

Purely Functional Data Structures and Monoids

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Purely Functional Data Structures

Why Do We Need Them?

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To answer that question, we're going to look at a very simple algorithm in an imperative language, and we're going to see how *not* to translate it into Haskell.

The mistake we make may well be one which you have made in past!

A Simple Imperative Algorithm

A Simple Imperative Algorithm

(in Python)

A Simple Imperative Algorithm

We're going to write a function to create an array filled with some `ints`.

A Simple Imperative Algorithm

It works like this.

```
>>> create_array_up_to(5)  
[0,1,2,3,4]
```

A Simple Imperative Algorithm

This is its implementation.

```
def create_array_up_to(n):  
    array = []  
    for i in range(n):  
        array.append(i)  
    return array
```

A Simple Imperative Algorithm

We first initialise an empty array.

```
def create_array_up_to(n):  
    array = []  
    for i in range(n):  
        array.append(i)  
    return array
```



A Simple Imperative Algorithm

And then we loop through the numbers from 0 to $n-1$.

```
def create_array_up_to(n):  
    array = []  
    for i in range(n):  
        array.append(i)  
    return array
```



A Simple Imperative Algorithm

We append each number on
to the array.

```
def create_array_up_to(n):  
    array = []  
    for i in range(n):  
        array.append(i)  
    return array
```



A Simple Imperative Algorithm

And we return the array.

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A Simple Imperative Algorithm

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>>> create_array_up_to(5)  
[0,1,2,3,4]
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The append function *mutates* array:
after calling append, the value of the
variable array changes.
array has different values before and
after line 3.

We can't do that in an immutable language! A variable's value cannot change from one line to the next in Haskell.

Append in Haskell

Instead of mutating variables, in Haskell when we want to change a data structure we usually write a function which returns a new variable equal to the old data structure with the change applied.

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$$\text{append} :: \text{Array } a \rightarrow a \rightarrow \text{Array } a$$

```
myArray = [1, 2, 3]
```

```
myArray2 = myArray 'append' 4
```

```
main = do
```

```
  print myArray
```

```
  print myArray2
```

Translating it to Haskell

Let's look at the imperative algorithm, and try to translate it bit-by-bit.

Translating it to Haskell

```
def create_array_up_to(n):  
    array = []  
    for i in range(n):  
        array.append(i)  
    return array
```

First we'll need to write the type signature and skeleton of the Haskell function.

What should the type be?

Translating it to Haskell

```
def create_array_up_to(n):  
    array = []  
    for i in range(n):  
        array.append(i)  
    return array
```

```
createArrayUpTo :: Int → Array Int  
createArrayUpTo n =
```

Translating it to Haskell

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We tend not to use loops in functional languages, but this loop in particular follows a very common pattern which has a name and function in Haskell.

What is it?

Translating it to Haskell

```
def create_array_up_to(n):  
    array = []  
    for i in range(n):  
        array.append(i)  
    return array
```

createArrayUpTo :: *Int* → *Array Int*

createArrayUpTo *n* =

foldl

$[0..n-1]$

foldl is the function we need.

How would the output have differed if we used *foldr* instead?

Translating it to Haskell

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    foldl  
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        emptyArray  
        [0..n-1]
```

Is there a shorter way to write this, that doesn't include a lambda?

Translating it to Haskell

```
def create_array_up_to(n):  
    array = []  
    for i in range(n):  
        array.append(i)  
    return array
```

$$\mathcal{O}(n)$$

```
createArrayUpTo :: Int → Array Int  
createArrayUpTo n =  
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```

$$\mathcal{O}(n^2)$$

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createArrayUpTo n =  
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```

Both implementations call *append* n times, which causes the difference in asymptotics.

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To run this code efficiently, most imperative interpreters will look for the space next to 3 in memory, and put 4 there: an $\mathcal{O}(1)$ operation.

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```
1 array = [1,2,3]
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```

(Of course, sometimes the “space next to 3” will already be occupied! There are clever algorithms you can use to handle this case.)

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To run this code efficiently, most imperative interpreters will look for the space next to 3 in memory, and put 4 there: an $\mathcal{O}(1)$ operation.

```
1 array = [1,2,3]
2 print(array)
3 array.append(4)
4 print(array)
```

Semantically, in an imperative language we are allowed to “forget” the contents of array on line 1: `[1,2,3]`. That array has been irreversibly replaced by `[1,2,3,4]`.

