# Parallel Functional Programming Lecture 8 <br> Data Parallelism I 

## Mary Sheeran

http://www.cse.chalmers.se/edu/course/pfp

## Data parallelism

Introduce parallel data structures and make operations on them parallel

Often data parallel arrays

Canonical example : NESL (NESted-parallel Language) (Blelloch)

## NESL

concise (good for specification, prototyping)
allows programming in familiar style (but still gives parallelism)
allows nested parallelism (see later)
associated language-based cost model
gave decent speedups on wide-vector parallel machines of the day

Hugely influential!
http://www.cs.cmu.edu/~scandal/nesl.html

## NESL

Parallelism without concurrency!

Completely deterministic (modulo floating point noise)

No threads, processes, locks, channels, messages, monitors, barriers, or even futures, at source level

Based on Blelloch's thesis work: Vector Models for Data-Parallel Computing, MIT Press 1990

## NESL

NESL is a sugared typed lambda calculus with a set of array primitives and an explicit parallel map over arrays

To be useful for analyzing parallel algorithms, NESL was designed with rules for calculating the work (the total number of operations executed) and depth (the longest chain of sequential dependence) of a computation.

# Quotes are from ICFP'96 paper 

A Provable Time and Space Efficient Implementation of NESL

Guy E. Blelloch and John Greiner<br>Carnegie Mellon University<br>\{blelloch,jdg\}@cs.cmu.edu


#### Abstract

In this paper we prove time and space bounds for the implementation of the programming language NESL on various parallel machine models. NESL is a sugared typed $\lambda$-calculus with a set of array primitives and an explicit parallel map over arrays. Our results extend previous work on provable implementation bounds for functional languages by considering space and by including arrays. For modeling the cost of NESL we augment a standard call-by-value operational semantics to return two cost measures: a DAG representing the sequential dependences in the computation, and a measure of the space taken by a sequential implementation. We show that a Nesl program with $w$ work (nodes in the DAG), $d$ depth (levels in the DAG), and $s$ sequential space can be implemented on a $p$ processor butterfly network, hypercube, or CRCW PRAM using $O(w / p+d \log p)$ time and $O(s+d p \log p)$ reachable space. ${ }^{1}$ For programs with sufficient parallelism these bounds are optimal in that they give linear speedup and use space within a constant factor of the sequential space.


The idea of a provably efficient implementation is to add to the semantics of the language an accounting of costs, and then to prove a mapping of these costs into running time and/or space of the implementation on concrete machine models (or possibly to costs in other languages). The motivation is to assure that the costs of a program are well defined and to make guarantees about the performance of the implementation. In previous work we have studied provably time efficient parallel implementations of the $\lambda$-calculus using both call-by-value [3] and speculative parallelism [18]. These results accounted for work and depth of a computation using a profiling semantics $[29,30]$ and then related work and depth to running time on various machine models.

This paper applies these ideas to the language NBSL and extends the work in two ways. First, it includes sequences (arrays) as a primitive data type and accounts for them in both the cost semantics and the implementation. This is motivated by the fact that arrays cannot be simulated efficiently in the $\lambda$-calculus without arrays (the simulation of an array of length $n$ using recursive types requires a $\Omega(\log n)$ slowdown). Second, it augments the profiling semantics with

# Quotes <br> > This paper adds the accounting of costs to the semantics of the language and proves a mapping of those costs into running time / space on concrete machine models <br> <br> This paper adds the accounting of costs to the semantics <br> <br> This paper adds the accounting of costs to the semantics of the language and proves a mapping of those costs into of the language and proves a mapping of those costs into running time / space on concrete machine models 

 running time / space on concrete machine models}

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The idea of a provably efficient implementation is to add to the semantics of the language an accounting of costs, and then to prove a mapping of these costs into running time and/or space of the implementation on concrete machine models (or possibly to costs in other languages). The motivation is to assure that the costs of a program are well defined and to make guarantees about the performance of the implementation. In previous work we have studied provably time efficient parallel implementations of the $\lambda$-calculus using both call-by-value [3] and speculative parallelism [18]. These results accounted for work and depth of a computation using a profiling semantics $[29,30]$ and then related work and depth to running time on various machine models.

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Connection Machine

First commercial massively parallel machine

65k processors
can see CM-1 and CM-5 (from 1993) at Computer History Museum, Mountain View
Image: © Thinking Machines Corporation, 1986. Photo: Steve Grohe.
http://www.venturenavigator.co.uk/content/152

## NESL array operations

function factorial $(\mathrm{n})=$ if ( $n<=1$ ) then 1 else $n *$ factorial( $n-1$ );
\{factorial(i) : in [3, 1, 7]\};
apply to each = parallel map (works with user-defined functions
=> load balancing)
list comprehension style notation

## Online interpreter © $^{-}$

## The result of:

function factorial( n ) $=$ if $(\mathrm{n}<=1)$ then 1 else $\mathrm{n}^{*}$ factorial( $\mathrm{n}-1$ );
\{factorial(i) : in $[3,1,7]\} ;$
is:
factorial $=\mathrm{fn}:$ int $->$ int
it $=[6,1,5040]:[i n t]$
Bye.

