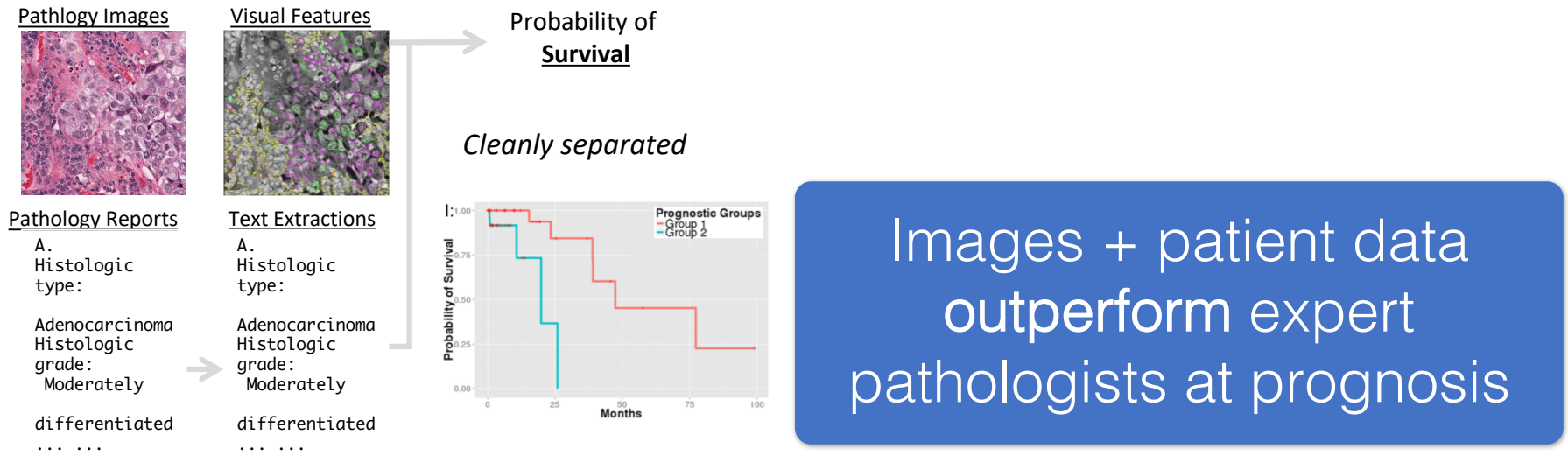
Designing Computer Systems for Software 2.0

Kunle Olukotun
Stanford University
SambaNova Systems

ISCA ’18 Keynote, June 5, 2018

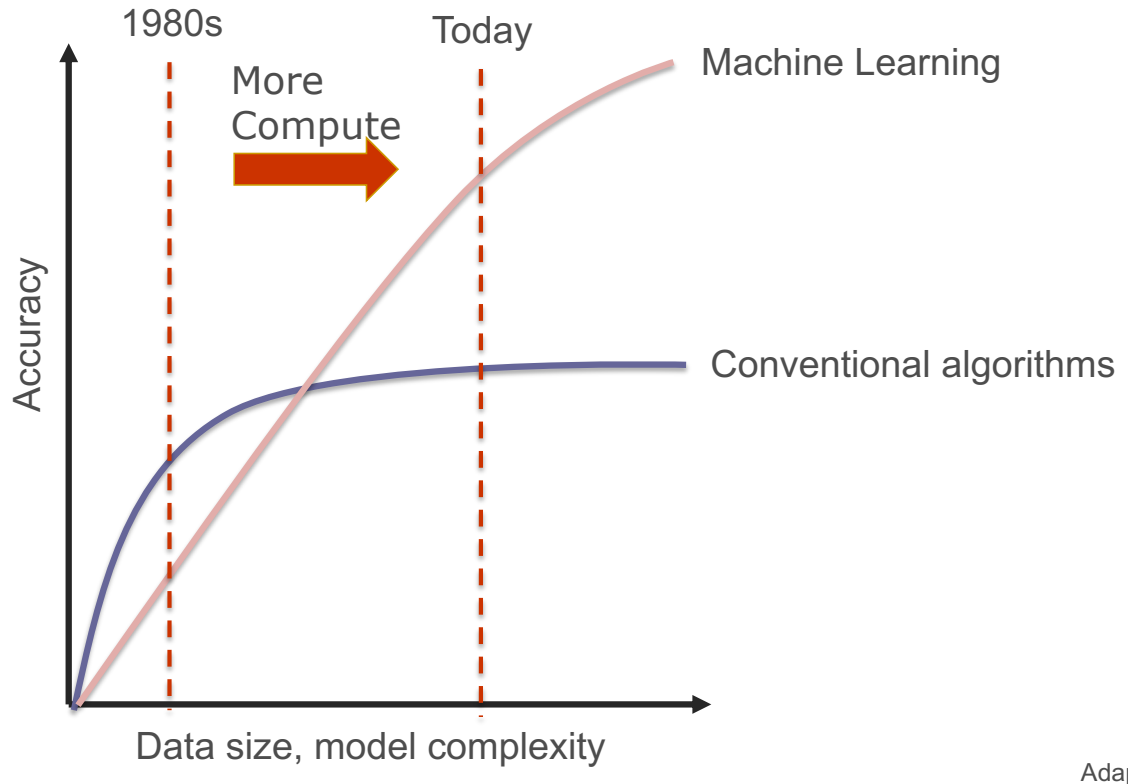
The Era of Machine Learning

- Incredible advances in image recognition, natural language processing, planning and knowledge bases
- Society-scale impact: autonomous vehicles, personalized recommendations and personalized medicine
- Many applications of ML just with supervised learning



Tumor grade & stage classification from histopathology slides (Nature Comm., Hsing-Yu et. al.)

Machine Learning Today



Adapted from Jeff Dean
HotChips 2017

Software 1.0 vs Software 2.0

- Written in code (C++, …)
- Requires domain expertise
  1. Decompose the problem
  2. Design algorithms
  3. Compose into a system

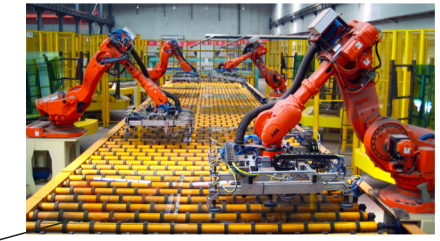
- Written in the weights of a neural network model by optimization

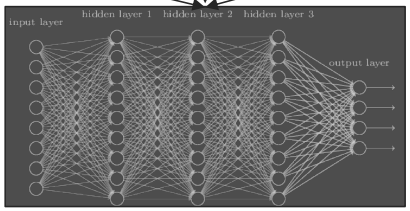
Andrej Karpathy
Scaled ML 2018 talk

Software 2.0 is Eating Software 1.0

Easier to build and deploy

- Build products faster
- Predictable runtimes and memory use: easier qualification





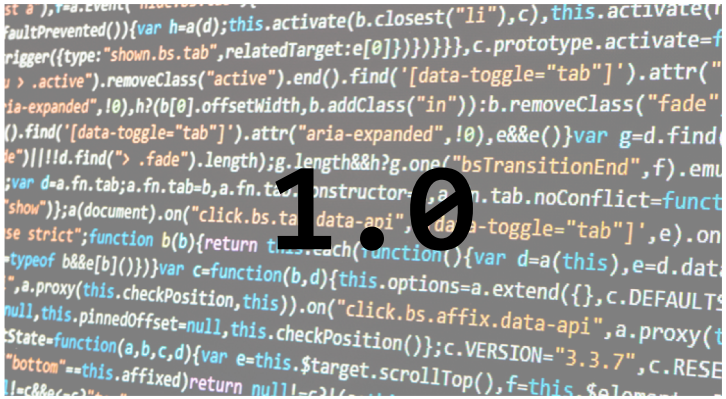
1000x Productivity: Google shrinks language translation code from 500k LoC to 500

Classical problems

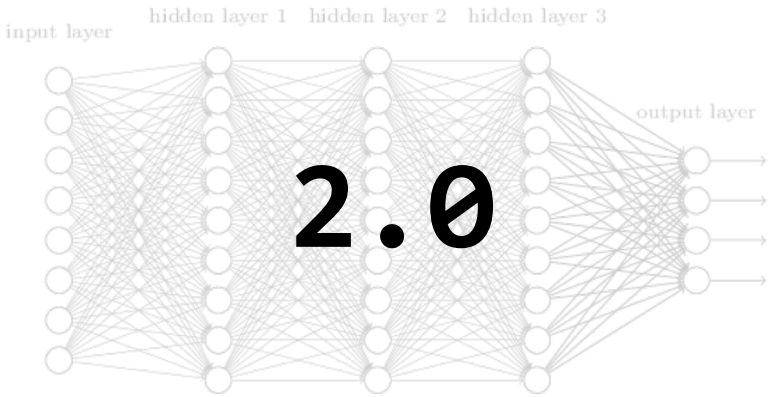
- Data cleaning (Holoclean.io)
- Self-driving DBMS (Peloton)
- Self-driving networks (Pensieve)

https://jack-clark.net/2017/10/09/import-ai-63-google-shrinks-language-translation-code-from-500000-to-500-lines-with-ai-only-25-of-surveyed-people-believe-automationbetter-jobs

Training Data: The New Input to Software 2.0



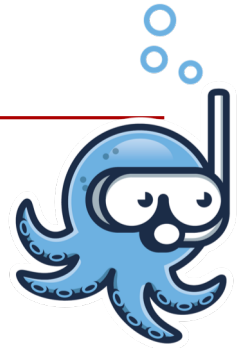
- Input: Algorithms in code
- Compiled to: Machine instructions



- Input: Training data
- Compiled to: Learned parameters

https://medium.com/@karpathy/

Better Training Data with Snorkel



- Training data is the critical interface to program Software 2.0
  - Expensive & slow especially when domain expertise is needed
- Snorkel
  - Get users to provide higher-level (but noisier) training data
    - weak supervision
    - Data programming
  - Then model & de-noise it to train high-quality models
- Implications of Snorkel
  - Two model training steps
  - New training pipeline: data operations interleaved with training

Alex Ratner

Chris Ré

ML Training is Limited by Computation

From EE Times – September 27, 2016

"Today the job of training machine learning models is limited by compute, if we had faster processors we'd run bigger models...in practice we train on a reasonable subset of data that can finish in a matter of months. We could use improvements of several orders of magnitude – 100x or greater."