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The Haskell version of append looks similar at first glance:

$$myArray = [1, 2, 3]$$
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```
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```

```
>>> main
[1,2,3]
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```


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```

But we can't edit the array [1, 2, 3] in memory, because *myArray* still exists!

<i>main</i> = do	>>> <i>main</i>
<i>print myArray</i>	[1,2,3]
<i>print myArray₂</i>	[1,2,3,4]

As a result, our only option is to copy, which is $\mathcal{O}(n)$.

The Problem

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Solutions?

1. Find a way to disallow access of old versions of data structures.

This approach is beyond the scope of this lecture!

However, for interested students: **linear** type systems can enforce this property. You may have heard of **Rust**, a programming language with linear types.

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Solutions?

1. Find a way to disallow access of old versions of data structures.
2. Find a way to implement data structures that keep their old versions efficiently.

This is the approach we're going to look at today.

Keeping History Efficiently

Consider the linked list.



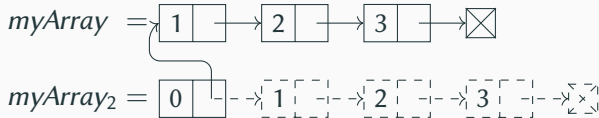
Keeping History Efficiently

To “prepend” an element (i.e. append to front), you might assume we would have to copy again:



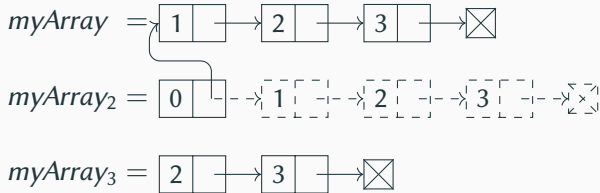
Keeping History Efficiently

However, this is not the case.

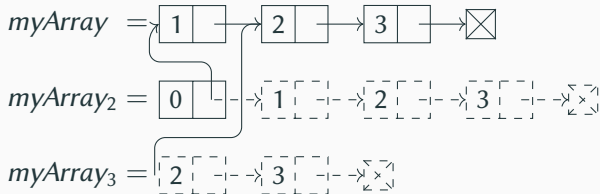


Keeping History Efficiently

The same trick also works with deletion.



Keeping History Efficiently



Persistent Data Structures

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An array is “persistent” in some sense, if all operations are implemented by copying. It just isn’t very *efficient*.

A linked list is much better: it can do persistent *cons* and *uncons* in $\mathcal{O}(1)$ time.

Immutability

While the semantics of languages like Haskell necessitate this property, they also *facilitate* it.

After several additions and deletions onto some linked structure we will be left with a real rat’s nest of pointers and references: strong guarantees that no-one will mutate anything is essential for that mess to be manageable.

As it happens, all of you have
already been using a persistent data structure!

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Git is perhaps the most widely-used persistent data structure in the world.

It works like a persistent file system: when you make a change to a file, git *remembers* the old version, instead of deleting it!

To do this efficiently it doesn't just store a new copy of the repository whenever a change is made, it instead uses some of the tricks and techniques we're going to look at in the rest of this talk.

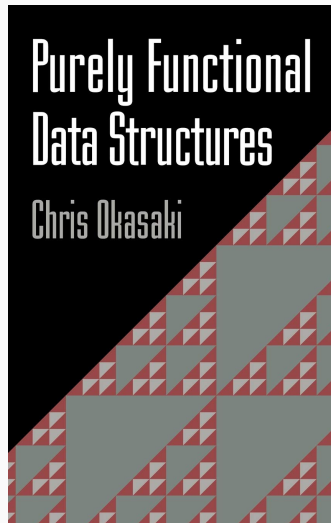
The Book

Chris Okasaki. *Purely Functional Data Structures*.

**Cambridge University Press,
June 1999**

Much of the material in this lecture comes directly from this book.

It's also on your reading list for your algorithms course next year.



While our linked list can replace a normal array for some applications, in general it's missing some of the key operations we might want.

Indexing in particular is $\mathcal{O}(n)$ on a linked list but $\mathcal{O}(1)$ on an array.

We're going to build a data structure which gets to $\mathcal{O}(\log n)$ indexing in a pure way.

Implementing a Functional Algorithm: Merge Sort

Merge Sort

Merge sort is a classic divide-and-conquer algorithm.

It divides up a list into singleton lists, and then repeatedly merges adjacent sublists until only one is left.

Visualisation of Merge Sort

2	6	10	7	8	1	9	3	4	5
---	---	----	---	---	---	---	---	---	---

Visualisation of Merge Sort

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2

6

10

7

8

1

9

3

4

5

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4	5
---	---

Visualisation of Merge Sort

1	2	3	6	7	8	9	10
---	---	---	---	---	---	---	----

4	5
---	---

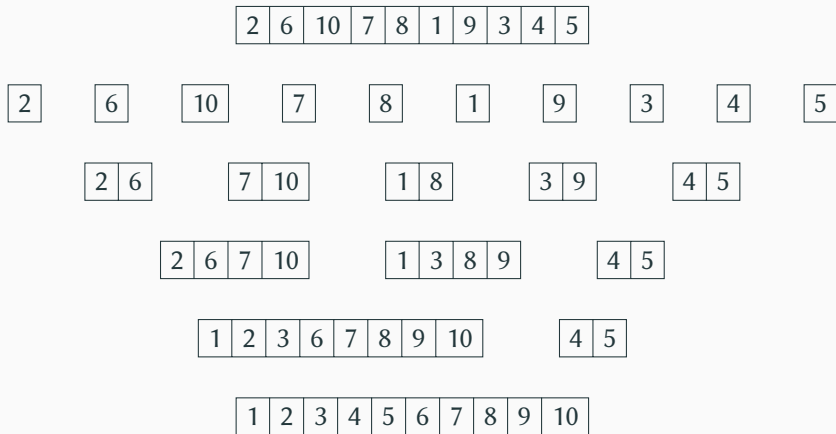
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Visualisation of Merge Sort



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You do not need to understand the following slide!