## apply to each (multiple sequencs)

The result of:
$\{\mathrm{a}+\mathrm{b}: \mathrm{a}$ in $[3,-4,-9] ; \mathrm{b}$ in $[1,2,3]\} ;$ is:
it $=[4,-2,-6]:[i n t]$
Bye.

## apply to each (multiple sequencs)

## The result of:

$\{\mathrm{a}+\mathrm{b}: \mathrm{a}$ in $[3,-4,-9] ; \mathrm{b}$ in $[1,2,3]\} ;$
is:
it $=[4,-2,-6]:[i n t]$
Bye.

Qualifiers in comprehensions are zipping rather than nested as in Haskell Prelude> [ $a+b \mid a<-[3,-4,-9]$, $b<-[1,2,3]$ ]
[4,5,6,-3,-2,-1,-8,-7,-6]

## Filtering too

## The result of:

$\{a * a: a$ in $[3,-4,-9,5] \mid a>0\} ;$
is:
it $=[9,25]:[i n t]$
Bye

## scan (Haskell first)

*Main> scanl1 (+) [1..10]
[1,3,6,10,15,21,28,36,45,55]
*Main> scanl1 (*) [1..10]
[1,2,6,24,120,720,5040,40320,362880,3628800]

## $\begin{array}{llllllllll}1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10\end{array}$

## $1 \begin{array}{lllllllll}10 & 3 & 4 & 6 & 7 & 9 & 10\end{array}$ 3

## $1 \begin{array}{lllllllll}10 & 3 & 4 & 6 & 7 & 9 & 10\end{array}$ 3 <br> 6

## $1 \begin{array}{lllllllll}10 & 3 & 4 & 6 & 8 & 10\end{array}$ 3 <br> 6 <br> 10

## $\begin{array}{llllllllll}1 & 2 & 3 & 4 & 5 & 6 & 8 & 9 & 10\end{array}$ 3

6
10
15

## $\begin{array}{llllllllll}1 & 2 & 3 & 4 & 5 & 6 & 8 & 9 & 10\end{array}$ <br> 3

6
time

## 10

15

## scan diagram


y
binary operator

## Brent Kung ('79)



## Brent Kung


forward tree + several reverse trees
recursive decomposition


$$
s_{i}^{j}=a_{i} * a_{i+1} * \ldots * a_{j}
$$

indices from 1 here

## recursive decomposition



$$
s_{i}^{j}=a_{i} * a_{i+1} * \ldots * a_{j}
$$


divide
conquer
combine

## prescan

scan "shifted right by one" prescan of
$\left[a_{1}, a_{2}, \quad, a_{3}, \quad, a_{4}, \ldots \quad, a_{n}\right]$ is
$\left[1, a_{1}, a_{1} * a_{2}, a_{1} * a_{2} * a_{3}, \ldots, a_{1} * \ldots * a_{n-1}\right]$

> identity element

## scan from prescan

easy (constant time)
$\left[1, \quad a_{1}, a_{1} * a_{2}, a_{1} * a_{2} * a_{3}, \ldots, a_{1} * \ldots * a_{n-1}\right] a_{n}$
$\left[a_{1}, a_{1} * a_{2}, a_{1} * a_{2} * a_{3}, \ldots, a_{1} * \ldots * a_{n-1}, a_{1} * \ldots * a_{n}\right]$

## the power of scan

Blelloch pointed out that once you have scan you can do LOTS of interesting algorithms, inc.

To lexically compare strings of characters. For example, to determine that "strategy" should appear before "stratification" in a dictionary
To evaluate polynomials
To solve recurrences. For example, to solve the recurrences

$$
x_{i}=a_{i} x_{i-1}+b_{i} x_{i-2} \text { and } x_{i}=a_{i}+b_{i} / x_{i-1}
$$

To implement radix sort
To implement quicksort
To solve tridiagonal linear systems
To delete marked elements from an array
To dynamically allocate processors
To perform lexical analysis. For example, to parse a program into tokens and many more
http://www.cs.cmu.edu/~blelloch/papers/Ble93.pdf

## prescan in NESL

```
function scan_op(op,identity,a) =
if #a == 1 then [identity]
else
    let e = even_elts(a);
        o = odd__elts(a);
        s = scan_op(op,identity,{op(e,o): e in e; o in o})
    in interleave(s,{op(s,e): s in s; e in e});
```