Greg Diamos, Senior Researcher, SVAIL, Baidu

Power and Performance

Performance

Energy efficiency

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

FIXED

Specialization ⇒ better energy efficiency

Key Questions

- How do we speed up machine learning by 100x?
  - Moore's law slow down and power wall
  - >100x improvement in performance/watt
  - Enable new ML applications and capabilities
  - Make ML easier to use (e.g. neural architecture search, Snorkel)
- How do we balance performance and programmability?
  - ASIC-like performance/Watt
  - Processor-like flexibility
- Need a "full-stack" solution
  1. ML Algorithms
  2. Domain Specific Languages and Compilers
  3. Hardware

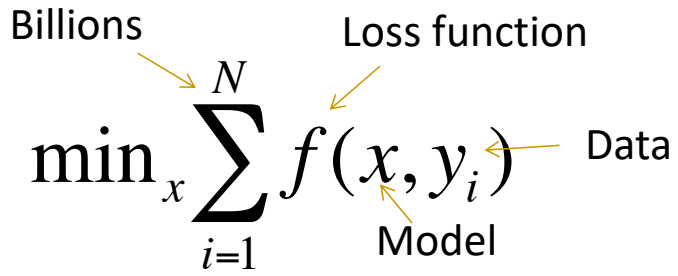
ML Algorithms

Computational Models

- Software 1.0 model
  - Deterministic computations with algorithms
  - Computation must be correct for debugging
- Software 2.0 model
  - Probabilistic machine-learned models trained from data
  - Computation only has to be statistically correct
- Creates many opportunities for improved performance

Machine Learning Training

Optimization Problem:



E.g.: Classification, Recommendation, Deep Learning

Solving large-scale problems:

Stochastic Gradient Descent (SGD)

$$x^{k+1} = x^k - \alpha N \nabla f(x^k, y_j)$$

Select one term, j, and estimate gradient

Billions of tiny sequential iterations: how to parallelize?

SGD: Two Kinds of Efficiency

- **Statistical efficiency**: **how many iterations** do we need to get the desired accuracy level?
  - Depends on **the problem** and implementation
- **Hardware efficiency**: **how long** it takes to run each iteration?
  - Depends on **the hardware** and implementation

trade off hardware and statistical efficiency
to maximize performance

Training Optimization Opportunities

- **Consistency** of algorithms can be relaxed to reduce overheads
- **Sparsity** to reduce communication and computation cost
- **Low precision** arithmetic to reduce computation cost

SGD On Shared Memory

SGD consists of **BILLIONS** of tiny threads that update a single data structure (x)!

Implemented with locking SGD actually gets *slower* with more cores

So what can we do?

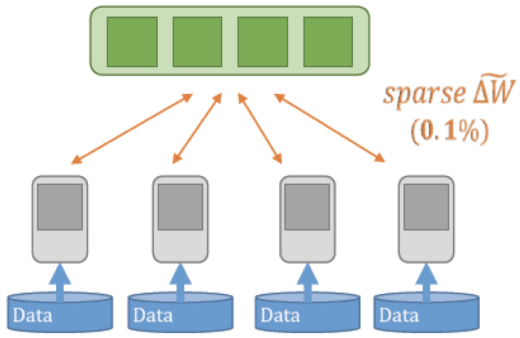
Asynchronous Update Strategy (Hogwild!)

- Run multiple worker threads without locks
  - Threads work together and modify a single copy of the model creating many data races
  - Improves hardware efficiency

- What about the data races?
  - Races introduce errors we can model as noise
  - Below existing noise floor → negligible effect on statistical efficiency
  - Theorem (roughly, Niu et. al. NIPS11): If we do no locking, SGD converges to correct answer—at essentially the same rate!

SGD Communication Reduction

- Shared memory
  - Obstinate cache: probabilistically drop 99% of invalidates
  - No impact on statistical efficiency
  - De Sa, Feldman, Ré, Olukotun*: ISCA 2017*
- Distributed Memory
  - Sparsity: 99.9% of the gradient exchange in distributed SGD is redundant
  - Use momentum correction to maintain accuracy
  - Lin, Han, Mao, Wang, Dally: *ICLR 18*

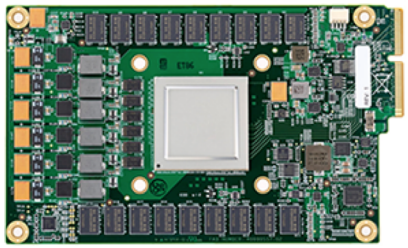


Low Precision: The Pros

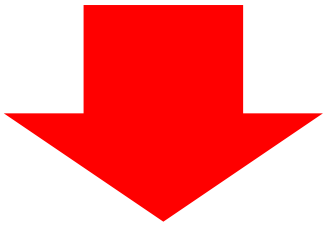
Energy

Memory

Throughput



Low Precision: The Con



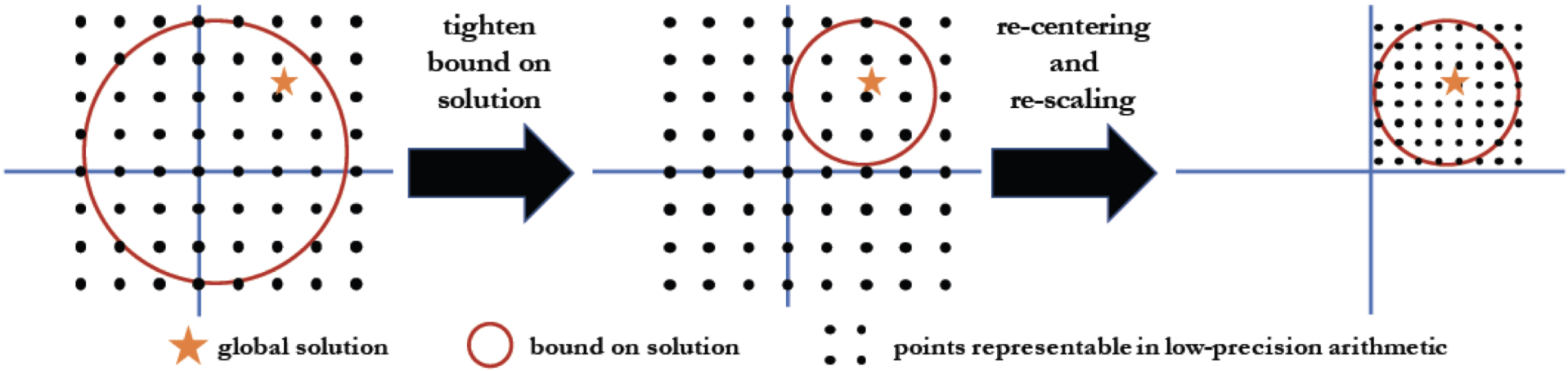
Accuracy

Low precision works for inference (e.g. TPU, Brainwave)

