# Parallel Sequences 

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## Parallel Programming



## Programming with shared mutable data is very hard!

## How can we leverage

- pure functions
- immutable data
- function composition to write large-scale parallel programs?


## What if you had a really big job to do?

Example: Create an index of every web page on the planet.

- Google does that regularly!
- There are billions of them!

Example: Search facebook for a friend or twitter for a tweet

To get big jobs done, we typically need 1000s of computers, but:

- how do we distribute work across all those computers?
- you definitely can't use shared-memory parallelism because the computers don't share memory!
- when you use 1 computer, you just hope it doesn't fail. If it does, you go to the store, buy a new one and restart the job.
- when you use 1000s of computers at a time, failures become the norm. what to do when 1 of 1000 computers fail? Start over?


## Big Jobs ---> Better Abstractions

Need high-level interfaces to shield application programmers from the complex details. Complex implementations solve the problems of distribution, fault tolerance and performance.

Common abstraction: Parallel collections

Example collections: sets, tables, dictionaries, sequences
Example bulk operations: create, map, reduce, join, filter


## COMPLEXITY OF PARALLEL ALGORITHMS

## Visualizing Computational Costs

let $x=1+2$ in $3+x$

dependence:

$$
x=1+2 \text { happens before } 3+x
$$

## Visualizing Computational Costs



Execution of dependency diagrams: A processor can only begin executing the computation associated with a block when the computations of all of its predecessor blocks have been completed.

## Visualizing Computational Costs

step 1:
execute first block


Cost so far: 0

## Visualizing Computational Costs

step 1:
execute first block


Cost so far: 1

## Visualizing Computational Costs

## step 2:

execute second block because all of its predecessors have
 been completed

Cost so far: 1

## Visualizing Computational Costs

## step 2:

execute second block because all of its predecessors have
 been completed

Cost so far: $1+1$

## Visualizing Computational Costs

let $x=1+2$ in $3+x$

total cost
= 1 + 1
$=2$

## Visualizing Computational Costs

(1 + 2 ||f3)
parallel pair:
compute both left and right-hand sides independently return pair of values
(easy to implement using futures)

## Visualizing Computational Costs



## Visualizing Computational Costs



Suppose we have 1 processor. How much time does this computation take?

## Visualizing Computational Costs



Suppose we have 1 processor. How much time does this computation take? Schedule A-B-C-D: $1+1+7+1$

## Visualizing Computational Costs



Suppose we have 1 processor. How much time does this computation take? Schedule A-C-B-D: $1+1+7+1$

## Visualizing Computational Costs



Suppose we have 2 processors. How much time does this computation take?

## Visualizing Computational Costs



Suppose we have 2 processors. How much time does this computation take? Cost so far: 1

## Visualizing Computational Costs



Suppose we have 2 processors. How much time does this computation take? Cost so far: $1+\max (1,7)$

## Visualizing Computational Costs



Suppose we have 2 processors. How much time does this computation take? Cost so far: $1+\max (1,7)+1$

## Visualizing Computational Costs



Suppose we have 2 processors. How much time does this computation take? Total cost: $1+\max (1,7)+1$. We say the schedule we used was: A-CB-D

## Visualizing Computational Costs



Suppose we have 3 processors. How much time does this computation take?

## Visualizing Computational Costs



Suppose we have 3 processors. How much time does this computation take? Schedule A-BC-D: $1+\max (1,7)+1=9$

## Visualizing Computational Costs



Suppose we have infinite processors. How much time does this computation take? Schedule A-BC-D: $1+\max (1,7)+1=9$

## Work and Span

Understanding the complexity of a parallel program is a little more complex than a sequential program

- the number of processors has a significant effect

One way to approximate the cost is to consider a parallel algorithm independently of the machine it runs on is to consider two metrics:

- Work: The cost of executing a program with just 1 processor.
- Span: The cost of executing a program with an infinite number of processors

Always good to minimize work

- Every instruction executed consumes energy
- Minimize span as a second consideration
- Communication costs are also crucial (we are ignoring them)


## Parallelism

The parallelism of an algorithm is an estimate of the maximum number of processors an algorithm can profit from.

- parallelism = work / span

If work = span then parallelism $=1$.

- We can only use 1 processor
- It's a sequential algorithm

If span $=1 / 2$ work then parallelism $=2$

- We can use up to 2 processors

If work $=100$, span $=1$

- All operations are independent \& can be executed in parallel
- We can use up to 100 processors


## Series-Parallel Graphs


one operation

two operations in sequence
e1; e2

two operations in parallel (e1 || e2)

Series-parallel graphs arise from execution of functional programs with parallel pairs. Also known as well-structured, nested parallelism.