## prescan in NESL

```
function scan_op(op,identity,a) =
if #a == 1 then [identity]
else
    let e = even_elts(a);
        o = odd__elts(a);
    s = scan_op(op,identity,{op(e,o): e in e; o in o})
    in interleave(s, op(s,e): s in s; e in e});
```

zipWith op e o zipWith op se

## prescan

```
function scan_op(op,identity,a) =
if #a == 1 then [identity]
else
    let e = even_elts(a);
        o = odd_elts(a);
        s = scan_op(op,identity,{op(e,o): e in e; o in o})
    in interleave(s,{op(s,e): s in s; e in e});
scan_op('+, 0, [2, 8, 3, -4, 1, 9, -2, 7]);
is:
scan_op = fn : ((b, b) -> b, b, [b]) -> [b] :: (a in any; b in any)
it = [0, 2, 10, 13, 9, 10, 19, 17] : [int]
```


## prescan

```
function scan_op(op,identity,a) =
if #a == 1 then [identity]
else
    let e = even_elts(a);
        o = odd_elts(a);
        s = scan_op(op,identity,{op(e,o): e in e; o in o})
    in interleave(s,{op(s,e): s in s; e in e});
scan_op(max, 0, [2, 8, 3, -4, 1, 9, -2, 7]);
is:
scan_op = fn : ((b, b) -> b, b, [b]) -> [b] :: (a in any; b in any)
it =[0, 2, 8, 8, 8, 8, 9, 9] : [int]
```


## Exercise

Try to write scan (as distinct from prescan)

Call it oscan (as scan is built in (gives both prescan list and the final element))

Note that apply-to-each on two sequences demands that the two sequences have equal length (unlike zipWith)

Assume first that the sequence has length a power of two

Type your answer into one of the boxes on http://www.cs.cmu.edu/~scandal/nesl/tutorial2.html

## Outline of one possible solution

```
function init is = take(is,#is-1);
function tail is = drop(is,1);
function oscan(op,v) =
    if #v == 1 then v
    else let es = even_elts(v);
        os = odd_elts(v);
        is = oscan(...);
        us = ...
    in interleave ... ;
```


## Outline of one possible solution

```
function init is = take(is,#is-1);
function tail is = drop(is,1);
function oscan(op,v) =
    if #v == 1 then v
    else let es = even_elts(v);
            os = odd_elts(v);
            is = os interleave([1,2,3],[4,5,6]);
            us =
                        it = [1, 4, 2, 5, 3, 6] : [int]
                        interleave([1,2,3],[4,5]);
                            it = [1, 4, 2, 5, 3] : [int]
                            interleave([1,2,3],[4]);
                            RUNTIME ERROR: Length mismatch for function INTERLEAVE.
```


## Batcher's bitonic merge

```
function bitonic_sort(a) =
if (#a == 1) then a
else
    let
        bot = subseq(a,0,#a/2);
        top = subseq(a,#a/2,#a);
        mins = {min(bot,top):bot;top};
        maxs = {max(bot,top):bot;top};
    in flatten({bitonic_sort(x) : x in [mins,maxs]});
```


## bitonic_sort (merger)



## bitonic_sort (merger)




## bitonic sort

function batcher_sort(a) = if $(\# a==1)$ then $a$ else
let $\mathrm{b}=\{$ batcher_sort( x ) : x in bottop(a) $\}$; in bitonic_sort(b[0]++reverse(b[1]));

## bitonic sort



## bitonic sort



For some fun with sorting networks in Obsidian, see http://www.cse.chalmers.se/~joels/writing/expressive.pdf

## parentheses matching

For each index, return the index of the matching parenthesis

```
function parentheses_match(string) =
let
    depth = plus_scan({if c==`` then 1 else -1 : c in string});
    depth = {d + (if c==`( then 1 else 0): c in string; d in depth};
    rnk = permute([0:#string], rank(depth));
    ret = interleave(odd_elts(rnk), even_elts(rnk))
in permute(ret, rnk);
```

one scan, a map, a zipWith, two permutes and an interleave, also rank and odd_elts and even_elts

## parentheses matching

$$
\begin{aligned}
& \text { permute }([7,8,9],[2,1,0]) ; \\
& \text { permute }([7,8,9],[1,2,0]) \text {; }
\end{aligned}
$$

For each index, return me in

```
function parentheses_match(
let
    it = [9, 7, 8] : [int]
    depth = plus_scan({if c==`( then 1 else -1 : c in string});
    depth = {d + (if c==`( then 1 else 0): c in string; d in depth};
    rnk = permute([0:#string], rank(depth));
    ret = interleave(odd_elts(rnk), even_elts(rnk))
in permute(ret, rnk);
```

    it \(=[9,8,7]:[i n t]\)
    one scan, a map, a zipWith, two permutes and an interleave, also rank and odd_elts and even_elts

