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# Autotuning Programs with Algorithmic Choice

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# High Performance Search Problem

• Parallelism

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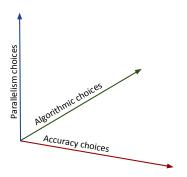
### High Performance Search Problem

- Parallelism Performance
  - Exploiting parallelism is necessary but not sufficient

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# High Performance Search Problem

#### Performance search space:



- Parallelism Performance
  - Exploiting parallelism is necessary but not sufficient
- Performance is a multi-dimensional search problem
- Normally done by expert programmers
- Optimization decisions often change program results

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## High Performance Search Problem

#### Goal of this work

To automate the process of program optimization to create programs that can adapt to changing environments and goals.

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# High Performance Search Problem

#### Goal of this work

To automate the process of program optimization to create programs that can adapt to changing environments and goals.

- Language level solutions for concisely representing algorithmic choice spaces.
- Processes and compilation techniques to manage and explore these spaces.
- Autotuning techniques to efficiently solve these search problems.

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# Research Covered in This Talk

- The PetaBricks programming language: algorithmic choice at the language level [PLDI'09]
- Language level support for variable accuracy [CGO'11]
- Automated construction of multigrid V-cycles [SC'09]
- Code generation and autotuning for heterogeneous CPU/GPU mix of parallel processing units [ASPLOS'13]
- Solution for input sensitivity based on adaptive overhead-aware classifiers [Under review]
- OpenTuner: an extensible framework for program autotuning [Under review]

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- Solution for input sensitivity based on adaptive overhead-aware classifiers [Under review]
- OpenTuner: an extensible framework for program autotuning [Under review]
- Won't be talking about work in: ASPLOS'09, ASPLOS'12, GECCO'11, IPDPS'09, PLDI'11, and many others

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### A Motivating Example for Algorithmic Choice

• How would you write a *fast* sorting algorithm?

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# A Motivating Example for Algorithmic Choice

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- Insertion sort
- Quick sort
- Merge sort
- Radix sort

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# A Motivating Example for Algorithmic Choice

• How would you write a *fast* sorting algorithm?

- Insertion sort
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- Radix sort
- Poly-algorithms

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#### std::stable\_sort

```
/usr/include/c++/4.5.2/bits/stl_algo.h lines 3350-3367
/// This is a helper function for the stable sorting routines.
template<typename RandomAccessIterator>
  void
  inplace stable sort( RandomAccessIterator first,
                      RandomAccessIterator last)
  {
    if ( last - first < 15)
      ł
        std:: insertion sort( first, last);
        return:
    RandomAccessIterator middle = first + ( last - first) / 2;
    std:: inplace stable sort( first, middle);
    std:: inplace stable sort( middle, last);
    std:: merge without buffer( first, middle, last,
                                middle first,
                              last - middle);
  }
```

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#### std::stable\_sort

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      Ł
        std:: insertion sort( first, last);
        return:
    RandomAccessIterator middle = first + ( last - first) / 2;
    std:: inplace stable sort( first, middle);
    std:: inplace stable sort( middle, last);
    std:: merge without buffer( first, middle, last,
                                middle - first,
                              last - middle);
  }
```

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# Why 15?

• Why 15?

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# Why 15?

- Why 15?
- Dates back to at least 2000 (June 2000 SGI release)
- Still in current C++ STL shipped with GCC
- cutoff = 15 survived 10+ years
- In the source code for millions<sup>1</sup> of C++ programs
- There is nothing the compiler can do about it

<sup>1</sup>Any C++ program with "#include <algorithm>", conservative estimate based on: http://c2.com/cgi/wiki?ProgrammingLanguageUsageStatistics

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# Is 15 The Right Number?

- The best cutoff (CO) changes
- Depends on competing costs:
  - Cost of computation (< operator, call overhead, etc)
  - Cost of communication (swaps)
  - Cache behavior (misses, prefetcher, locality)

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# Is 15 The Right Number?

- The best cutoff (CO) changes
- Depends on competing costs:
  - Cost of computation (< operator, call overhead, etc)
  - Cost of communication (swaps)
  - Cache behavior (misses, prefetcher, locality)
- Sorting 100000 doubles with std::stable\_sort:
  - $CO \approx 200$  optimal on a Phenom 905e (15% speedup)
  - $CO \approx 400$  optimal on a Opteron 6168 (15% speedup)
  - $CO \approx 500$  optimal on a Xeon E5320 (34% speedup)
  - $CO \approx 700$  optimal on a Xeon X5460 (25% speedup)
- If the best cutoff has changed, perhaps best algorithm has also changed

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#### Algorithmic Choice

- Compiler's hands are tied, it is stuck with 15
- Need a better way to represent algorithmic choices
- PetaBricks is the first language with support for algorithmic choice

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#### Sort in PetaBricks

