Taming Heterogeneous Parallelism with Domain Specific Languages

Kunle Olukotun
Pervasive Parallelism Laboratory
Stanford University
ppl.stanford.edu

2020 Vision for Parallelism

- Make parallelism accessible to all programmers
- Parallelism is not for the average programmer
  - Too difficult to find parallelism, to debug, maintain and get good performance for the masses
  - Need a solution for "Joe/Jane the programmer"
- Can't expose average programmers to parallelism
  - But auto parallelizatoin doesn't work

Computing System Power

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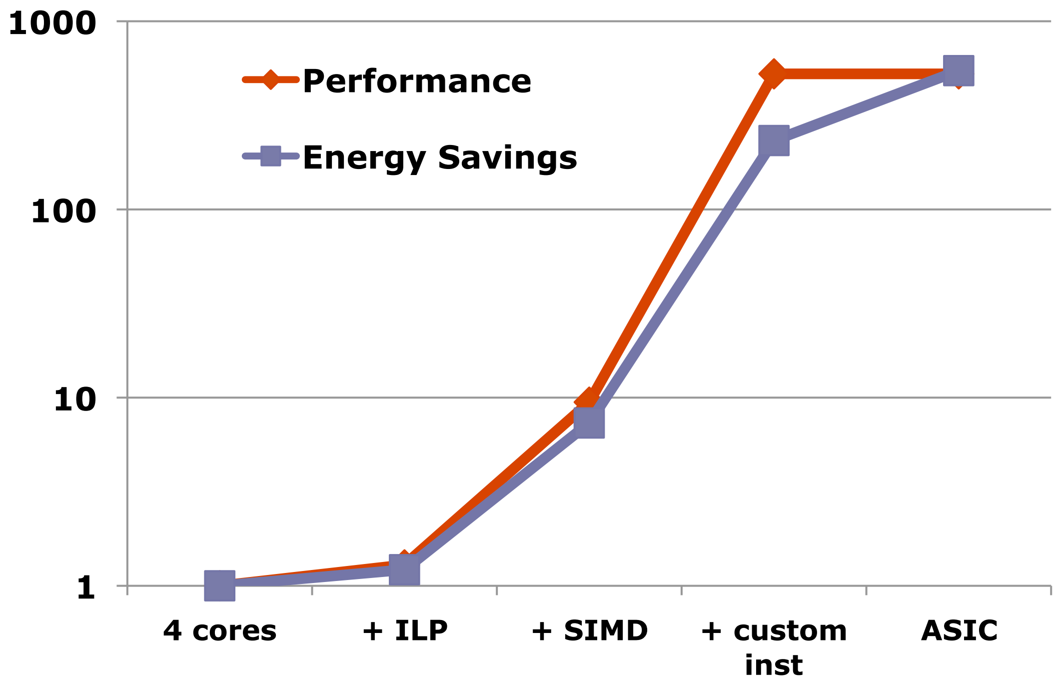
$$Power = Energy_{Op} \times \frac{Ops}{second}$$

FIXED

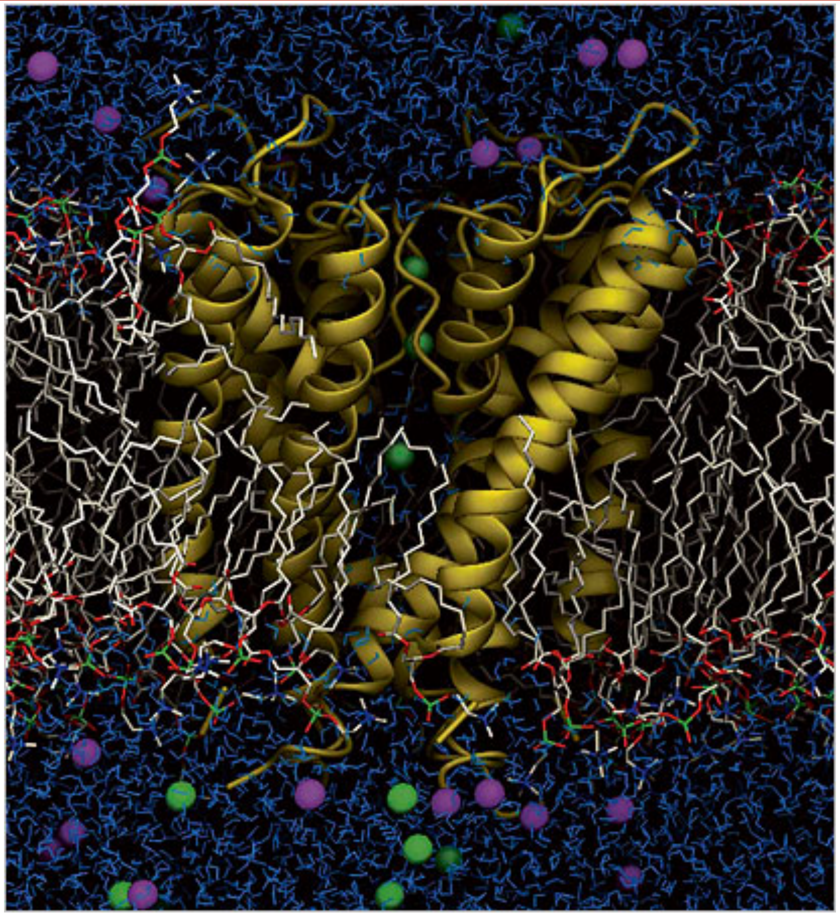
Heterogeneous Hardware

- Heterogeneous HW for energy efficiency
  - Multi-core, ILP, threads, data-parallel engines, custom engines
- H.264 encode study



Source: Understanding Sources of Inefficiency in General-Purpose Chips (ISCA'10)

DE Shaw Research: Anton

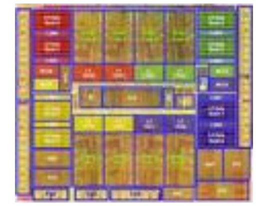


Molecular dynamics computer

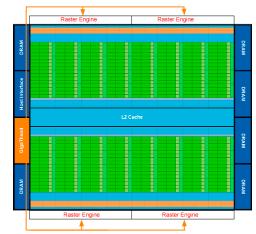
100 times more power efficient

D. E. Shaw et al. SC 2009, Best Paper and Gordon Bell Prize

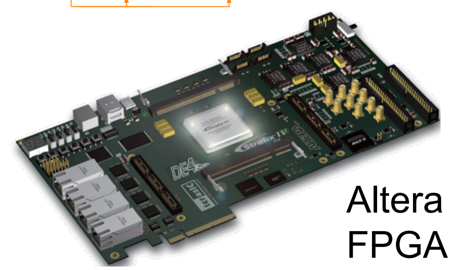
Heterogeneous Parallel Architectures Today