## parentheses matching

```
                        rank([6,8,9,7]);
                        it = [0, 2, 3, 1]: [int]
For each index, return the in
```

```
function parentheses_match(
```

function parentheses_match(
let
let
depth = plus_scan({if c==`` it = [0, 2, 3, 1, 4]: [int]     depth = plus_scan({if c==`` it = [0, 2, 3, 1, 4]: [int]
depth = {d + (if c==`` then 1 <     depth = {d + (if c==`` then 1 <
rnk = permute([0:\#string], rank(depth));
rnk = permute([0:\#string], rank(depth));
ret = interleave(odd_elts(rnk), even_elts(rnk))
ret = interleave(odd_elts(rnk), even_elts(rnk))
in permute(ret, rnk);

```
in permute(ret, rnk);
```

one scan, a map, a zipWith, two permutes and an interleave, also rank and odd_elts and even_elts

## parentheses matching

For each index, return the index of the matching pa

A "step through" of this function is provided at end of these slides

```
function parentheses_match(string) =
let
    depth = plus_scan({if c==`( then 1 else -1 : c in string});
    depth = {d + (if c==`( then 1 else 0): c in string; d in depth};
    rnk = permute([0:#string], rank(depth));
    ret = interleave(odd_elts(rnk), even_elts(rnk))
in permute(ret, rnk);
```

one scan, a map, a zipWith, two permutes and an interleave, also rank and odd_elts and even_elts

## Break?

## What does Nested mean??

\{plus_scan(a) : a in $[[2,3],[8,3,9],[7]]\} ;$

$$
\text { it }=[[0,2],[0,8,11],[0]]:[[\text { int }]]
$$

## What does Nested mean??

## sequence of sequences apply to each of a PARALLEL function

\{plus_scan(a) : a in $[[2,3],[8,3,9],[7]]\} ;$

$$
\text { it }=[[0,2],[0,8,11],[0]]:[[\text { int }]]
$$

## What does Nested mean??



Implemented using Blelloch's Flattening Transformation, which converts nested parallelism into flat. Brilliant idea, challenging to make work in fancier languages (see DPH and good work on Manticore (ML))

# What does Nested mean?? Another example 

```
function svxv (sv, v)=
sum({x*v[i]:(x, i) in sv});
```

function smxv (sm, v) =
\{ $\operatorname{svxv}($ row, v$)$ : row in sm \}

## Nested parallelism

Arbitrarily nested parallel loops + fork-join

Assumes no synchronization among parallel tasks except at join points => a task can only sync with its parent (sometimes called fully strict)

Deterministic (in absence of race conditions)

Advantages (according to Blelloch):
Good schedulers are known
Easy to understand, debug, and analyze

## Nested Parallelism

## Dependence graph is series-parallel



## Nested Parallelism

## Dependence graph is series-parallel



Task can only synchronise with its parent

## But not



## But not



Here, a task can only synchronise with an ancestor (strict (but not fully strict))

## Back to examples

## this prescan is actually flat

```
function scan_op(op,identity,a) =
if #a == 1 then [identity]
else
    let e = even_elts(a);
        o = odd__elts(a);
    s = scan_op(op,identity,{op(e,o): e in e; o in o})
    in interleave(s,{op(s,e): s in s; e in e});
```


## Back to examples Batcher's bitonic merge IS NESTED

```
function bitonic_sort(a) =
if (#a == 1) then a
else
    let
        bot = subseq(a,0,#a/2);
        top = subseq(a,#a/2,#a);
        mins = {min(bot,top):bot;top};
        maxs = {max(bot,top):bot;top};
    in flatten({bitonic_sort(x) : x in [mins,maxs]});
```

and so is the sort

## Back to examples Batcher's bitonic merge IS NESTED

```
function bitonic_sort(a) =
if (#a == 1) then a
else
    let
        bot = subseq(a,0,#a/2);
        top = subseq(a,#a/2,#a);
        mins = {min(bot,top):bot;top};
        maxs = {max(bot,top):bot;top};
    in flatten({bitonic_sort(x) : x in [mins,maxs]});
```

function bitonic_sort(a) =
if $(\# a==1)$ then $a$ else
let

$$
\text { bot }=\text { subseq(a,0,\#a/2); }
$$

top = subseq(a,\#a/2,\#a);

$$
\operatorname{mins}=\{\min (\text { bot,top }): \text { bot;top }\} ;
$$

$$
\operatorname{maxs}=\{\max (b o t, t o p): \text { bot;top }\} ;
$$

in flatten(\{bitonic_sort(x) : x in [mins,maxs]\});
nestedness is good for D\&C and for irregular computations

## Back to examples

## parentheses matching is FLAT

For each index, return the index of the matching parenthesis

```
function parentheses_match(string) =
let
    depth = plus_scan({if c==`( then 1 else -1 : c in string});
    depth = {d + (if c==`( then 1 else 0): c in string; d in depth};
    rnk = permute([0:#string], rank(depth));
    ret = interleave(odd_elts(rnk), even_elts(rnk))
in permute(ret, rnk);
```


