

Optimal Binary Search Trees

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Abstract

This article formalizes recursive algorithms for the construction of optimal binary search trees given fixed access frequencies. We follow Knuth [1], Yao [4] and Mehlhorn [2].

The algorithms are memoized with the help of an AFP entry for memoization [3], thus yielding dynamic programming algorithms.

Contents

1	Introduction	1
1.1	Data Representation	2
2	Weighted Path Length of BST	2
3	Optimal BSTs: The ‘Cubic’ Algorithm	4
3.1	Function <i>argmin</i>	4
3.2	The ‘Cubic’ Algorithm	5
3.2.1	Functions <i>wpl</i> and <i>min_wpl</i>	5
3.2.2	Function <i>opt_bst</i>	6
3.2.3	Function <i>opt_bst_wpl</i>	6
4	Quadrangle Inequality	7
5	Optimal BSTs: The ‘Quadratic’ Algorithm	9
6	Code Generation (unmemoized)	13
7	Memoization	13

1 Introduction

These theories formalize algorithms for the construction of optimal binary search trees from fixed access frequencies for a fixed list of items. The work

is based on the original article by Knuth [1] and the textbook by Mehlhorn [2, Part III, Chapter 4].

Initially the algorithms are expressed as naive recursive functions and have exponential complexity. Nevertheless we already refer to them as the cubic (Section 3) and the quadratic algorithm (Section 5), their running times of their fully memoized dynamic programming versions. In Section 7 the algorithms are memoized with the help of an existing framework [3].

1.1 Data Representation

Instead of labeling our BSTs with (ascending) keys $x_i < \dots < x_j$ we label them with the indices of the actual keys, some interval of integers. Functions taking two integer arguments i and j construct or analyze trees such that $\text{inorder } t = [i..j]$.

The access frequencies are given by two tables (functions) a and b :

$a\ k$ ($i \leq k \leq j + 1$) is the frequency of (failing) searches with a key in the interval (x_{k-1}, x_k) .

$b\ k$ ($i \leq k \leq j$) is the frequency of (successful) searches with key x_k .

2 Weighted Path Length of BST

```
theory Weighted_Path_Length
imports HOL-Library.Tree
begin
```

This theory presents two definitions of the *weighted path length* of a BST, the objective function we want to minimize, and proves them equivalent. Function Wpl is the intuitive global definition that sums a over all leaves and b over all nodes, taking their depth (= number of comparisons to reach that point) into account. Function wpl is a recursive definition and thus suitable for the later dynamic programming approaches to building a BST with the minimal weighted path length.

```
lemma inorder_upto_split:
  assumes inorder  $\langle l, k, r \rangle = [i..j]$ 
  shows inorder  $l = [i..k-1]$  inorder  $r = [k+1..j]$   $i \leq k$   $k \leq j$ 
 $\langle \text{proof} \rangle$ 
```

```
fun incr2 :: int  $\times$  nat  $\Rightarrow$  int  $\times$  nat where
incr2  $(x, n) = (x, n + 1)$ 
```

```
fun leaves :: int  $\Rightarrow$  int tree  $\Rightarrow$  (int  $*$  nat) set where
leaves  $i$  Leaf =  $\{(i, 0)\}$  |
leaves  $i$  (Node  $l\ k\ r$ ) = incr2 ' (leaves  $i\ l \cup$  leaves  $(k+1)\ r$ )
```

```
fun nodes :: int tree  $\Rightarrow$  (int  $*$  nat) set where
```

$nodes\ Leaf = \{\}$ |
 $nodes\ (Node\ l\ k\ r) = \{(k,1)\} \cup incr2\ ' (nodes\ l \cup nodes\ r)$

lemma *finite_nodes*: $finite\ (nodes\ t)$
 $\langle proof \rangle$

lemma *finite_leaves*: $finite\ (leaves\ i\ t)$
 $\langle proof \rangle$

lemma *notin_nodes0*: $(k, 0) \notin nodes\ t$
 $\langle proof \rangle$

lemma *sum_incr2*: $sum\ f\ (incr2\ ' A) = sum\ (\lambda xy. f(fst\ xy, snd\ xy+1))\ A$
 $\langle proof \rangle$

lemma *fst_nodes*: $fst\ ' nodes\ t = set_tree\ t$
 $\langle proof \rangle$

lemma *fst_leaves*: $\llbracket inorder\ t = [i..j];\ i \leq j+1 \rrbracket \implies fst\ ' leaves\ i\ t = \{i..j+1\}$
 $\langle proof \rangle$