```
Language
```

```
function Sort
to out[n]
from in [n]
{
  either {
    InsertionSort(out, in);
  }
   or {
    QuickSort(out, in);
  } or {
    MergeSort(out, in);
  }
    or {
    RadixSort(out, in);
  }
}
```

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### Sort in PetaBricks

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Language
```

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```

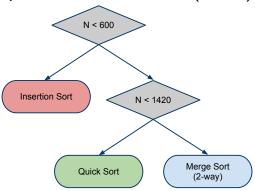
#### Representation

⇒ Decision tree synthesized by our autotuner

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## **Decision Trees**

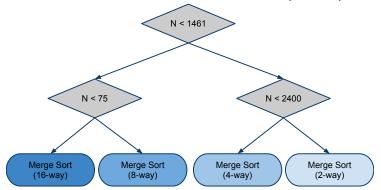
Optimized for a Xeon E7340 (8 cores):



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### **Decision Trees**

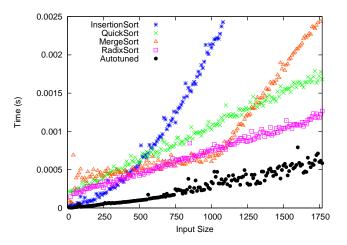
Optimized for Sun Fire T200 Niagara (8 cores):



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# Sort Algorithm Timings<sup>2</sup>

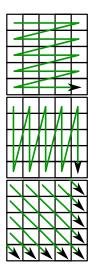


<sup>2</sup>On an 8-way Xeon E7340 system

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# Iteration Order Choices



- Many other choices related to execution order
  - By rows?
  - By columns?
  - Diagonal? Reverse order? Blocked?
  - Parallel?
- Choices both within a single (possibly parallel) task and between different tasks

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# Iteration Order Choices



- Many other choices related to execution order
  - By rows?
  - By columns?
  - Diagonal? Reverse order? Blocked?
  - Parallel?
  - Choices both within a single (possibly parallel) task and between different tasks
- This is main motivation for a new language as opposed to a library

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# Synthesized Outer Control Flow

- PetaBricks programs have synthesized outer control flow
  - Declarative (data flow like) outer syntax
  - Imperative inner code
- Programs start as completely parallel
- Added dependencies restrict the space of legal executions
- May only access data explicitly depended on

Parallel loop

X.cell(i) from() { ... }

### Sequential loop

X. cell(i) from(X. cell(i-1) left) { ... }

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### Matrix Multiply

```
transform MatrixMultiply
to AB[w,h]
from A[c,h], B[w,c]
{
    AB.cell(x,y) from(A.row(y) a, B.column(x) b){
        return dot(a, b);
    }
}
```

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### Matrix Multiply

```
transform MatrixMultiply
to AB[w,h]
from A[c,h], B[w,c]
ł
 AB. cell(x,y) from (A.row(y) a, B.column(x) b)
    return dot(a, b);
  }
  to (AB. region (x, y, x + 4, y + 4) out)
  from (A, region (0, y, c, y + 4)) a,
       B. region (x, 0, x + 4, c) b
     // ... compute 4 x 4 block ...
 }
}
```

