OptiML: An Implicitly Parallel Domain-Specific Language for ML

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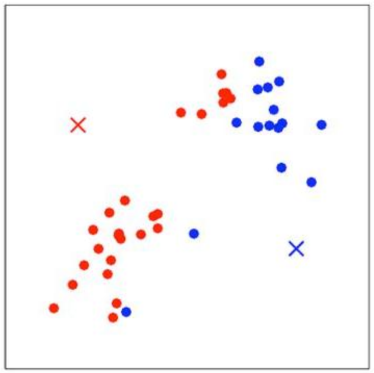
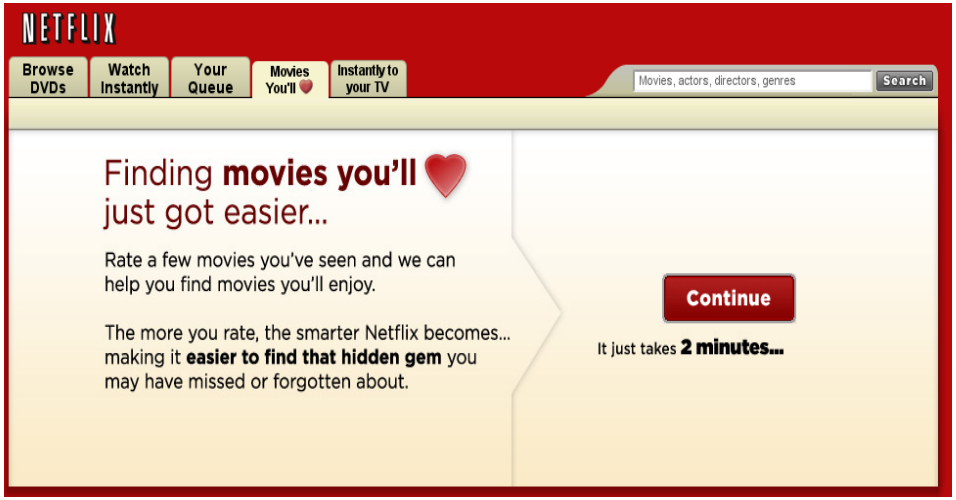
Machine Learning

- Learning patterns from data
  - Regression
  - Classification (e.g. SVMs)
  - Clustering (e.g. K-Means)
  - Density estimation (e.g. Expectation Maximization)
  - Inference (e.g. Loopy Belief Propagation)
  - Adaptive (e.g. Reinforcement Learning)
- A good domain for studying parallelism
  - Many applications and datasets are time-bound in practice
  - A combination of regular and irregular parallelism at varying granularities
  - At the core of many emerging applications (speech recognition, robotic control, data mining etc.)

Machine Learning Applications





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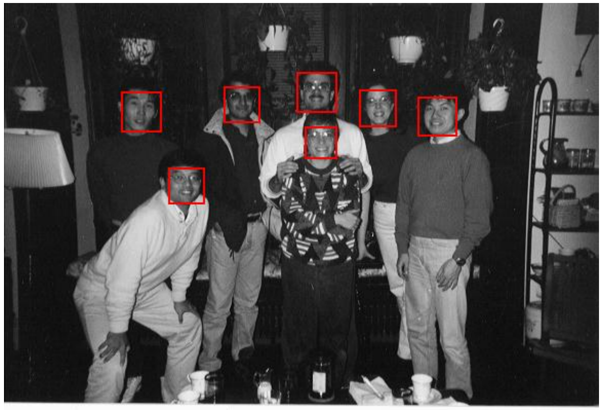
Google translate

Report Spam



Example algorithms

Computing parameters:

Naïve Bayes $\sum_{i=1}^{n} \log(P(x_i|y=1)) + \log(P(y=1))$

GDA $E = \frac{1}{m}\sum_i (x^{(i)} - \mu_{y^{(i)}})(x^{(i)} - \mu_{y^{(i)}})^T$

Iterative convergence:

linear regression (gradient descent)

Netwon's method (numerical approximation)

Data manipulation:

collaborative filtering (group, map)

image processing (slicing, filtering, searching)

DESIGNING DSLS: REQUIRED EXPERTISE

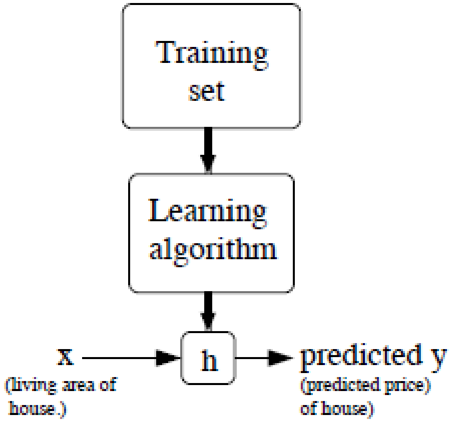
Major Challenges

- Expressing the important problems
- Elegant, natural and simple design
- Implementing efficiently and portably