lemma *sum_leaves*: $\llbracket inorder\ t = [i..j];\ i \leq j+1 \rrbracket \implies$
 $(\sum_{x \in leaves\ i\ t. (f(fst\ x) :: nat)) = sum\ f\ \{i..j+1\}$
 $\langle proof \rangle$

lemma *sum_nodes*: $inorder\ t = [i..j] \implies$
 $(\sum_{xy \in nodes\ t. (f(fst\ xy) :: nat)) = sum\ f\ \{i..j\}$
 $\langle proof \rangle$

locale *wpl* =
fixes $w :: int \Rightarrow int \Rightarrow nat$
begin

fun *wpl* :: $int \Rightarrow int \Rightarrow int\ tree \Rightarrow nat$ **where**
 $wpl\ i\ j\ Leaf = 0$ |
 $wpl\ i\ j\ (Node\ l\ k\ r) = wpl\ i\ (k-1)\ l + wpl\ (k+1)\ j\ r + w\ i\ j$

end

locale *Wpl* =
fixes $a\ b :: int \Rightarrow nat$
begin

definition *Wpl* :: $int \Rightarrow int\ tree \Rightarrow nat$ **where**
 $Wpl\ i\ t = sum\ (\lambda(k,c). c * b\ k)\ (nodes\ t) + sum\ (\lambda(k,c). c * a\ k)\ (leaves\ i\ t)$

definition *w* :: $int \Rightarrow int \Rightarrow nat$ **where**
 $w\ i\ j = sum\ a\ \{i..j+1\} + sum\ b\ \{i..j\}$

sublocale *wpl* **where** $w = w$ $\langle proof \rangle$

lemma $inorder\ t = [i..j] \implies wpl\ i\ j\ t = Wpl\ i\ t$
 $\langle proof \rangle$

end

end

3 Optimal BSTs: The ‘Cubic’ Algorithm

theory *Optimal_BST*

imports *Weighted_Path_Length Monad_Memo_DP.OptBST*

begin

3.1 Function *argmin*

Function *argmin* was moved to *Monad_Memo_DP.argmin*. It iterates over a list and returns the rightmost element that minimizes a given function:

$argmin\ ?f\ (?x\ \#\ ?xs) =$
 $(if\ ?xs = []\ then\ ?x$
 $else\ let\ m = argmin\ ?f\ ?xs\ in\ if\ ?f\ ?x < ?f\ m\ then\ ?x\ else\ m)$

An optimized version that avoids repeated computation of $f\ x$:

fun *argmin2* :: $(a \Rightarrow (b::linorder)) \Rightarrow 'a\ list \Rightarrow 'a * 'b$ **where**

$argmin2\ f\ (x\ \#\ xs) =$
 $(let\ fx = f\ x$
 $in\ if\ xs = []\ then\ (x,\ fx)$
 $else\ let\ mfm = argmin2\ f\ xs$
 $in\ if\ fx < snd\ mfm\ then\ (x,\ fx)\ else\ mfm)$

lemma *argmin2_argmin*: $xs \neq [] \implies argmin2\ f\ xs = (argmin\ f\ xs,\ f(argmin\ f\ xs))$
 $\langle proof \rangle$

lemma *argmin_argmin2*[code]: $argmin\ f\ xs = (if\ xs = []\ then\ undefined\ else\ fst(argmin2\ f\ xs))$
 $\langle proof \rangle$

lemma *argmin_in*: $xs \neq [] \implies argmin\ f\ xs \in set\ xs$
 $\langle proof \rangle$

lemma *argmin_pairs*: $xs \neq [] \implies$
 $(argmin\ f\ xs.\ f\ (argmin\ f\ xs)) = argmin\ snd\ (map\ (\lambda x.\ (x,\ f\ x))\ xs)$
 $\langle proof \rangle$

lemma *argmin_map*: $xs \neq [] \implies \text{argmin } c \text{ (map } f \text{ } xs) = f(\text{argmin } (c \circ f) \text{ } xs)$
 ⟨*proof*⟩

3.2 The ‘Cubic’ Algorithm

We hide the details of the access frequencies a and b by working with an abstract version of function w defined above (summing a and b). Later we interpret w accordingly.

locale *Optimal_BST* =
fixes $w :: \text{int} \Rightarrow \text{int} \Rightarrow \text{nat}$
begin