## Parallel Pairs



> let both $f \times g y=$ let $\mathrm{ff}=\mathrm{future} \mathrm{f} x$ in let $\mathrm{gv}=\mathrm{g} y$ in (force $\mathrm{ff}, \mathrm{gv}$ )

## Series-Parallel Graphs Compose


one operation

two graphs
in sequence

two graphs
in parallel

In general, a series-parallel graph has a source and a sink and is:

- a single node, or
- two series-parallel graphs in sequence, or
- two series-parallel graphs in parallel


## Not a Series-Parallel Graph



However:
The results about greedy schedulers (next few slides) do apply to DAG schedules as well as series-parallel schedules!

## Work and Span of Acyclic Graphs

Let's assume each node costs 1.


## Work and Span of Acyclic Graphs

Let's assume each node costs 1.


$$
\begin{aligned}
& \text { work }=10 \\
& \text { span }=5
\end{aligned}
$$

## Scheduling

Let's assume each node costs 1.


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## Greedy Schedulers

Greedy schedulers will schedule some task to a processor as soon as that processor is free.

- Doesn't sound so smart!


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Properties (for p processors):

- T(p) < work/p + span
- won't be worse than dividing up the data perfectly between processors, except for the last little bit, which causes you to add the span on top of the perfect division
- T(p) >= max(work/p, span)
- can't do better than perfect division between processors (work/p)
- can't be faster than span


## Greedy Schedulers

## Properties (for p processors):

$\max ($ work $/ \mathrm{p}, \mathrm{span})<=\mathrm{T}(\mathrm{p})<$ work/p + span

## Consequences:

- as span gets small relative to work/p
- work/p + span ==> work/p
- max(work/p, span) ==> work/p
- so $T(p)==>$ work/p -- greedy schedulers converge to the optimum!
- if span approaches the work
- work/p + span ==> span
- max(work/p, span) ==> span
- so $T(p)==>$ span - greedy schedulers converge to the optimum!


## And therefore

Even though greedy schedulers are simple to implement,
they can be effective in building a parallel programming system.
and

This supports the idea that work and span are useful ways to reason about the cost of parallel programs.

## PARALLEL SEQUENCES

## Parallel Sequences

## Parallel sequences

$$
<\mathrm{e} 1, \mathrm{e} 2, \mathrm{e} 3, \ldots, \mathrm{en}>
$$

Operations:

- creation (called tabulate)
- indexing an element in constant span
- map
- scan -- like a fold: <u, u + e1, u + e1 + e2, ...> $\log n$ span!

Languages:

- Nesl [Blelloch]
- Data-parallel Haskell


## Parallel Sequences: Selected Operations

```
tabulate : (int -> 'a) -> int -> 'a seq
tabulate f n == <f 0, f 1, ..., f (n-1)>
work = O(n) span = O(1)
```


## Parallel Sequences: Selected Operations

```
tabulate : (int -> 'a) -> int -> 'a seq
tabulate f n == <f 0, f 1, ..., f (n-1)>
work = O(n) span = O(1)
```

```
nth : 'a seq -> int -> 'a
nth <e0, e1, ..., e(n-1)> i == ei
work = O(1) span = O(1)
```


## Parallel Sequences: Selected Operations

```
tabulate : (int -> 'a) -> int -> 'a seq
tabulate f n == <f 0, f 1, ..., f (n-1)>
work = O(n) span = O(1)
```

```
nth : 'a seq -> int -> 'a
nth <e0, e1, ..., e(n-1)> i == ei
work = O(1) span = O(1)
```

length : 'a seq -> int
length $<e 0, ~ e 1, \ldots, e(n-1)>==n$
work $=O(1) \quad \operatorname{span}=O(1)$

## Example Problems

Write a function that creates the sequence <0, ..., n-1> with Span $=O(1)$ and Work $=O(n)$.

