PetaBricks and Julia

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Backgroun

Approach

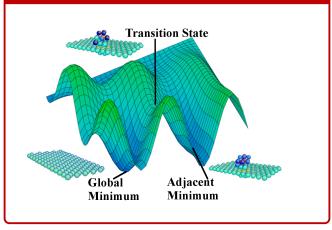
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The Programmer's Dilemma





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The Programmer's Dilemma

which algorithm is best? 1 #ifndef EIGENFINDHEADERDEF 2 #define EIGENFINDHEADERDEF 4 #include <iostream> 5 #include <cmath> 6 #include "Vector.hpp" 7 #include "Matrix.hpp" 8 #include "BLAS.hpp' 10 #include "Atom.hpp" 11 #include "RW.hpp" 12 #include "RunLammps.hpp" 14 using namespace std: 16 double LanczosNew(Vector &eigenvector, int lanczos number, vector<Atom> atoms_old, ofstream &outfile, char* filename, 18 char* newfile, int mynode, char* hess lammps, char* hess data, 19 int dim, int local_count); 20 double LanczosHess(Vector &eigenvector, Matrix &hess, int lanczos number); 21 void getForces(vector<Atom> &atoms_old, Vector r, Vector &forces_new, 22 ofstream &outfile. char* filename. char* newfile. int mynode. char* hess lammps. char* hess_data, int dim); 24 void getForces2ndOrder(vector<Atom> &atoms old, Vector r, Vector &forces new, ofstream &outfile, char* filename, char* newfile, int mynode, char* hess lammps, 26 char* hess data. int dim): 27 void getForces(vector<Atom> &atoms new, Vector &forces new, 28 ofstream &outfile. char* filename. char* newfile. int mynode. char* hess lammps. 29 char* hess data, int dim); 30 double TDISPowerMethod(int size, Vector &a, Vector &b, Vector &O, int freq, float shift): 31 double ORSolver(Vector &a, Vector&b, Vector &y, int size); 32 void QRdecomp(Matrix A, Matrix &Q, Matrix &R, int size); 33 double Householder(Vector &w, Matrix &A, int index, int size);

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The Programmer's Dilemma



Goal: determine the best algorithm for the applicationwhich may be machine dependent Approach

Results

Parallel Programming

| 1#LIDdef EIGENFINDHEADERDEF |
|----------------------------------------------------------------------------------------------------------------------------------------------------------|
| 2 #define ELGENEINDHEADERDEE |
| 3 |
| 4 #include <iostrean></iostrean> |
| 5 #include <cnath></cnath> |
| 6 #include "Vector.hpp" |
| 7 Winclude "Matrix.hpp" |
| 8 #lnclude "BLAS.hpp" |
| 9 |
| 10 #include "Atom.hpp" |
| 11 #include "RW.hpp" |
| 12 #include "RunLammps.hpp" |
| 13 |
| 14 using namespace std; |
| 15 |
| 16 double LanczosNew(Vector &eigenvector, int lanczos_number, 17 vector <atom> atoms old, ofstream &outfile, char* filename.</atom> |
| 1/ Vector <atoms aduttie,="" atoms_old,="" cmar*="" filename,<br="" orstream="">18 char* newfile, int nynode, char* hess lamps, char* hess data.</atoms> |
| 10 char's newrite, the hymode, char's ness_tamps, char's ness_oata, 19 int dim. int local count): |
| 20 double LanczosHess(Vector & delegevector, Matrix &hess, int lanczos number): |
| 21 void getForces(vector-Atoms &atoms old, Vector r. Vector &forces new. |
| 22 ofstream &outfile, char* filename, char* newfile, int mynode, char* hess lammps, |
| 23 char* hess data, int dim): |
| 24 void getForces2nd0rder(vector <atom> &atoms old, Vector r, Vector &forces new,</atom> |
| 25 ofstream &outfile, char* filename, char* newfile, int nynode, char* hess lamps, |
| 26 char* hess data, int din); |
| 27 void getForces(vector <aton> &atons_new, Vector &forces_new,</aton> |
| 28 ofstream &outfile, char* filename, char* newfile, int mynode, char* hess_lammps, |
| 29 char* hess_data, int dim); |
| 30 double TDISPowerMethod(int size, Vector &a, Vector &b, Vector &Q, int freq, float shift); |
| 31 double QRSolver(Vector &a, Vector&b, Vector &y, int size); |
| 32 void QRdecomp(Matrix A, Matrix &Q, Matrix &R, int size); |
| 33 double Householder(Vector &w, Matrix &A, int index, int size); |
| |
| |