## What about a cost model?

Blelloch empasises

1) work: total number of operations
represents total cost (integral of needed resources over time = running time on one processor)
2) depth or span: longest chain of sequential (functional) dependencies best possible running time on an unlimited number of processors
claims:
3) easier to think about algorithms based on work and depth than to use running time on machine with P processors (e.g. PRAM)
4) work and depth predict running time on various different machines (at least in the abstract)

## What about a cost model?

Blelloch empasises

1) work : total number of operations
cost model is language based rather than machine based $\quad ?=$ running time on
2) $d \epsilon$
dependencies
best possible running time on an unlim.
„† processors
claims:
3) easier to think about algorithms based on work ana depth than to use running time on machine with P processors (e.g. PRAM)
4) work and depth predict running time on various different machines (at least in the abstract)

## Part 1: simple language based performance model

## Call-by-value $\lambda$-calculus

$$
\begin{gathered}
\lambda x . e \Downarrow \lambda x . e \\
\frac{e_{1} \Downarrow \lambda x . e \quad e_{2} \Downarrow v \quad e[v / x] \Downarrow v^{\prime}}{e_{1} e_{2} \Downarrow v^{\prime}}(\mathrm{APP})
\end{gathered}
$$

## The Parallel $\lambda$-calculus: cost model

$$
e \Downarrow v ; w, d
$$

Reads: expression $e$ evaluates to $v$ with work $w$ and span $d$.

- Work (W): sequential work
- Span (D): parallel depth

The Parallel $\lambda$-calculus: cost model

$$
\begin{align*}
& \lambda x . \mathrm{e} \Downarrow \lambda x \text { e: } ; 11  \tag{LAM}\\
& \frac{e_{1} \Downarrow \lambda x \cdot e ; w_{1} d_{1} e_{2} \Downarrow v ; w_{2}, d_{2} e[v / x] \Downarrow v^{\prime} ; w_{3} / d_{3}}{e_{1} e_{2} \Downarrow v^{\prime} ; 1+w_{1}+w_{2}+w_{3}, 1+\max \left(d_{1}, d_{2}\right)+d_{3}} \text { (APP) }
\end{align*}
$$

Work adds
Span adds sequentially, and max in parallel

slide from Blelloch's ICFP10 invited talk

## The Parallel $\lambda$-calculus: cost model



## The Parallel $\lambda$-calculus cost model

$$
\begin{gather*}
\lambda x . \mathrm{e} \Downarrow \lambda x . \mathrm{e} ; 1,1 \\
\frac{e_{1} \Downarrow \lambda x . e ; w_{1}, d_{1} \quad e_{2} \Downarrow v ; w_{2}, d_{2} \quad e[v / x] \Downarrow v^{\prime} ; w_{3}, d_{3}}{e_{1} e_{2} \Downarrow v^{\prime} ; 1+w_{1}+w_{2}+w_{3}, 1+\max \left(d_{1}, d_{2}\right)+d_{3}} \quad(\mathrm{API})  \tag{APP}\\
c \Downarrow c ; 1,1 \quad \text { (CONST) }  \tag{CONST}\\
\frac{e_{1} \Downarrow c ; w_{1}, d_{1} \quad e_{2} \Downarrow v ; w_{2}, d_{2} \quad \delta(c, v) \Downarrow v^{\prime}}{e_{1} e_{2} \Downarrow v^{\prime} ; 1+w_{1}+w_{2}, 1+\max \left(d_{1}, d_{2}\right)} \quad \text { (APPC) } \\
c_{n}=0, \cdots, n,+,+_{0}, \cdots,+_{\mathrm{n}},<,<_{0}, \cdots,<_{\mathrm{n}}, \times, \times_{0}, \cdots, \times_{\mathrm{n}}, \cdots \text { (constants) }
\end{gather*}
$$

## Adding Functional Arrays: NESL

$$
\begin{aligned}
& \qquad\left\{e_{1}: x \text { in } e_{2} \mid e_{3}\right\} \\
& \frac{e^{\prime}\left[v_{i} / x\right] \Downarrow v_{i}^{\prime} ; w_{i}, d_{i} \quad i \in\{1 \ldots n\}}{\left\{e^{\prime}: x \text { in }\left[v_{1} \ldots v_{n}\right]\right\} \Downarrow\left[v_{1}^{\prime} \ldots v_{n}^{\prime}\right] ; 1+\sum_{i=1}^{n} w_{i}, 1+\max _{i=1}^{|v|} d_{i}} \\
& \text { Primitives: } \\
& <-: \text { 'a seq * (int,'a) seq }->\text { 'a seq } \\
& \text { • [g,c,a,p]<-[(0,d),(2,f),(0,i)]} \quad[\mathbf{i}, \mathbf{c}, \mathbf{f}, \mathrm{p}]
\end{aligned} \begin{aligned}
& \text { [ICFP95 } \\
& \text { elt, index, length }
\end{aligned}
$$

[ICFP95]

