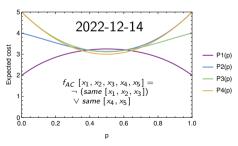
Level-p-complexity of Boolean Functions

Using thinning, memoization, and polynomials

Patrik Jansson¹

Functional Programming unit, Chalmers University of Technology



 $DSL \to \delta\sigma\lambda$ $DSL_{S/Math}$

¹Joint work with Julia Jansson, PhD student, Mathematical sciences, Chalmers

Some key results (teaser)

We want to find a decision tree with minimal cost for a boolean function.

We specify the problem as "generate all, select a smallest".

For an example 5-bit function f_{AC} there are already **54192** different decision trees.

$$t_5 = size (genAlg \ 5 \ f_{AC} :: Set \ DecTree)$$



Some key results (teaser)

We want to find a decision tree with minimal cost for a boolean function.

We specify the problem as "generate all, select a smallest".

For an example 5-bit function f_{AC} there are already **54192** different decision trees.

$$t_5 = size (genAlg \ 5 \ f_{AC} :: Set \ DecTree)$$

For a 9-bit function we can estimate the number of trees as

$$t_9 = 9 * t_8^2;$$
 $t_8 = 8 * t_7^2;$ $t_7 = 7 * t_6^2;$ $t_6 = 6 * t_5^2$

This estimate gives us $1.29 * 10^{89}$ decision trees!

Clearly, a naive implementation will take far too long to terminate.



Some key results (teaser)

We want to find a decision tree with minimal cost for a boolean function.

We specify the problem as "generate all, select a smallest".

For an example 5-bit function f_{AC} there are already **54192** different decision trees.

$$t_5 = size (genAlg \ 5 \ f_{AC} :: Set \ DecTree)$$

For a 9-bit function we can estimate the number of trees as

$$t_9 = 9 * t_8^2;$$
 $t_8 = 8 * t_7^2;$ $t_7 = 7 * t_6^2;$ $t_6 = 6 * t_5^2$

This estimate gives us $1.29 * 10^{89}$ decision trees!

Clearly, a naive implementation will take far too long to terminate.

By using **thinning**, **memoization**, and exact comparisions of **polynomials** we get down to a **singleton set** for iterated majority:

$$ps9 = genAlgThinMemoPoly \ 9 \ maj2 :: Set \ (Poly \ Rational) -- ps9 = fromList \ [P \ [4,4,6,9,-61,23,67,-64,16]]$$



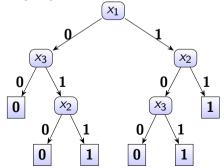
Some key types and definitions

- A Boolean function $f : BoolFun \ n$ takes a tuple of n bits to one bit.
- A tuple t: Tuple n is just a vector of n bits (**type** Bit = Bool; $\mathbf{0} = False$; $\mathbf{1} = True$).
- A decision tree describes a way to evaluate a BoolFun:

Haskell version:

```
type Index = \mathbb{N}
data DecTree where
  Res :: Bool \rightarrow DecTree
  Pick ·· Index → DecTree → DecTree
ex1 :: DecTree
ex1 = Pick \ 1 \ (Pick \ 3 \ (Res \ 0))
                      (Pick 2 (Res 0) (Res 1)))
              (Pick 2 (Pick 3 (Res 0) (Res 1))
                       (Res 1))
```

A decision tree (ex1) for the 3-bit majority function:



Some key types and definitions

A decision tree describes a way to evaluate a BoolFun

Haskell version:

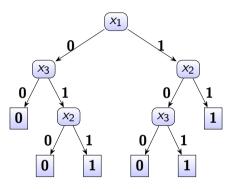
```
type Index = \mathbb{N}
data DecTree where
Res :: Bool \rightarrow DecTree
Pick :: Index \rightarrow DecTree \rightarrow DecTree \rightarrow DecTree
```