Training usually requires at least 16 bit floating point numbers

High Accuracy Low Precision (HALP) SGD

Bit Centering: bound, re-center, re-scale

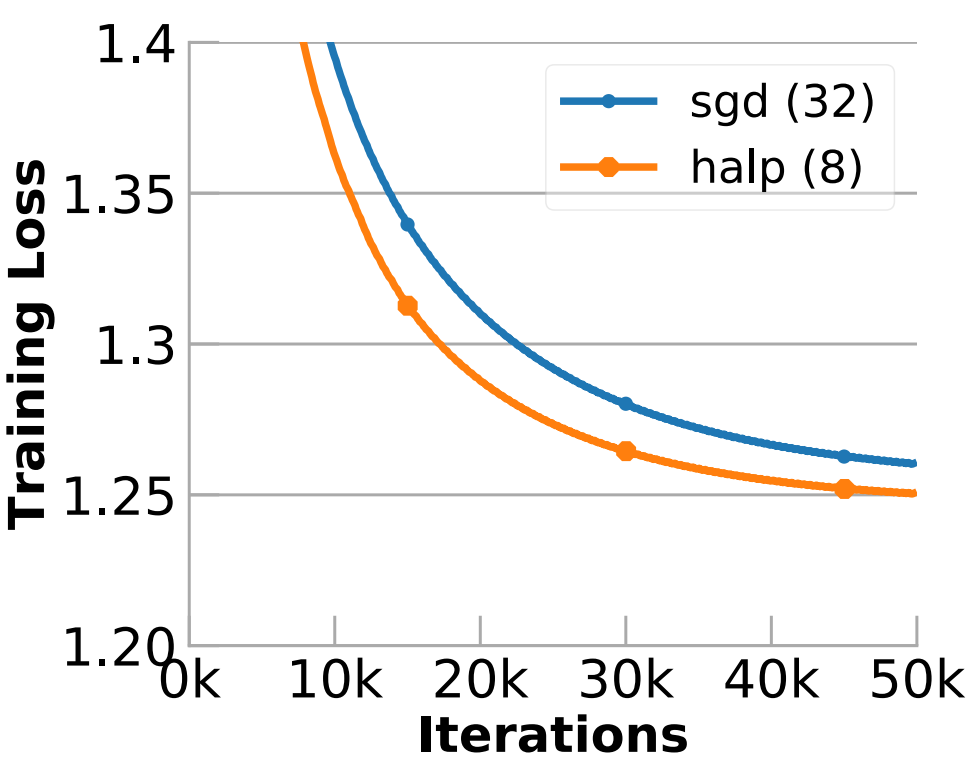


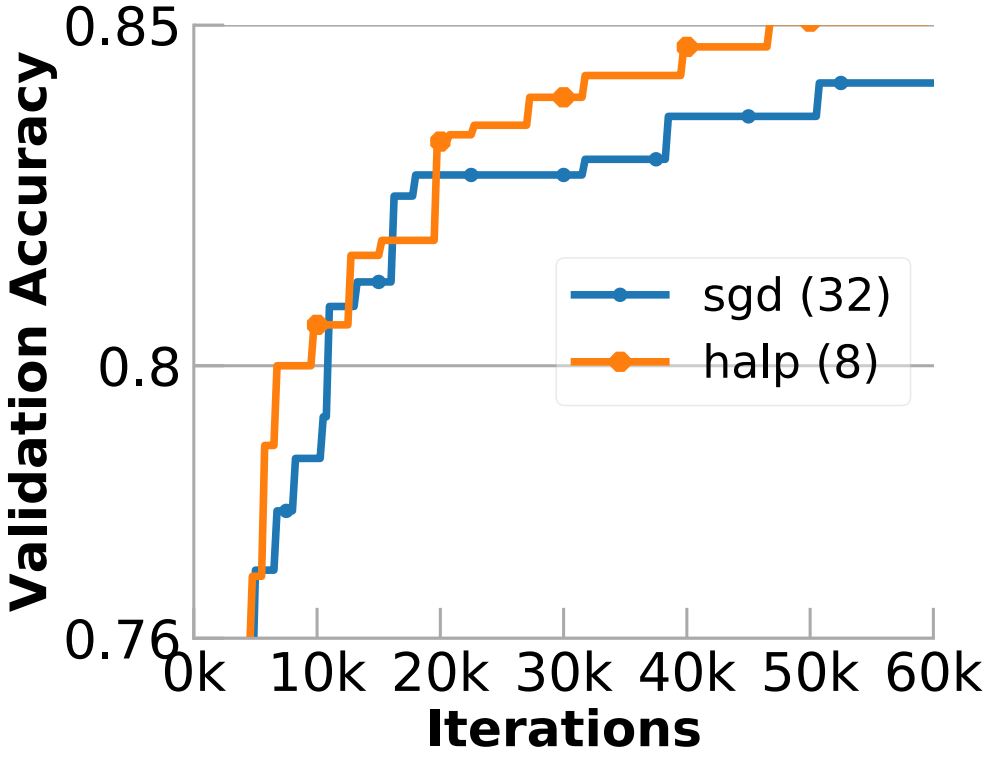
- The gradients get smaller as we approach the optimum
- Dynamically rescale the fixed-point representation
- Get **less error** with the **same number of bits**

Chris De Sa | Chris Aberger | Megan Leszczynski | Jian Zhang | Alana Marzoev | Kunle Olukotun | Chris Ré

CNN: HALP versus Full-Precision Algorithms

14-layer ResNet on CIFAR10





- HALP has better statistical efficiency than SGD!

Relax, It's Only Machine Learning

- Relax synchronization: data races are better
  - HogWild! [De Sa, Olukotun, Ré: *ICML 2016*, ICML Best Paper]
- Relax cache coherence: incoherence is better
  - [De Sa, Feldman, Ré, Olukotun*: ISCA 2017*]
- Relax communication: sparse communication is better
  - [Lin, Han et. al.: *ICLR 18*]
- Relax precision: small integers are better
  - HALP [De Sa, Aberger, *et. al*.]


Chris De Sa


Song Han

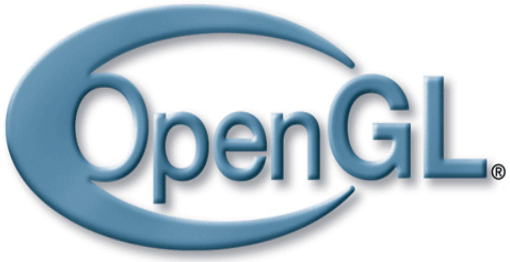

Chris Aberger

Better hardware efficiency
with negligible impact on statistical efficiency

Domain Specific Languages

Domain Specific Languages

- Domain Specific Languages (DSLs)
  - Programming language with restricted expressiveness for a particular domain (operators and data types)
  - High-level, usually declarative, and deterministic
  - Focused on productivity



K-means Clustering in OptiML

```
untilconverged(kMeans, tol){kMeans =>
  val clusters = samples.groupRowsBy { sample =>
       kMeans.mapRows(mean => dist(sample, mean)).minIndex
  }
  val newKmeans = clusters.map(e => e.sum / e.length)
  newKmeans
}
```

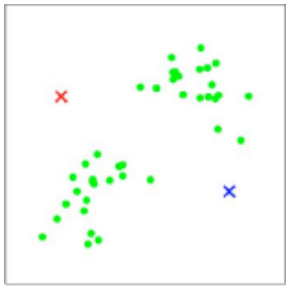
assign each sample to the closest mean

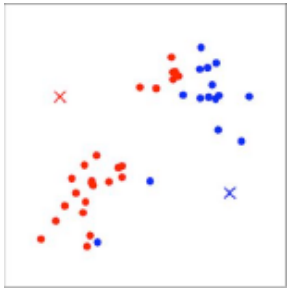
calculate distances to current means

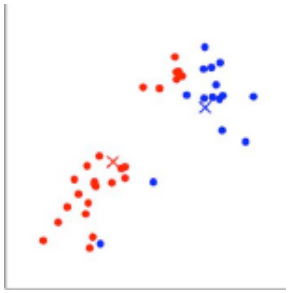
move each cluster centroid to the mean of the points assigned to it

Arvind Sujeeth

- No explicit map-reduce, no key-value pairs
- No distributed data structures (e.g. RDDs)
- Efficient multicore, cluster and GPU execution







A. Sujeeth et. al., "OptiML: An Implicitly Parallel Domain-Specific Language for Machine Learning," *ICML, 2011*.

K-means Clustering in TensorFlow

```
points = tf.constant(np.random.uniform(0, 10, (points_n, 2)))
centroids = tf.Variable(tf.slice(tf.random_shuffle(points), [0, 0], [clusters_n, -1]))

points_expanded = tf.expand_dims(points, 0)
centroids_expanded = tf.expand_dims(centroids, 1)

distances = tf.reduce_sum(tf.square(tf.sub(points_expanded, centroids_expanded)), 2)
assignments = tf.argmin(distances, 0)

means = []
for c in xrange(clusters_n):
    means.append(tf.reduce_mean(
      tf.gather(points,
                tf.reshape(
                  tf.where(
                    tf.equal(assignments, c)
                  ),[1,-1])
                ),reduction_indices=[1]))

new_centroids = tf.concat(0, means)

update_centroids = tf.assign(centroids, new_centroids)
```

calculate distances to current means

assign each sample to the closest mean

move each cluster centroid to the mean of the points assigned to it

Open, standard software for general machine learning

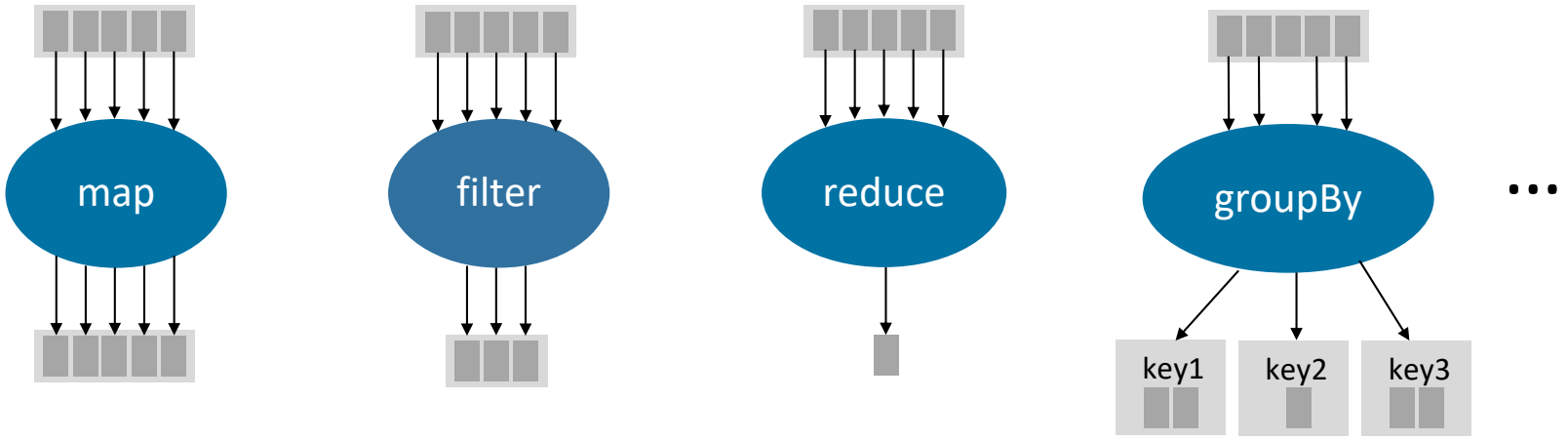
Great for Deep Learning in particular

First released Nov 2015

DSL IR: Parallel Patterns

Most data analytic computations including ML can be expressed as functional data parallel patterns on collections (e.g. sets, arrays, tables, n-d matrices)

Nested parallel patterns



Map, Zip, Filter, FlatMap, Reduce, GroupBy, Join, Sort, …

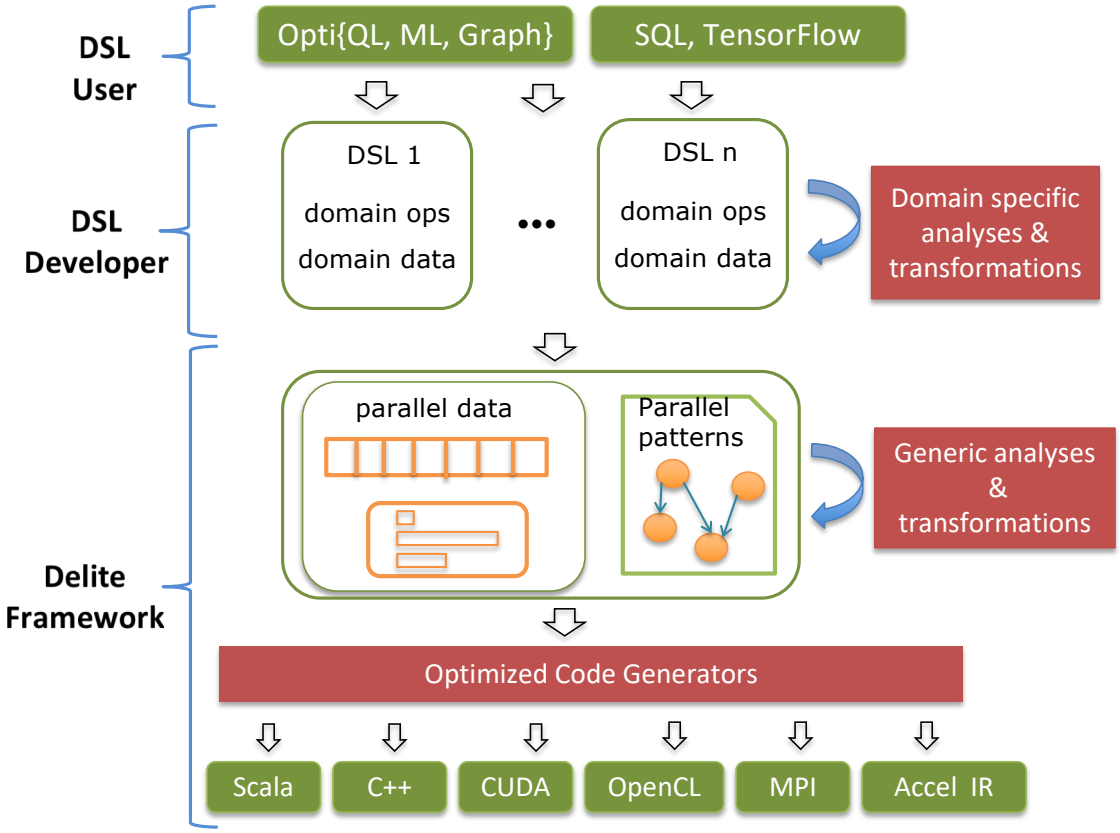
Parallel Pattern Language ➔ High Level Parallel ISA