Domain Expertise

Gradient Descent

Images, Video, Audio



Convex Optimization

Message-passing graphs

Probabilistic

Linear Algebra

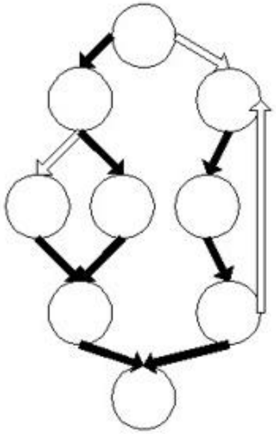
Streaming training sets

Expressing the important problems

Language Expertise

Abstract Syntax Tree

Control Flow Graph



Program Transformation

Alias Analysis

Code Generation

Loop-invariant Code Motion

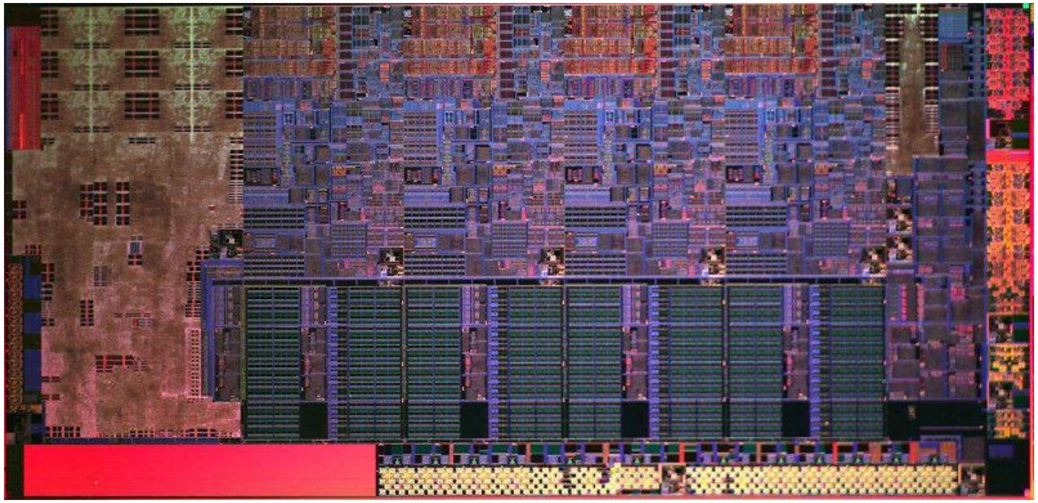
Performance Expertise

Thread

False Sharing

Locality

Mutex



SSE

Synchronization

Coherency Protocol

TLB Shootdown

Bandwidth

DSL Implementations

- Stand-alone
  - Domain expertise, language expertise and performance expertise
- Embedded in a host language
  - Domain expertise and performance expertise
- Embedded with a common framework
  - DSL author … nly on domain expertise
  - Framework authors provide language and performance expertise

Delite

OptiML: Approach

- Identify high-level abstractions common in ML
- Provide those abstractions as first-class data types or functional operators
- Use knowledge of those operators to optimize and generate efficient, imperative code