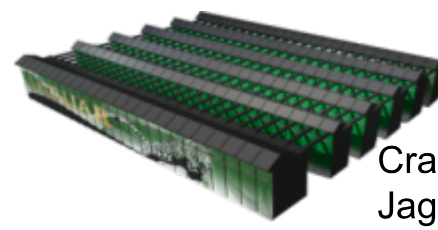
Sun T2



Nvidia Fermi



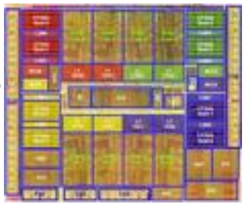
Altera FPGA



Cray Jaguar

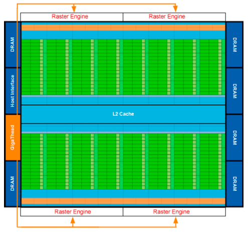
Heterogeneous Parallel Programming

Pthreads
OpenMP



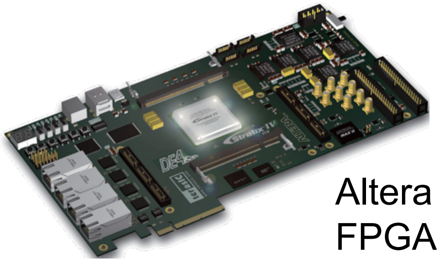
Sun
T2

CUDA
OpenCL



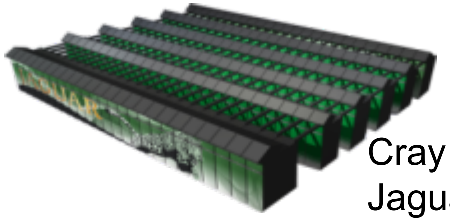
Nvidia
Fermi

Verilog
VHDL



Altera
FPGA

MPI
PGAS



Cray
Jaguar

Programmability Chasm

Applications

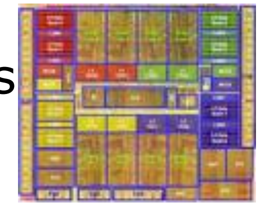
Scientific Engineering

Virtual Worlds

Personal Robotics

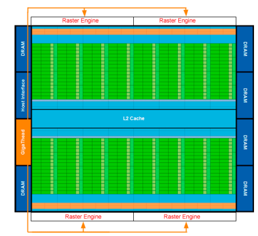
Data informatics

Pthreads
OpenMP



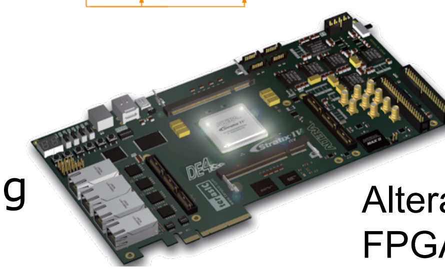
Sun T2

CUDA
OpenCL



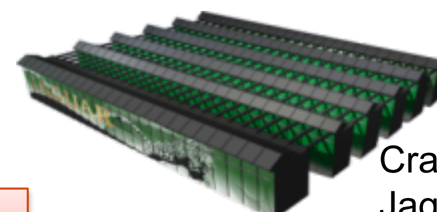
Nvidia Fermi

Verilog
VHDL



Altera FPGA

MPI
PGAS



Cray Jaguar

Too many different programming models

Hypothesis

It is possible to write one program
and
run it on all these machines

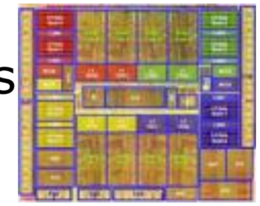
Programmability Chasm

Applications

- Scientific Engineering
- Virtual Worlds
- Personal Robotics
- Data informatics

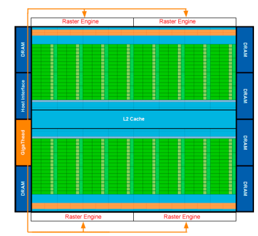
Ideal Parallel Programming Language

Pthreads
OpenMP



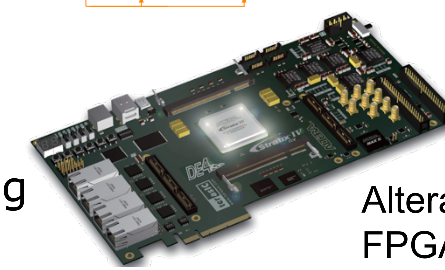
Sun T2

CUDA
OpenCL



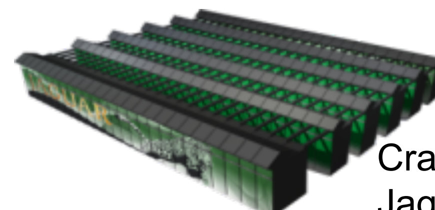
Nvidia Fermi