- A data-parallel language that supports nested parallel patterns {{{}}}
- Example application: *k*-means

```
val clusters = samples GroupBy { sample =>
  val dists = kMeans Map { mean =>
    mean.Zip(sample){ (a,b) => sq(a - b) } Reduce { (a,b) => a + b }
  }
  Range(0, dists.length) Reduce { (i,j) =>
    if (dists(i) < dists(j)) i else j
  }
}
val newKmeans = clusters Map { e =>
  val sum = e Reduce { (v1,v2) => v1.Zip(v2){ (a,b) => a + b } }
  val count = e Map { v => 1 } Reduce { (a,b) => a + b }

  sum Map { a => a / count }
}
```

Delite Overview

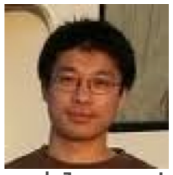


Key elements

- IR embedded in Scala
- Domain specific optimization
- General parallelism and locality optimizations
  - Structured computation
  - Structured data
- Optimized mapping to HW targets

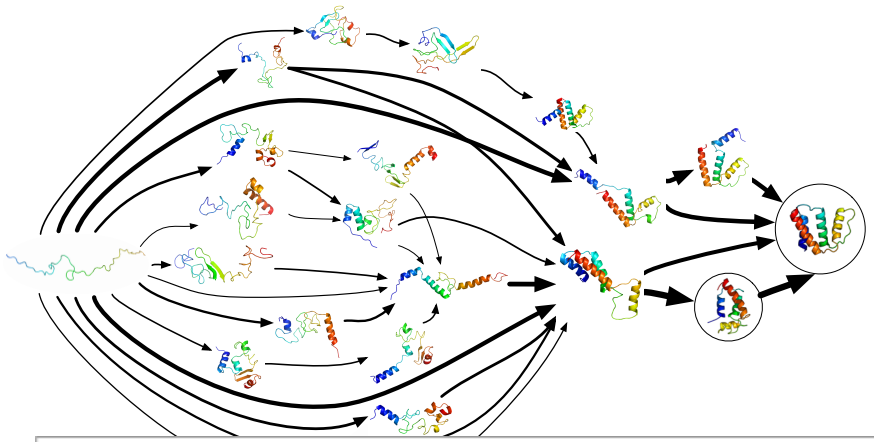

Hassan Chafi


Kevin Brown

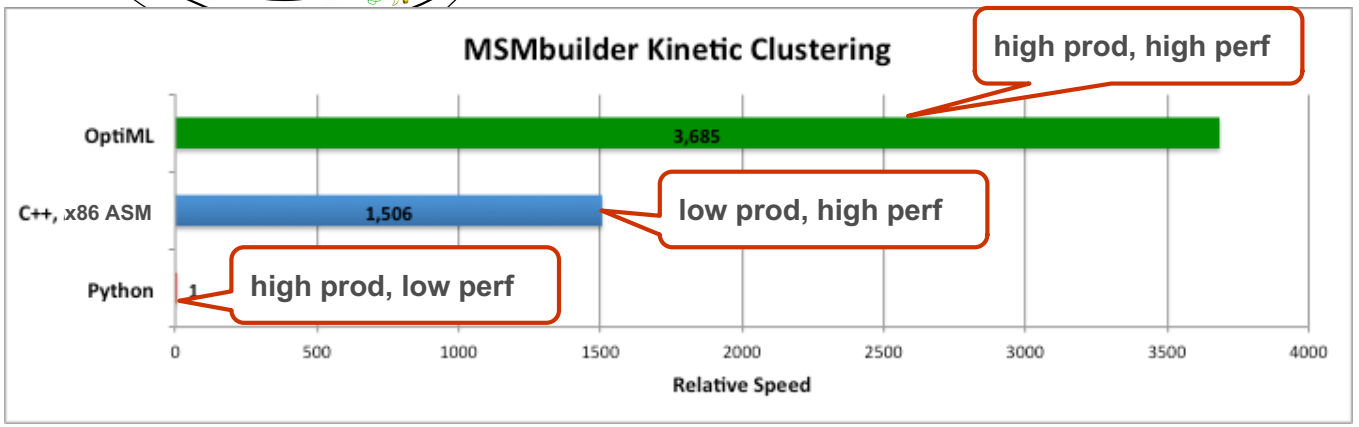

HyoukJoong Lee

MSM Builder Using OptiML

with Vijay Pande

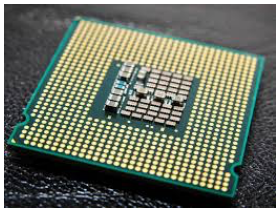


Markov State Models (MSMs)
MSMs are a powerful means of modeling the structure and dynamics of molecular systems, like proteins



Hardware

Accelerators for ML



CPU
- Threads
- SIMD

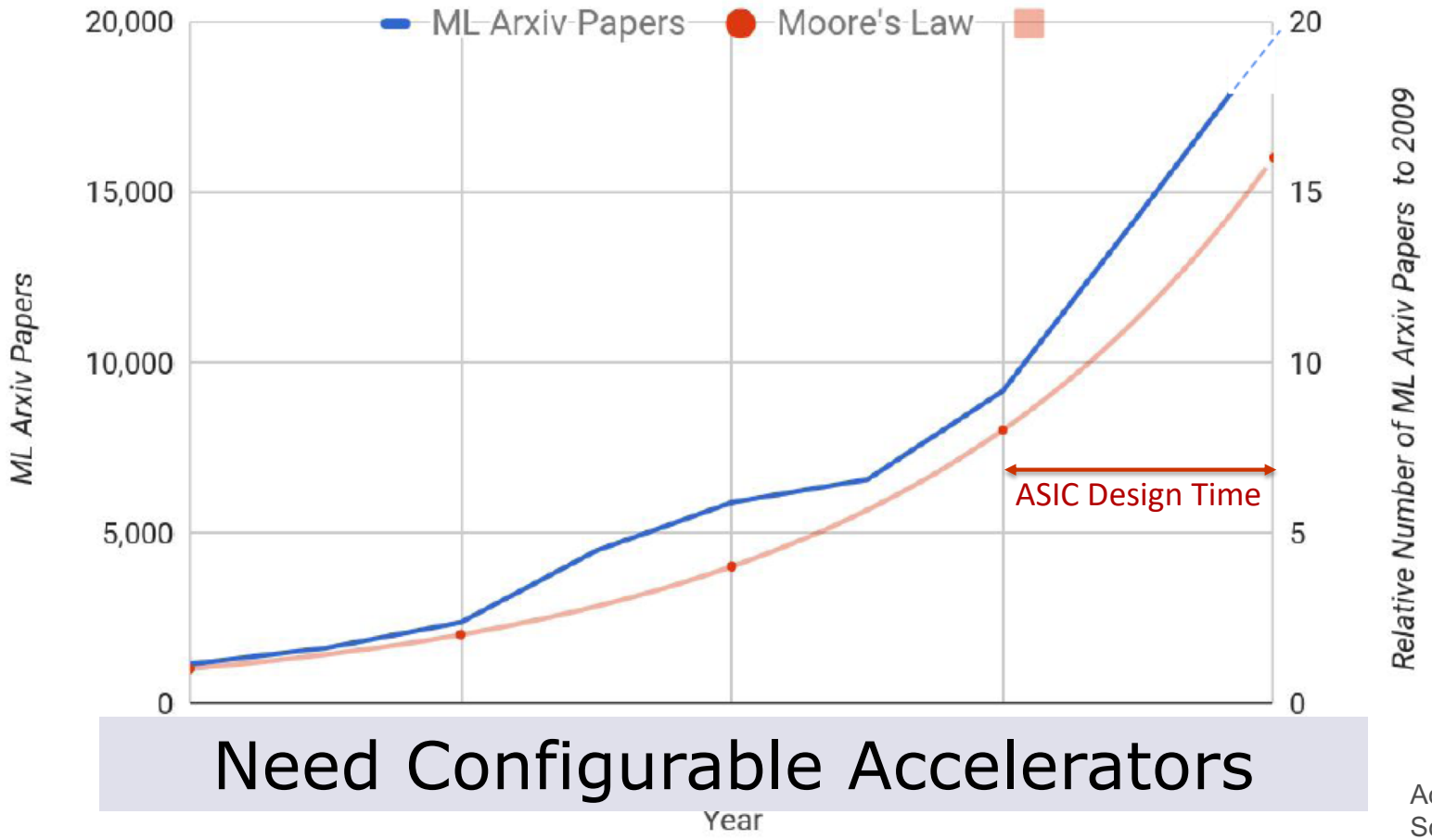
GPU
- Massive threads
- SIMD
- HBM

FPGA
- LUTs
- DSP
- BRAM

TPU
- MM unit
- BRAM

?