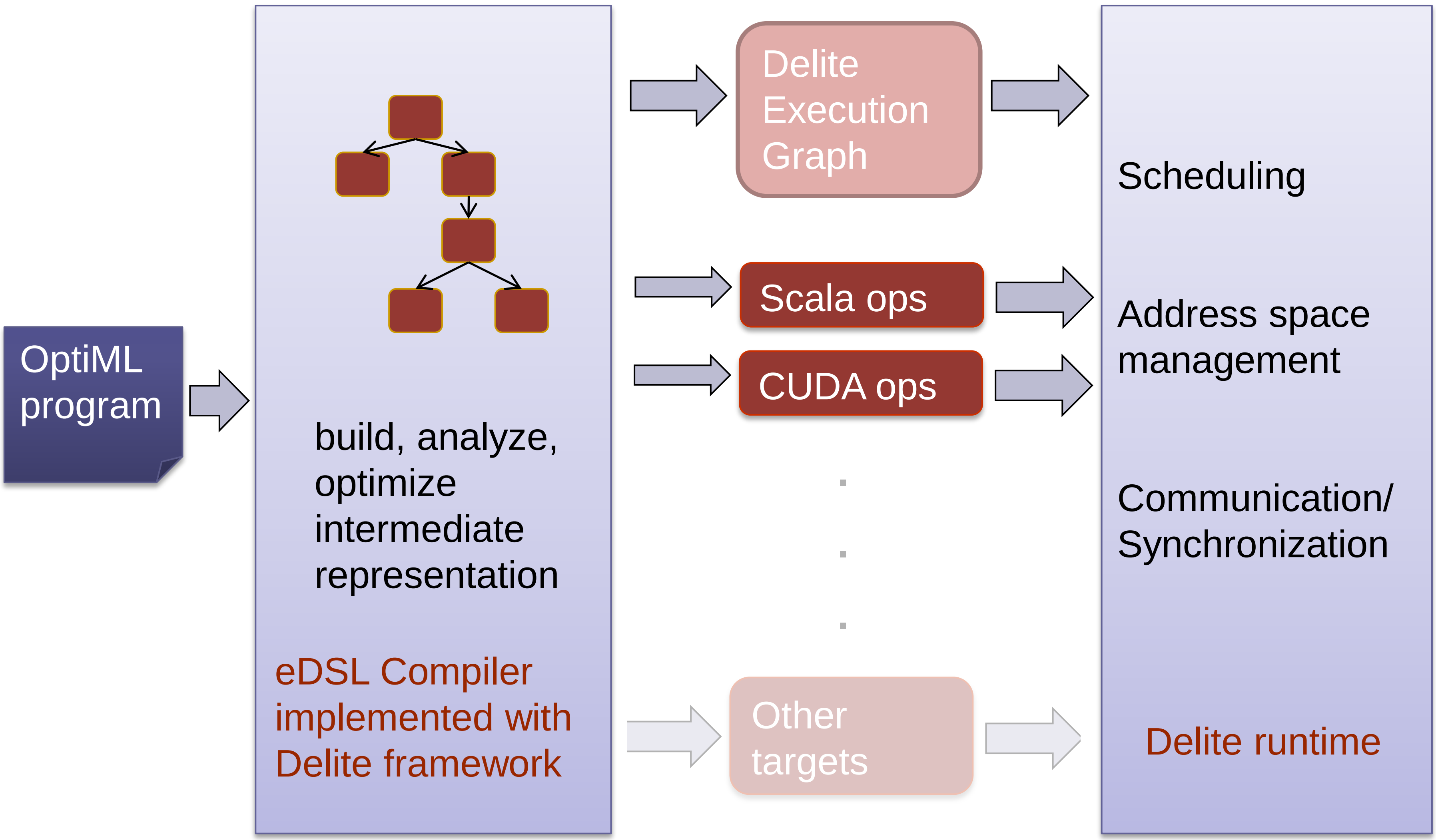
OptiML: Overview

- 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
  - Base types
    - Vector[T], Matrix[T], Graph[V,E], Stream[T]
  - Subtypes
    - TrainingSet, IndexVector, Image, …
- Implicitly parallel control structures
  - sum{…}, (0::end) {…}, gradient { … }, untilconverged { … }
  - Allow anonymous functions with restricted semantics to be passed as arguments of the control structures

Newton's Method in OptiML

```
// f, df, x0, tol, nmax inputs
var x = x0 - (f(x0)/df(x0))   // approximation to root
var ex = abs(x-x0)            // error estimate
untilconverged(ex, tol) { ex =>
  val x2 = x – (f(x)/df(x))
  val err = abs(x-x2)
  x = x2
  err
}
```

OptiML: Implementation



OptiML: Advantages

- Productive
  - Operate at a higher level of abstraction
  - Focus on algorithmic description, get parallel performance
- Portable
  - Single source => Multiple heterogeneous targets
  - Not possible with today's MATLAB support
- High Performance
  - Builds and optimizes an intermediate representation (IR) of programs
  - Generates efficient code specialized to each target

Manipulating Vectors and Matrices

```
val a = Vector(1,2,3,4,5)
val b = Matrix(a,Vector(4,5,6,7,8))
```

Literal construction

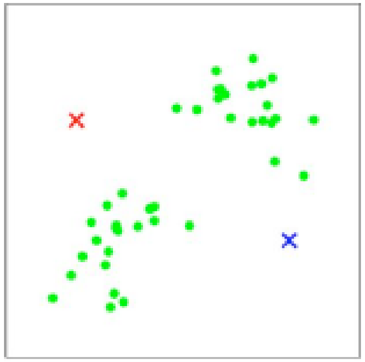
```
val c = (0::100) { i => i*2 }
val d = (0::10,0::10) { (i,j) => i*j }
val e = (0::100,*) { i =>
  Vector.rand(10)
}
```

Using vector/matrix constructor functions

```
val f = b*a.t+(c.slice(0,2)*log(2)).t
(f map { e => e + 2 }).min
```

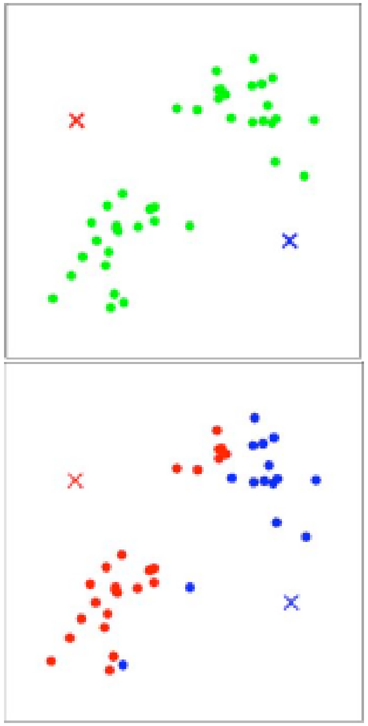
Mathematical and functional syntax

k-Means Clustering



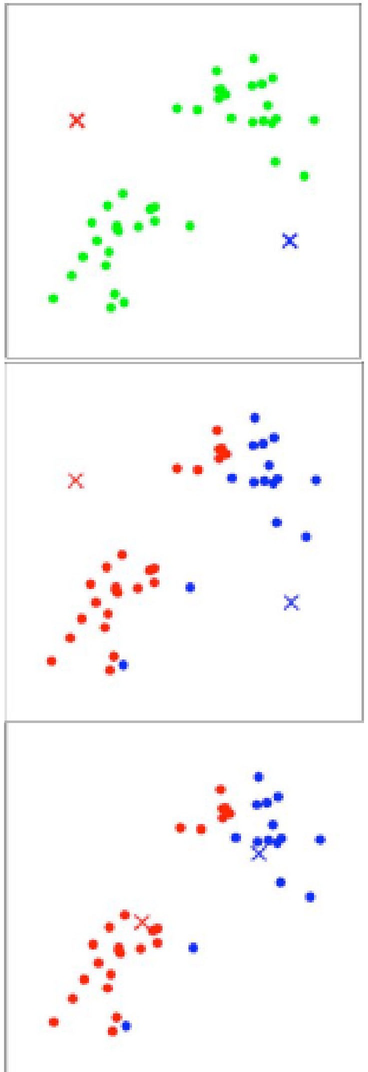
```
untilconverged(mu, tol){ mu =>
    // calculate distances to current centroids




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



}
```