```

def merge_sort(arr):
    lsz, tsz, acc = 1, len(arr), []
    while lsz < tsz:
        for ll in range(0, tsz-lsz, lsz*2):
            lu, rl, ru = ll+lsz, ll+lsz, min(tsz, ll+lsz*2)
            while ll < lu and rl < ru:
                if arr[ll] <= arr[rl]:
                    acc.append(arr[ll])
                    ll += 1
                else:
                    acc.append(arr[rl])
                    rl += 1
            acc += arr[ll:lu] + arr[rl:ru]
        acc += arr[len(acc):]
        arr, lsz, acc = acc, lsz*2, []
    return arr

```

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Merge sort is actually an algorithm perfectly suited to a functional implementation.

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- We will add a healthy sprinkle of types.

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Granted, all of these improvements could have been made to the Python code, too.

Merge in Haskell

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$$\text{merge} :: \text{Ord } a \Rightarrow [a] \rightarrow [a] \rightarrow [a]$$
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$$\text{merge } xs [] = xs$$
$$\text{merge } (x : xs) (y : ys)$$
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$$| \text{otherwise} = y : \text{merge } (x : xs) ys$$

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```
>>> merge [1,8] [3,9]
```

```
[1,3,8,9]
```

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foldr?

The Problem with *foldr*

sort :: **Ord** a \Rightarrow [a] \rightarrow [a]

sort xs = *foldr merge* [] [[x] | x \leftarrow xs]

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sort :: Ord a => [a] -> [a]
sort xs = foldr merge [] [[x] | x <- xs]
```

Unfortunately, this is
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```
merge [x] ys = insert x ys
```

The problem is that *foldr* is too unbalanced.

```
foldr (⊕) ∅ [1..5] =
  1 ⊕ (2 ⊕ (3 ⊕ (4 ⊕ (5 ⊕ ∅))))
```