- many parts of these algorithms can be written in parallel
- often they can be parallelized in many different ways
- optimizing these options is a challenge

Determine the best way to parallelize the programwhich will be machine dependent Approach

Results

Parallel Programming

| 1#\fodef EIGENFINDHEADERDEF |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 2 #define EIGENFINDHEADERDEF |
| a solution crock interpreter |
| 4 #include <iostrean></iostrean> |
| S #include <cnath></cnath> |
| 6 #include 'Vector.hpp' |
| 7 #include "Natrix.hpp" |
| 8 #include "BLAS.hpp" |
| 9 |
| 10 #include "Atom.hop" |
| 11#include "RN.hpp" |
| 12 #include "RunLamps.hpp" |
| 13 |
| 14 using namespace std; |
| 15 |
| 16 double LanczosNew(Vector &eigenvector, int lanczos_number, |
| 17 vector <aton> atons_old, ofstream &outfile, char* filename,</aton> |
| 18 char* newfile, int mynode, char* hess_lammps, char* hess_data, |
| 19 int dim, int local_count); |
| 20 double LanczosHess(Vector &eigenvector, Matrix &hess, int lanczos_number); |
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| 22 ofstream &outfile, char* filename, char* newfile, int mynode, char* hess_lammps, |
| 23 char* hess_data, int dim); |
| 24 void getForces2ndOrder(vector <aton> &atoms_old, Vector r, Vector &forces_new,</aton> |
| 25 ofstream &outfile, char* filename, char* newfile, int mynode, char* hess_lammps, |
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| 28 ofstream aduttite, char filename, char newrite, int mynode, char mess_lammps, 29 char hess data int dim): |
| 30 double TDISPowerMethod(int size, Vector &a, Vector &b, Vector &0, int freq, float shift); |
| 31 double ORSolver(Vector &a, Vector &a, Vector av, int size): |
| 32 void ORdecomp(Natrix A, Matrix 80, Matrix 84, int size); |
| 33 double Householder (Vector aw. Matrix &A. int index. int size): |
| so debte nosenotari (vector av, net tx av, the thexx, the stee), |
| |
| |

- many parts of these algorithms can be written in parallel
- often they can be parallelized in many different ways
- optimizing these options is a challenge

Determine the best way to parallelize the programwhich will be machine dependent

Background

Motivation Background Approach Results Recommendations Ind Petabricks – Algorithmic Choice

> PetaBricks was developed to alleviate some of the optimization responsibility from the programmer

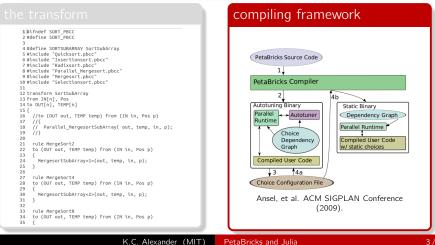
the transform

```
1 #ifndef SORT PBCC
 2 #define SORT PBCC
 4 #define SORTSUBARRAY SortSubArray
 5 #include "Ouicksort.pbcc"
 6 #include "Insertionsort.pbcc"
 7 #include "Radixsort.pbcc"
 8 #include "Parallel Mergesort.pbcc"
 9 #include "Mergesort.pbcc"
10 #include "Selectionsort.pbcc"
12 transform SortSubArray
13 from IN[n], Pos
14 to OUT[n], TEMP[n]
15 {
16
   //to (OUT out, TEMP temp) from (IN in, Pos p)
17 //{
18
   // Parallel MergesortSubArray( out, temp, in, p);
19
20
21
   rule MergeSort2
22
    to (OUT out, TEMP temp) from (IN in, Pos p)
23
24
      MergesortSubArray<1>(out, temp, in, p);
25
27
   rule MergeSort4
    to (OUT out, TEMP temp) from (IN in, Pos p)
28
29
30
      MergesortSubArrav<2>(out, temp, in, p);
31
32
33
   rule MergeSort8
34 to (OUT out, TEMP temp) from (IN in, Pos p)
```

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 Petabricks – Algorithmic Choice
 Algorithmic Cho

PetaBricks was developed to alleviate some of the optimization responsibility from the programmer

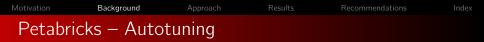


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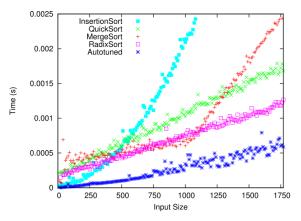
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the autotuner determines the best configuration for the machine under the tuning constraints



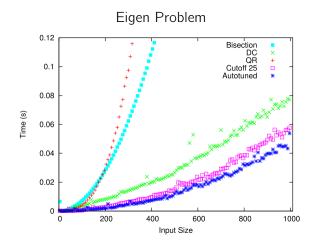




Ansel, et al. ACM SIGPLAN Conference (2009).