k-Means Clustering



```
untilconverged(mu, tol){ mu =>
    // calculate distances to current centroids
    val c = (0::m){i =>
       val allDistances = mu mapRows { centroid =>
          dist(x(i), centroid)
       }
       allDistances.minIndex
    }

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

}
```

k-Means Clustering



```
untilconverged(mu, tol){ mu =>
    // calculate distances to current centroids
    val c = (0::m){i =>
       val allDistances = mu mapRows { centroid =>
          dist(x(i), centroid)
       }
       allDistances.minIndex
    }

    // move each cluster centroid to the
    // mean of the points assigned to it
    val newMu = (0::k,*){ i =>
       val (weightedpoints, points) = sum(0,m) { j =>
          if (c(i) == j) (x(i),1)
       }
       if (points == 0) Vector.zeros(n)
       else weightedpoints / points
    }
    newMu
}
```

OptiML vs. MATLAB

- OptiML
  - Statically typed
  - No explicit parallelization
  - Automatic GPU data management via run-time support
  - Inherits Scala features and tool-chain
  - Machine learning specific abstractions

- MATLAB
  - Dynamically typed
  - Applications must explicitly choose between vectorization or parallelization
  - Explicit GPU data management
  - Widely used, numerous libraries and toolboxes

MATLAB parallelism

- \`parfor\` is nice, but not always best
  - MATLAB uses heavy-weight MPI processes under the hood
  - Precludes vectorization, a common practice for best performance
  - GPU code requires different constructs
- The application developer must choose an implementation, and these details are all over the code

```
ind = sort(randsample(1:size(data,2),length(min_dist)));
data_tmp = data(:,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
all_dist(all_dist==0)=max(max(all_dist));
```

OptiML is Declarative and Restricted

- Allows only a small subset of Scala
- User-defined data structures must be structs (no
m
- Ar s
s!)

OptiML does not have to be conservative

Guarantees major properties (e.g. parallelizable) by construction

- Object instances cannot be mutated unless .mutable is called first

```
val v = Vector(1,2,3,4)
v(0) = 5 // compile error!
val v2 = v.mutable
v2(0) = 5
```

OptiML Optimizations

- Common subexpression elimination (CSE), Dead code elimination (DCE), Code motion
- Pattern rewritings
  - Linear algebra simplifications
  - Shortcuts to help fusing
- Op fusing
  - can be especially useful in ML due to fine-grained operations and low arithmetic intensity

Coarse-grained: optimizations happen on vectors and matrices

OptiML Linear Algebra Rewrite Example

- A straightforward translation of the Gaussian Discriminant Analysis (GDA) algorithm from the mathematical description produces the following code:

```
val sigma = sum(0,m) { i =>
  if (x.labels(i) == false) {
    ((x(i) - mu0).t) ** (x(i) - mu0)
  else
    ((x(i) - mu1).t) ** (x(i) - mu1)
  }
}
```

- A much more efficient implementation recognizes that

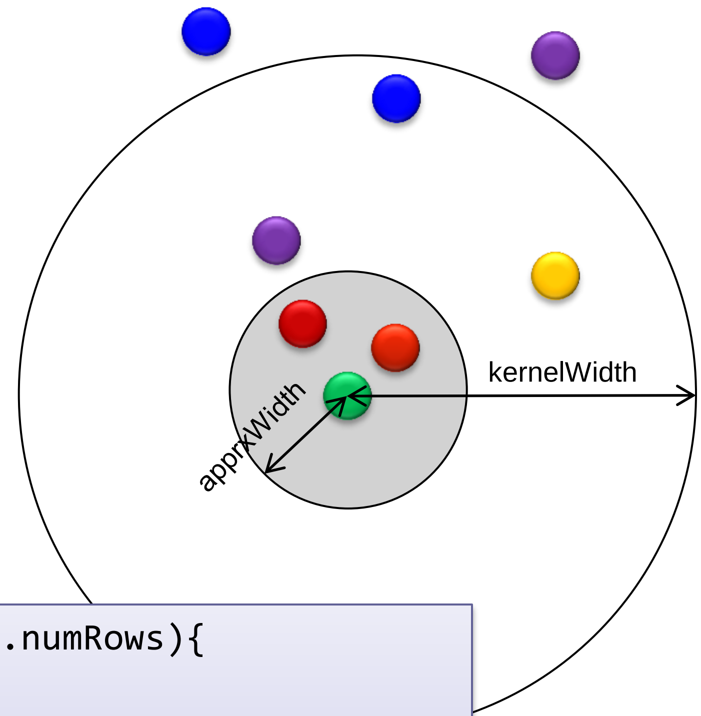
$$\sum_{i=0}^{n} \overrightarrow{x_i} * \overrightarrow{y_i} \rightarrow \sum_{i=0}^{n} X(:,i) * Y(i,:) = X * Y$$

- Transformed code was 20.4x faster with 1 thread and 48.3x faster with 8 threads.