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#### Strassen Matrix Multiply

```
transform Strassen
to AB[n,n]
from A[n,n], B[n,n]
using M1[n/2, n/2], M2[n/2, n/2], M3[n/2, n/2], M4[n/2, n/2],
     M5[n/2, n/2], M6[n/2, n/2], M7[n/2, n/2]
  to(M1 m1)
  from (A. region (0, 0, n/2, n/2) all,
      A. region (n/2, n/2, n, n) a22,
      B. region (0, 0, n/2, n/2) b11,
      B. region (n/2, n/2, n, n) b22)
  using(t1[n / 2, n / 2], t2[n/2, n / 2]) {
    spawn MatrixAdd(t1, a11, a22);
    spawn MatrixAdd(t2, b11, b22);
    sync;
    Strassen(m1, t1, t2);
  }
  // Compute one quadrant of output with strassen decomposition
  to(AB.region(n/2, 0, n, n/2) c12) from(M3 m3, M5 m5){
    MatrixAdd(c12, m3, m5);
  }
 // Or, compute element in output directly (same as last slide)
 AB. cell(x,y) from (A.row(y) a, B.column(x) b)
    return dot(a, b);
  }
```

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# Variable Accuracy Algorithms

- Many problems don't have a single correct answer, optimizations often trade-off accuracy and performance.
  - Soft computing
  - DSP algorithms
  - Iterative algorithms

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# Variable Accuracy Algorithms

- Many problems don't have a single correct answer, optimizations often trade-off accuracy and performance.
  - Soft computing
  - DSP algorithms
  - Iterative algorithms
- Variable accuracy, supported in the PetaBricks language, is a fundamental part of algorithmic choice which enables new classes of programs to be represented.

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#### K-Means Example

```
transform kmeans
from Points [n,2] // Array of points (each column
                 // stores x and y coordinates)
using Centroids [sqrt(n),2]
to Assignments[n]
 // Rule 1:
  // One possible initial condition: Random
  // set of points
  to(Centroids.column(i) c) from(Points p) {
    c=p.column(rand(0,n))
  }
 // Rule 2:
  // Another initial condition: Centerplus initial
  // centers (kmeans++)
  to(Centroids c) from(Points p) {
    CenterPlus(c, p);
  }
  // Rule 3:
  // The kmeans iterative algorithm
  to(Assignments a) from(Points p, Centroids c) {
    while (true) {
      int change;
      AssignClusters(a, change, p, c, a);
      if (change==0) return; // Reached fixed point
      NewClusterLocations(c, p, a);
   }
  }
```

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### K-Means Example (Variable Accuracy)

```
transform kmeans
accuracy_metric kmeansaccuracy
accuracy_variable k
from Points [n,2] // Array of points (each column
                 // stores x and y coordinates)
using Centroids [k,2]
to Assignments [n]
     Rule 3:
  // The kmeans iterative algorithm
  to(Assignments a) from(Points p, Centroids c) {
    for_enough {
      int change:
      AssignClusters(a, change, p, c, a);
      if (change==0) return; // Reached fixed point
      NewClusterLocations(c, p, a);
  }
transform kmeansaccuracy
from Assignments[n], Points[n,2]
to Accuracy
  Accuracy from (Assignments a, Points p) {
    return sqrt(2*n/SumClusterDistanceSquared(a,p));
```

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### Semantics of Variable Accuracy

Running the *accuracy\_metric* on the output will return a value that, in expectation, exceeds the *accuracy target* more than P percent of the time.

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# Semantics of Variable Accuracy

Running the *accuracy\_metric* on the output will return a value that, in expectation, exceeds the *accuracy target* more than P percent of the time.