3.2.1 Functions wpl and min_wpl

sublocale *wpl* **where** $w = w$ ⟨*proof*⟩

Function $min_wpl \ i \ j$ computes the minimal weighted path length of any tree t where $inorder \ t = [i..j]$. It simply tries all possible indices between i and j as the root. Thus it implicitly constructs all possible trees.

declare *conj_cong* [*fundef_cong*]
function $min_wpl :: \text{int} \Rightarrow \text{int} \Rightarrow \text{nat}$ **where**
 $min_wpl \ i \ j =$
 (*if* $i > j$ *then* 0
 else $Min \ ((\lambda k. min_wpl \ i \ (k-1) + min_wpl \ (k+1) \ j) \ \{i..j\}) + w \ i \ j$)
 ⟨*proof*⟩
termination ⟨*proof*⟩
declare $min_wpl.simps$ [*simp del*]

Note that for efficiency reasons we have pulled $+ \ w \ i \ j$ out of Min . In the lemma below this is reversed because it simplifies the proofs. Similar optimizations are possible in other functions below.

lemma min_wpl_simps [*simp*]:
 $i > j \implies min_wpl \ i \ j = 0$
 $i \leq j \implies min_wpl \ i \ j =$
 $Min \ ((\lambda k. min_wpl \ i \ (k-1) + min_wpl \ (k+1) \ j + w \ i \ j) \ \{i..j\})$
 ⟨*proof*⟩

lemma *upto_split1*:
 $[i \leq j; j \leq k] \implies [i..k] = [i..j-1] @ [j..k]$
 ⟨*proof*⟩

Function $local.min_wpl$ returns a lower bound for all possible BSTs:

theorem $min_wpl_is_optimal$:
 $inorder \ t = [i..j] \implies min_wpl \ i \ j \leq wpl \ i \ j \ t$
 ⟨*proof*⟩

Now we show that the lower bound computed by $local.min_wpl$ is the wpl of an optimal tree that can be computed in the same manner.

3.2.2 Function *opt_bst*

This is the functional equivalent of the standard cubic imperative algorithm. Unless it is memoized, the complexity is again exponential. The pattern of recursion is the same as for *local.min_wpl* but instead of the minimal weight it computes a tree with the minimal weight:

```
function opt_bst :: int ⇒ int ⇒ int tree where
opt_bst i j =
  (if i > j then Leaf
   else argmin (wpl i j) [(opt_bst i (k-1), k, opt_bst (k+1) j). k ← [i..j]])
⟨proof⟩
termination ⟨proof⟩
declare opt_bst.simps[simp del]
```

```
corollary opt_bst_simps[simp]:
  i > j ⇒ opt_bst i j = Leaf
  i ≤ j ⇒ opt_bst i j =
    (argmin (wpl i j) [(opt_bst i (k-1), k, opt_bst (k+1) j). k ← [i..j]])
⟨proof⟩
```

As promised, *local.opt_bst* computes a tree with the minimal wpl:

```
theorem wpl_opt_bst: wpl i j (opt_bst i j) = min_wpl i j
⟨proof⟩
```

```
corollary opt_bst_is_optimal:
  inorder t = [i..j] ⇒ wpl i j (opt_bst i j) ≤ wpl i j t
⟨proof⟩
```

3.2.3 Function *opt_bst_wpl*

Function *local.opt_bst* is simplistic because it computes the wpl of each tree anew rather than returning it with the tree. That is what *opt_bst_wpl* does:

```
function opt_bst_wpl :: int ⇒ int ⇒ int tree × nat where
opt_bst_wpl i j =
  (if i > j then (Leaf, 0)
   else argmin snd [let (t1,c1) = opt_bst_wpl i (k-1);
                      (t2,c2) = opt_bst_wpl (k+1) j
                      in ((t1,k,t2), c1 + c2 + w i j). k ← [i..j]])
⟨proof⟩
termination
⟨proof⟩
declare opt_bst_wpl.simps[simp del]
```