Verilog
VHDL



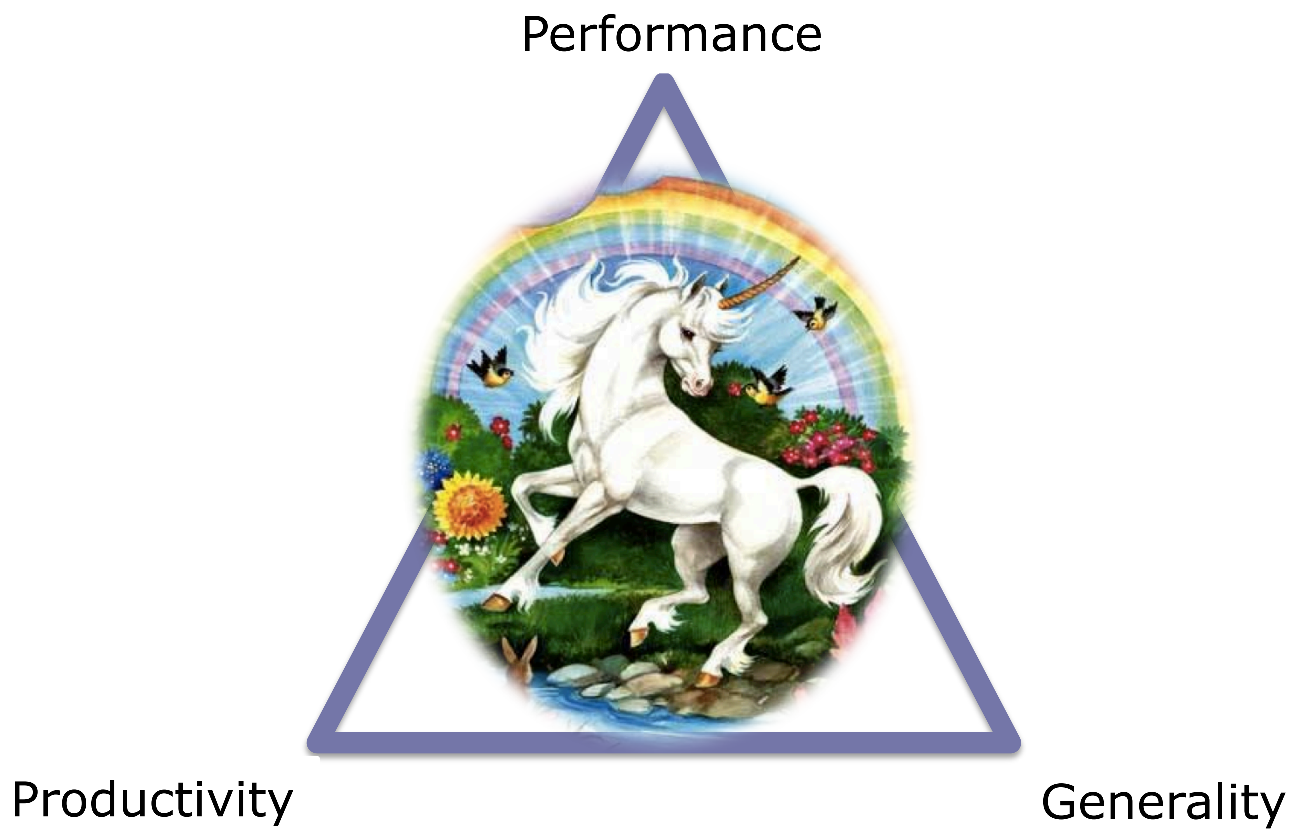
Altera FPGA

MPI
PGAS

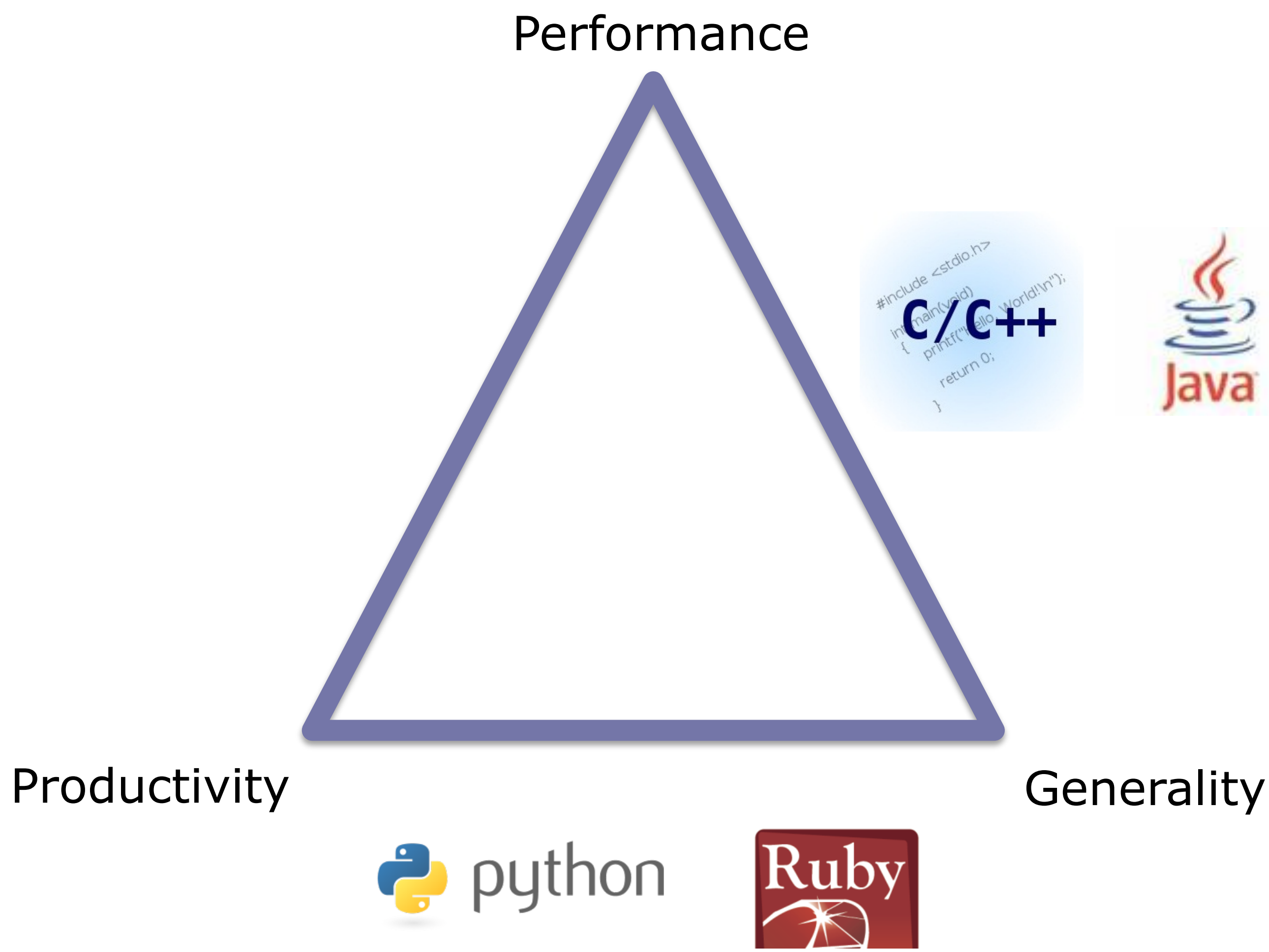


Cray Jaguar

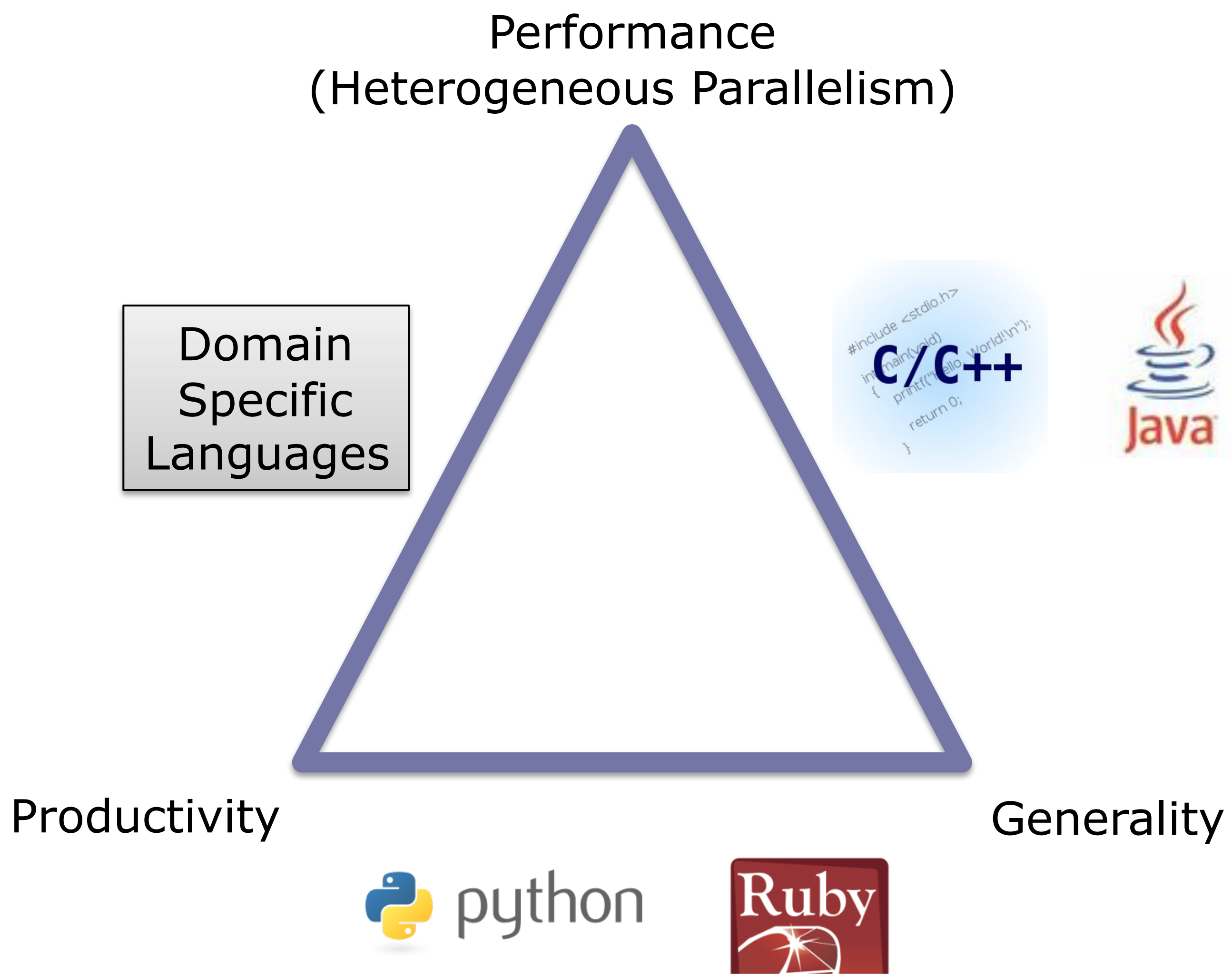
The Ideal Parallel Programming Language



Successful Languages



True Hypothesis ⇒ Domain Specific Languages



Domain Specific Languages

- Domain Specific Languages (DSLs)
  - Programming language with restricted expressiveness for a particular domain
  - High-level, usually declarative, and deterministic

Benefits of Using DSLs for Parallelism

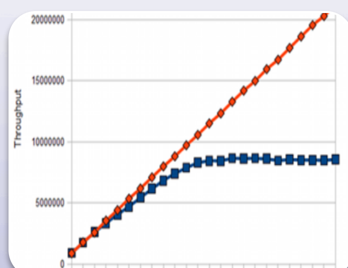
Productivity

- Shield average programmers from the difficulty of parallel programming
- Focus on developing algorithms and applications and not on low level implementation details

Performance

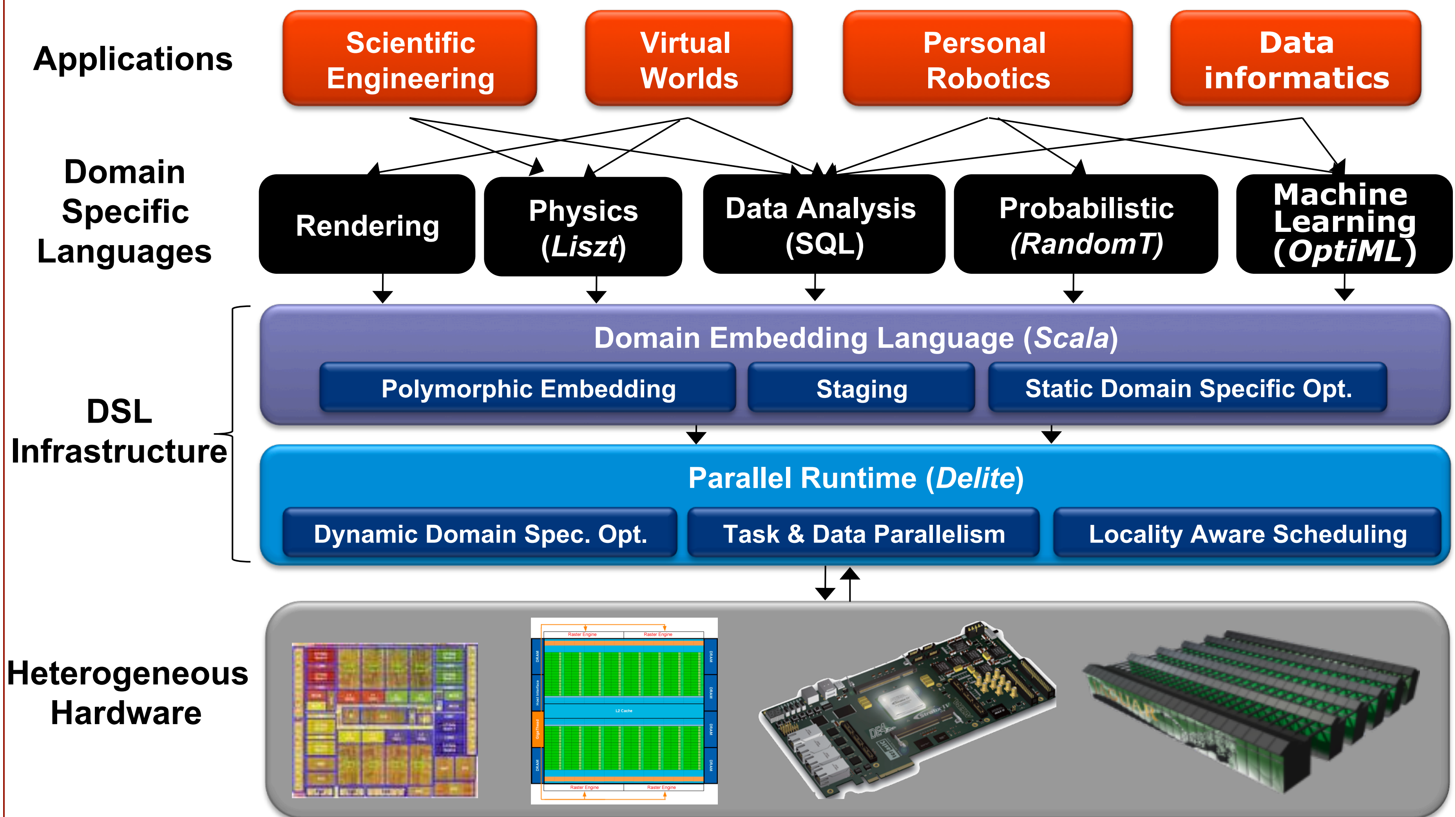
- Match high level domain abstraction to generic parallel execution patterns
- Restrict expressiveness to more easily and fully extract available parallelism
- Use domain knowledge for static/dynamic optimizations

Portability and forward scalability



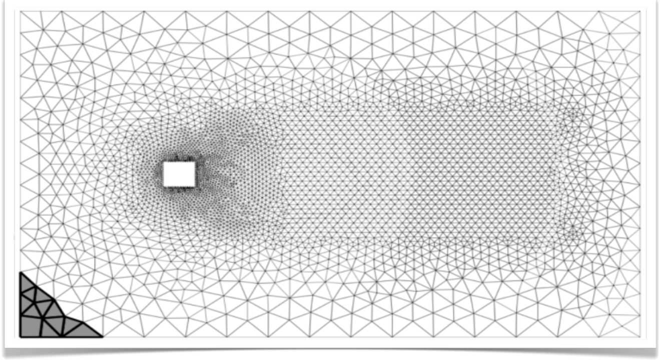
- DSL & Runtime can be evolved to take advantage of latest hardware features
- Applications remain unchanged
- Allows innovative HW without worrying about application portability