Agda version:

```
data DecTree: (n:\mathbb{N}) \to (f:BoolFun\ n) \to Set where Res: (b:Bool) \to DecTree\ n\ (const\ b) Pick: \{f:BoolFun\ (suc\ n)\} \to (i:Fin\ (suc\ n)) \to DecTree\ n\ (setBit\ i\ 1\ f) \to DecTree\ (suc\ n)\ f
```

 $\mathsf{setBit}: \mathsf{Fin}\ (\mathsf{suc}\ \mathsf{n}) o \mathsf{Bit} o \mathsf{BoolFun}\ (\mathsf{suc}\ \mathsf{n}) o \mathsf{BoolFun}\ \mathsf{n}$

Decision trees, cost and complexity

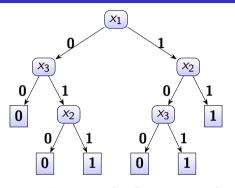


The decision tree ex1 for the 3-bit majority function maj:

- Note that the left subtree is for the function $f_0 = setBit \ 1 \ 0 \ maj = (\land)$
- and the right subtree for the function $f_1 = setBit \ 1 \ 1 \ maj = (\lor)$

²We assume *n* independent bits, all with probability *p* to be 1. The polynomials are defined over any *Ring*.

Decision trees, cost and complexity



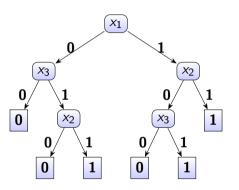
The decision tree ex1 for the 3-bit majority function maj:

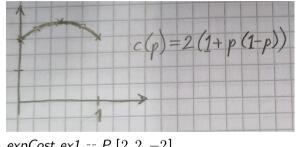
- Note that the left subtree is for the function $f_0 = setBit \ 1 \ 0 \ maj = (\land)$
- and the right subtree for the function $f_1 = setBit \ 1 \ maj = (\lor)$

• The cost of a DecTree is a function from Tuple n to \mathbb{N} : cost : $\{n : \mathbb{N}\} \to \{f : BoolFun \ n\} \to DecTree \ n \ f \to Tuple \ n \to \mathbb{N}$

²We assume n independent bits, all with probability p to be 1. The polynomials are defined over any Ring.

Decision trees, cost and complexity

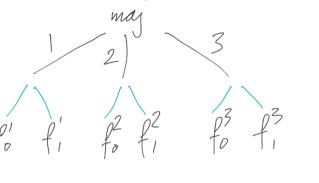




 $expCost \ ex1 = P[2, 2, -2]$

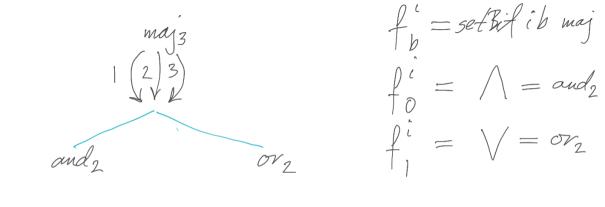
• Finally, the expected $cost^2$, is a polynomial in the probability p that a bit is 1: $expCost: \{n: \mathbb{N}\} \rightarrow \{f: BoolFun n\} \rightarrow DecTree \ n \ f \rightarrow Poly \ n$

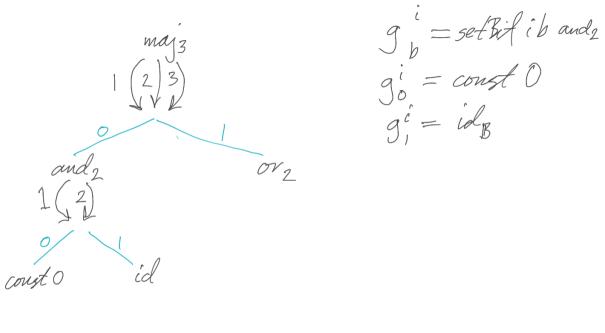
²We assume n independent bits, all with probability p to be 1. The polynomials are defined over any Ring.