Function *opt_bst_wpl* returns an optimal tree and its wpl:

```
lemma opt_bst_wpl_eq_pair:
  opt_bst_wpl i j = (opt_bst i j, wpl i j (opt_bst i j))
⟨proof⟩
```

corollary *opt_bst_wpl_eq_pair'*: $opt_bst_wpl\ i\ j = (opt_bst\ i\ j, min_wpl\ i\ j)$
 <proof>

end

end

4 Quadrangle Inequality

theory *Quadrilateral_Inequality*
imports *Main*
begin

definition *is_arg_min_on* :: ('a ⇒ ('b::linorder)) ⇒ 'a set ⇒ 'a ⇒ bool **where**
is_arg_min_on *f* *S* *x* = ($x \in S \wedge (\forall y \in S. f\ x \leq f\ y)$)

definition *Args_min_on* :: (int ⇒ ('b::linorder)) ⇒ int set ⇒ int set **where**
Args_min_on *f* *I* = {*k*. *is_arg_min_on* *f* *I* *k*}

lemmas *Args_min_simps* = *Args_min_on_def is_arg_min_on_def*

lemma *is_arg_min_on_antimono*: **fixes** *f* :: _ ⇒ _::order
shows $\llbracket is_arg_min_on\ f\ S\ x; f\ y \leq f\ x; y \in S \rrbracket \Longrightarrow is_arg_min_on\ f\ S\ y$
 <proof>

lemma *ex_is_arg_min_on_if_finite*: **fixes** *f* :: 'a ⇒ 'b :: linorder
shows $\llbracket finite\ S; S \neq \{\} \rrbracket \Longrightarrow \exists x. is_arg_min_on\ f\ S\ x$
 <proof>

locale *QI* =

fixes *c_k* :: int ⇒ int ⇒ int ⇒ nat

fixes *c* :: int ⇒ int ⇒ nat

and *w* :: int ⇒ int ⇒ nat

assumes *QI_w*: $\llbracket i \leq i'; i' < j; j \leq j' \rrbracket \Longrightarrow$

$w\ i\ j + w\ i'\ j' \leq w\ i'\ j + w\ i\ j'$

assumes *monotone_w*: $\llbracket i \leq i'; i' < j; j \leq j' \rrbracket \Longrightarrow w\ i'\ j \leq w\ i\ j'$

assumes *c_def*: $i < j \Longrightarrow c\ i\ j = Min\ ((c_k\ i\ j)\ ' \{i+1..j\})$

assumes *c_k_def*: $\llbracket i < j; k \in \{i+1..j\} \rrbracket \Longrightarrow$

$c_k\ i\ j\ k = w\ i\ j + c\ i\ (k-1) + c\ k\ j$

begin

abbreviation *mins* *i* *j* ≡ *Args_min_on* (*c_k* *i* *j*) {*i*+1..*j*}

definition *K* *i* *j* ≡ (if *i* = *j* then *i* else *Max* (*mins* *i* *j*))

lemma *c_def_rec*:

$i < j \Longrightarrow c\ i\ j = Min\ ((\lambda k. c\ i\ (k-1) + c\ k\ j + w\ i\ j)\ ' \{i+1..j\})$

<proof>

lemma *mins_subset*: $\text{mins } i j \subseteq \{i+1..j\}$
<proof>

lemma *mins_nonempty*: $i < j \implies \text{mins } i j \neq \{\}$
<proof>

lemma *finite_mins*: $\text{finite}(\text{mins } i j)$
<proof>

lemma *is_arg_min_on_Min*:
assumes *finite A is_arg_min_on f A a* **shows** $\text{Min } (f \text{ ` } A) = f a$
<proof>

lemma *c_k_with_K*: $i < j \implies c \ i \ j = c_k \ i \ j \ (K \ i \ j)$
<proof>

lemma *K_subset*: **assumes** $i \leq j$ **shows** $K \ i \ j \in \{i..j\}$ *<proof>*

lemma *lemma_2*:
[[$l = \text{nat } (j' - i); \ i \leq i'; \ i' \leq j; \ j \leq j' \]]$
 $\implies c \ i \ j + c \ i' \ j' \leq c \ i \ j' + c \ i' \ j$
<proof>

corollary *QI'*: **assumes** $i < k \ k \leq k' \ k' \leq j \ c_k \ i \ j \ k' \leq c_k \ i \ j \ k$
shows $c_k \ i \ (j+1) \ k' \leq c_k \ i \ (j+1) \ k$
<proof>

corollary *QI''*: **assumes** $i+1 < k \ k \leq k' \ k' \leq j+1 \ c_k \ i \ (j+1) \ k' \leq c_k \ i \ (j+1) \ k$
shows $c_k \ (i+1) \ (j+1) \ k' \leq c_k \ (i+1) \ (j+1) \ k$
<proof>