The Problem with *foldr*

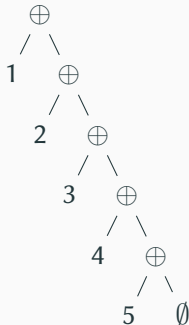
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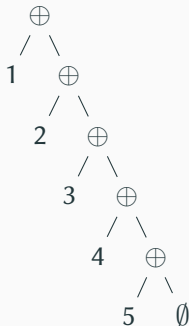
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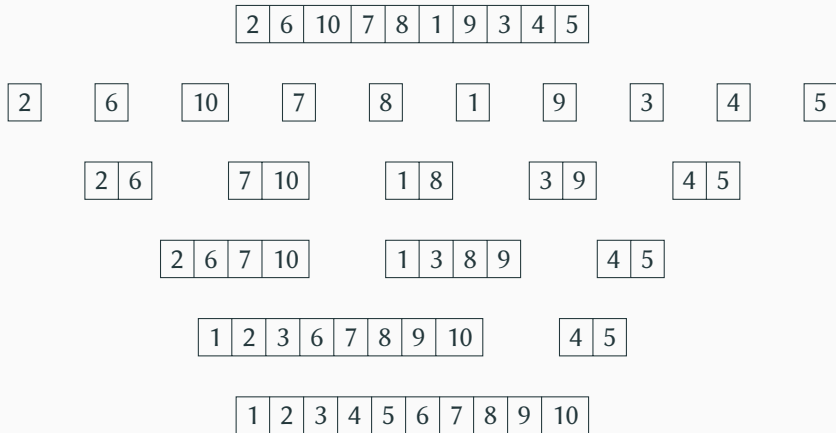
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Merge sort crucially divides the work in a balanced way!

Visualisation of Merge Sort



A More Balanced Fold

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$treeFold :: (a \rightarrow a \rightarrow a) \rightarrow [a] \rightarrow a$

$treeFold (\oplus) [x] = x$

$treeFold (\oplus) xs = treeFold (\oplus) (pairMap xs)$

where

$pairMap (x_1 : x_2 : xs) = x_1 \oplus x_2 : pairMap xs$

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$$\text{treeFold } (\oplus) [x] = x$$
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$$\text{pairMap } xs = xs$$

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$$\text{sum} = \text{treeFold } (+)$$

(although we would probably change the definition a little to catch the empty list, but we won't look at that here)

The fundamental difference between this fold and, say, *foldr* is that it's *balanced*, which is extremely important for merge sort.

Visualisation of *treeFold*

$$\begin{aligned} \text{treeFold } (\oplus) [1..10] = \\ \text{treeFold } (\oplus) [1, 2, 3, 4, 5, 6, 7, 8, 9, 10] \end{aligned}$$

1 2 3 4 5 6 7 8 9 10

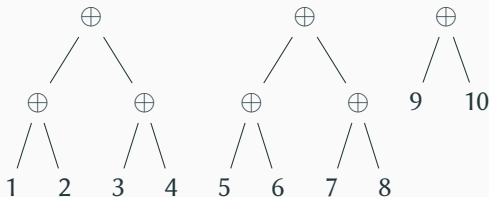
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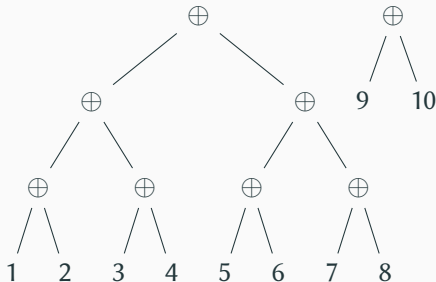
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$\text{treeFold } (\oplus) [1..10] =$

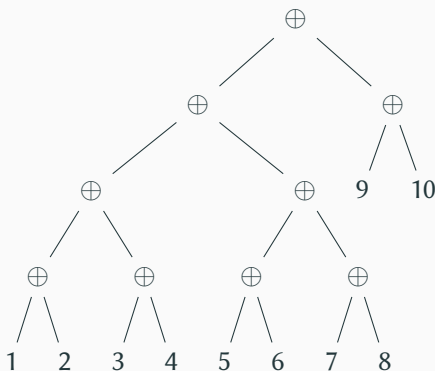
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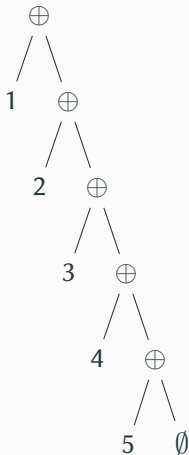
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Visualisation of *foldr*