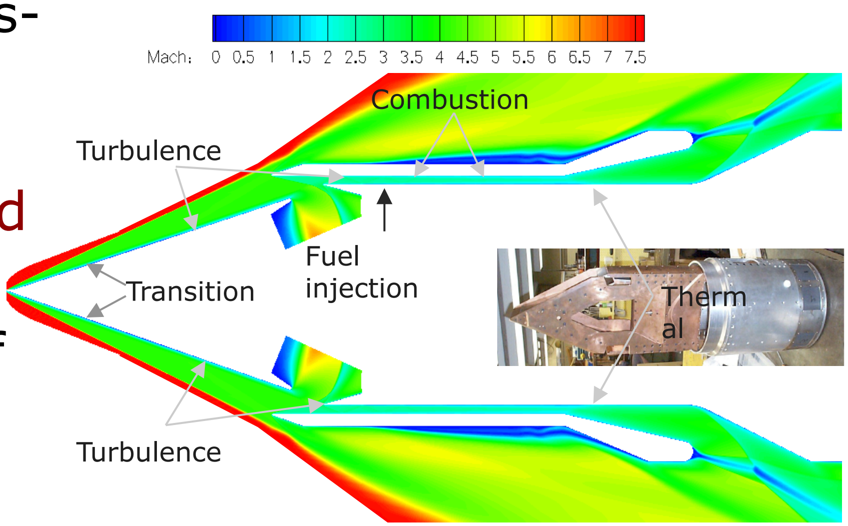
Bridging the Programmability Chasm



Liszt: DSL for Mesh PDEs

- Z. DeVito, N. Joubert, P. Hanrahan
- Solvers for mesh-based PDEs
  - Complex physical systems
  - Huge domains
  - millions of cells
  - Example: Unstructured Reynolds-averaged Navier Stokes (RANS) solver
- Goal: simplify code of mesh-based PDE solvers
  - Write once, run on any type of parallel machine
  - From multi-cores and GPUs to clusters





Liszt Language Features

- Minimal Programming language
  - Aritmetic, short vectors, functions, control flow
- Built-in mesh interface for arbitrary polyhedra
  - `Vertex, Edge, Face, Cell`
  - `Optimized memory representation of mesh`
- Collections of mesh elements
  - `Element Sets: faces(c:Cell), edgesCCW(f:Face)`
- Mapping mesh elements to fields
  - `Fields: val vert_position = position(v)`
- Parallelizable iteration
  - `forall statements: for( f <- faces(cell) ) { … }`

Liszt Code Example

```
for(edge <- edges(mesh)) {
    val flux = flux_calc(edge)
    val v0 = head(edge)
    val v1 = tail(edge)
    Flux(v0) += flux
    Flux(v1) -= flux
}
```

Simple Set Comprehension

Functions, Function Calls

Mesh Topology Operators

Field Data Storage

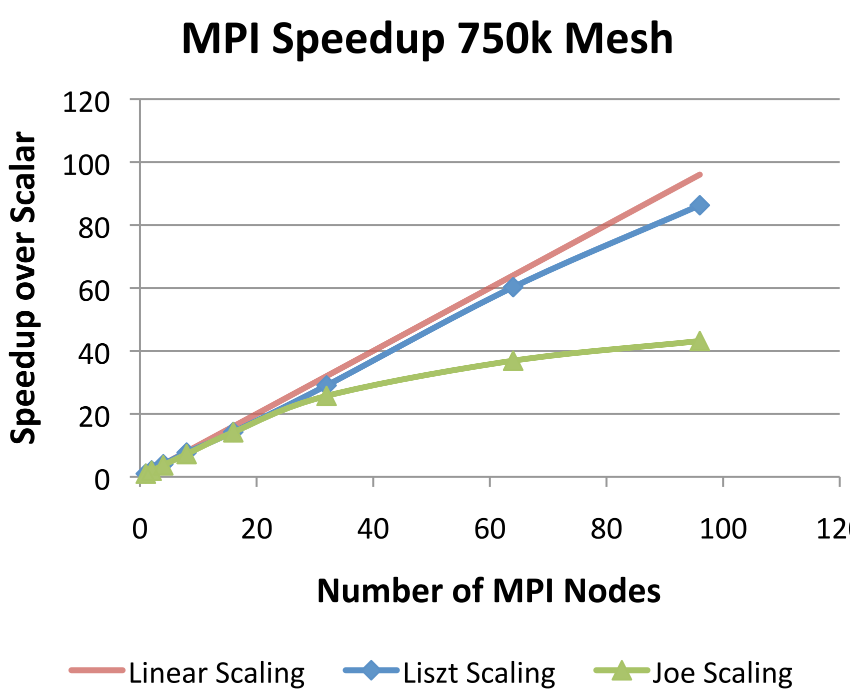
Code contains possible write conflicts!

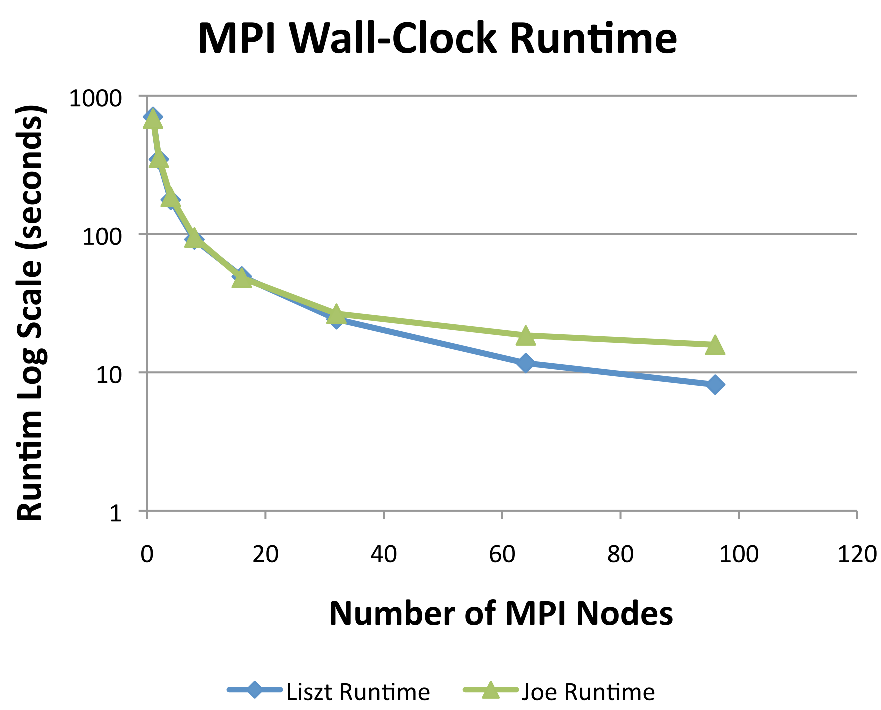
We use architecture specific strategies guided by domain knowledge

- MPI: Ghost cell-based message passing
- GPU: Coloring-based use of shared memory

MPI Performance

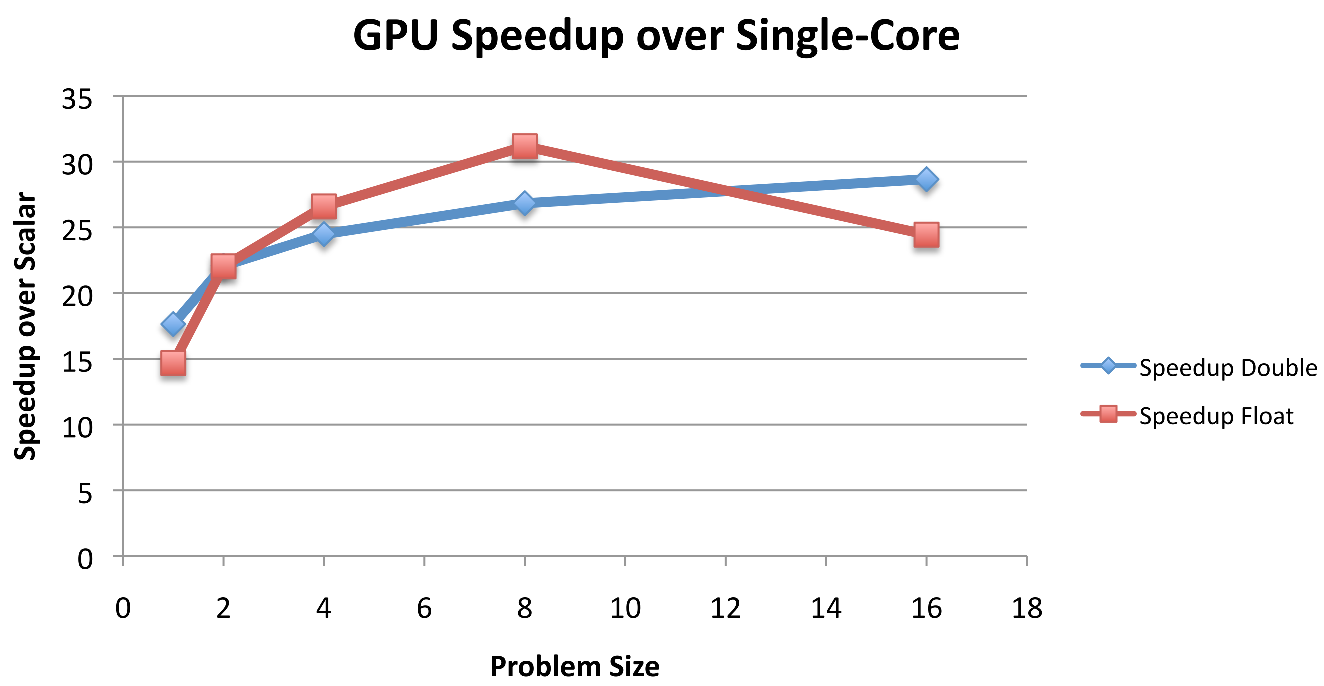
- Using 8 cores per node, scaling up to 96 cores (12 nodes, 8 cores per node, all communication using MPI)