Putting it all together: SPADE

Downsample:

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




```
val distances = Stream[Double](data.numRows, data.numRows){
  (i,j) => dist(data(i),data(j))
}

for (row <- distances.rows) {
  if(densities(row.index) == 0) {
    val neighbors = row find { _ < apprxWidth }
    densities(neighbors) = row count { _ < kernelWidth }
  }
}
```

SPADE transformations

```
val distances = Stream[Double](data.numRows, data.numRows){
  (i,j) => dist(data(i),data(j))
}

for (row <- distances.rows) {
  row.init // expensive! part of the stream foreach operation
  if(densities(row.index) == 0) {
    val neighbors = row find { _ < apprxWidth }
    densities(neighbors) = row count { _ < kernelWidth }
  }
}
```

row is 235,000 elements
in one typical dataset –
fusing is a big win!

SPADE generated code

```
// FOR EACH ELEMENT IN ROW
while (x155 < x61) {
   val x168 = x155 * x64
   var x180 = 0

   // INITIALIZE STREAM VALUE (dist(i,j))
   while (x180 < x64) {
      val x248 = x164 + x180
      // . . .
   }

   // VECTOR FIND
   if (x245) x201.insert(x201.length, x155)

   // VECTOR COUNT
   if (x246) {
      val x207 = x208 + 1; x208 = x207
   }
   x155 += 1
}
```

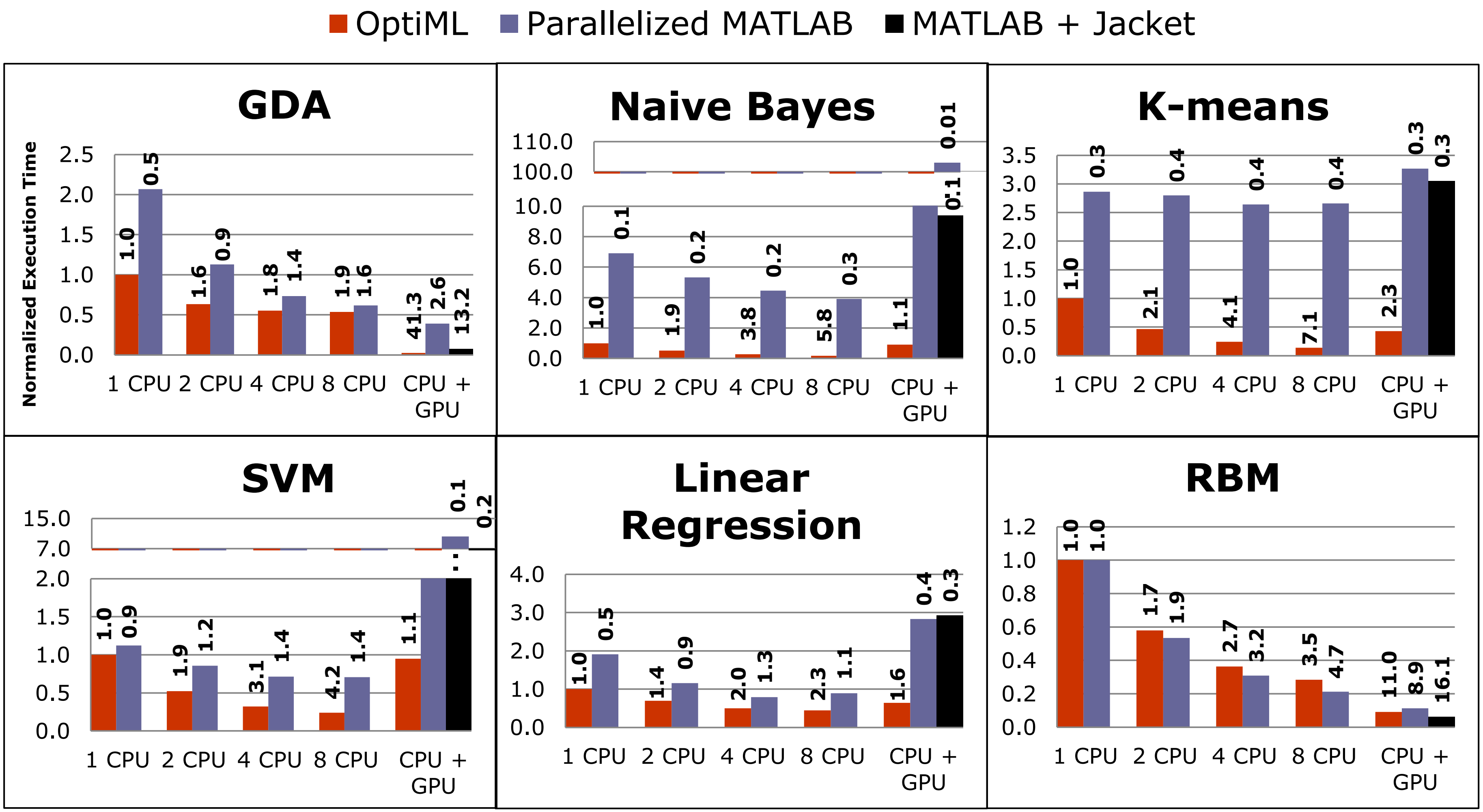
From a ~5 line algorithm description in OptiML

…to an efficient, fused, imperative version that closely resembles a hand-optimized C++ baseline!