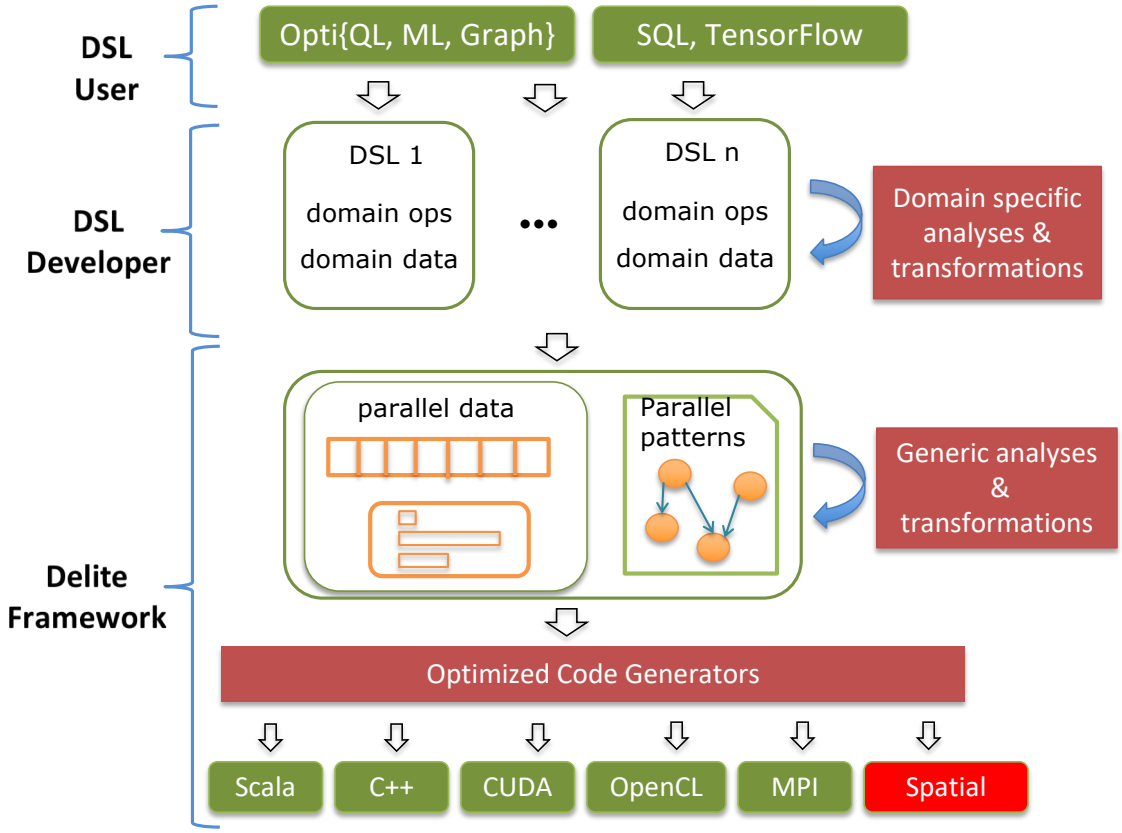
What to Accelerate? ML Arxiv Papers Per Year



Need Configurable Accelerators

Adapted from Jeff Dean
Scaled ML 2018

Parallel Patterns to Spatial



Accelerator IR: Spatial

- Interface to configurable accelerator

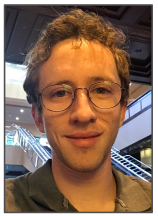
Generate Accelerator IR

- Tile parallel patterns
- Transform nested parallel patterns to hierarchical pipelines

Spatial: Accelerator IR/Language

- Simplify configurable accelerator design
  - IR that can be mapped to many hardware targets: FPGA, ASIC, …
  - Constructs to express:
    - Parallel patterns as parallel and pipelined datapaths
    - Hierarchical control
    - Explicit memory hierarchies
    - Explicit parameters
  - Optimizes parameters for each target: parallelization, pipelining, memory size, memory banking
- Allows programmers and high-level compilers to focus on specifying parallelism and locality
  - Designed for performance oriented programmers
  - Focus on dataflow instead of threads

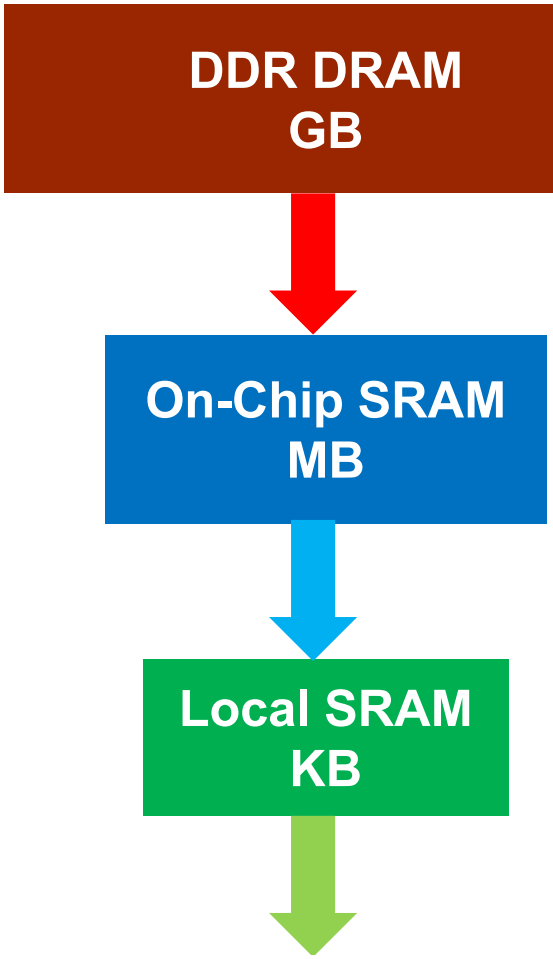
David Koeplinger



Matt Feldman

D. Koeplinger et. al., "Spatial: A Language and Compiler for Application Accelerators" *PLDI 2018*.

Programing Locality: Memory Templates




```
val image  = DRAM[UInt8](H,W)
```

```
buffer load   image(i, j::j+C) // dense
buffer gather image(a)         // sparse
```

```
val buffer = SRAM[UInt8](C)
```

```
val accum  = Reg[Double]
val fifo   = FIFO[Float](D)
val lbuf   = LineBuffer[Int](R,C)
val pixels = RegFile[UInt8](R,C)
```

GDA in Spatial

```
1  type V = FixPt[TRUE,_9,_7]
2  val x_dram = DRAM[V](R, C)
3  val y_dram = DRAM[Bit](R)
4  val mu0    = SRAM[V](C)
5  val mu1    = SRAM[V](C)
6  val sigma  = SRAM[V](C,C)
7
8  MemReduce(sigma)(R by T){r =>
9    val x = SRAM[V](T, C)
10   val y = SRAM[Bit](T)
11   x load x_dram(r::r+T, 0::C)
12   y load y_dram(r::r+T)
13
14   MemReduce(SRAM[V](C,C))(T by 1){rr =>
15     val sub = SRAM[V](C)
16     val sigma_blk = SRAM[V](C,C)
17     Foreach(C by 1){c =>
18       sub(c) = x(c) - mux(y(c), mu1(c), mu0(c))
19     }
20     Foreach(C by 1, C by 1){(i,j) =>
21       sigma_blk(i,j) = sub(i) * sub(j)
22     }
23     sigma_blk
24   }{(a,b) => a + b }
25 }{(a,b) => a + b }
```