GPU Performance

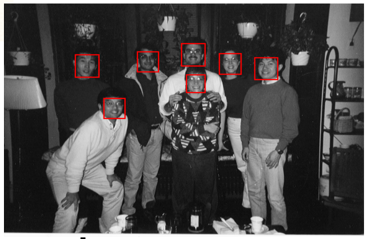
- Scaling mesh size from 50K (unit-sized) cells to 750K (16x) on a Tesla C2050. Comparison is against single threaded runtime on host CPU (Core 2 Quad 2.66Ghz)



Single-Precision: 31.5x, Double-precision: 28x

OptiML: A DSL for ML

- A. Sujeeth and H. Chafi
- Machine Learning domain
  - Learning patterns from data
  - Applying the learned models to tasks
    - Regression, classification, clustering, estimation
  - Computationally expensive
  - Regular and irregular parallelism



- Motivation for OptiML
  - Raise the level of abstraction
  - Use domain knowledge to identify coarse-grained parallelism
  - Single source ⇒ multiple heterogeneous targets
  - Domain specific optimizations

OptiML Language Features

- Provides a familiar (MATLAB-like) language and API for writing ML applications
  - Ex. val c = a * b (a, b are Matrix[Double])
- Implicitly parallel data structures
  - General data types : Vector[T], Matrix[T]
    - Independent from the underlying implementation
  - Special data types : TrainingSet, TestSet, IndexVector, Image, Video ..
    - Encode semantic information
- Implicitly parallel control structures
  - sum{…}, (0::end) {…}, gradient { … }, untilconverged { … }
  - Allow anonymous functions with restricted semantics to be passed as arguments of the control structures

Example OptiML / MATLAB code (Gaussian Discriminant Analysis)

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ML-specific data types

```
// x : TrainingSet[Double]
// mu0, mu1 : Vector[Double]

val sigma = sum(0,x.numSamples) {
  if (x.labels(_) == false) {
    (x(_)-mu0).trans.outer(x(_)-mu0)
  }
  else {
    (x(_)-mu1).trans.outer(x(_)-mu1)
  }
}
```

Implicitly parallel control structures

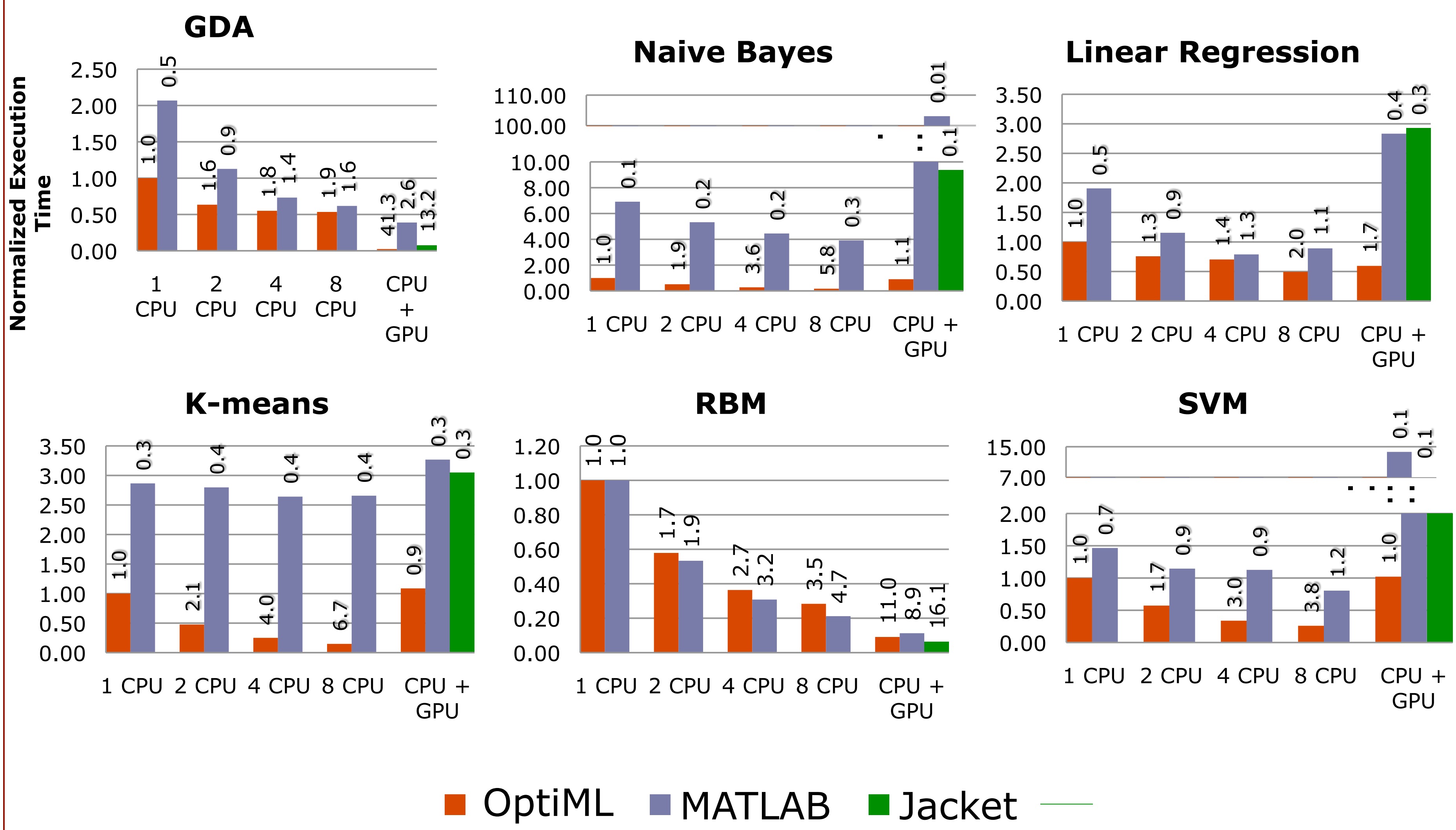
Restricted index semantics

```
% x : Matrix, y: Vector
% mu0, mu1: Vector

n = size(x,2);
sigma = zeros(n,n);

parfor i=1:length(y)
  if (y(i) == 0)
    sigma = sigma + (x(i,:)-mu0)'*(x(i,:)-mu0);
  else
    sigma = sigma + (x(i,:)-mu1)'*(x(i,:)-mu1);
  end
end
```

OptiML code

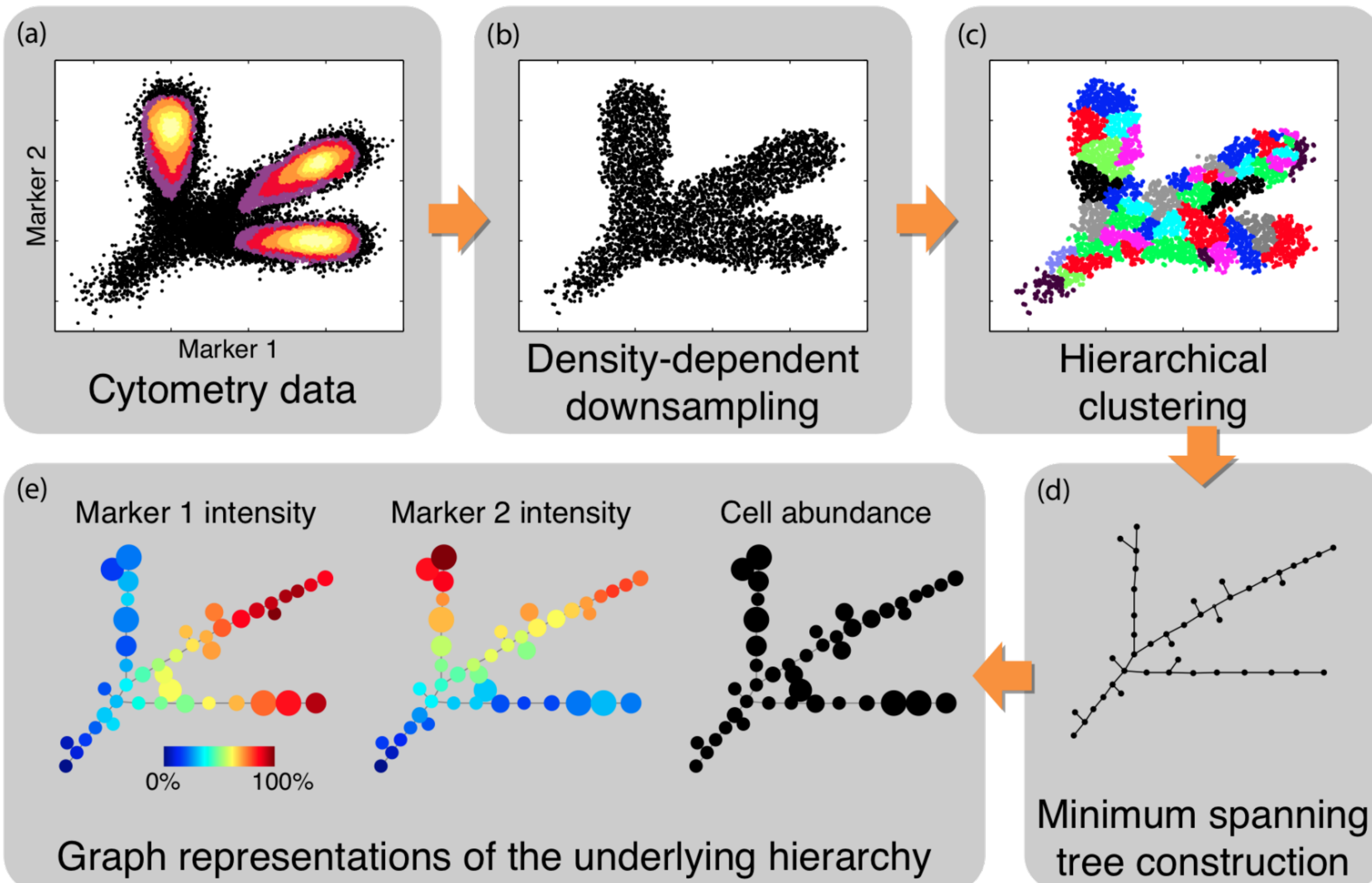
(parallel) MATLAB code

OptiML vs. MATLAB



Measuring Intracellular Signaling with Mass Cytometry

- Bioinformatics Algorithm
  - Spanning-tree Progression Analysis of Density-normalized Events (SPADE)
  - P. Qiu, E. Simonds, M. Linderman, P. Nolan