Operations:

|  |  | Work | Span |
| :--- | :--- | :--- | :--- |
| tabulate f n | n | 1 |  |
| nth i s |  | 1 | 1 |
| length s |  | 1 | 1 |

## Example Problems

Write a function that creates the sequence $<0, \ldots, n-1>$ with Span $=O(1)$ and Work $=O(n)$.
(* create $n=<0,1, \ldots, n-1\rangle *$ )
let create $\mathrm{n}=$

Operations:

|  |  | Work | Span |
| :--- | :--- | :--- | :--- |
| tabulate f n | n | 1 |  |
| nth i s |  | 1 | 1 |
| length s |  | 1 | 1 |

## Example Problems

Write a function that creates the sequence $<0, \ldots, n-1>$ with Span $=O(1)$ and Work $=O(n)$.

```
(* create n == <0, 1, ..., n-1> *)
let create n =
    tabulate (fun i -> i) n
```

Operations:

|  |  | Work | Span |
| :--- | :--- | :--- | :--- |
| tabulate f n | n | 1 |  |
| nth i s |  | 1 | 1 |
| length s |  | 1 | 1 |

## Example Problems

Write a function such that given a sequence <v0, ..., vn-1>, maps $f$ over each element of the sequence with $\operatorname{Span}=O(1)$ and Work $=O(n)$, returning the new sequence (if $f$ is constant work)

Operations:

|  |  | Work | Span |
| :--- | :--- | :--- | :--- |
| tabulate f n | n | 1 |  |
| nth i s |  | 1 | 1 |
| length s |  | 1 | 1 |

## Example Problems

Write a function such that given a sequence <v0, ..., vn-1>, maps $f$ over each element of the sequence with $\operatorname{Span}=O(1)$ and
Work $=O(n)$, returning the new sequence (if $f$ is constant work)

> (* map f <v0, ..., vn-1> == <f v0, ..., f vn-1> *)
let map f s =

Operations:

|  |  | Work |
| :--- | :--- | :--- |
| tabulate f | Span |  |
| nth i s |  | 1 |
| length $s$ |  | 1 |

## Example Problems

Write a function such that given a sequence <v0, ..., vn-1>, maps $f$ over each element of the sequence with $\operatorname{Span}=O(1)$ and
Work $=O(n)$, returning the new sequence (if $f$ is constant work)

```
(* map f <v0, ..., vn-1> == <f v0, ..., f vn-1> *)
let map f s =
    tabulate (fun i -> f (nth s i)) (length s)
```

Operations:

|  |  | Work | Span |
| :--- | :--- | :--- | :--- |
| tabulate f n | n | 1 |  |
| nth i s |  | 1 | 1 |
| length s |  | 1 | 1 |

## Example Problems

Write a function such that given a sequence $<\mathrm{v} 0, \ldots, \mathrm{vn}-1>$, reverses the sequence. with Span $=0(1)$ and Work $=O(n)$

Operations:

|  |  | Work | Span |
| :--- | :--- | :--- | :--- |
| tabulate f $n$ | $n$ | 1 |  |
| nth i $s$ |  | 1 | 1 |
| length $s$ |  | 1 | 1 |

## Example Problems

Write a function such that given a sequence $<\mathrm{v} 0, \ldots, \mathrm{vn}-1>$, reverses the sequence. with Span $=O(1)$ and Work $=O(n)$
(* reverse <v0, ..., vn-1> == <vn-1, ..., v0> *)
let reverse $s=$

Operations:

|  |  | Work | Span |
| :--- | :--- | :--- | :--- |
| tabulate f n | n | 1 |  |
| nth i s |  | 1 | 1 |
| length s |  | 1 | 1 |

## Example Problems

Write a function such that given a sequence $<\mathrm{v} 0, \ldots, \mathrm{vn}-1>$, reverses the sequence. with Span $=O(1)$ and Work $=O(n)$

```
(* reverse <v0, ..., vn-1> == <vn-1, ..., v0> *)
let reverse s =
    let }\textrm{n}=\mathrm{ length s in
    tabulate (fun i -> nth s (n-i-1)) n
```

Operations:

|  |  | Work | Span |
| :--- | :--- | :--- | :--- |
| tabulate f n | n | 1 |  |
| nth i s |  | 1 | 1 |
| length s |  | 1 | 1 |

## A Parallel Sequence API

| type 'a seq | Work | Span |
| :---: | :---: | :---: |
| tabulate : (int -> 'a) -> int -> 'a seq | $\mathrm{O}(\mathrm{N})$ | $\mathrm{O}(1)$ |
| length : 'a seq -> int | $\mathrm{O}(1)$ | $\mathrm{O}(1)$ |
| nth : 'a seq -> int -> 'a | $\mathrm{O}(1)$ | $\mathrm{O}(1)$ |
| append : 'a seq -> 'a seq -> 'a seq (can build this from tabulate, nth, length) | $\mathrm{O}(\mathrm{N}+\mathrm{M})$ | $\mathrm{O}(1)$ |
| split : 'a seq -> int -> 'a seq * 'a seq | $\mathrm{O}(\mathrm{N})$ | $\mathrm{O}(1)$ |