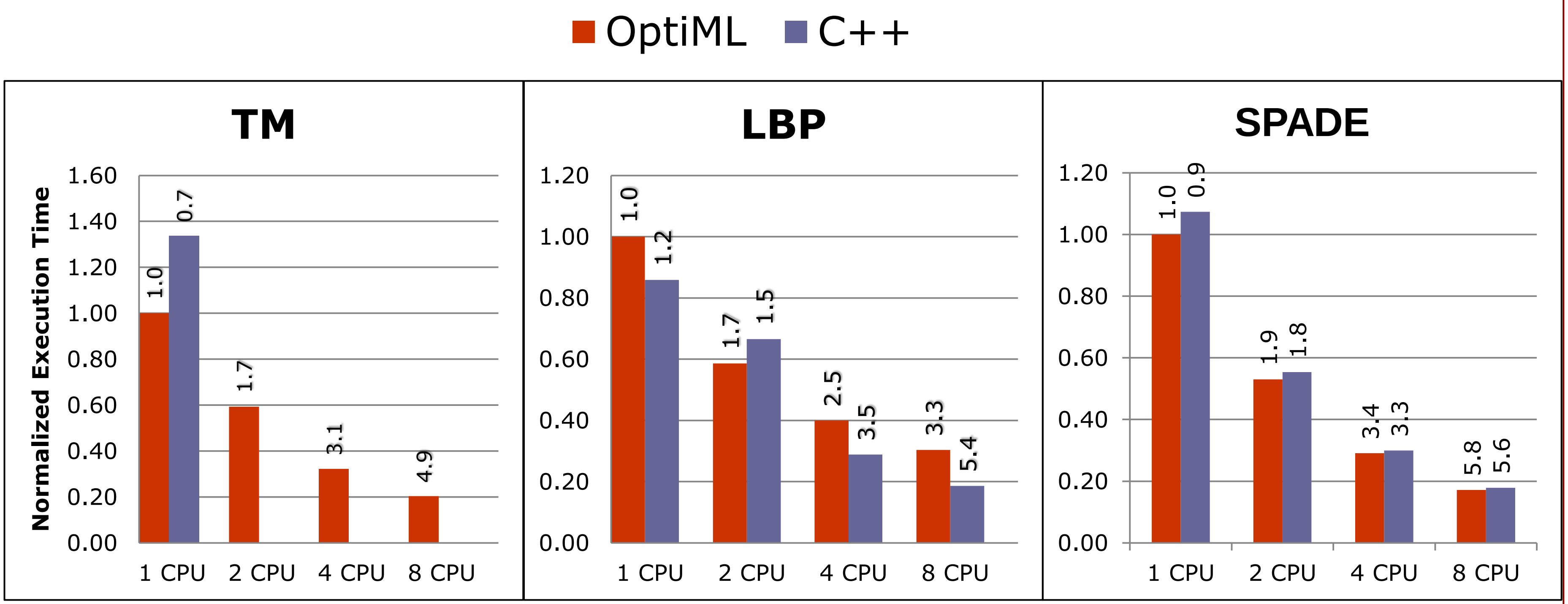
Performance Results

- Machine
  - Two quad-core Nehalem 2.67 GHz processors
  - NVidia Tesla C2050 GPU
- Application Versions
  - OptiML + Delite
  - MATLAB
    - version 1: multi-core (parallelization using "parfor" construct and BLAS)
    - version 2: MATLAB GPU support
    - version 3: Accelereyes Jacket GPU support
  - C++
    - Optimized reference baselines for larger applications