Peng Qiu

SPADE is computationally intensive

<u>Processing time for 30 files:</u>

Matlab (parfor & vectorized loops)
2.5 days

C++ (hand-optimized OpenMP)
2.5 hours

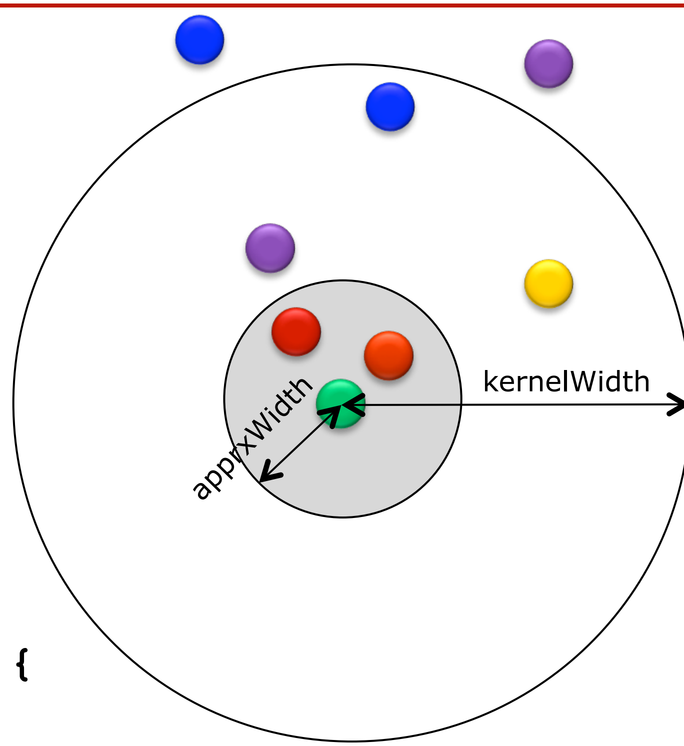
…what happens when we have 1,000 files?

SPADE Downsample: OptiML

B. Wang and A. Sujeeth

Downsample:

L1 distances between all 10^6 events in 13D space… reduce to 50,000 events

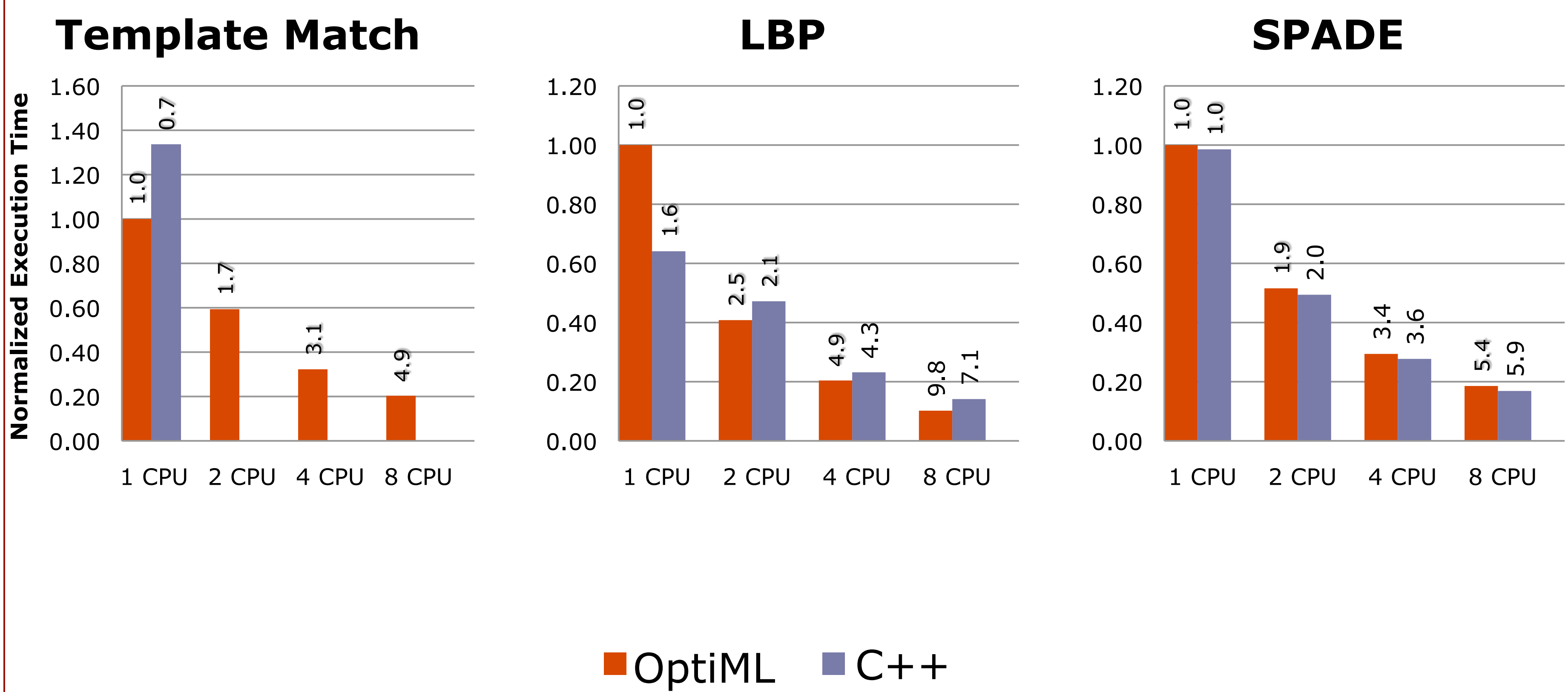



```
for(node <- G.nodes if node.density == 0) {
  val (closeNbrs,closerNbrs) =
      node.neighbors filter {dist(_,node) < kernelWidth}
                            {dist(_,node) < approxWidth}
  node.density = closeNbrs.count
  for(nbr <- closerNbrs) {
      nbr.density = closeNbrs.count
  }
}
```

SPADE Downsample: Matlab

```
while sum(local_density==0)~=0
    % process no more than 1000 nodes each time
    ind = find(local_density==0);  ind = ind(1:min(1000,end));

    data_tmp = data(:,ind);
    local_density_tmp = local_density(ind);
    all_dist = zeros(length(ind), size(data,2));

    parfor i=1:size(data,2)
        all_dist(:,i) = sum(abs(repmat(data(:,i),1,size(data_tmp,2)) –
                                  data_tmp),1)';
    end

    for i=1:size(data_tmp,2)
        local_density_tmp(i) = sum(all_dist(i,:) < kernel_width);
        local_density(all_dist(i,:) < apprx_width) = local_density_tmp(i);
    end
end
```

OptiML vs. C++



- OptiML provides much simpler programming model
- OptiML performance as good as C++ on full applications

New Problem

- We need to develop all of these DSLs
- Current DSL methods are unsatisfactory

Current DSL Development Approaches

- Stand-alone DSLs
  - Can include extensive optimizations
  - Enormous effort to develop to a sufficient degree of maturity
    - Actual Compiler/Optimizations
    - Tooling (IDE, Debuggers,…)
  - Interoperation between multiple DSLs is very difficult