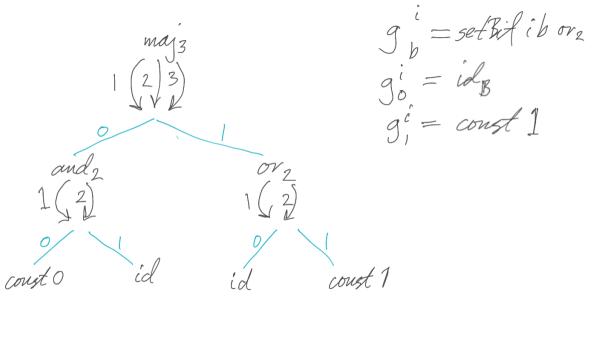


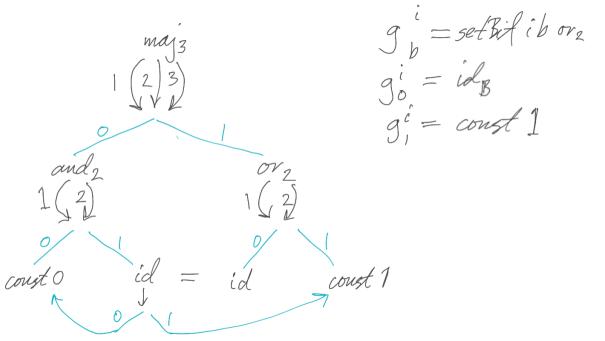


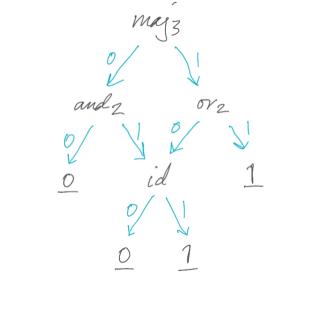
f' = setBifib maj

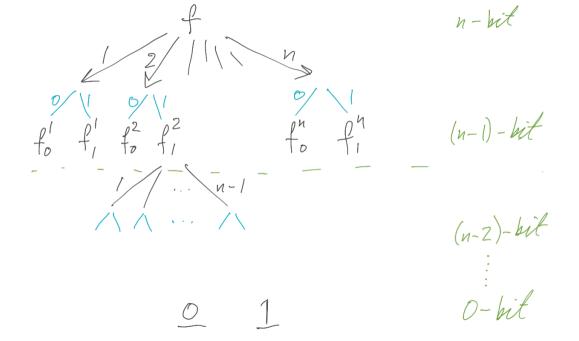












A class of Boolean functions

We abstract from the actual type for Boolean functions to a type class:

class BoFun bf where

isConst :: bf ightarrow Maybe Bool

 $setBit :: Index \rightarrow Bool \rightarrow bf \rightarrow bf$

We only use one instance: Binary Decision Diagrams (BDDs) which allows good sharing and fast operations.

Similarly, for decision trees, we use a class of tree algebras:

class TreeAlg a where res :: Bool \rightarrow a pic :: Index \rightarrow a \rightarrow a \rightarrow a

ex1 :: TreeAlg
$$a \Rightarrow a$$

ex1 = pic 1 (pic 3 (res $\mathbf{0}$) (pic 2 (res $\mathbf{0}$) (res $\mathbf{1}$)))
(pic 2 (pic 3 (res $\mathbf{0}$) (res $\mathbf{1}$)) (res $\mathbf{1}$))

```
instance TreeAlg DecTree where res = Res; pic = Pick; instance TreeAlg CostFun where res = resC; pic = pickC instance Ring \ a \Rightarrow TreeAlg \ (ExpCost \ a) where res = resPoly; pic = pickPoly
```