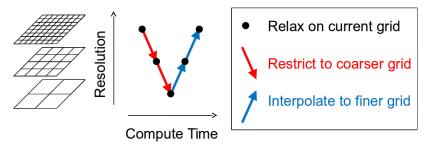
- Expected distribution of accuracy measured during autotuning time, not at runtime.
- When *fixed accuracy* code calls *variable accuracy* code, an accuracy target must be specified.
- When *variable accuracy* code call code containing *variable accuracy* components, only the outer most accuracy target will be honored.



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# A Brief Multigrid Intro

- Used to iteratively solve PDEs over a gridded domain
- Relaxations update points using neighboring values (stencil computations)
- Restrictions and Interpolations compute new grid with coarser or finer discretization

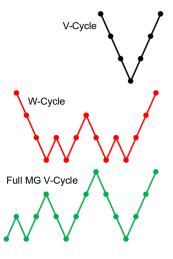


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# Standard Cycle Shaps

- Cycle shapes effect accuracy and performance
  - Equation, accuracy target, data, and execution platform effect efficacy of different shapes
- Entire papers published about new cycle shapes!

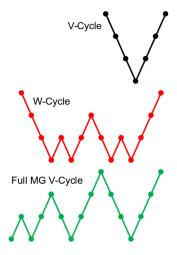


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# Standard Cycle Shaps

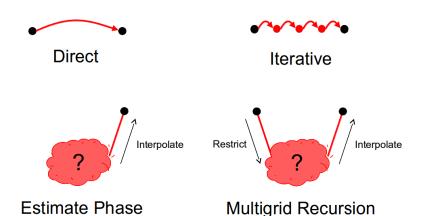
- Cycle shapes effect accuracy and performance
  - Equation, accuracy target, data, and execution platform effect efficacy of different shapes
- Entire papers published about new cycle shapes!
- We fundamentally change the status quo in this domain
  - Define the search space of cycle shapes once
  - Autotune to find a cycle shape tailored to *your* problem



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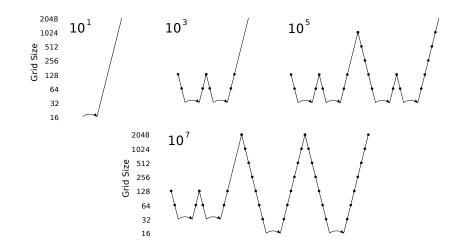
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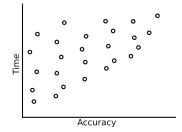
## Autotuned V-cycle Shapes



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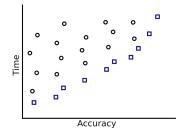
Dynamic Programming Technique for Autotuning Multigrid



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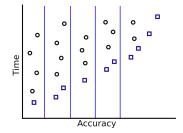
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Dynamic Programming Technique for Autotuning Multigrid



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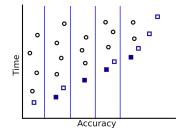
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Partition accuracy space into discrete levels

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Dynamic Programming Technique for Autotuning Multigrid



Partition accuracy space into discrete levels

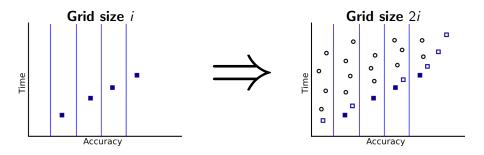
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Conclusions

Dynamic Programming Technique for Autotuning Multigrid

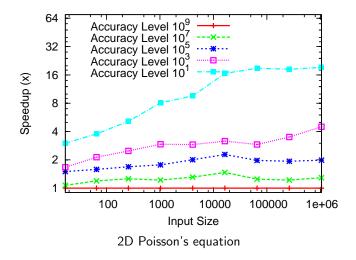


- Partition accuracy space into discrete levels
- Base space of candidate algorithms on optimal algorithms from coarser level