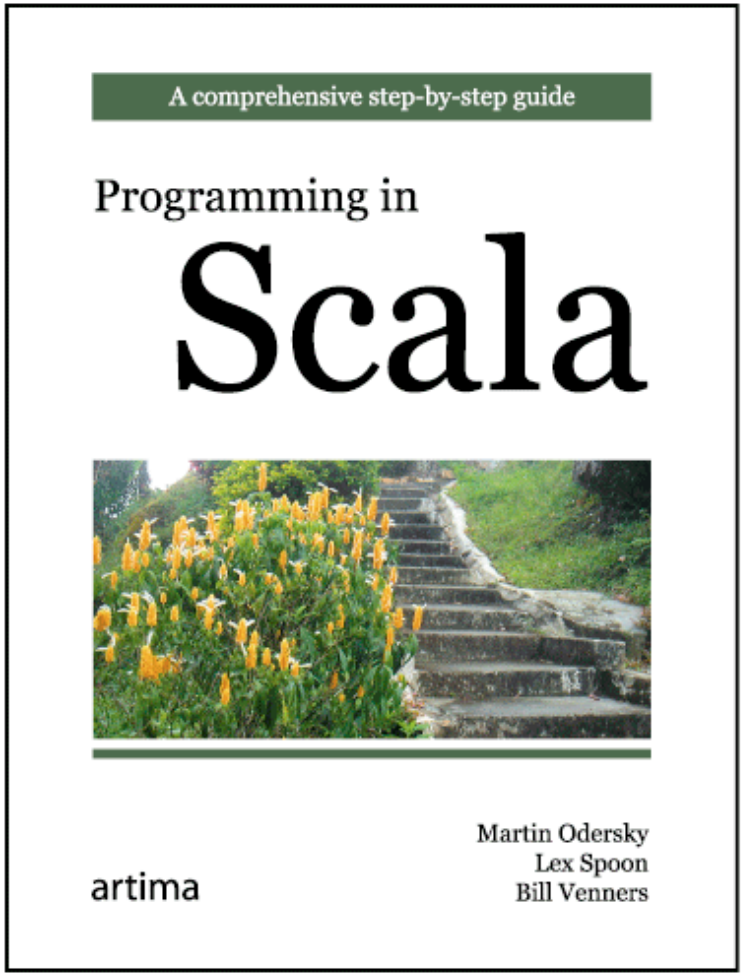
- Purely embedded DSLs ⇒ “just a library”
  - Easy to develop (can reuse full host language)
  - Easier to learn DSL
  - Can Combine multiple DSLs in one program
  - Can Share DSL infrastructure among several DSLs
  - Hard to optimize using domain knowledge
  - Target same architecture as host language

Need to do better

Need to Do Better

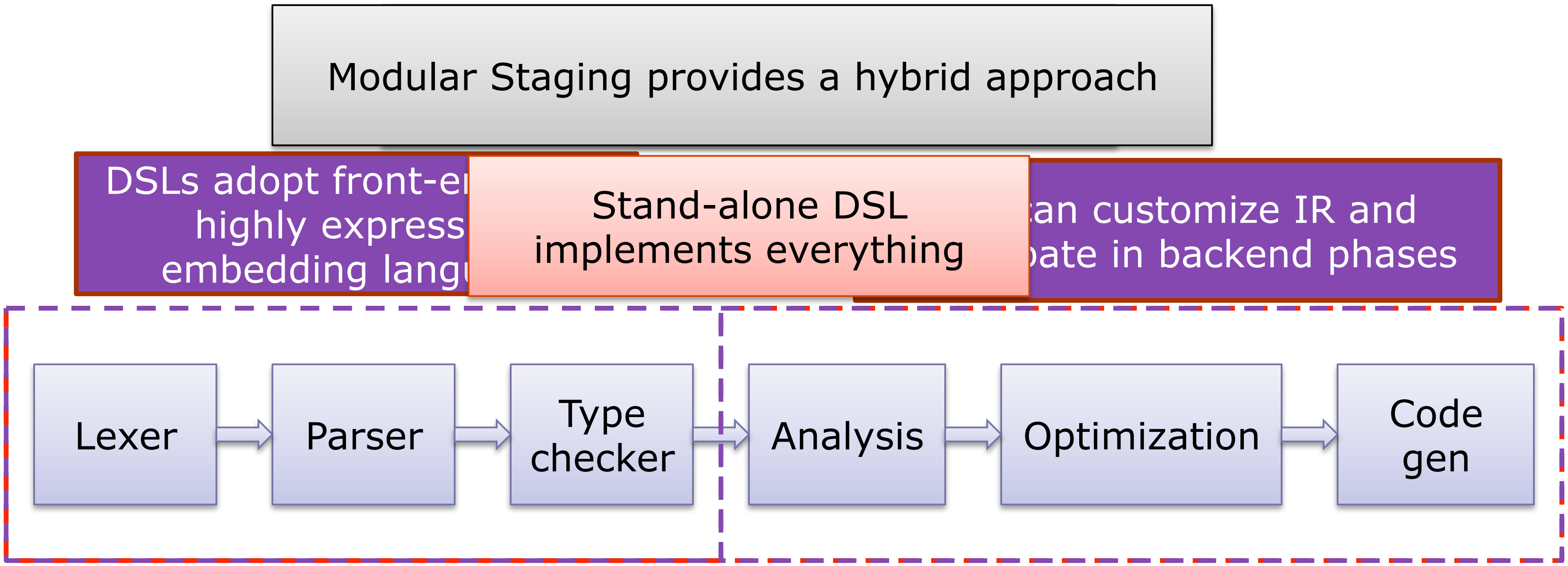
- Goal: Develop embedded DSLs that perform as well as stand-alone ones
- Intuition: General-purpose languages should be designed with DSL embedding in mind

DSL Embedding Language



- Mixes OO and FP paradigms
  - Targets JVM
- Expressive type system allows powerful abstraction
- Scalable language
- Stanford/EPFL collaboration on leveraging Scala for parallelism
- "Language Virtualization for Heterogeneous Parallel Computing" Onward 2010, Reno

Lightweight Modular Staging Approach

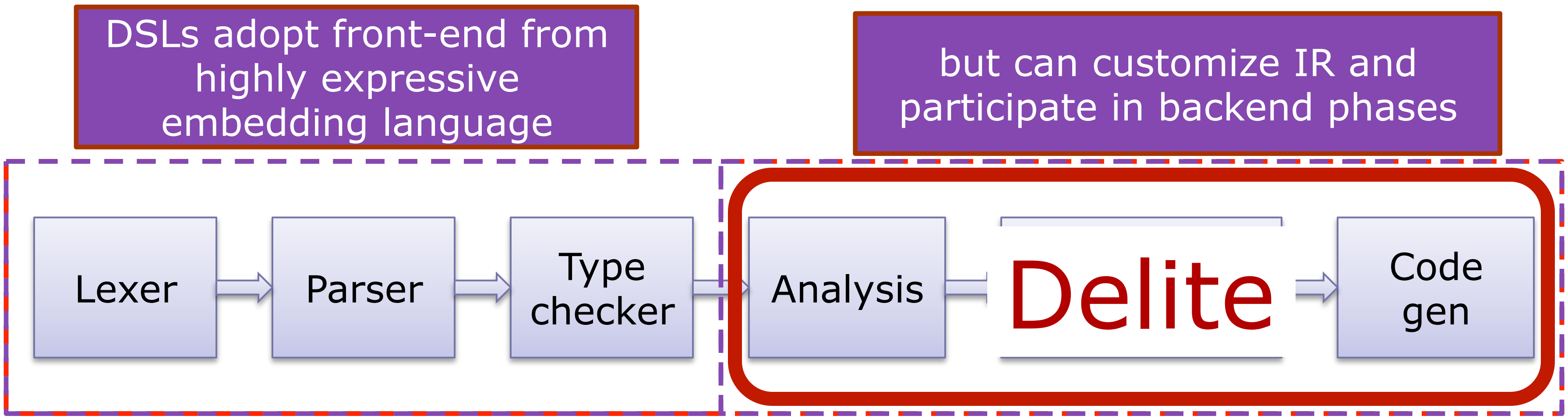


Typical Compiler

GPCE'10: Lightweight modular staging: a pragmatic approach to runtime code generation and compiled DSLs