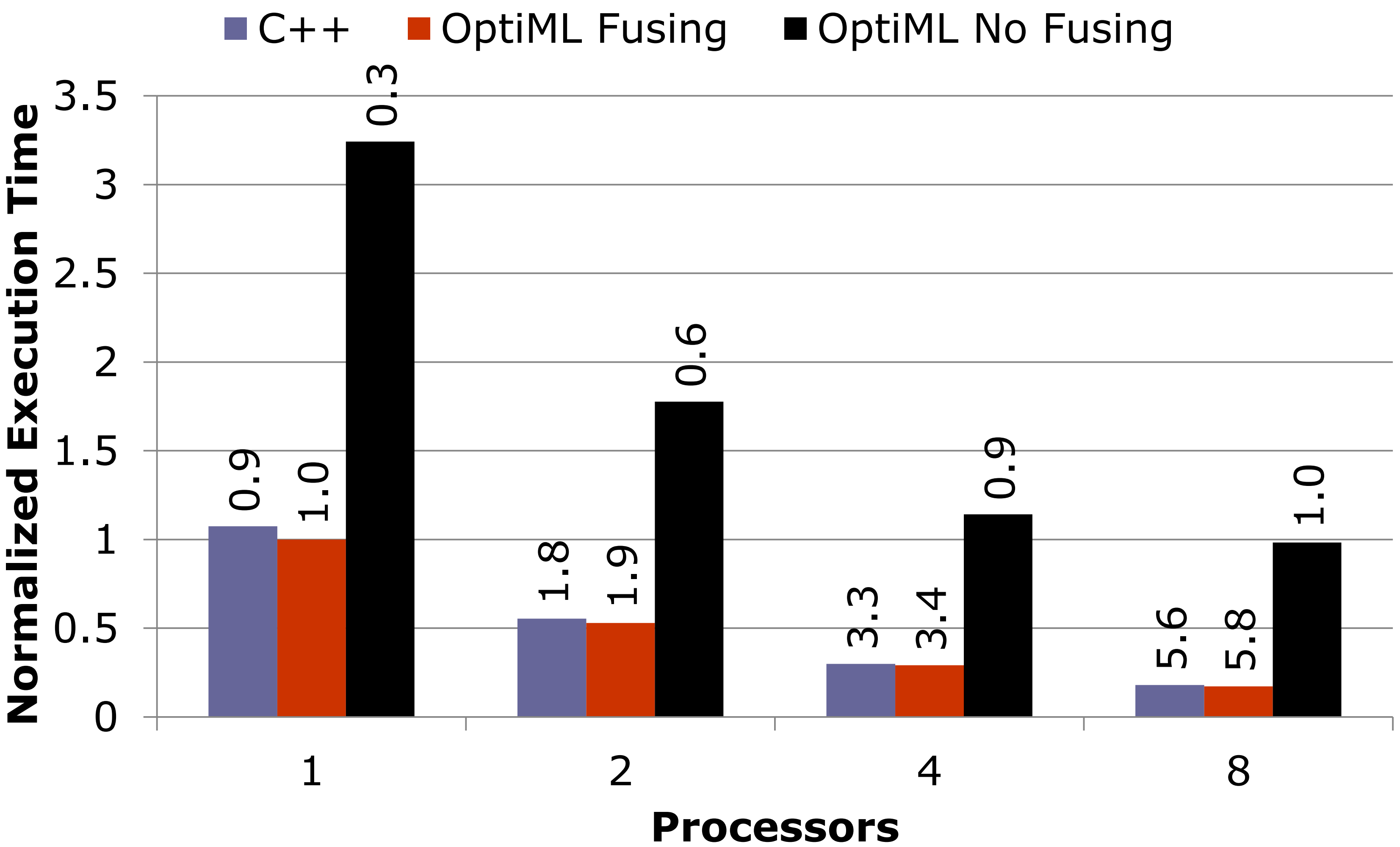
Experiments on ML kernels



Experiments on larger apps



Impact of Op Fusion



Summary

- OptiML is a proof-of-concept DSL for ML embedded in Scala using the Delite framework
- OptiML translates simple, declarative machine learning operations to optimized code for multiple platforms
- Outperforms MATLAB and C++ on a set of well- known machine learning applications

Thank you!

- Find us on Github:
  - https://github.com/stanford-ppl/Delite/optiml
- Mailing list
  - http://groups.google.com/group/optiml
- Comments and criticism welcome
- Questions?

backup

OptiML: Approach

- Encourage a functional, parallelizable style through restricted semantics
  - Fine-grained, composable map-reduce operators
- Ma
  (d

OptiML does not have to be conservative

Guarantees major properties (e.g. parallelizable) by construction

- Automatically synchronize parallel iteration over domain-specific data structures
  - Exploit structured communication patterns (nodes in a graph may only access neighbors, etc.)
- Defer as many implementation-specific details to compiler and runtime as possible

Example OptiML / MATLAB code (Gaussian Discriminant Analysis)

