The Three Beaars

Basically, Every Array Allocation Reduces Speed

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October 10, 2012

Abstract

Functional array language compiler and interpreter designers try to reduce the number of arrays created during application execution, because the negative impact of arrays on performance is so dramatic.
Just as The Three Bears had different requirements for their own satisfaction, so do differing array shapes have different requirements for their elimination. The problem itself is a bear: scalar operations are the baby bear, typified here by dynamic programming and the Floyd-Warshall algorithm; operations on small arrays, such as numerically intense computations on complex arrays, is the mama bear; operations on large arrays, typified by acoustic signal processing, is the papa bear.
We compare interpreted to compiled APL performance for several applications with different array shapes, and give an overview of the various optimizations that enable those speedups, in both serial and parallel contexts.

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- These characteristics are a mixed blessing...

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- *vs.* compiled scalar code: 10ops

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- (cheap ASUS M4A88T-M desktop machine)

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siz←⍳(⍴D)[0]
:For k :In siz
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- But, no parallelism: Adding threads just makes it slower!
- What about array-based solutions? It's papa bear time!

Array-based Floyd-Warshall Algorithm

- j64-602, from J Essays (CDC STAR APL algorithm variant)

```
floyd=: 3 :
('for_j. i.#y';'do.
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inline int[.,.] floydSbs1(int[.,.] D ) {
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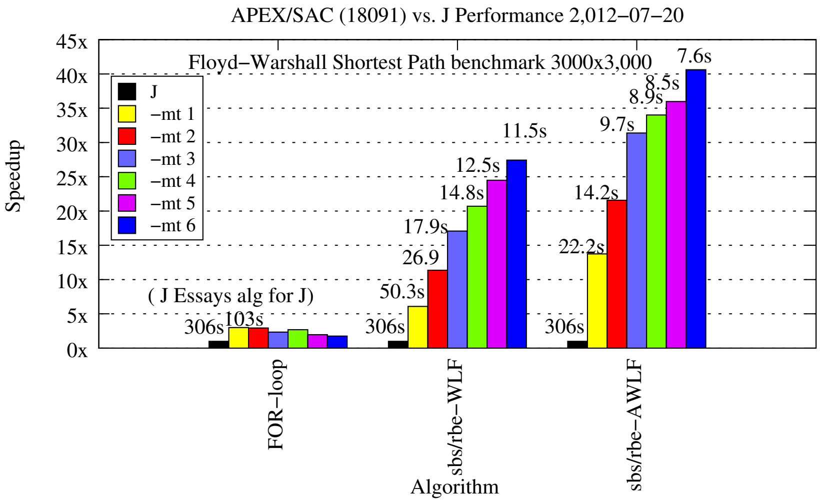
- A "with-loop" is a nested data-parallel FORALL loop

Array-based Floyd-Warshall Algorithm Speedup

Lesson: Array-based code and optimizers are good for you



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- Benefit: Improved parallelism, in some compilers

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- Acoustic signal processing (delta modulation):

```
logd←{¯50⌈50⌊50×(DIFF 0,ω)÷0.01+ω}
DIFF←{¯1↓ω−¯1⌽ω}
```

WLF/AWLF example: Acoustic Signal Processing

- `logd` on 200E6-element double-precision vector

sac2c options	Serial elapsed time sec	Parallel (-mt 6) elapsed time sec	Speedup
APL	7.8s	n/a	n/a
-nowlf -O3	10.7s	5.5s	1.9X
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- Mandatory for good performance: array-valued temps removed

WLF/AWLF/WLS example: Poisson 2-D Relaxation Kernel

From Sven-Bodo Scholz: *With-Loop-Folding in Sac*

A good argument for Ken Iverson's mask verb!