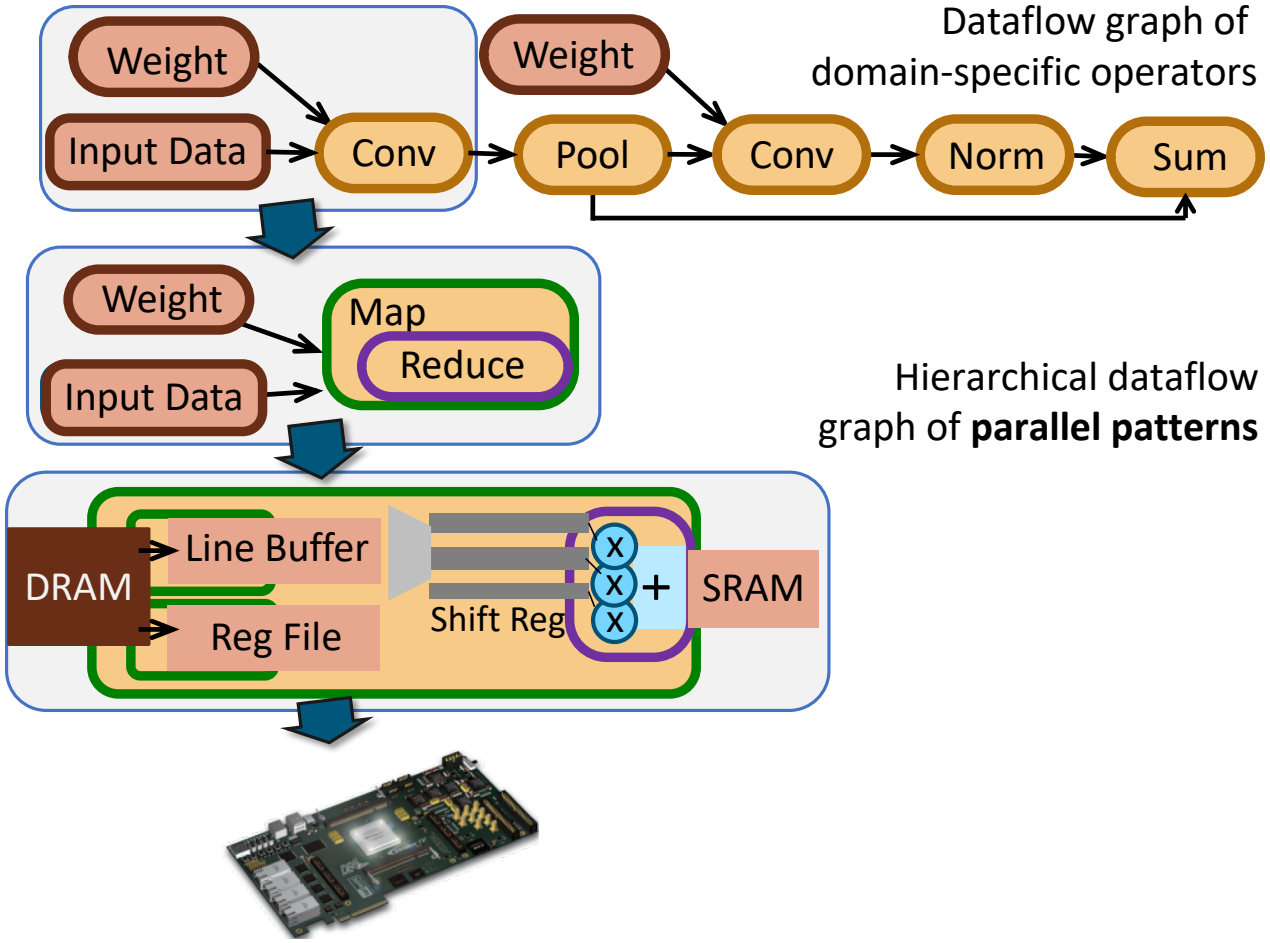
Arbitrary precision custom types

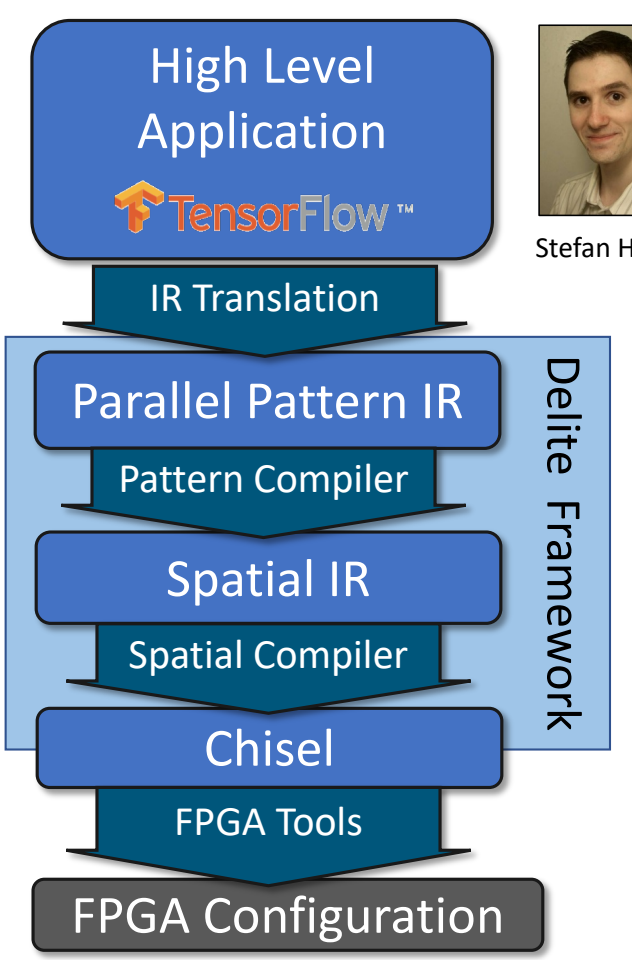
Off-chip memory allocations

On-chip memory allocations

Explicit memory transfers

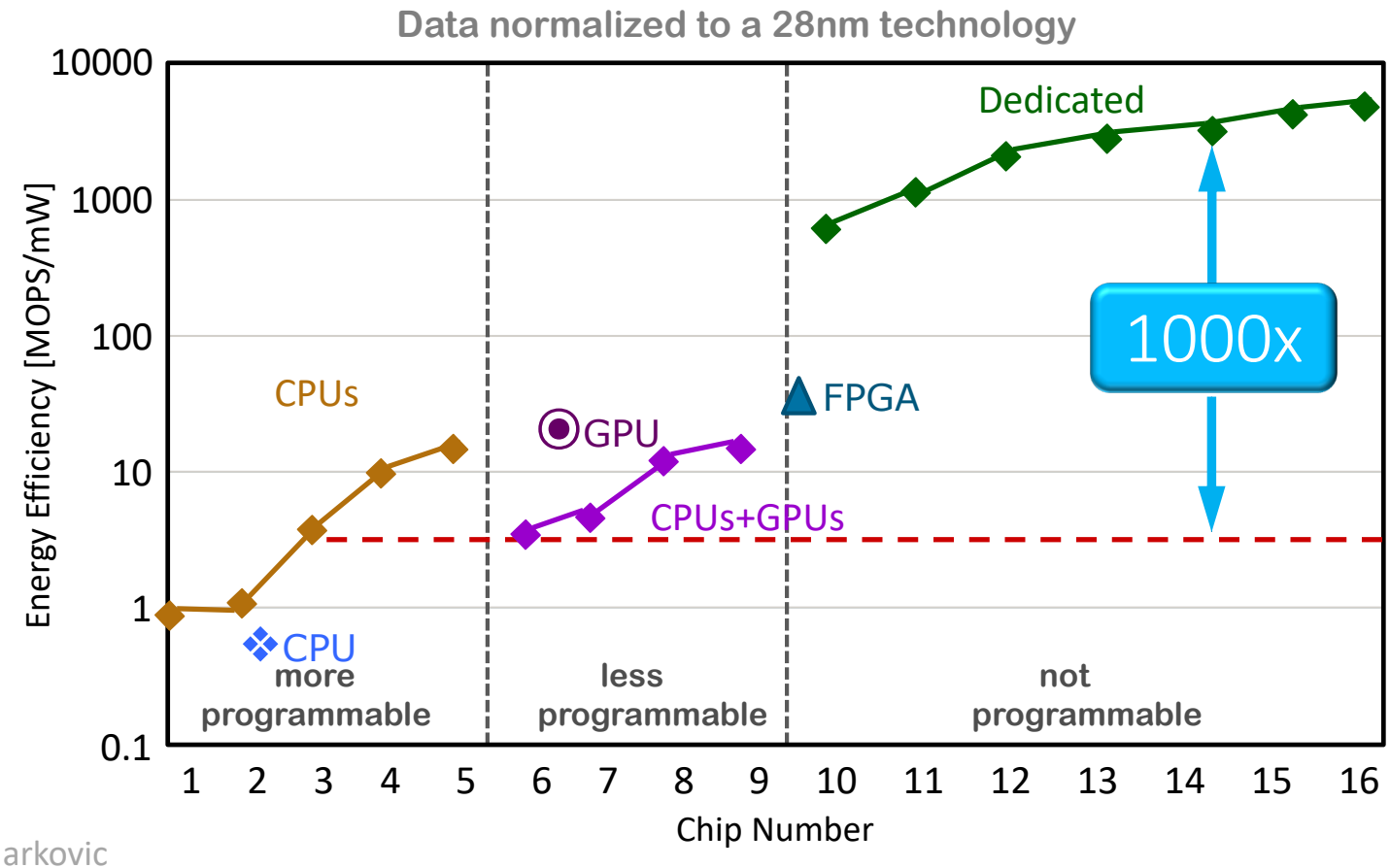
TensorFlow to FPGA





Stefan Hadjis

Programmability vs. Energy Efficiency



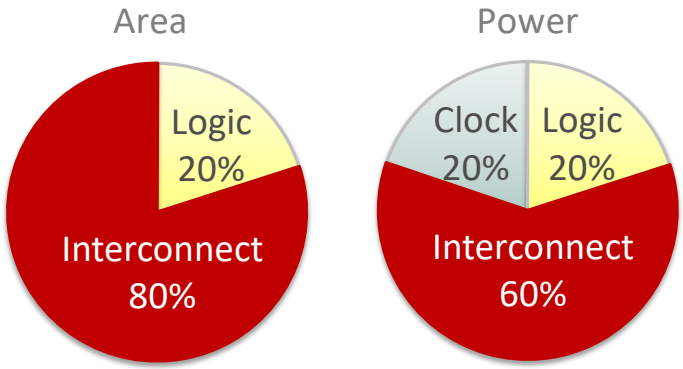
Source: Dejan Markovic

FPGA: Good, Bad and Ugly

Bit-level reconfigurable logic elements + static interconnect

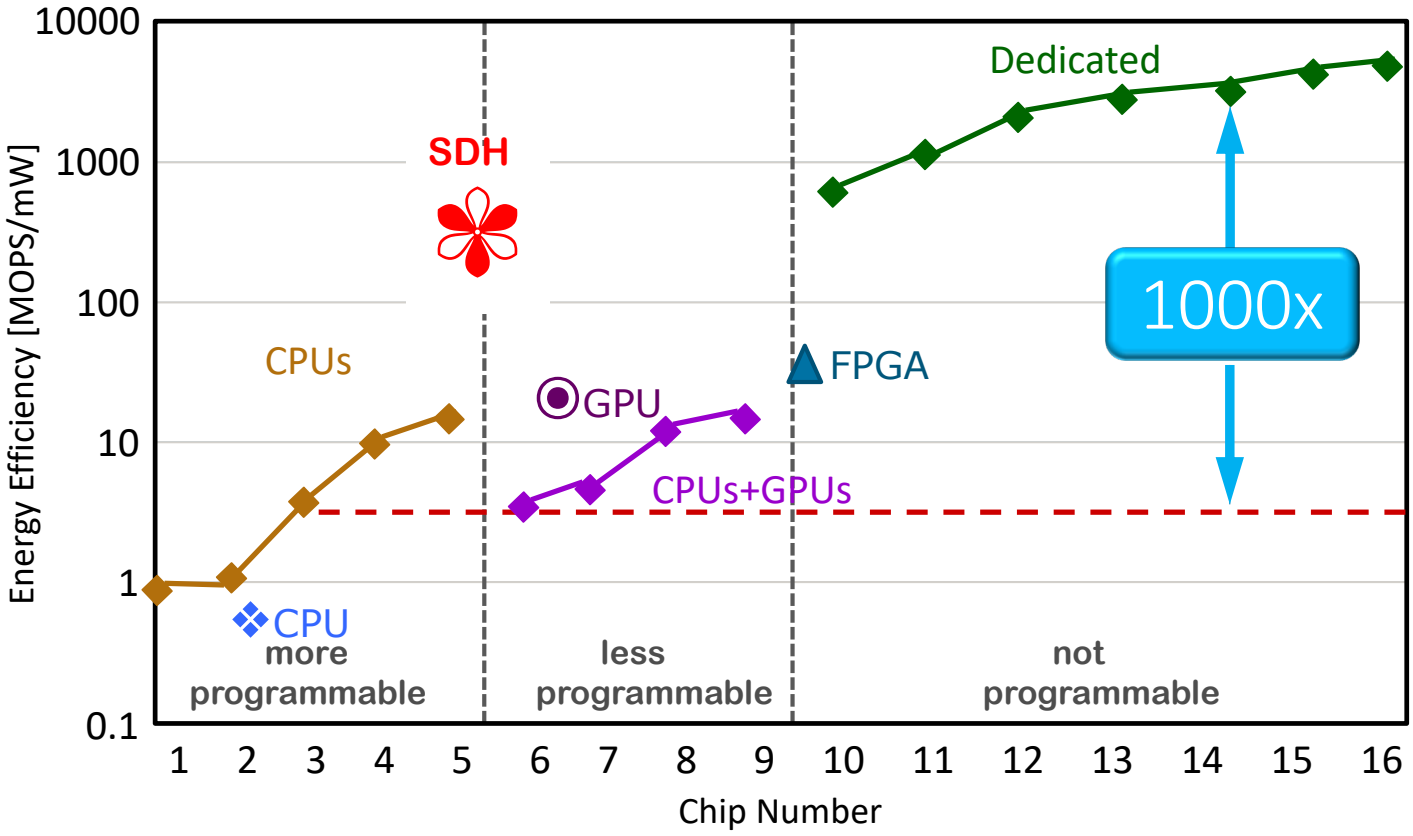
- Flexibility
- No instruction overhead
- Performance / Watt