For efficient implementations, see Blelloch's NESL project: http://www.cs.cmu.edu/~scandal/nesl.html

## Fold and Reduce

We have seen many sequential algorithms can be programmed succinctly using fold or reduce. Eg: sum all elements:
sum:


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let sum_all (l:int list) $=$ reduce $(+) 0$ l

## Fold and Reduce

We have seen many sequential algorithms can be programmed succinctly using fold or reduce. Eg: sum all elements:


```
let sum_all (l:int list) = reduce (+) 0 l
```

Key to parallelization: Notice that because sum is an associative operator, we do not have to add the elements strictly left-to-right:

$$
((((\text { init }+v 1)+v 2)+v 3)+v 4)+v 5)==((\text { init }+v 1)+v 2)+((v 3+v 4)+v 5)
$$

## Side Note

The key is associativity:

$$
((((\text { init }+v 1)+v 2)+v 3)+v 4)+v 5)==((\text { init }+v 1)+v 2)+((v 3+v 4)+v 5)
$$

add on processor 2

Commutativity not needed!
Commutativity allows us to reorder the elements:

$$
v 1+v 2==v 2+v 1
$$

But we don't have to reorder elements to obtain a significant speedup; we just have to reorder the execution of the operations.

## Parallel Sum



## Parallel Sum



## Parallel Sum

let both $\mathrm{fxgy=}$ let $\mathrm{ff}=$ future $\mathrm{f} x$ in let $g v=g y$ in (force ff, gv)

```
let rec psum (s : int seq) : int =
    match length s with
        0 -> 0
    | 1 -> nth s 0
    | n ->
        let (s1,s2) = split (n/2) s in
        let (a1, a2) = both psum s1
        psum s2 in
        a1 + a2
```


## Parallel Reduce



If op is associative and the base case has the properties:

$$
\text { op base } X==X \quad \text { op } X \text { base }=X
$$

then the parallel reduce is equivalent to the sequential left-to-right fold.

## Parallel Reduce

let rec reduce (f:'a -> 'a -> 'a) (base:'a) (s:'a seq) = match length s with

0 -> base
| 1 -> nth s 0
| n ->
let (s1,s2) = split (n/2) s in
let (ni, n2) = both (reduce f base) si
(reduce f base) sQ in
f ni n2

## Parallel Reduce

let rec reduce (f:'a -> 'a -> 'a) (base:'a) (s:'a seq) = match length $s$ with

0 -> base
| $1 \rightarrow$ nth $s$
| $\mathrm{n}->$
let $(s 1, s 2)=\operatorname{split}(n / 2) s$ in
let (ni, ne) $=$ both (reduce $f$ base) si
(reduce f base) st in
f n 1 n 2
let sum $s=$ reduce $(+) 0$ s

## A little more general

let rec mapreduce (inject: 'a -> 'b)
(combine:'b -> 'b -> 'b)
(base:'b)
(s:'a seq) =
match length $s$ with
0 -> base
| 1 -> inject (nth $s$ 0)
| n ->
let $(s 1, s 2)=s p l i t(n / 2) s$ in
let (n1, n2) $=$ both

$$
\begin{aligned}
& \text { (mapreduce inject combine base) } \mathrm{s} 1 \\
& \text { (mapreduce inject combine base) s2 in }
\end{aligned}
$$

combine n1 n2

## A little more general

let rec mapreduce (inject: 'a -> 'b)
(combine:'b -> 'b -> 'b)
(base:'b)
(s:'a seq) =
match length s with
0 -> base
| 1 -> inject (nth s 0)
| n ->
let $(s 1, s 2)=\operatorname{split}(n / 2) s i n$
let ( $\mathrm{n} 1, \mathrm{n} 2$ ) $=$ both
(mapreduce inject combine base) sI
(mapreduce inject combine base) s2 in
combine ni ne
let average $s=$
let (count, total) =
mapreduce (fun $x \rightarrow(1, x)$ )
(fun (c1,t1) (c2,t2) -> (c1+c2, ti + th))
$(0,0) \mathrm{s}$ in
if count $=0$ then 0 else total / count