lemma *lemma_3_1*: **assumes** $i \leq j$ **shows** $K \ i \ j \leq K \ i \ (j+1)$
<proof>

lemma *lemma_3_2*: **assumes** $i \leq j$ **shows** $K \ i \ (j+1) \leq K \ (i+1) \ (j+1)$
<proof>

lemma *lemma_3*: **assumes** $i \leq j$
shows $K \ i \ j \leq K \ i \ (j+1) \ K \ i \ (j+1) \leq K \ (i+1) \ (j+1)$
<proof>

end

end

5 Optimal BSTs: The ‘Quadratic’ Algorithm

```

theory Optimal_BST2
imports
  Optimal_BST
  Quadrilateral_Inequality
begin

```

Knuth presented an optimization of the previously known cubic dynamic programming algorithm to a quadratic one. A simplified proof of this optimization was found by Yao [4]. Mehlhorn follows Yao closely. The core of the optimization argument is given abstractly in theory *Optimal_BST.Quadrilateral_Inequality*. In addition we first need to establish some more properties of *argmin*.

An index-based specification of *argmin* expressing that the last minimal list-element is picked:

```

lemma argmin_takes_last:  $xs \neq [] \implies$ 
   $argmin\ f\ xs = xs\ !\ Max\ \{i.\ i < length\ xs \wedge (\forall x \in set\ xs.\ f(xs!i) \leq f\ x)\}$ 
  (is  $\_ \implies \_ = \_ !\ Max\ (?M\ xs)$ )
<proof>

```

```

lemma Min_ex:  $\llbracket finite\ F; F \neq \{\} \rrbracket \implies \exists m \in F.\ \forall n \in F.\ m \leq (n::\_::linorder)$ 
<proof>

```

A consequence of *argmin_takes_last*:

```

lemma argmin_Max_Args_min_on: assumes [arith]:  $i \leq j$ 
shows  $argmin\ f\ [i..j] = Max\ (Args\_min\_on\ f\ \{i..j\})$ 
<proof>

```

As a consequence of *argmin_Max_Args_min_on* the following lemma allows us to justify the restriction of the index range of *argmin* used below in the optimized (quadratic) algorithm.

```

lemma argmin_red_ivl:
assumes  $i \leq i' \wedge argmin\ f\ [i..j] \in \{i'..j'\} \wedge j' \leq j$ 
shows  $argmin\ f\ [i'..j'] = argmin\ f\ [i..j]$ 
<proof>

```

```

fun root:: 'a tree  $\Rightarrow$  'a where
  root  $\langle \_, r, \_ \rangle = r$ 

```

Now we can formulate and verify the improved algorithm. This requires two assumptions on the weight function *w*.

```

locale Optimal_BST2 = Optimal_BST +
assumes monotone_w:  $\llbracket i \leq i'; i' \leq j; j \leq j' \rrbracket \implies w\ i'\ j \leq w\ i\ j'$ 
assumes QI_w:  $\llbracket i \leq i'; i' \leq j; j \leq j' \rrbracket \implies w\ i\ j + w\ i'\ j' \leq w\ i'\ j + w\ i\ j'$ 
begin

```

When finding an optimal tree for $[i..j]$ the optimization consists in reducing the search for the root from $[i..j]$ to $[root (opt_bst2 i (j - (1::'b)))..root (opt_bst2 (i + (1::'a)) j)]$:

```
function opt_bst2 :: int => int => int tree where
opt_bst2 i j =
  (if i > j then Leaf else
   if i = j then Node Leaf i Leaf else
   let left = root (opt_bst2 i (j-1)) in
   let right = root (opt_bst2 (i+1) j) in
   argmin (wpl i j) [(opt_bst2 i (k-1), k, opt_bst2 (k+1) j). k <- [left..right]])
⟨proof⟩
```

The termination of `opt_bst2` is not completely obvious. We first need to establish some functional properties of the terminating computations. We start by showing that the root of the returned tree is always between `left` and `right`. This is essentially equivalent to proving that $left \leq right$ because otherwise `argmin` is applied to `[]`, which is undefined.

```
lemma left_le_right:
opt_bst2_dom(i,j) ==>
  (i=j -> root(opt_bst2 i j) = i) ^
  (i<j -> root(opt_bst2 i j) ∈ {root(opt_bst2 i (j-1)) .. root(opt_bst2 (i+1) j)})
⟨proof⟩
```