```
z←relax A;m;n. . .
 m←(⍴A)[0]
 n←(⍴A)[1]
 B←((1⊖A)+(¯1⊖A)+(1⌽A)+(¯1⌽A))÷4
 upperA←(1,n)↑A
 lowerA←((m−1),0)↓A
 leftA←1 0↓((m−1),1)↑A
 rightA←((m−2),1)↑(1,n−1)↓A
 innerB←((m−2),n−2)↑1 1↓B
 middle←leftA,innerB,rightA
 z←upperA⍪middle⍪lowerA
```

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- APEX/SAC 18091: multi-threaded (no source code changes!)

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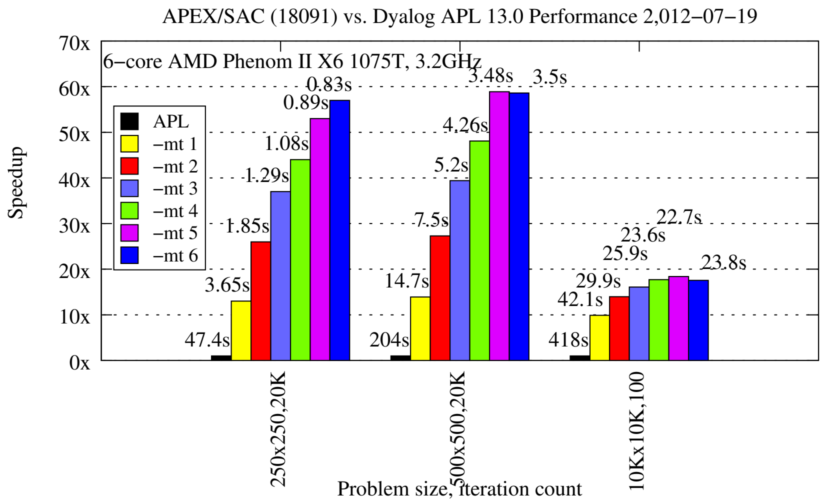

Figure: APEX vs. APL CPU time performance

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- Therefore, speedup is eventually memory-limited on cheapo system

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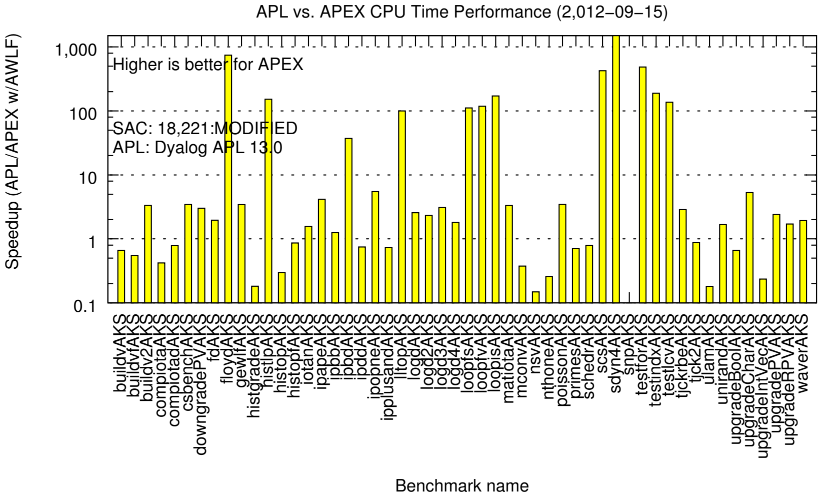
- Lesson: Array optimizations are VERY good for you.

Mama Bear Motivation

Why is interpreted APL faster than compiled code for some tests?



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- Index vector generation for indexed assign
- Shape vector generation for variable result shapes
- Generation of small arrays, *e.g.*, complex scalars
- No SaC FOR-loop analog to with-loop

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- `mandelbrot_opt`: Hand-scalarized - pair of scalars

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- Execution times, with LS,LACSI,LACSO opts enabled/disabled

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GPU (CUDA) Support Without Suffering

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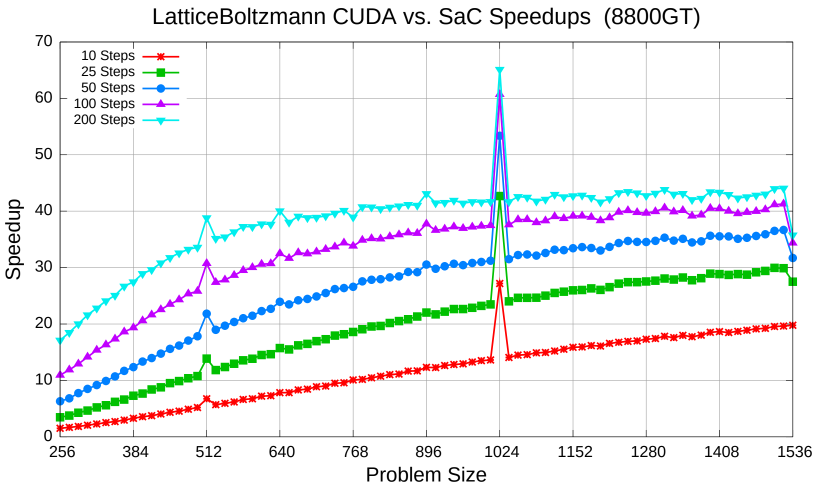

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- Performance is so-so: Optimistic optimizations required

Summary and Future Work

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Bear	Array size	Optimizers	Serial speedup	Parallel speedup
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- And, they lived more or less happily ever after! Thank you!