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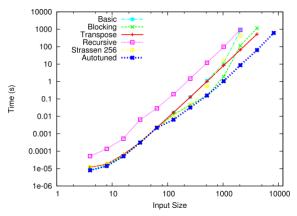


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Matrix Multiply

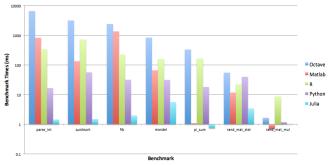


Ansel, et al. ACM SIGPLAN Conference (2009).

| Motivation | Background | Approach | | |
|------------|------------|----------|--|--|
| Julia | | | | |

- Julia was developed to bridge the gap between interpreted and compiled scientific computing
- streamlining parallelization techniques has been a priority

| Motivation | Background | Approach | | |
|------------|------------|----------|--|--|
| Julia | | | | |



Benchmark Times Relative to C++ (Smaller is Better)

http://forio.com/julia/julia

| Motivation | Background | Approach | | |
|------------|------------|----------|--|--|
| Julia | | | | |

Benchmark Times Relative to C++ (Smaller is Better) 10000 1000 **Benchmark Times (ms)** 100 Octave Matlab Python 10 Julia parse int quicksort fib mandel oi sum rand mat stat rand mat mul 0.1 Benchmark

http://forio.com/julia/julia

Question: is there room for overlap between the PetaBricks and Julia approaches?

Approach

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| Op | tions for Impler | nentation | | | |
| | Julia in PetaBricks | | | | |
| | • can utilize Petal | Bricks autotı | uner and cor | npiler | |
| | PetaBricks com | oiler needs to | o interpret J | ulia | |
| | | | | | |

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|--------------|------------------------------------------------------|----------------|----------------|----------------------|-------|--|--|--|
| Option | Options for Implementation | | | | | | | |
| Julia | in PetaBricks | | | | | | | |
| | an utilize Petal PetaBricks com | | | | | | | |
| Peta | Bricks in Julia | | | | | | | |
| • n | an run PetaBri o PetaBricks sl oesn't take adv | nared object f | files, functio | ons require disk i/o | | | | |
| | | | | | | | | |

Approach

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|----------|---------------------------------------------------|----------------|---------------|---------------------|---|
| Options | s for Imple | mentation | | | |
| Julia i | | | | | h |
| | n utilize Peta etaBricks com | | | | |
| PetaE | | | | | ĥ |
| • nc | n run PetaBri PetaBricks sl pesn't take adv | hared object f | iles, functio | ns require disk i/o | |
| Julia - | + OpenTuner | | | | ň |
| • ap | oply PetaBrick | s framework t | to Julia | | ٦ |

Approach

• utilize OpenTuner to optimize Julia

| Motivation | | Approach | | |
|------------|----------|----------|--|--|
| Approac | h Used H | ere | | |

PetaBricks in Julia

- can run PetaBricks binaries inside Julia
- no PetaBricks shared object files, functions require disk i/o
- doesn't take advantage of JuliaLang

| Motivation | | Approach | | |
|------------|----------|----------|--|--|
| Approac | h Used H | ere | | |

PetaBricks in Julia

- can run PetaBricks binaries inside Julia
- no PetaBricks shared object files, functions require disk i/o
- doesn't take advantage of JuliaLang

\Rightarrow most naive approach possible:

- \rightarrow compile PetaBricks executable, exe
- \rightarrow julia > run('\$exe \$in \$out')

| Motivation | | Approach | | |
|------------|-----------|----------|--|--|
| Approad | ch Used H | ere | | |

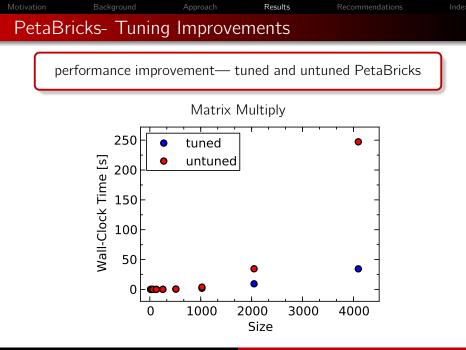
PetaBricks in Julia

- can run PetaBricks binaries inside Julia
- no PetaBricks shared object files, functions require disk i/o
- doesn't take advantage of JuliaLang

⇒ most naive approach possible: → compile PetaBricks executable, exe → julia > run('\$exe \$in \$out')

 \Rightarrow compare with PetaBricks and Julia alone \rightarrow lower bound of performance improvement \rightarrow is there proof of benefit?