Now we can bound the result of `opt_bst2` easily:

```
lemma root_opt_bst2_bound:
opt_bst2_dom (i,j) ==> i ≤ j ==> root (opt_bst2 i j) ∈ {i..j}
⟨proof⟩
```

Now termination follows easily:

```
lemma opt_bst2_dom: ∀ args. opt_bst2_dom args
⟨proof⟩
```

```
termination ⟨proof⟩
```

```
declare opt_bst2.simps[simp del]
```

```
abbreviation min_wpl3 i j k ≡ min_wpl i (k-1) + min_wpl (k+1) j + w i j
```

The correctness proof [?] is based on a general theory of ‘quadrilateral inequalities’ developed in locale `QI` that we now instantiate:

```
interpretation QI
where
  c = λi j. min_wpl (i+1) j
  and c_k = λi j. min_wpl3 (i+1) j
  and w = λi j. w (i+1) j
⟨proof⟩
```

```
lemma K_argmin: i < j ==> K i j = argmin (min_wpl3 (i+1) j) [i+1..j]
```

<proof>

theorem *opt_bst2_opt_bst*: $opt_bst2\ i\ j = opt_bst\ i\ j$

<proof>

corollary *opt_bst2_is_optimal*: $wpl\ i\ j\ (opt_bst2\ i\ j) = min_wpl\ i\ j$

<proof>

function *opt_bst_wpl2* :: $int \Rightarrow int \Rightarrow int\ tree \times nat$ **where**

opt_bst_wpl2 *i j* =

(if $i > j$ then (Leaf,0) else

if $i = j$ then (Node Leaf *i* Leaf, $w\ i\ i$) else

let $l = root(fst(opt_bst_wpl2\ i\ (j-1)))$;

$r = root(fst(opt_bst_wpl2\ (i+1)\ j))$ in

argmin *snd*

[let $(tl,wl) = opt_bst_wpl2\ i\ (k-1)$; $(tr,wr) = opt_bst_wpl2\ (k+1)\ j$

in $(\langle tl, k, tr \rangle, wl + wr + w\ i\ j) . k \leftarrow [l..r]$]

<proof>

lemma *left_le_right2*:

opt_bst_wpl2_dom(*i,j*) \implies

($i=j \longrightarrow root(fst(opt_bst_wpl2\ i\ j)) = i$) \wedge

($i < j \longrightarrow root(fst(opt_bst_wpl2\ i\ j)) \in$

$\{root(fst(opt_bst_wpl2\ i\ (j-1))) .. root(fst(opt_bst_wpl2\ (i+1)\ j))\}$)

<proof>

Now we can bound the result of *opt_bst_wpl2*:

lemma *root_opt_bst_wpl2_bound*:

opt_bst_wpl2_dom (*i,j*) $\implies i \leq j \implies root\ (fst(opt_bst_wpl2\ i\ j)) \in \{i..j\}$

<proof>

Now termination follows easily:

lemma *opt_bst_wpl2_dom*: $\forall\ args.\ opt_bst_wpl2_dom\ args$

<proof>

termination *<proof>*

declare *opt_bst_wpl2.simps*[*simp del*]

lemma *opt_bst_wpl2_eq_pair*:

opt_bst_wpl2 *i j* = (*opt_bst2* *i j*, *wpl* *i j* (*opt_bst2* *i j*))

<proof>

corollary *opt_bst_wpl2_eq_pair'*: $opt_bst_wpl2\ i\ j = (opt_bst\ i\ j, min_wpl\ i\ j)$

<proof>

end

end

theory *Optimal_BST_Examples*
imports *HOL-Library.Tree*
begin

Example by Mehlhorn:

definition *a_ex1* :: *int* \Rightarrow *nat* **where**
a_ex1 *i* = [4,0,0,3,10] ! *nat* *i*

definition *b_ex1* :: *int* \Rightarrow *nat* **where**
b_ex1 *i* = [1,3,3,0] ! *nat* *i*

definition *t_opt_ex1* :: *int tree* **where**
t_opt_ex1 = $\langle\langle\rangle, 0, \langle\rangle, 1, \langle\rangle\rangle, 2, \langle\rangle, 3, \langle\rangle\rangle$

