indiana.edu/~achauhan>

<http://phi.cs.indiana.edu/>



Bonus Material

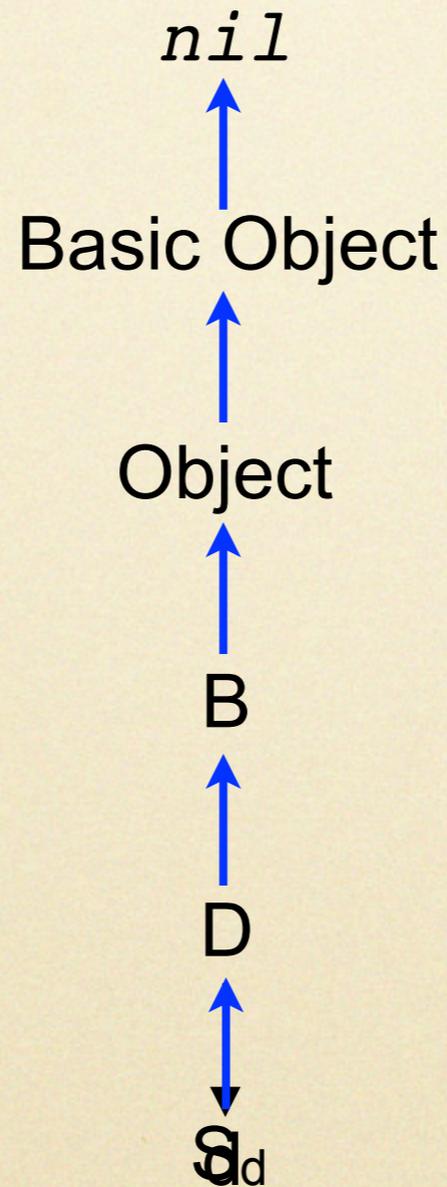


Ruby Class Hierarchy

```
class B < Object
  ...
end

class D < B
  ...
end

d = D.new
def d.newMeth
  ...
end
```



Objects store values
Classes store methods

Ruby Classes as Objects