## Adding Functional Arrays: NESL

$$
\begin{gathered}
\left\{e_{1}: x \text { in } e_{2} \mid e_{3}\right\} \\
e^{\prime}\left[v_{i} / x\right] \Downarrow v_{i}^{\prime} ; w_{i}, d_{i} \quad i \in\{1 \ldots n\}
\end{gathered}
$$

## Brings us back to the paper at the beginning (which is from ICFP 96)

- $[g, c, a, p]<-\quad[(0, d),(2, f), 1$

$$
[i, c, f, p]
$$

elt, index, length
[ICFP95]
slide from Blelloch's ICFP10 invited talk

## Adding Functional Arrays: NESL

$$
\left\{e_{1}: x \text { in } e_{2} \mid e_{3}\right\}
$$

```
Blelloch:
programming based cost models could change the way people think about
costs and open door for other kinds of abstract costs
doing it in terms of machines.... "that's so last century"
    <- : `a seq * (int,'a) seq -> `a seq
- [g,c,a,p] <- [ (0,d),(2,f),(0,i)]
            [i,c,f,p]
elt, index, length
```

    [ICFP95]
    
## Aside: Research needed!

Blelloch has pointed the way

ICFP96

Spoonhower et al (JFP'11)
https://www.cs.cmu.edu/afs/cs.cmu.edu/Web/People/blelloch/papers/SBHG11.pdf

Cache and IO efficient functional algs (with Harper, POPL 13)
http://www.cs.cmu.edu/~rwh/papers/iolambda/short.pdf

Cost models that programmers can really use need to be developed

## Back to ICFP96 paper

## The Second Half: <br> Provable Implementation Bounds

Theorem [FPCA95]:If $e \Downarrow v ; w, d$ then $v$ can be calculated from $e$ on a CREW PRAM with p processors in $o\left(\frac{w}{p}+d \log p\right)$ time.

Can't really do better than: $\max \left(\frac{w}{p}, d\right)$
If $w / p>d \log p$ then "work dominates"
We refer to $w / p$ as the parallelism.

Ba $\begin{aligned} & \text { Brent's Lemma: might expect } \mathrm{O}(\mathrm{w} / \mathrm{p}+\mathrm{d}) \\ & \text { log } p \text { term is because }\end{aligned}$
$\log p$ term is because of how flattening is done (flatten the arrays and use segmented scans)
So scan is essential in the implementation too, not just a tool for the programmer

## Provapie II

## ron Bounas

Theorem [FPCA95]. $\quad v ; w, d$ then $v$ can be calculated from $e c$ a CREW PRAM with p processors in $o\left(\frac{w}{p}+d \log p\right)$ time.

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## Background info: Brent's lemma

If a computation can be performed in $t$ steps with $q$ operations on a parallel computer (formally, a PRAM) with an unbounded number of processors, then the computation can be performed in $t+(q-t) / p$ steps with $p$ processors
http://maths-people.anu.edu.au/~brent/pd/rpb022.pdf
(paper from '74)

## Back to our scan


oblivious or data independent computation
$N=2^{n}$ inputs, work of dot is 1
work = ?
depth = ?
and bitonic sort? (see Blelloch's ICFP10 invited talk for quicksort etc.)

## From the NESL quick reference

Basic Sequence Functions Basic Operations Description
\#a Length of a
a[i] ith element of a
dist(a,n) Create sequence of length $n$ with a in each element.
zip( $a, b$ ) Elementwise zip two sequences together into a sequence of pairs.
[s:e] Create sequence of integers from $s$ to e (not inclusive of e)
[s:e:d] Same as [s:e] but with a stride d.
Scans
plus_scan(a) min_scan(a) max_scan(a) or_scan(a) and_scan(a)

Execute a scan on a using the + operator
Execute a scan on a using the minimum operator
Execute a scan on a using the maximum operator
Execute a scan on a using the or operator
Execute a scan on a using the and operator

| Work | Depth |
| :--- | :--- |
| $\mathrm{O}(1)$ | $\mathrm{O}(1)$ |
| $\mathrm{O}(1)$ | $\mathrm{O}(1)$ |
| $\mathrm{O}(\mathrm{n})$ | $\mathrm{O}(1)$ |
| $\mathrm{O}(\mathrm{n})$ | $\mathrm{O}(1)$ |
| $\mathrm{O}(\mathrm{e}-\mathrm{s})$ | $\mathrm{O}(1)$ |
| $\mathrm{O}((\mathrm{e}-\mathrm{s}) / \mathrm{d})$ | $\mathrm{O}(1)$ |

$O(n) \quad O(\log n)$
$O(n) \quad O(\log n)$
$O(n) \quad O(\log n)$
$O(n) \quad O(\log n)$
$O(n) \quad O(\log n)$

## Data Parallel Haskell (DPH) intentions

NESL was a seminal breakthrough but, fifteen years later it remains largely un-exploited. Our goal is to adopt the key insights of NESL, embody them in a modern, widely-used functional programming language, namely Haskell, and implement them in a state-of-theart Haskell compiler (GHC). The resulting system, Data Parallel Haskell, will make nested data parallelism available to real users.