Example by Knuth:

definition *a_ex2* :: *int* \Rightarrow *nat* **where**
a_ex2 *i* = 0

definition *b_ex2* :: *int* \Rightarrow *nat* **where**
b_ex2 *i* = [32,7,69,13,6,15,10,8,64,142,22,79,18,9] ! *nat* *i*

definition *t_opt_ex2* :: *int tree* **where**
t_opt_ex2 =

```
<
  <
    <<>, 0, <<>, 1, <>>,
    2,
    <
      <
        <<>, 3, <<>, 4, <>>,
        5,
        <<>, 6, <<>, 7, <>>
      >,
      8,
      <>
    >
  >,
  9,
  <<<>, 10, <>>,
  11,
  <<>, 12, <<>, 13, <>
>
>
>
```

end

6 Code Generation (unmemoized)

```
theory Optimal_BST_Code
imports
  Optimal_BST2
  Optimal_BST_Examples
begin

locale Wpl_Optimal_BST = Wpl a b + Optimal_BST where w = Wpl.w a b
for a b

locale Wpl_Optimal_BST2 = Wpl a b + Optimal_BST2 where w = Wpl.w a b
for a b

global_interpretation Wpl_Optimal_BST + Wpl_Optimal_BST2
defines wpl_ab = wpl and opt_bst_ab = opt_bst and opt_bst2_ab = opt_bst2
  <proof>

  Examples:

lemma opt_bst_ab a_ex1 b_ex1 0 3 = t_opt_ex1
  <proof>

lemma opt_bst2_ab a_ex2 b_ex2 0 13 = t_opt_ex2
  <proof>

end
```

7 Memoization

```
theory Optimal_BST_Memo
imports
  Optimal_BST
  Monad_Memo_DP.State_Main
  HOL-Library.Product_Lexorder
  HOL-Library.RBT_Mapping
  Optimal_BST_Examples
begin
```

This theory memoizes the recursive algorithms with the help of our generic memoization framework. Note that currently only the tree building (function *Optimal_BST.opt_bst*) is memoized but not the computation of *w*.

```
global_interpretation Wpl
where a = a and b = b for a b
defines w_ab = w and wpl_ab = wpl.wpl w_ab <proof>
```

First we express *argmin* via *fold*. Primarily because we have a monadic version of *fold* already. At the same time we improve efficiency.

lemma *fold_argmin*: *fold* ($\lambda x (m, fm)$). *let* $fx = f x$ *in* *if* $fx \leq fm$ *then* (x, fx) *else* (m, fm) *xs* $(x, f x)$
 = $(\text{argmin } f (x\#xs), f(\text{argmin } f (x\#xs)))$
<proof>

lemma *argmin_fold*: *argmin* $f xs = (\text{case } xs \text{ of } [] \Rightarrow \text{undefined} \mid$
 $x\#xs \Rightarrow \text{fst}(\text{fold } (\lambda x (m, fm)$. *let* $fx = f x$ *in* *if* $fx \leq fm$ *then* (x, fx) *else* (m, fm))
 $xs (x, f x))$
<proof>

The actual memoization of the cubic algorithm:

context *Optimal_BST*
begin

memoize_fun *opt_bst_m*: *opt_bst* **with_memory** *dp_consistency_mapping*
monadifies (*state*) *opt_bst.simps*[*unfolded_argmin_fold*]

thm *opt_bst_m'*.*simps*

memoize_correct
<proof>

lemmas [*code*] = *opt_bst_m.memoized_correct*

end

Code generation:

global_interpretation *Optimal_BST*
where $w = w_{ab} a b$
rewrites *wpl.wpl* $(w_{ab} a b) = wpl_{ab} a b$ **for** $a b$
defines *opt_bst_{ab}* = *opt_bst* **and** *opt_bst_{ab}'* = *opt_bst_m'*
<proof>

Examples:

lemma *opt_bst_{ab}* $a_{ex1} b_{ex1} 0 3 = t_{opt_{ex1}}$
<proof>

lemma *opt_bst_{ab}* $a_{ex2} b_{ex2} 0 13 = t_{opt_{ex2}}$
<proof>

end

References

- [1] D. E. Knuth. Optimum binary search trees. *Acta Inf.*, 1:14–25, 1971.
- [2] K. Mehlhorn. *Data Structures and Algorithms 1: Sorting and Searching*, volume 1 of *EATCS Monographs on Theoretical Computer Science*. Springer, 1984.

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- [4] F. F. Yao. Efficient dynamic programming using quadrangle inequalities. In *STOC*, pages 429–435. ACM, 1980.