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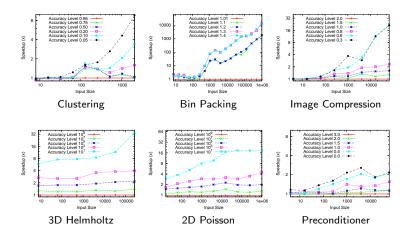
#### 2D Poisson's Equation (uses Multigrid)



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#### More Variable Accuracy Results



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## Results on Different Systems

#### **Test Systems**

Codename	CPU(s)	Cores	GPU	OpenCL Runtime
Desktop	Core i7 920 @2.67GHz	4	NVIDIA Tesla C2070	CUDA Toolkit 3.2
Server	4× Xeon X7550 @2GHz	32	None	AMD APP SDK 2.5
Laptop	Core i5 2520M @2.5GHz	2	AMD Radeon HD 6630M	Xcode 4.2

#### **Benchmarks**

Name	# Possible Configs	Generated OpenCL Kernels	Mean Autotuning Time	Testing Input Size
SeparableConv.	10 <sup>1358</sup>	9	3.82 hours	3520 <sup>2</sup>
Black-Sholes	10 <sup>130</sup>	1	3.09 hours	500000
Poisson2D SOR	10 <sup>1358</sup>	25	15.37 hours	2048 <sup>2</sup>
Sort	10 <sup>920</sup>	7	3.56 hours	2 <sup>20</sup>
Strassen	10 <sup>1509</sup>	9	3.05 hours	1024 <sup>2</sup>
SVD	10 <sup>2435</sup>	8	1.79 hours	256 <sup>2</sup>
Tridiagonal Solver	10 <sup>1040</sup>	8	5.56 hours	1024 <sup>2</sup>

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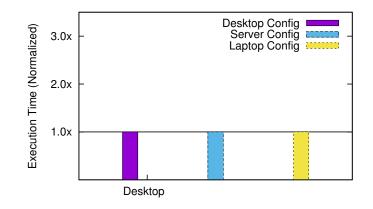
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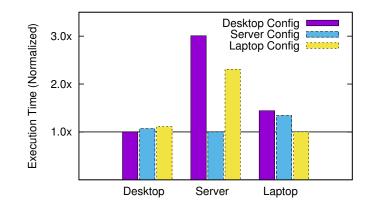
### Separable Convolution (width=7)



	Desktop Config	Server Config	Laptop Config
SeparableConv.	1D kernel+local memory on GPU	1D kernel on OpenCL	2D kernel+local memory on GPU

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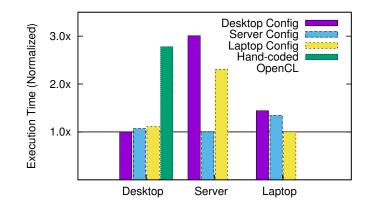
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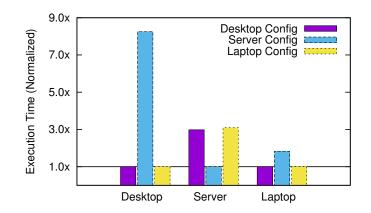
### Separable Convolution (width=7)



	Desktop Config	Server Config	Laptop Config
SeparableConv.	1D kernel+local memory on GPU	1D kernel on OpenCL	2D kernel+local memory on GPU

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## Poisson 2D SOR

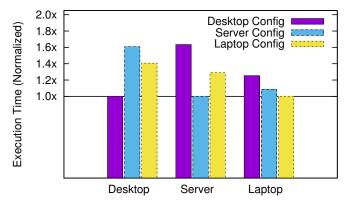


	Desktop Config	Server Config	Laptop Config
	Split on CPU followed by	Split some parts on OpenCL	Split on CPU followed by
PUISSUIIZD SUK	compute on GPU	followed by compute on CPU	compute on GPU



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## Singular Value Decomposition (SVD)