Doing so is not straightforward. NESL a first-order language, has very few data types, was focused entirely on nested data parallelism, and its implementation is an interpreter. Haskell is a higher-order language with an extremely rich type system; it already includes several other sorts of parallel execution; and its implementation is a compiler.

# Nested Data-Parallelism on the GPU 

Lars Bergstrom<br>University of Chicago<br>larsberg@cs.uchicago.edu

John Reppy<br>University of Chicago<br>jhr@cs.uchicago.edu


#### Abstract

Graphics processing units (GPUs) provide both memory bandwidth and arithmetic performance far greater than that available on CPUs but, because of their Single-Instruction-Multiple-Data (SIMD) architecture, they are hard to program. Most of the programs ported to GPUs thus far use traditional data-level parallelism, performing only operations that operate uniformly over vectors.

NESL is a first-order functional language that was designed to allow programmers to write irregular-parallel programs - such as parallel divide-and-conquer algorithms - for wide-vector parallel computers. This paper presents our port of the NESL implementation to work on GPUs and provides empirical evidence that nested data-parallelism (NDP) on GPUs significantly outperforms CPUbased implementations and matches or beats newer GPU languages that support only flat parallelism. While our performance does not match that of hand-tuned CUDA programs, we argue that the notational conciseness of NeSL is worth the loss in performance. This work provides the first language implementation that directly supports NDP on a GPU.


uniform problem subdivisions and non-uniform memory access, such as divide-and-conquer algorithms.

Most GPU programming is done with the CUDA [NVI11b] and OpenCL [Khr11] languages, which provide the illusion of C-style general-purpose programming, but which actually impose restrictions. There have been a number of efforts to support GPU programming from higher-level languages, usually by embedding a data-parallel DSL into the host language, but these efforts have been limited to regular parallelism [CBS11, MM10, $\mathrm{CKL}^{+} 11$ ].

The current best practice for irregular parallelism on a GPU is for skilled programmers to laboriously hand code applications. The literature is rife with implementations of specific irregularparallel algorithms for GPUs [BP11, DR11, MLBP12, MGG12]. These efforts typically require many programmer-months of effort to even meet the performance of the original optimized sequential C program.

GPUs have some common characteristics with the wide-vector supercomputers of the 1980 's, which similarly provided highperformance SIMD computations. NESL is a first-order functional language developed by Guy Blelloch in the early 1990's that was

## NESL on GPU!

## First NDP language on GPU

PREPRINT: To be presented at ICFP '12, September 9-15, 2012, Copenhagen, Denmark.

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## End

## Next lecture (Thursday)

DPH (nested)
Repa (flat)

## parentheses matching

For each index, return the index of the matching parenthesis

```
function parentheses_match(string) =
let
    depth = plus_scan({if c==`( then 1 else -1 : c in string});
    depth = {d + (if c==`( then 1 else 0): c in string; d in depth};
    rnk = permute([0:#string], rank(depth));
    ret = interleave(odd_elts(rnk), even_elts(rnk))
in permute(ret, rnk);
```

$$
\begin{aligned}
& \text { ( ) ( ( ) ( ) ) ( ( ( ) ) ) } \\
& \begin{array}{llllllllllll}
1 & -1 & 1 & 1 & -1 & 1-1 & -1 & 1 & 1 & 1 & -1 & -1
\end{array} \text {-1 }
\end{aligned}
$$



$$
\begin{aligned}
& \text { ( ) ( ( ) ( ) ) ( ( ( ) ) ) } \\
& \text { 1-1 } 1 \text { 1 }-1 \begin{array}{llllllll}
1 & -1 & -1 & 1 & 1 & 1 & -1 & -1
\end{array} \\
& 01012121012321 \\
& \begin{array}{lllllllllllll}
1 & 1 & 1 & 2 & 2 & 2 & 2 & 1 & 2 & 3 & 3 & 2
\end{array}
\end{aligned}
$$

$$
\left.\begin{array}{llllllllllllll} 
& 1 & ( & ( & ) & 1 & ) & ( & ( & ( & ) & ) & \\
1 & -1 & 1 & 1 & -1 & 1 & -1 & -1 & 1 & 1 & 1 & -1 & -1 & -1 \\
\\
0 & 1 & 0 & 1 & 2 & 1 & 2 & 1 & 0 & 1 & 2 & 3 & 2 & 1 \\
1 & 1 & 1 & 2 & 2 & 2 & 2 & 1 & 1 & 2 & 3 & 3 & 2 & 1
\end{array}\right] \text { depth }
$$