Similarly, for decision trees, we use a class of tree algebras:

class TreeAlg a where res :: Bool \rightarrow a pic :: Index \rightarrow a \rightarrow a \rightarrow a $ex1 :: TreeAlg \ a \Rightarrow a$ $ex1 = pic \ 1 \ (pic \ 3 \ (res \ 0) \ (pic \ 2 \ (res \ 0) \ (res \ 1)))$ (pic 2 (pic 3 (res **0**) (res **1**)) (res **1**)) **instance** TreeAlg DecTree where res = Res; pic = Pick;

data DecTree where

```
Res :: Bool \rightarrow DecTree
Pick :: Index \rightarrow DecTree \rightarrow DecTree \rightarrow DecTree
```

Similarly, for decision trees, we use a class of tree algebras:

```
class TreeAlg\ a where
res::Bool \rightarrow a
pic::Index \rightarrow a \rightarrow a \rightarrow a
ex1::TreeAlg\ a \Rightarrow a
ex1 = pic\ 1\ (pic\ 3\ (res\ 0)\ (pic\ 2\ (res\ 0)\ (res\ 1)))
(pic\ 2\ (pic\ 3\ (res\ 0)\ (res\ 1))\ (res\ 1))
```

instance TreeAlg CostFun where res = resC; pic = pickC **type** CostFun = Tuple \rightarrow Int resC b = const 0 pickC i c_0 $c_1 = \lambda t \rightarrow 1 + if$ index t i then c_1 t else c_0 t

Similarly, for decision trees, we use a class of tree algebras:

class TreeAlg a where

$$res :: Bool \rightarrow a$$

 $pic :: Index \rightarrow a \rightarrow a \rightarrow a$

$$\begin{array}{l} \textit{ex1} :: \textit{TreeAlg } \textit{a} \Rightarrow \textit{a} \\ \textit{ex1} = \textit{pic } 1 \; (\textit{pic } 3 \; (\textit{res } \textbf{0}) \; (\textit{pic } 2 \; (\textit{res } \textbf{0}) \; (\textit{res } \textbf{1}))) \\ & \; (\textit{pic } 2 \; (\textit{pic } 3 \; (\textit{res } \textbf{0}) \; (\textit{res } \textbf{1})) \; (\textit{res } \textbf{1})) \end{array}$$

```
instance Ring a \Rightarrow TreeAlg (ExpCost a) where res = resPoly; pic = pickPoly type ExpCost a = Poly a resPoly \_b = zero pickPoly \_p_0 p_1 = one + (one - xP) * p_0 + xP * p_1
```

Problem formulation: compute the *complexity*

generate all DecTrees for a given function

$$genAlg :: (BoFun\ bf\ ,\ TreeAlg\ ta) \Rightarrow bf \to Set\ ta$$

• find a small(est) set of dominating trees

$$minWith :: Preorder \ b \Rightarrow (a \rightarrow b) \rightarrow Set \ a \rightarrow Set \ a$$

then just keep their costs

complexity :: (BoFun bf, Ring a)
$$\Rightarrow$$
 bf \rightarrow Set (Poly a) complexity = mapS expCost \circ minWith expCost \circ genAlg

Calculation steps

• We can push the map on the other side of minWith

```
complexity = mapS \ expCost \circ minWith \ expCost \circ genAlg -- is equal to complexity = minWith \ id \circ mapS \ expCost \circ genAlg
```

 Note that this makes the computation more efficient, beacause several trees map to the same polynomial

Calculation step, cont.