	Desktop Config	Server Config	Laptop Config
SVD	First phase: task parallism be- tween CPU/GPU; matrix multi- ply: 8-way parallel recursive de- composition on CPU, call LA- PACK when $< 42 \times 42$	First phase: all on CPU; ma- trix multiply: 8-way parallel re- cursive decomposition on CPU, call LAPACK when < 170×170	trix multiply: 4-way parallel re- cursive decomposition on CPU,

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## **Results Takeaways**

- Different configurations are required for best performance on different systems
- Not just changing block sizes
- Can not be easily solved by a simple heuristic
- Motivates the need for algorithmic choice and autotuning

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# Autotuning Challenges

- Evaluating quality of candidate algorithms is expensive
  - Must run the program (at least once)
  - More expensive for unfit solutions
  - Scales poorly with larger problem sizes
- Fitness is noisy
  - Randomness from parallel races and system noise
  - Testing each candidate only once often produces a worse algorithm
  - Running many trials is expensive
- Decision tree structures are complex
  - Not easy to hill-climb
  - We artificially bound them

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## Input Sensitivity

- Input sensitivity is a major challenge
- Different algorithms may be better for different inputs
- Use fast algorithm for easy inputs, slow algorithm for hard inputs
- Avoid pathological cases

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## Input Sensitivity Today

- Vast majority of programs today use a single algorithm for all inputs
  - This forces design for the "worst case" input
  - Wastes time and resources

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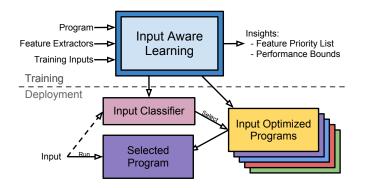
## Input Sensitivity Today

- Vast majority of programs today use a single algorithm for all inputs
  - This forces design for the "worst case" input
  - Wastes time and resources
- Related work:
  - Uses hand written heuristics to adapt to inputs
  - Rectify inputs for security [Long el al.]
- Our system automatically classifies inputs and runs a program optimized for the type of input being processed

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## Input Sensitivity Overview



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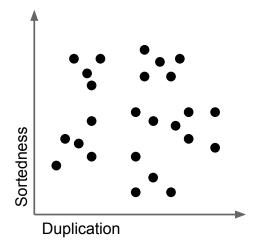
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#### Input Features

```
function Sort
to out[n]
from in [n]
input_feature Sortedness, Duplication
{ ... }
function Sortedness
from in [n]
to sortedness
tunable double level (0.0, 1.0)
  int sortedcount = 0;
  int count = 0:
  int step = (int)(level*n);
  for(int i=0; i+step < n; i+=step) {
    if(in[i] <= in[i+step]) {
      // increment for correctly ordered
      // pairs of elements
      sortedcount += 1:
    count += 1;
  if(count > 0)
    sortedness = sortedcount / (double) count;
  else
    sortedness = 0.0:
function Duplication
from in [n]
to duplication
\{ ... \}
```

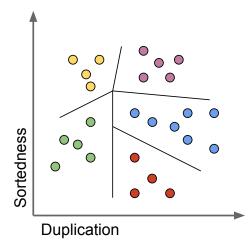
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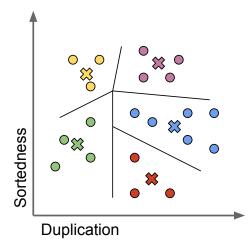
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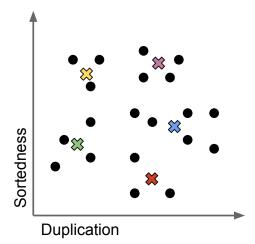
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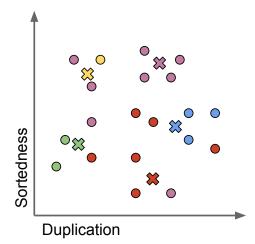
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PetaBricks