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

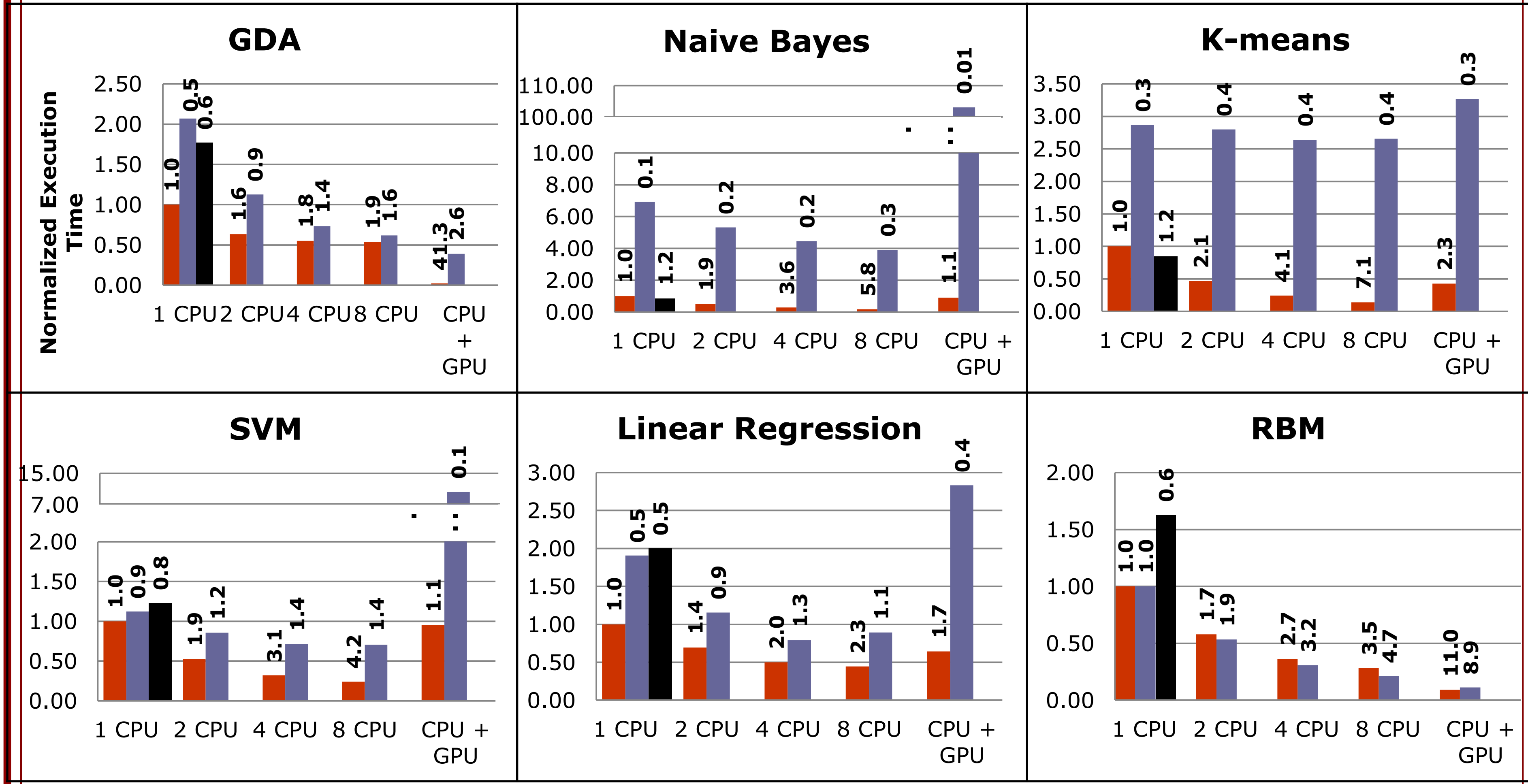
```
% x : Matrix, y: Vector
% mu0, mu1: Vector

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

Experiments on ML kernels (C++)

OptiML

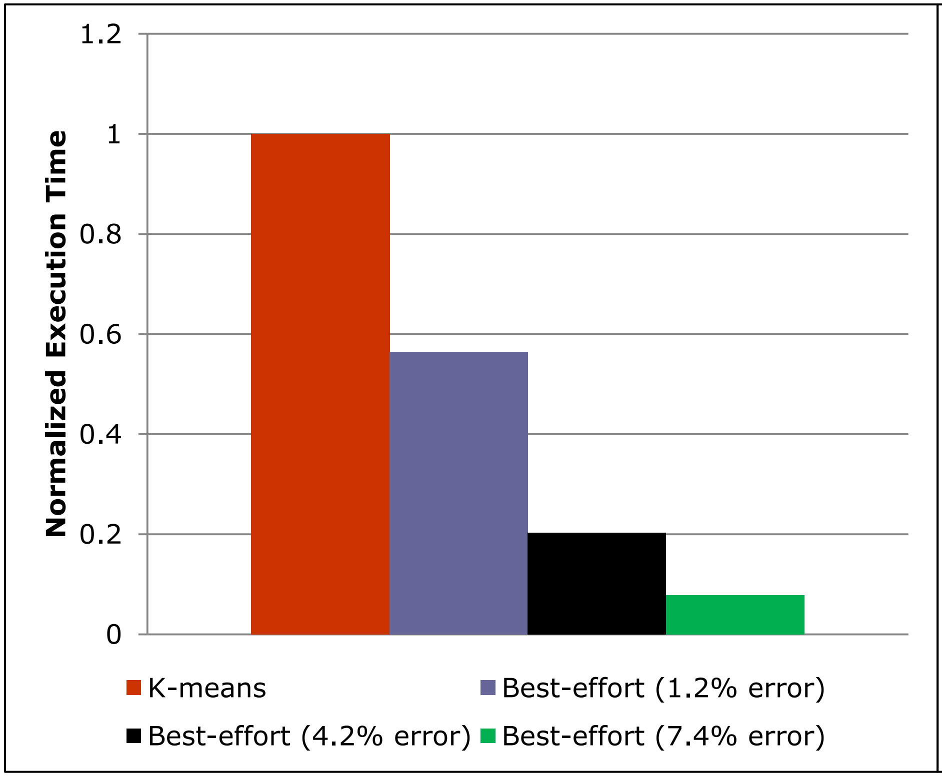


Dynamic Optimizations

- Relaxed dependencies
  - Iterative algorithms with inter-loop dependencies prohibit task parallelism
  - Dependencies can be relaxed at the cost of a marginal loss in accuracy
  - Relaxation percentage is run-time configurable
- Best effort computations
  - Some computations can be dropped and still generate acceptable results
  - Provide data structures with “best effort” semantics, along with policies that can be chosen by DSL users

Dynamic optimizations

K-means Best Effort



SVM Relaxed Dependencies