- Fine-grained reconfigurability overheads:
  - >60% area and power spent on interconnect
- Long compile times (days)



Design reconfigurable hardware with the right abstractions

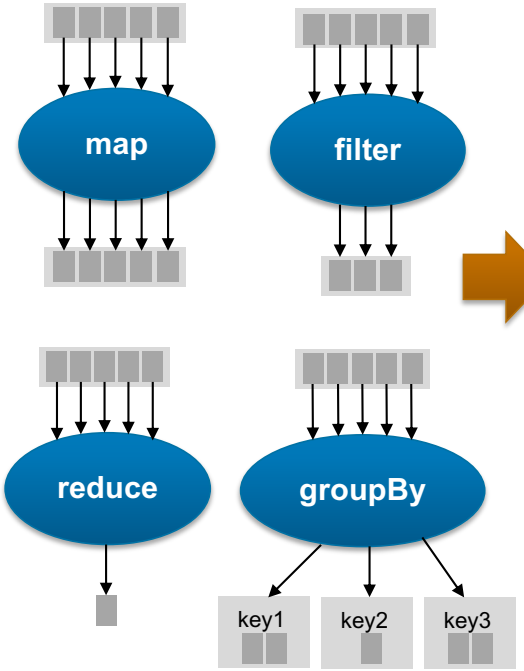
DARPA Software Defined Hardware (SDH) Program



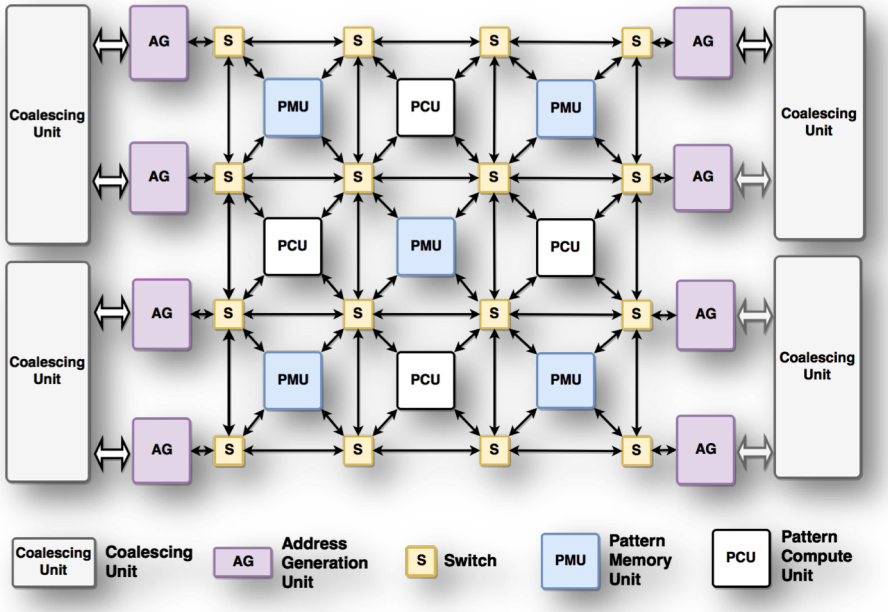
The goal of the SDH program is to build runtime-reconfigurable hardware and software that enables near ASIC performance without sacrificing programmability for data-intensive algorithms.

Plasticine: A Reconfigurable Architecture for Parallel Patterns

High-level Parallel Patterns (Spatial)



Plasticine Accelerator



Tiled architecture with reconfigurable SIMD pipelines, distributed scratchpads, and statically programmed switches