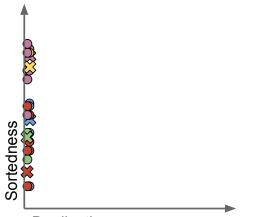
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# Input Space Sampling

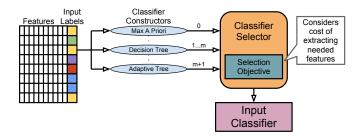


Duplication

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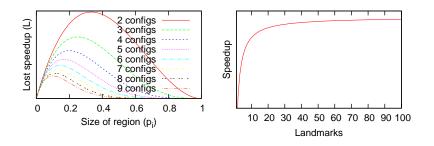
# Training



PetaBricks

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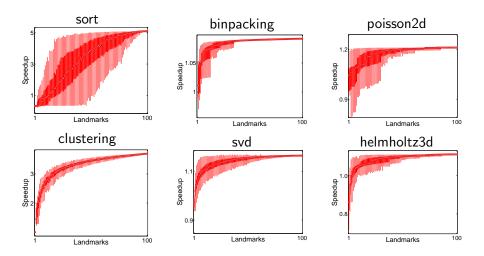
## How Many Landmarks Are Enough?



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#### Input Adaptation Results



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#### **Related Projects**

#### A small selection of many related projects:

Package	Domain	Search Method
Active Harmony	Runtime System	Nelder-Mead
ATLAS	Dense Linear Algebra	Exhaustive
Code Perforation	Compiler	Exhaustive + Simulated Annealing
Dynamic Knobs	Runtime System	Control Theory
FFTW	Fast Fourier Transform	Exhaustive / Dynamic Prog.
Insieme	Compiler	Differential Evolution
Milepost GCC / cTuning	Compiler	IID Model + Central DB
OSKI	Sparse Linear Algebra	Exhaustive + Heuristic
PATUS	Stencil Computations	Nelder-Mead or Evolutionary
SEEC / Heartbeats	Runtime System	Control Theory
Sepya	Stencil Computations	Random-Restart Gradient Ascent
SPIRAL	DSP Algorithms	Pareto Active Learning

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SPIRAL	DSP Algorithms	Pareto Active Learning

- Simple techniques (exhaustive, hill climbers, etc) are popular
  - No single technique is best for all problems
- Representations are often just integers/floats/booleans

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# Limits of Existing Autotuning Projects

- We believe these factors limit the scope and efficiency of autotuning
- A hill climber works great for a block size, but completely fails at synthesizing poly-algorithms
- Many users of autotuning work hard to prune their search spaces to fit their techniques

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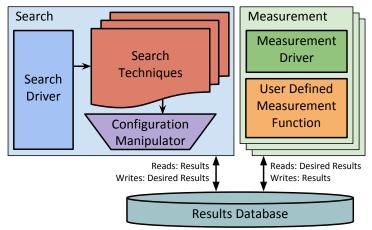
# Limits of Existing Autotuning Projects

- We believe these factors limit the scope and efficiency of autotuning
- A hill climber works great for a block size, but completely fails at synthesizing poly-algorithms
- Many users of autotuning work hard to prune their search spaces to fit their techniques
- OpenTuner provides extensible representations and ensembles of techniques which can solve more complex autotuning problems

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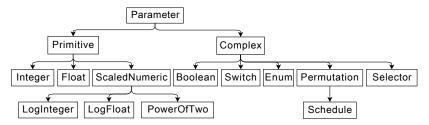
## **OpenTuner** Overview

OpenTuner: an extensible framework for program autotuning



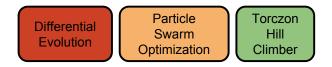
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# **OpenTuner Configuration Manipulator Parameters**

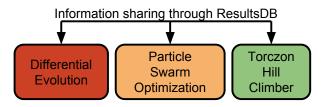


- Hierarchical structure of parameters, user defined parameter types can be added at any point
- Primitive parameters behave like bounded integers or floats
- Complex parameters have a set of stochastic mutation operators
- Technique-specific operators