 Next, we push the expCost computation into the tree generation, to get another gain in efficiency.

```
complexity = minWith id \circ mapS \ expCost \circ genAlg -- is equal to complexity = minWith id \circ genPoly
```

• Still generating too many polynomials - we can push some of *minWith* into the *genPoly* computation. This is the thinning step.

```
complexity = minWith id \circ thin \circ genPoly
-- is equal to (the proof is work in progress)
complexity = minWith id \circ genPolyThin
```

Unfolding boolean functions

```
genAlg :: (BoFun bf, TreeAlg ta) \Rightarrow bf \rightarrow Set ta
genAlg n f = case isConst f of
   Just b \rightarrow singleton (res b)
   Nothing \rightarrow crossSigma (\lambda i (t_0, t_1) \rightarrow pic i t_0 t_1) [1..n] \$ \lambda i \rightarrow
                        cross (genAlg (n-1) (setBit i 0 f))
                                (genAlg (n-1) (setBit i 1 f))
crossSigma :: (a \rightarrow b \rightarrow c) \rightarrow Set \ a \rightarrow (a \rightarrow Set \ b) \rightarrow Set \ c
      -- crossSigma op xs f = \{ op x y \mid x \leftarrow xs, y \leftarrow f x \}
cross :: Set a \rightarrow Set \ b \rightarrow Set \ (a, b)
cross \ xs \ vs = crossSigma (, ) \ xs ( \rightarrow vs )
      -- cross xs \ vs = \{ op \ x \ v \mid x \leftarrow xs, v \leftarrow vs \}
```

Unfold structure

- At this point recall the structure of the computation: We have an "unfold", co-algebra structure when we consume a boolean function and produce all dectrees.
- isConst maps an BoFun into either a const b case or the setBit case which for each i: Fin n has two subfunctions setBit i F f and setBit i T f.
- This can cause an enormous number of function calls, which indicates the need to do memoization (dynamic programming) when building up the "call graph".

Memoization

- Memoization reminder: naively computing fib (n + 2) = fib (n + 1) + fib n leads to exponential growth in the number of function calls.
- But if we fill in a table indexed by *n* with already computed results we get a the result in linear time.

Memoization in our case

- Similarly, here we "just" need to tabulate the result of the calls to complexity so as to avoid recomputation.
- The challenge is that the input is now a boolean function which is not as nicely structured as a natural number index.
- Fortunately, thanks to Hinze and others we have generic Tries only a hackage library away.
- Finally, putting these components together we can compute the level-p-complexity of (small) boolean functions in reasonable time.

Motivating example: 2-level iterated majority maj2:

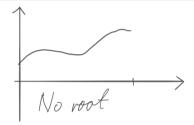
```
ps9 = genAlgThinMemoPoly \ 9 \ maj2 :: Set \ (Poly \ Rational) -- ps9 = fromList \ [P \ [4,4,6,9,-61,23,67,-64,16]]
```

Comparing polynomials

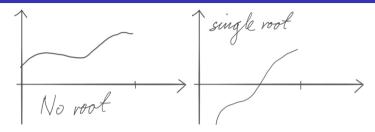
- Now, one of the challenges was actually the implementation of the comparison of polynomials. This is an interesting story in itself but perhaps not the main topic for today.
- Remember that the "complexity" we compute for each decision tree is actually a
 polynomial in the probability for a bit to be 1.
- And the mathematical definition of the level-p-complexity includes a "min" over all dec.trees, which in general results in a piecewise polynomial function.
- Ideally we should have a partition of the unit interval, labelled with polynomials, but we choose to represent such piecewise polynomial function simply as a set of polynomials.

Comparing polynomials, cont.

- For thinning we need a preorder on our polynomials, specified as $p \leqslant q = forall \ x. \ eval \ p \ x \leqslant eval \ q \ x.$
- This can be simplified to eval $(q p) \times \ge 0$ where q p is also a polynomial.
- We started with some ad-hoc special cases, but the sets did not shrink enough.
- Then we went to the wonderful world of polynomial algebra and root-counting.



• First, note that if a polynomial has no root in the interval, it is enough to evaluate in one point to find if it is always greater or less than zero.



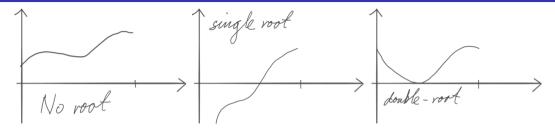
- First, note that if a polynomial has no root in the interval, it is enough to evaluate in one point to find if it is always greater or less than zero.
- Next, if there is any single root, the polynomial is on both sides and thus the original polynomials unrelated (neither $p \leqslant q$ nor $q \leqslant p$).