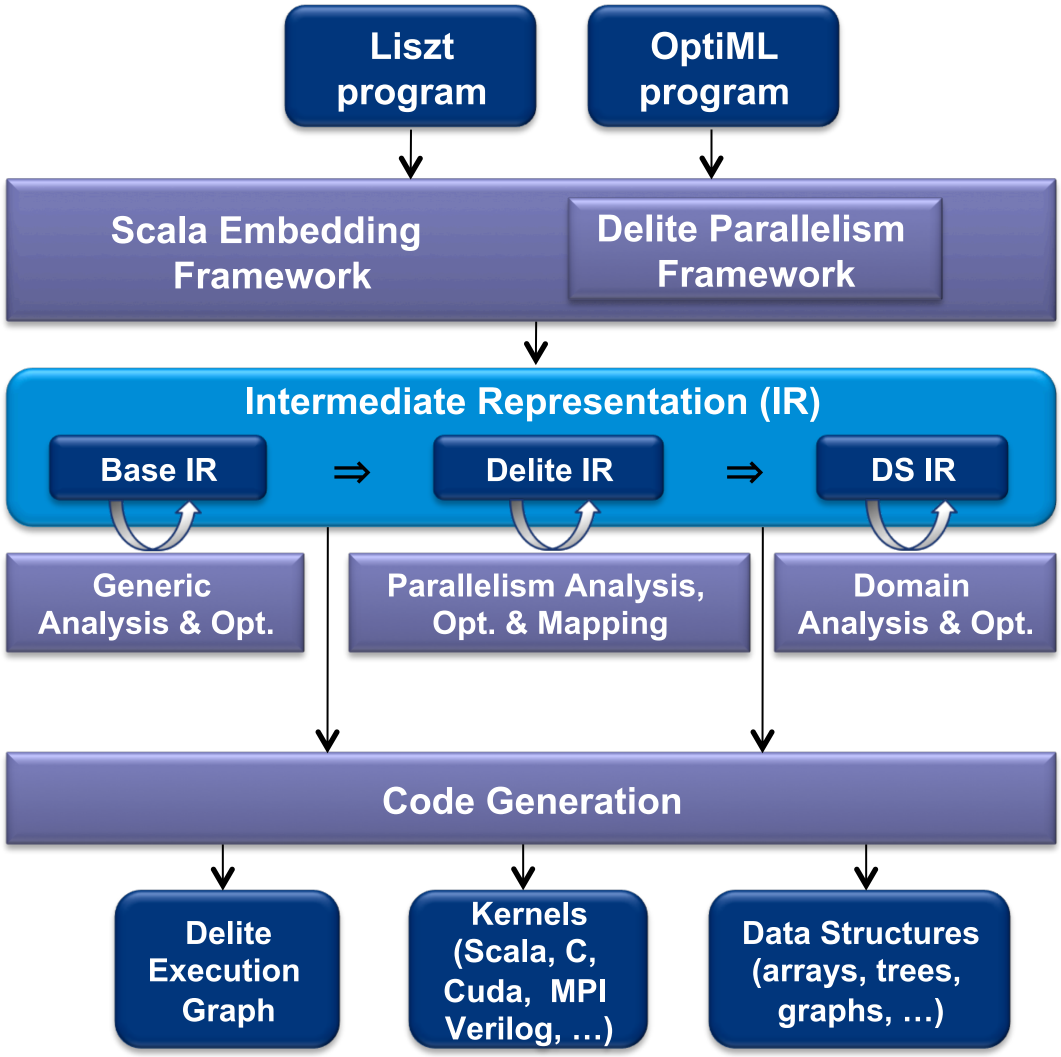
Delite: A Framework for DSL Parallelism

H. Chafi, A. Sujeeth, K. Brown, H. Lee



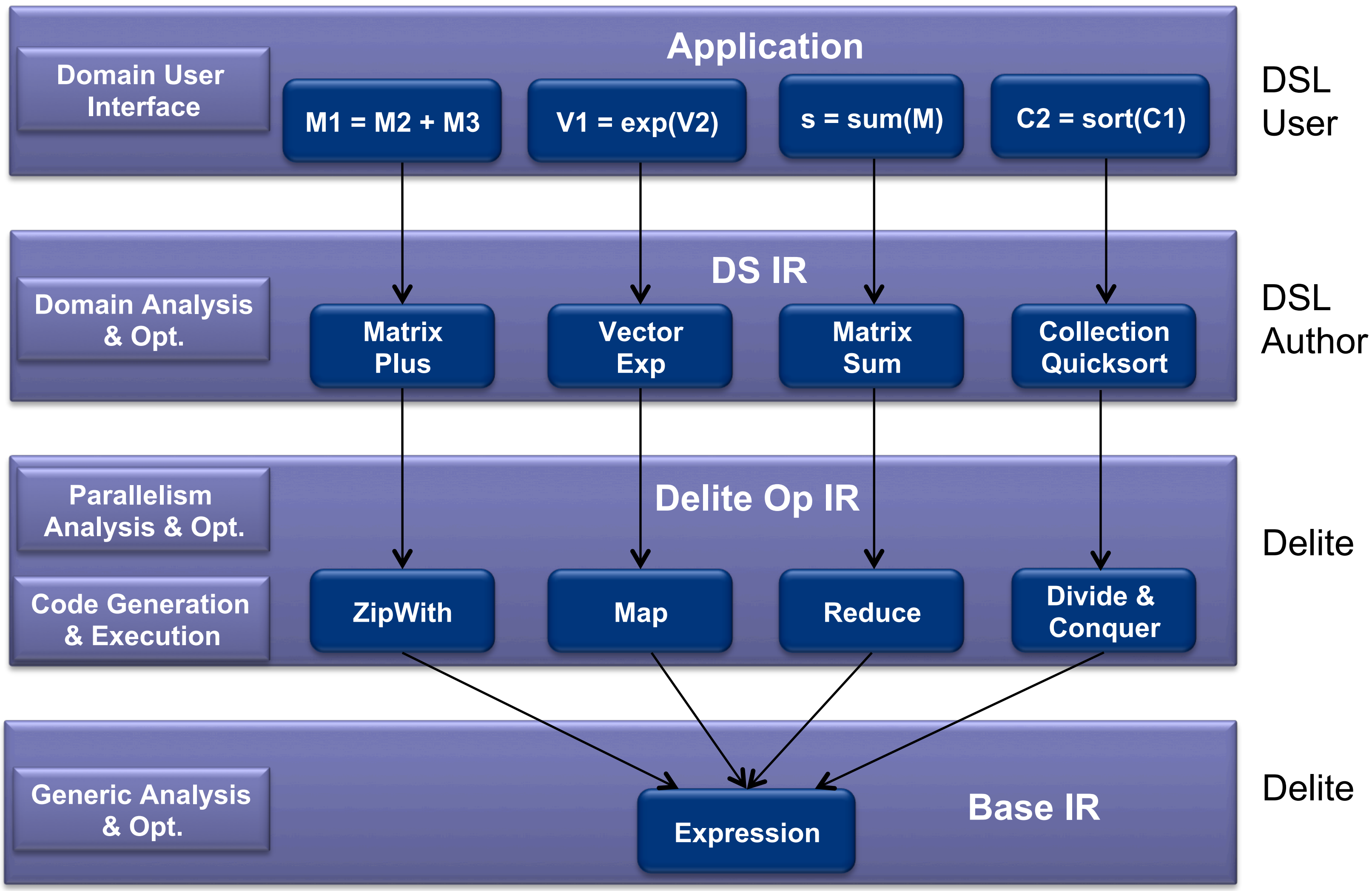
Need a framework to simplify development of DSL backends

Delite DSL Compiler

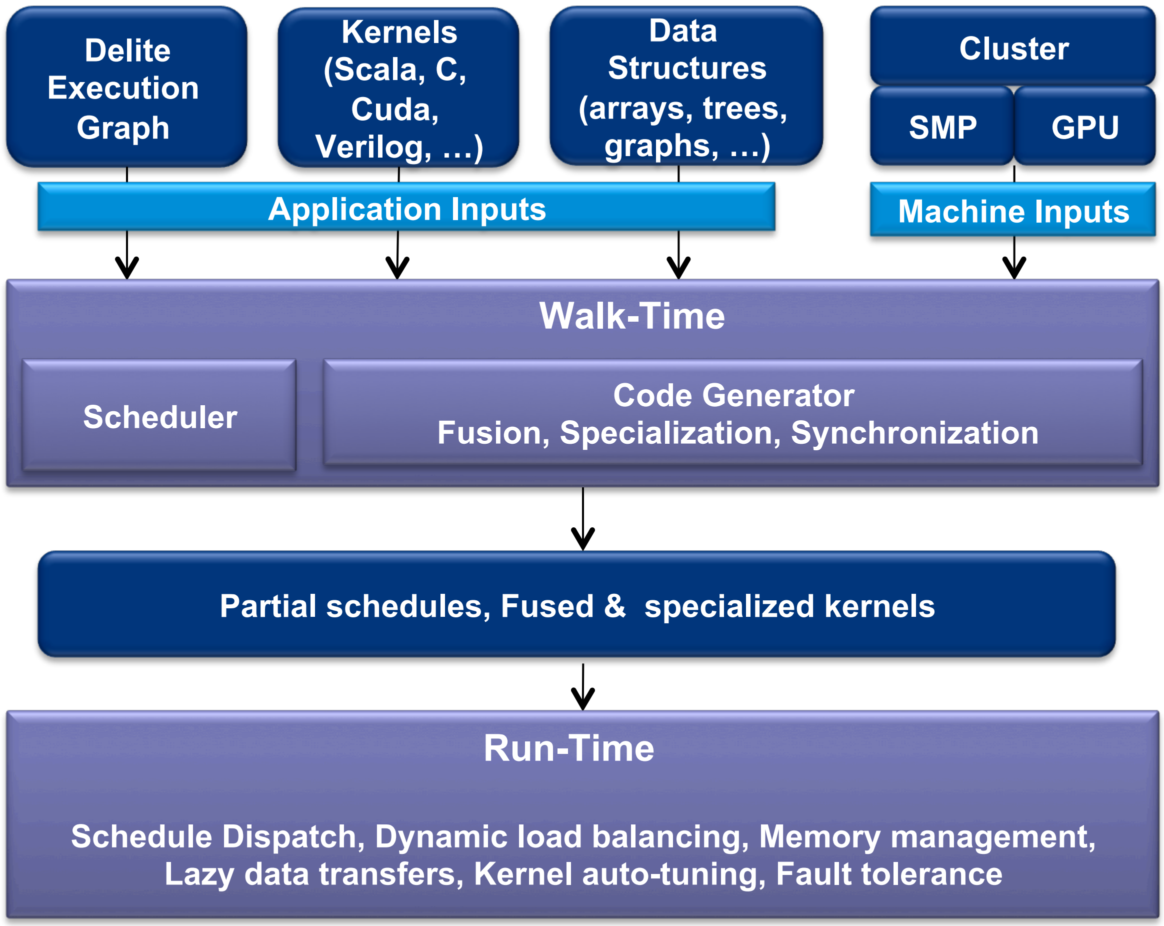


- Provide a common IR that can be extended while still benefitting from generic analysis and opt.
- Extend common IR and provide IR nodes that encode data parallel execution patterns
  - Now can do parallel optimizations and mapping
- DSL extends appropriate data parallel nodes for their operations
  - Now can do domain-specific analysis and opt.
- Generate an execution graph, kernels and data structures

The Delite IR



Delite Execution



- Maps the machine-agnostic DSL compiler output onto the machine configuration for execution
- Walk-time scheduling produces partial schedules
- Code generation produces fused, specialized kernels to be launched on each resource
- Run-time executor controls and optimizes execution

Conclusions

- DSLs have potential to solve the heterogeneous parallel programming problem
  - Don’t expose programmers to explicit parallelism unless they ask for it
  - Determinism is a byproduct
- Need to simplify the process of developing DSLs for parallelism
  - Need programming languages to be designed for flexible embedding
  - Lightweight modular staging in Scala allows for more powerful embedded DSLs
  - Delite provides a framework for adding parallelism
- Early embedded DSL results are very promising