$$
\left.\begin{array}{llllllllllllll} 
& 1 & ( & ( & ) & ( & ) & ) & ( & ( & ( & ) & ) & \text { string } \\
1 & -1 & 1 & 1 & -1 & 1 & -1 & -1 & 1 & 1 & 1 & -1 & -1 & -1
\end{array}\right]
$$

$$
\left.\begin{array}{cccccccccccccc} 
& 1 & ( & ( & ) & ( & ) & ) & ( & ( & ( & ) & ) & \text { string } \\
1 & -1 & 1 & 1 & -1 & 1 & -1 & -1 & 1 & 1 & 1 & -1 & -1 & -1
\end{array}\right]
$$

$$
\begin{array}{ccccccccccccccc}
( & ) & ( & ( & ) & ( & ) & ) & ( & ( & ( & ) & ) & ) & \text { string } \\
1 & -1 & 1 & 1 & -1 & 1 & -1 & -1 & 1 & 1 & 1 & -1 & -1 & -1 & \\
0 & 1 & 0 & 1 & 2 & 1 & 2 & 1 & 0 & 1 & 2 & 3 & 2 & 1 & \\
1 & 1 & 1 & 2 & 2 & 2 & 2 & 1 & 1 & 2 & 3 & 3 & 2 & 1 & \\
0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & \text { depth } \\
0 & 1 & 2 & 6 & 7 & 8 & 9 & 3 & 4 & 10 & 12 & 13 & 11 & 5 & \begin{array}{l}
\text { [0:\#tring] } \\
\text { rank(depth) }
\end{array} \\
0 & 1 & 2 & 7 & 8 & 13 & 3 & 4 & 5 & 6 & 0 & 14 & & \begin{array}{c}
\text { permute } \\
\text { ([0:\#string),rank(depth)); }
\end{array}
\end{array}
$$

$$
\begin{array}{lllllllllllllll}
( & ) & ( & ( & ) & ( & ) & ) & ( & ( & ( & ) & ) & \text { string } \\
1 & 1 & 1 & 2 & 2 & 2 & 2 & 1 & 1 & 2 & 3 & 3 & 2 & 1 & \text { depth } \\
0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & \text { [0:\#string] } \\
0 & 1 & 2 & 6 & 7 & 8 & 9 & 3 & 4 & 10 & 12 & 13 & 11 & 5 & \text { rank(depth) } \\
0 & 1 & 2 & 7 & 8 & 13 & 3 & 4 & 5 & 6 & 9 & 12 & 10 & 11 & \text { rnk } \\
\times & X & & & & & & & & & \\
1 & 0 & 7 & 2 & 13 & 8 & 4 & 3 & 6 & 5 & 2 & 9 & 11 & 10 & \text { ret }
\end{array}
$$

$$
\begin{array}{lllllllllllllll} 
& 1 & ( & ( & ) & ( & ) & ) & ( & ( & ( & ) & ) & \text { string } \\
1 & 1 & 1 & 2 & 2 & 2 & 2 & 1 & 1 & 2 & 3 & 3 & 2 & 1 & \text { depth } \\
0 & 1 & 2 & 6 & 7 & 8 & 9 & 3 & 4 & 10 & 12 & 13 & 11 & 5 & \text { rank(depth) } \\
0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & \text { [0:\#string] } \\
0 & 1 & 2 & 7 & 8 & 13 & 3 & 4 & 5 & 6 & 9 & 12 & 10 & 11 & \text { rnk } \\
\times & X & & & & & & & & \\
1 & 0 & 7 & 2 & 13 & 8 & 4 & 3 & 6 & & & & &
\end{array}
$$

$$
\begin{array}{lllllllllllllll} 
& 1 & ( & ( & ) & ( & ) & ) & ( & ( & ( & ) & ) & \text { string } \\
1 & 1 & 1 & 2 & 2 & 2 & 2 & 1 & 1 & 2 & 3 & 3 & 2 & 1 & \text { depth } \\
0 & 1 & 2 & 6 & 7 & 8 & 9 & 3 & 4 & 10 & 12 & 13 & 11 & 5 & \text { rank(depth) } \\
0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & \text { [0:\#string] } \\
1 & 0 & 7 & 2 & 13 & 8 & 4 & 3 & 6 & 5 & 2 & 9 & 11 & 10 & \text { ret } \\
0 & 1 & 2 & 7 & 8 & 13 & 3 & 4 & 5 & 6 & 9 & 12 & 10 & 11 & \text { rnk } \\
1 & 0 & 7 & 4 & 3 & 6 & 5 & 2 & 13 & 12 & 11 & 10 & 9 & 8 &
\end{array}
$$

$$
\left.\begin{array}{cccccccccccccc}
( & ) & ( & ( & ) & ( & ) & ) & ( & ( & ( & ) & ) & \text { string } \\
1 & 1 & 1 & 2 & 2 & 2 & 2 & 1 & 1 & 2 & 3 & 3 & 2 & 1
\end{array}\right] \text { depth } \quad \text { (dank(depth) }
$$