- First, note that if a polynomial has no root in the interval, it is enough to evaluate in one
 point to find if it is always greater or less than zero.
- Next, if there is any single root, the polynomial is on both sides and thus the original polynomials unrelated (neither $p \leqslant q$ nor $q \leqslant p$).
- For one double-root we are again on one side (or touching). In general, if we only have even-order roots, we are on one side.



- First, note that if a polynomial has no root in the interval, it is enough to evaluate in one
 point to find if it is always greater or less than zero.
- Next, if there is any single root, the polynomial is on both sides and thus the original polynomials unrelated (neither $p \leqslant q$ nor $q \leqslant p$).
- For one double-root we are again on one side (or touching). In general, if we only have even-order roots, we are on one side.
- Thus, we "only" need to count roots with exact multiplicities in the unit interval.



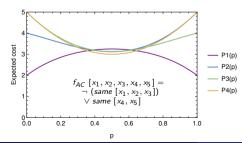
- First, note that if a polynomial has no root in the interval, it is enough to evaluate in one
 point to find if it is always greater or less than zero.
- Next, if there is any single root, the polynomial is on both sides and thus the original polynomials unrelated (neither $p \leqslant q$ nor $q \leqslant p$).
- For one double-root we are again on one side (or touching). In general, if we only have even-order roots, we are on one side.
- Thus, we "only" need to count roots with exact multiplicities in the unit interval.
- Note that we do not need to actually compute the roots, only count them.

- First, note that if a polynomial has no root in the interval, it is enough to evaluate in one point to find if it is always greater or less than zero.
- Next, if there is any single root, the polynomial is on both sides and thus the original polynomials unrelated (neither $p \leqslant q$ nor $q \leqslant p$).
- For one double-root we are again on one side (or touching). In general, if we only have even-order roots, we are on one side.
- Thus, we "only" need to count roots with exact multiplicities in the unit interval.
- Note that we do not need to actually compute the roots, only count them.
- We use Yun's algorithm for square-free factorisation and Descartes rule of signs in combination with interval-halving.

Conclusions

 By using thinning, memoization, and exact comparisions of polynomials we get down to a singleton set for iterated majority:

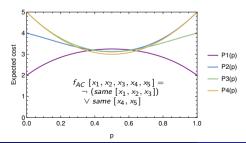
$$ps9 = genAlgThinMemoPoly \ 9 \ maj2 :: Set \ (Poly \ Rational) \\ -- ps9 = fromList \ [P \ [4,4,6,9,-61,23,67,-64,16]] \\ ps5 = genAlgThinMemoPoly \ 5 \ f_{AC} \ :: Set \ (Poly \ Rational) \\ check5 = ps5 == fromList \ [P \ [2,6,-10,8,-4], P \ [4,-2,-3,8,-2], \\ P \ [5,-8,9,0,-2], \ P \ [5,-8,8]]$$



Conclusions

 By using thinning, memoization, and exact comparisions of polynomials we get down to a singleton set for iterated majority:

$$ps9 = genAlgThinMemoPoly \ 9 \ maj2 :: Set \ (Poly \ Rational) \\ -- ps9 = fromList \ [P \ [4,4,6,9,-61,23,67,-64,16]] \\ ps5 = genAlgThinMemoPoly \ 5 \ f_{AC} \ :: Set \ (Poly \ Rational) \\ check5 = ps5 == fromList \ [P \ [2,6,-10,8,-4], P \ [4,-2,-3,8,-2], \\ P \ [5,-8,9,0,-2], \ P \ [5,-8,8]]$$



Future work:

- Clean up the calculations / proofs
- More efficient memoization
- Three-level iterated majority (27 bits)