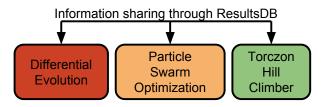
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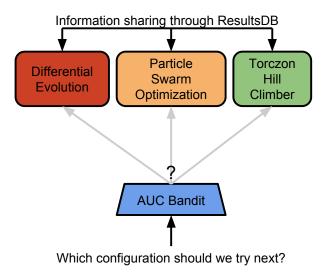


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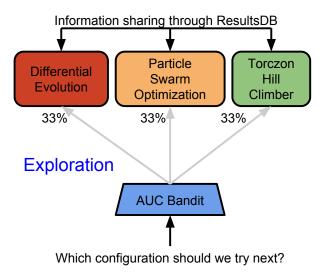




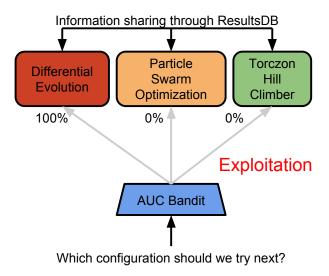
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## **OpenTuner** Results

Project	Benchmark	Possible Configurations
GCC/G++ Flags	all	10 <sup>806</sup>
Halide	Blur	10 <sup>52</sup>
Halide	Wavelet	10 <sup>44</sup>
HPL	n/a	10 <sup>9.9</sup>
PetaBricks	Poisson	10 <sup>3657</sup>
PetaBricks	Sort	10 <sup>90</sup>
PetaBricks	Strassen	10 <sup>188</sup>
PetaBricks	TriSolve	10 <sup>1559</sup>
Stencil	all	10 <sup>6.5</sup>
Unitary	n/a	10 <sup>21</sup>

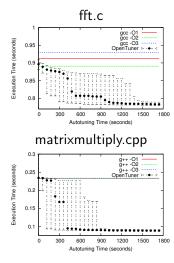
OpenTuner 000000000 Conclusions 000

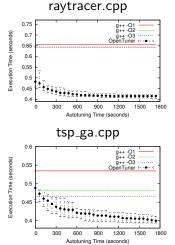
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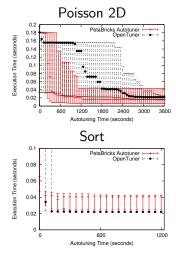
#### **OpenTuner Results: GCC Flags**

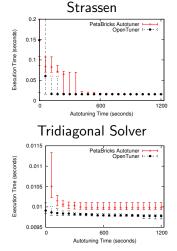




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#### OpenTuner Results: PetaBricks





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## Conclusions

- PetaBricks has pushed the limits of what can be done with algorithmic choice
  - Provides performance portability by allowing programs to adapt to their environment
  - Have shown: variable accuracy, multigrid, and input sensitivity
  - Hope that future main stream programming languages will incorperate algorithmic choice and autotuning
- OpenTuner can expand the scope of program autotuning for other projects
  - Extensible configuration representation
  - Ensembles of techniques
  - Hope that field of autotuning will expand to much more complex problems

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- Yufei Ding
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- Sam Fingeret
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- Shoaib Kamil
- Kevin Kelley
- Erika Lee
- Deepak Narayanan
- Marek Olszewski
- Una-May O'Reilly

- Maciej Pacula
- Phitchaya Mangpo Phothilimthana
- Jonathan Ragan-Kelley
- Xipeng Shen
- Michele Tartara
- Kalyan Veeramachaneni
- Yod Watanaprakornku
- Yee Lok Wong
- Kevin Wu
- Minshu Zhan
- Qin Zhao

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#### Thanks!

About me:

http://jasonansel.com/



http://opentuner.org/



http://projects.csail.mit.edu/petabricks/