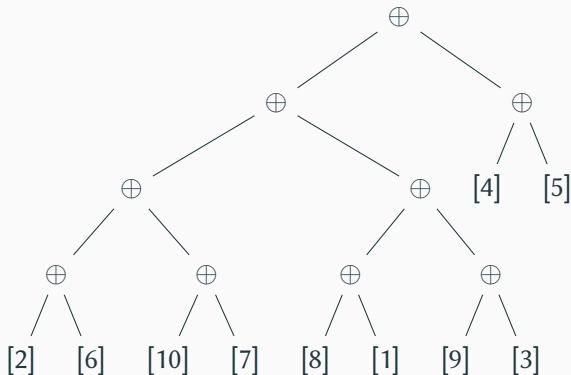
Compare to *foldr*:

$$\begin{aligned} & \textit{foldr} (\oplus) \emptyset [1..5] = \\ & 1 \oplus (2 \oplus (3 \oplus (4 \oplus (5 \oplus \emptyset)))) \end{aligned}$$



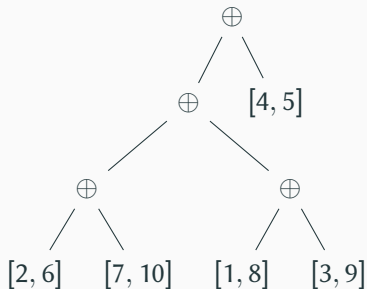
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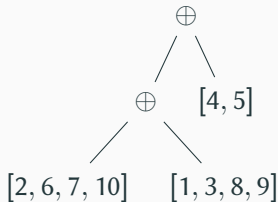
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Sort Algorithm

$sort :: Ord\ a \Rightarrow [a] \rightarrow [a]$

$sort\ [] = []$

$sort\ xs = treeFold\ merge\ [[x] \mid x \leftarrow xs]$

So Why Is This Algorithm Fast?

It's down to the pattern of the fold itself.

Because it splits the input evenly, the full algorithm is $\mathcal{O}(n \log n)$ time.

If we had just used *foldr*, we would have defined insertion sort, which is $\mathcal{O}(n^2)$.

Monoids

class Monoid *a* **where**

$\epsilon :: a$

$(\bullet) :: a \rightarrow a \rightarrow a$

Monoid

A monoid is a set with a neutral element ϵ , and a binary operator \bullet , such that:

$$(x \bullet y) \bullet z = x \bullet (y \bullet z)$$

$$x \bullet \epsilon = x$$

$$\epsilon \bullet x = x$$

Examples of Monoids

- \mathbb{N} , under either $+$ or \times .
- Lists:

instance *Monoid* $[a]$ **where**

$\epsilon = []$

$(\bullet) = (++)$

- *Ordered* lists, with *merge*.

Let's Rewrite *treeFold* to use Monoids

$treeFold :: \text{Monoid } a \Rightarrow [a] \rightarrow a$

$treeFold [] = \epsilon$

$treeFold [x] = x$

$treeFold xs = treeFold (pairMap xs)$

where

$pairMap (x_1 : x_2 : xs) = (x_1 \bullet x_2) : pairMap xs$

$pairMap xs = xs$

We can actually prove that this version returns the same results as *foldsr*, as long as the monoid laws are followed.

It just performs the fold in a more efficient way.

We've already seen one monoid we can use this fold with: ordered lists.

Another is floating-point numbers under summation. Using *foldr* or *foldl* will give you $\mathcal{O}(n)$ error growth, whereas using *treeFold* will give you $\mathcal{O}(\log n)$.

Let's Make It Incremental

treeFold currently processes the input in one big operation.

However, if we were able to process the input incrementally, with useful intermediate results, there are some other applications we can use the fold for.

A Binary Data Structure

We're going to build a data structure based on the binary numbers.

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(With each bit annotated with its significance)

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This number tells us how to arrange 10 elements into perfect trees.