## DON'T PARALLELIZE

AT TOO FINE A GRAIN

## Parallel Reduce with Sequential Cut-off

When data is small, the overhead of parallelization isn't worth it. Revert to the sequential version!

```
let sequential_reduce f base (s:'a seq) =
    let rec g i x =
            if i<0 then x else g (i-1) (f (nth a i) x)
        in g (length s - 1)
```

let $\mathrm{SHORT}=1000$
let rec reduce (f:'a -> 'a -> 'a) (base:'a) (s:'a seq) =
if length s < SHORT
then sequential_reduce f base s
else let (s1,s2) = split ((length s)/2) s in
let (ni, n2) = both (reduce f base) si
(reduce f base) sh in
f ni no

## BALANCED PARENTHESES

## The Balanced Parentheses Problem

Consider the problem of determining whether a sequence of parentheses is balanced or not. For example:

- balanced: ()()(())
- not balanced: (
- not balanced: )(
- not balanced: ()))

We will try formulating a divide-and-conquer parallel algorithm to solve this problem efficiently:

```
type paren = L | R (* L(eft) or R(ight) paren *)
let balanced (ps : paren seq) : bool = ...
```


## First, a sequential approach

fold from left to right, keep track of \# of unmatched left parens

| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |

0


## First, a sequential approach

fold from left to right, keep track of \# of unmatched left parens

| 1 | $($ | $)$ | $)$ | $)$ | $($ | $)$ | 1 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 1 |  |  |  |  |  |  |  |



## First, a sequential approach

fold from left to right, keep track of \# of unmatched left parens


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fold from left to right, keep track of \# of unmatched left parens


## First, a sequential approach

fold from left to right, keep track of
\# of unmatched left parens

too many right parens indicates no match

## First, a sequential approach


if you reach the end of the end of the sequence, you should have no unmatched left parens

## Easily Coded Using a Fold


let rec fold f b $\mathrm{s}=$
let rec aux n accum $=$
if $n>=$ length $s$ then
accum
else
aux ( $n+1$ ) (f (nth $s n$ ) accum)
in
aux 0 b

## Easily Coded Using a Fold

(* check to see if we have too many unmatched $R$ parens
sofar : number of unmatched parens so far or None if we have seen too many $R$ pares
*)
let check (p:paren) (so_far:int option) : int option = match (p, sofar) with
(_, None) -> None
| (L, Some c) -> Some (c+1)
(R, Some 0) -> None (* violation detected *)
| ( R , Some c) -> Some ( $\mathrm{c}-1$ )

## Easily Coded Using a Fold

```
let fold f base s = ...
let check so_far s = ...
let balanced (s: paren seq) : bool =
    match fold check (Some 0) s with
        Some 0 -> true
    | (None | Some n) -> false
```

That was easy enough. But the "check" function is not associative, that means it can't be used in a parallel "reduce".

That's what I was
warning about!

## Parallel Version

Key insights

- if you find () in a sequence, you can delete it without changing the balance


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## Parallel Version

Key insights

- if you find () in a sequence, you can delete it without changing the balance
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For divide-and-conquer, splitting a sequence of parens is easy
Combining two sequences where we have deleted all ():

- )) ) ... j ... ))) ((( ... k ... ((( ))) ... x ... ))) ((( ... y ... ((


## Parallel Version

Key insights

- if you find () in a sequence, you can delete it without changing the balance
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## Parallel Version

Key insights

- if you find () in a sequence, you can delete it without changing the balance
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- )) ) ... j ... ))) ((( ... k ... ((

For divide-and-conquer, splitting a sequence of parens is easy
Combining two sequences where we have deleted all ():

$$
\begin{aligned}
& -))) \ldots j \ldots \text { ) }))(((\ldots k \underbrace{\underbrace{. . .((()))} \ldots x \ldots)))}(((\ldots y \ldots(((
\end{aligned}
$$

- if $x \leq k$ then ))) ... j ... )) ) ((( ... $k-x$... ((( (( ... y ... ((


## Parallel Matcher

(* delete all () and return the (j, k) corresponding to:
)) ) ... j ... ) ) ) (( ( ... k ... (( (
*)
let rec matcher s =
match length s with

$$
\begin{aligned}
& 0->(0,0) \\
& \text { | } 1 \text {-> (match nth s } 0 \text { with } \\
& \text { | L -> }(0,1) \\
& \text { | R -> }(1,0)) \\
& \text { | n -> } \\
& \text { let (left, right) = split ( } \mathrm{n} / 2 \text { ) } \mathrm{s} \text { in } \\
& \text { let ((j, k), (x, y)) = both matcher left } \\
& \text { matcher right in } \\
& \text { if } \mathrm{x}>\mathrm{k} \\
& \text { then (j + ( } x-k), y \text { ) } \\
& \text { else (j, (k - x) + y) }
\end{aligned}
$$