Results



Comparing PetaBricks with Julia - Apples to Apples

PetaBricks

- → functions read in ASCII files and output same
- → determines parallelization during autotuning
- ightarrow autotuning can take days

Julia

- \rightarrow JIT for each independent execution
- → can addprocs(n), but may not parallelize
- \rightarrow can be used interactively

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 Comparing PetaBricks with Julia - Apples to Apples
 Apples

PetaBricks

- → functions read in ASCII files and output same
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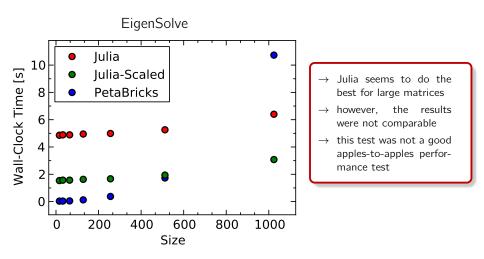
PetaBricks

- → JIT for each independent executable
- → can addprocs(n), but may not parallelize
- \rightarrow can be used interactively

- ightarrow make both programs do i/o
- ightarrow run both programs from shell
- \rightarrow try addprocs(n) in Julia, with no other instructions
- ightarrow subtract 'hello world' start-up time from Julia wall-clock

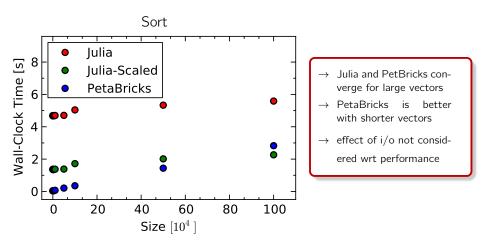
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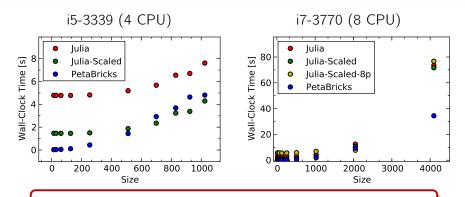
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 Comparing PetaBricks with Julia Matrix Multiply

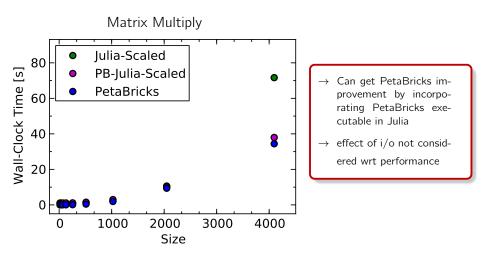


ightarrow Julia and PetBricks converge moderate matrix sizes on fewer cores

- ightarrow PetaBricks is better with smaller lists and larger matrices
- \rightarrow using addprocs(n) with no other instruction does not utilize parallel functionality in Julia

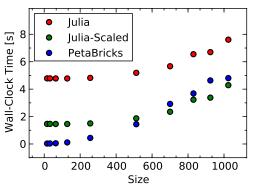
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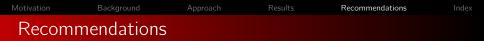
Recommendations

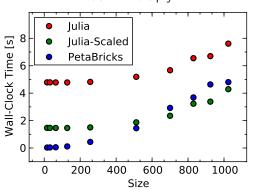
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| Recom | mendations | | | |



Matrix Multiply

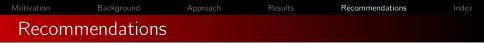
→ under many circumstances, Julia performs as well as PetaBricks without days of compilation

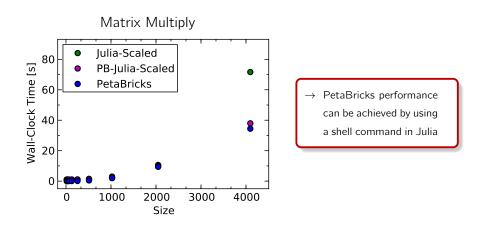




Matrix Multiply

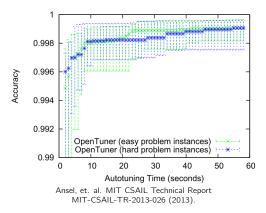
 there is room for improvement on the startup time for Julia







Recommendations



| \rightarrow | implementing | | Open- |
|---------------|-------------------------|-------|--------|
| | Tuner | (when | better |
| | documentation is avail- | | |
| | able) with Julia may be | | |
| | a reasonable long term | | |
| | goal for performance | | |
| | gains of this kind | | |
| | | | |

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