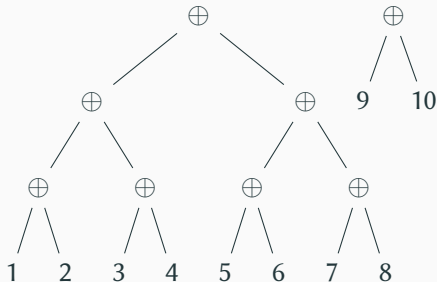
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The Incremental Type

We can write this as a datatype:

```
type Incremental a = [(Int, a)]
```

```
cons :: (a → a → a) → a → Incremental a → Incremental a
```

```
cons f = go 0
```

```
where
```

```
  go i x [] = [(i, x)]
```

```
  go i x ((0, y) : ys) = (i + 1, f x y) : ys
```

```
  go i x ((j, y) : ys) = (i, x) : (j - 1, y) : ys
```

```
run :: (a → a → a) → Incremental a → a
```

```
run f = foldr1 f ∘ map snd
```

And we can even implement *treeFold* using it:

```
treeFold :: (a → a → a) → [a] → a
```

```
treeFold f = run f ∘ foldr (cons f) []
```

We can now use the function incrementally.

$$\text{treeScanl } f = \text{map } (\text{run } f) \circ \text{tail} \circ \text{scanl } (\text{flip } (\text{cons } f)) []$$
$$\text{treeScanr } f = \text{map } (\text{run } f) \circ \text{init} \circ \text{scanr } (\text{cons } f) []$$

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We could, for instance, sort
all of the tails of a list
efficiently in this way.
(although I'm not sure why
you'd want to!)

treeScanr merge

$$\begin{aligned} &(\text{map pure } [2, 6, 1, 3, 4, 5]) \equiv \\ &[[1, 2, 3, 4, 5, 6] \\ & , [1, 3, 4, 5, 6] \\ & , [1, 3, 4, 5] \\ & , [3, 4, 5] \\ & , [4, 5] \\ & , [5]] \end{aligned}$$

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We could, for instance, sort
all of the tails of a list
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you'd want to!)

A more practical use is to extract the k smallest elements from a list,
which can be achieved with a variant on this fold.

But, as we saw already, the only required element here is the *Monoid*.

If we remember back to the $(\mathbb{N}, 0, +)$ monoid, we can build now a collection which tracks the number of elements it has.

```
data Tree a
  = Leaf { size :: Int, val :: a }
  | Node { size :: Int, lchild :: Tree a, rchild :: Tree a }

leaf :: a → Tree a
leaf x = Leaf 1 x

node :: Tree a → Tree a → Tree a
node xs ys = Node (size xs + size ys) xs ys
```

Not so useful, no, but remember that we have a way to build this type *incrementally*, in a *balanced* way.

type Array a = Incremental (Tree a)

Insertion is $\mathcal{O}(\log n)$:

insert :: a → Array a → Array a

insert x = cons node (leaf x)

fromList :: [a] → Array a

fromList = foldr insert []

And finally lookup, the key feature missing from our persistent implementation of arrays, is *also* $\mathcal{O}(\log n)$:

```
lookupTree :: Int → Tree a → a
lookupTree _ (Leaf _ x) = x
lookupTree i (Node _ xs ys)
  | i < size xs = lookupTree i xs
  | otherwise = lookupTree (i - size xs) ys

lookup :: Int → Array a → Maybe a
lookup = flip (foldr f b)
  where
    b _ = Nothing
    f (_, x) xs i
      | i < size x = Just (lookupTree i x)
      | otherwise = xs (i - size x)
```


Finger Trees

So we have seen a number of techniques today:

- Using pointers and sharing to make a data structure persistent.
- Using monoids to describe folding operations.
- Using *balanced* folding operations to take an $\mathcal{O}(n)$ operation to a $\mathcal{O}(\log n)$ one. (in terms of time and other things like error growth)
- Using a number-based data structure to incrementalise some of those folds.
- Using that incremental structure to implement things like lookup.

There is a single data structure which does pretty much all of this, and more: the Finger Tree.

Finger Trees

Ralf Hinze and Ross Paterson. Finger Trees: A Simple General-purpose Data Structure.

***Journal of Functional Programming*, 16(2):197–217, 2006**

A monoid-based tree-like structure, much like our “Incremental” type.

However, much more general.

Supports insertion, deletion, but also *concatenation*.

Also our lookup function is more generally described by the “split” operation.

All based around some monoid.

Uses for Finger Trees

Just by switching out the monoid for something else we can get an almost entirely different data structure.

- Priority Queues
- Search Trees
- Priority Search Queues (think: Dijkstra's Algorithm)
- Prefix Sum Trees
- Array-like random-access lists: this is precisely what's done in Haskell's `Data.Sequence`.