## Parallel Balance

(* *)
let matcher $s=\ldots$.
(* true if $s$ is a sequence of balanced parens *)
let balanced $s=$
match matcher $s$ with
$\mid(0,0) \rightarrow>$ true
| (j,k) $\rightarrow$ false

## Parallel Matcher

(* delete all () and return the (j, k) corresponding to:
)) ) ... j ... ) ) ) ((( ... k ... (( (
*)
let rec matcher $\mathrm{s}=$ match length s with

This looks just like mapreduce!

```
        0 -> (0, 0)
    | 1 -> (match nth s 0 with
        | L -> (0, 1)
                                | R -> (1, 0))
    | n ->
        let (left, right) = split (n/2) s in
        let ((j, k), (x, y)) = both matcher left
                                    matcher right in
        if x > k
        then (j + (x - k), y)
        else (j, (k - x) + y)
```


## Using a Parallel Fold

let rec mapreduce(inject: 'a -> 'b)
(combine:'b -> 'b -> 'b)
(base:'b)
(s:'a seq) = ...
let inject pare = match paren with

L -> $(0,1)$
| R -> $(1,0)$
let combine (j,k) (x,y) = if $x>k$ then $(j+(x-k), y)$
else $\quad(j,(k-x)+y)$
let balanced s = match mapreduce inject combine $(0,0)$ s with (0, 0) -> true (i,j) -> false

## Using a Parallel Fold

let rec mapreduce(inject: 'a -> 'b)
(combine:'b $->'^{\prime} b->\quad$ 'b)
(base:'b)
(s:'a seq) = ...
let inject pare = match paren with

$$
\text { L }->(0,1)
$$

$$
\text { | R -> }(1,0)
$$

let combine (j,k) (x,y) = if $x>k$ then ( $j+(x-k), y)$ else (j, (kex) + y)
 Span: O( log N)
let balanced s = match mapreduce inject combine $(0,0)$ s with ( 0,0 ) -> true (i,j) -> false

## Using a Parallel Fold

let rec mapreduce(inject: 'a -> 'b) (combine:'b $->\quad$ 'b $b>\quad$ 'b) (base: 'b)

$$
(s: ' a \text { seq })=\ldots
$$

let inject paren $=\quad$ For correctness, match paren with check the associativity

$$
\begin{aligned}
& L->(0,1) \\
& \left.\left\lvert\, \begin{array}{l}
L \\
\text { R }
\end{array}\right.\right)(1,0)
\end{aligned}
$$

of combine
also check:
let combine (jr) $(x, y)=$

$$
\begin{array}{ll}
\text { if } x>k \text { then }(j+(x-k), y) \\
\text { else } & (j,(k-x)+y)
\end{array}
$$

let balanced s =
match mapreduce inject combine $(0,0)$ s with
| (0, 0) -> true
| (i,j) -> false

## Summary

Parallel complexity can be described in terms of work and span

Folds and reduces are easily coded as parallel divide-andconquer algorithms with $\mathrm{O}(\mathrm{n})$ work and $\mathrm{O}(\log \mathrm{n})$ span

The map-reduce paradigm, inspired by functional programming, is a winner when it comes to big-data processing (more about that in the next lecture).

## Sanity checks

let combine (j,k) $(x, y)=$

$$
\begin{array}{ll}
\text { if } x>k \text { then } & (j+(x-k), y) \\
\text { else } & (j,(k-x)+y)
\end{array}
$$

base $=(0,0)$
check the associativity of combine
also check:
combine base $(\mathrm{i}, \mathrm{j})=(\mathrm{i}, \mathrm{j})$

Prove for yourself:
combine (combine $(j, k)(x, y))(a, b)=$ combine $(j, k)(\operatorname{combine}(x, y)(a, b))$
combine $(\mathrm{j}, \mathrm{k})(0,0)=(\mathrm{j}, \mathrm{k})$ combine $(0,0)(\mathrm{j}, \mathrm{k})=(\mathrm{j}, \mathrm{k})$