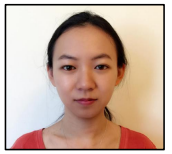
High Performance Energy Efficiency

Up to **95x** Performance

Up to **77x** Perf/W

vs. Stratix V FPGA

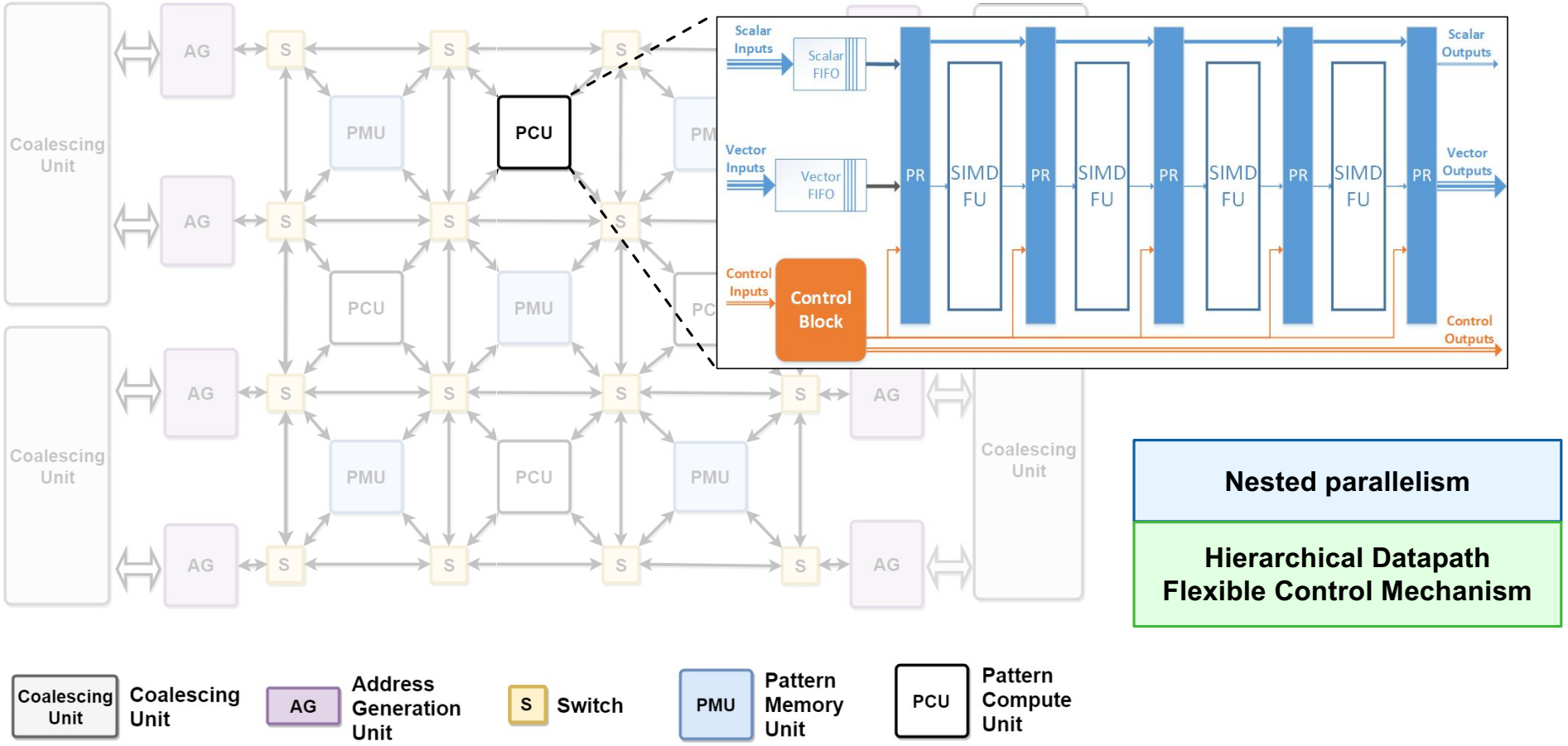
Raghu Prabhakar



Yaqi Zhang

Prabhakar, Zhang, et. al. ISCA 2017

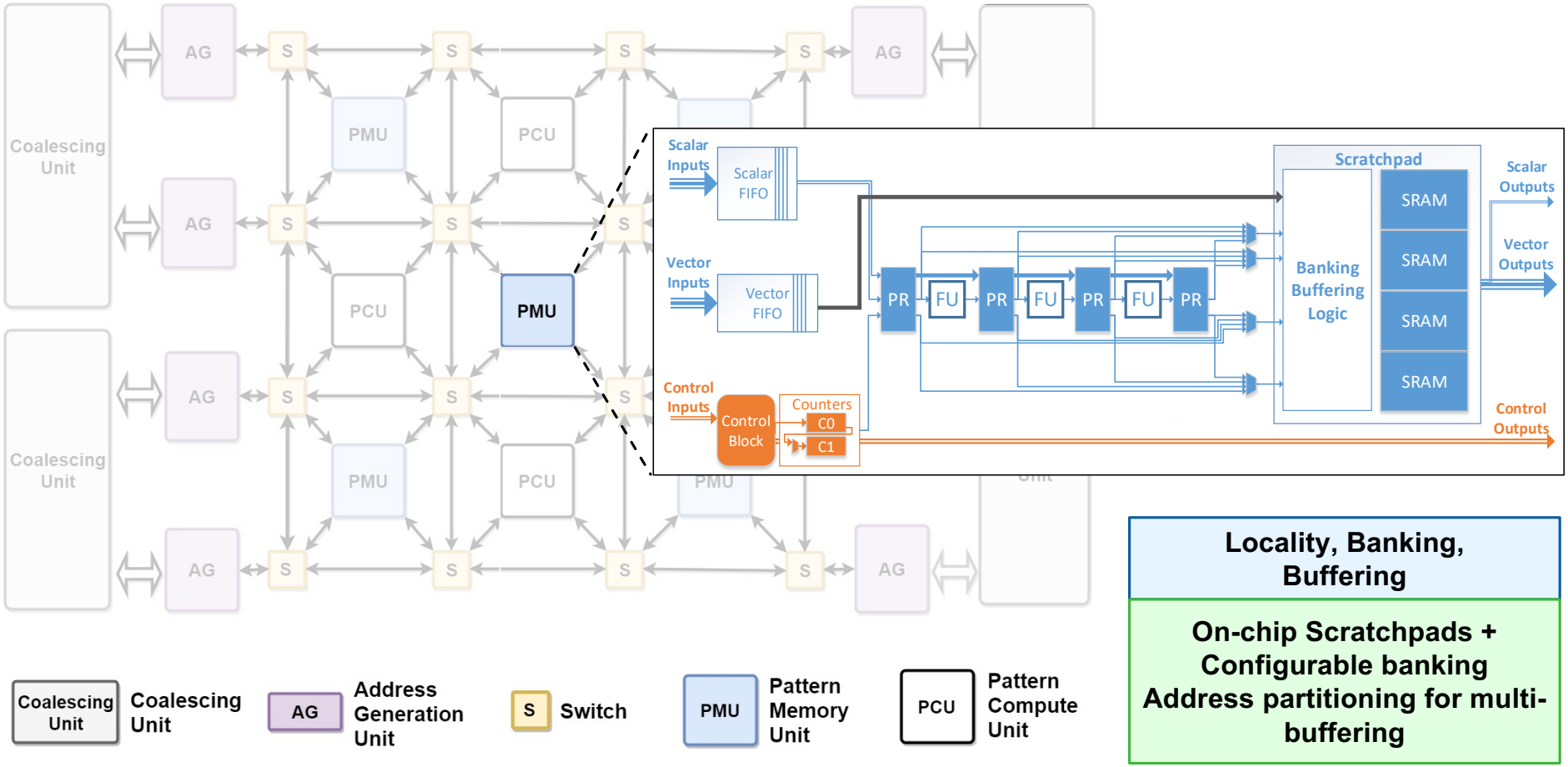
Plasticine: PCU



Nested parallelism

Hierarchical Datapath
Flexible Control Mechanism

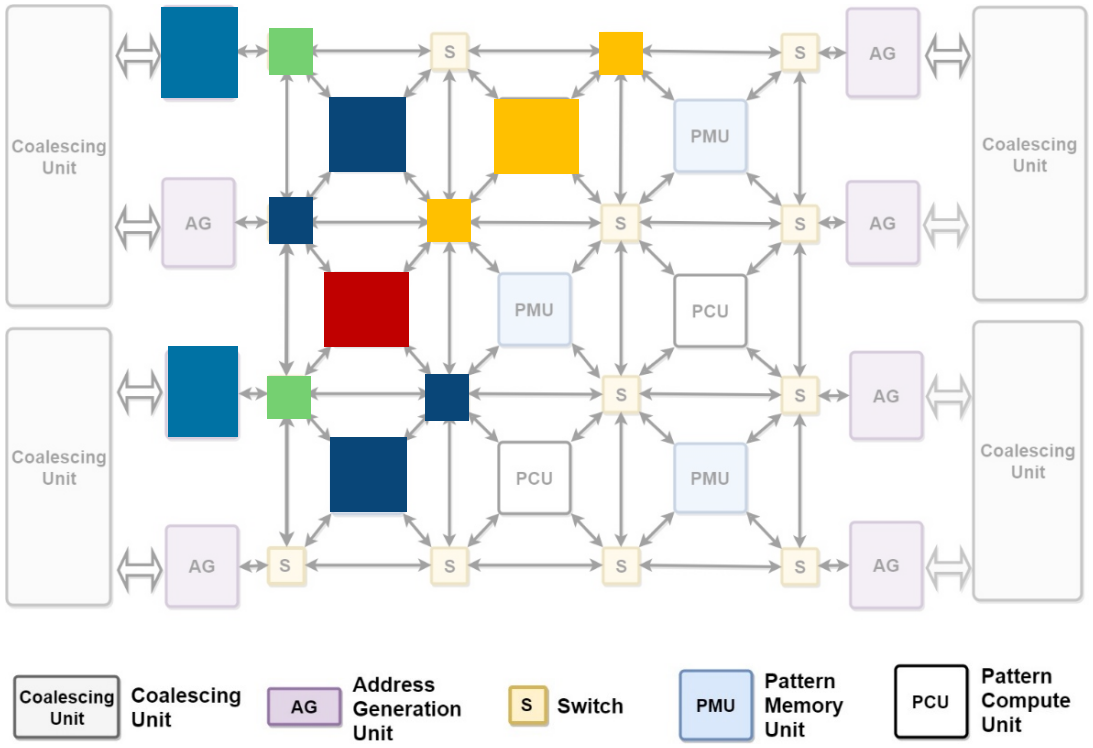
Plasticine: PMU

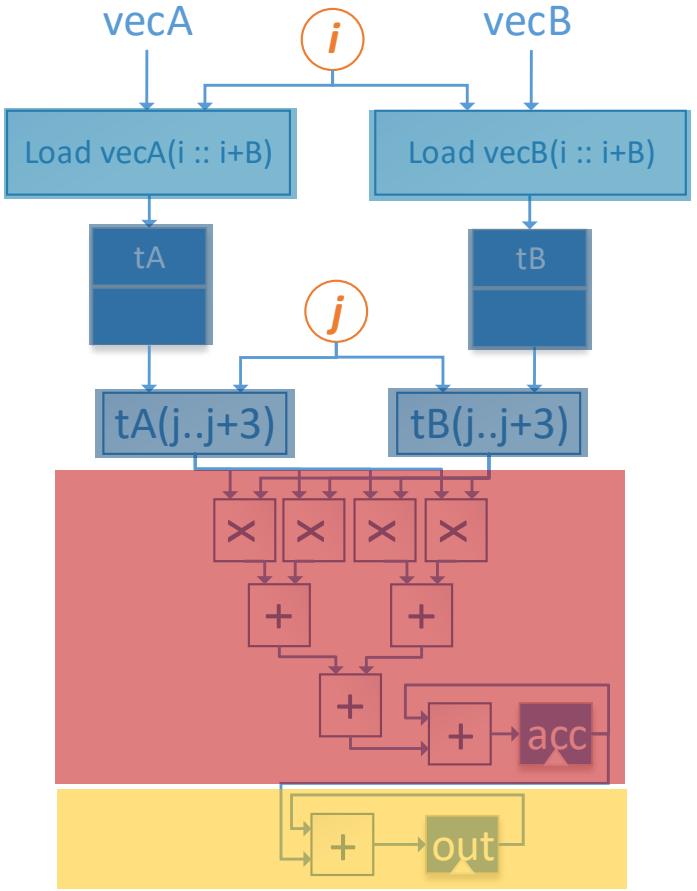


Locality, Banking, Buffering

On-chip Scratchpads + Configurable banking Address partitioning for multi-buffering

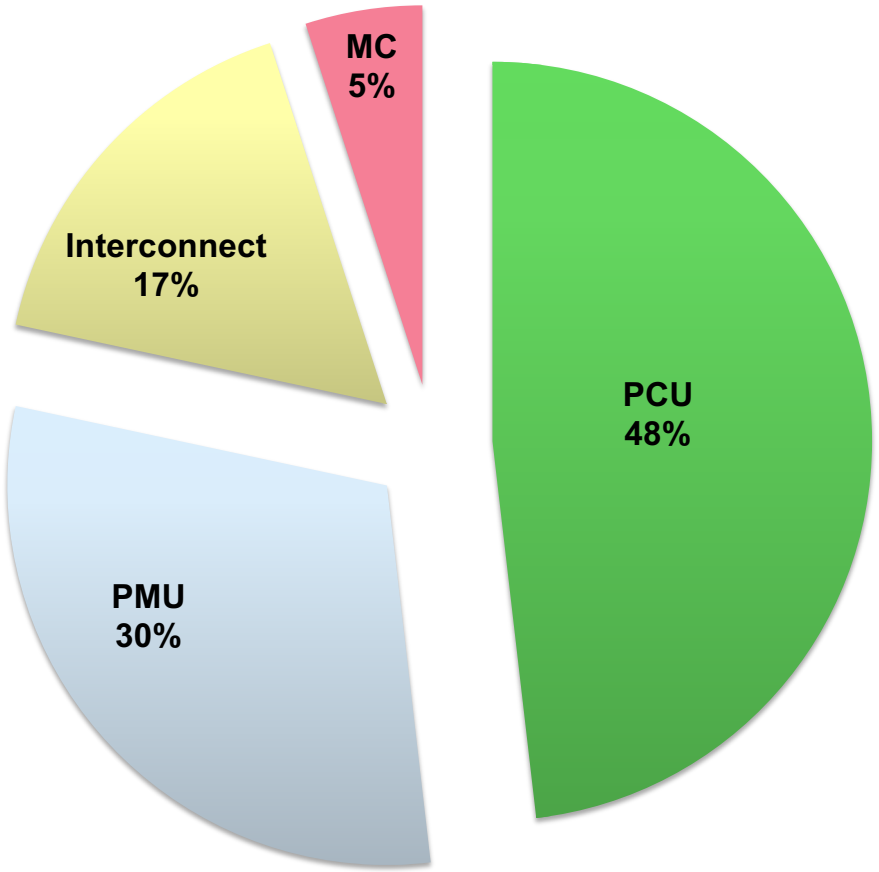
Mapping Spatial to Plasticine





Dot Product

Plasticine Area Breakdown



We Can Have It All with Software 2.0!

- Productivity
- Power
- Performance
- Programmability
- Portability

ML Algorithms (e.g. Hogwild!, HALP)

High Performance DSLs (e.g. OptiML, TensorFlow, PyTorch)

Accelerator IRs (e.g. Spatial)

Architectures (e.g. TPU, SDH)

Thank You!

- Questions?