

*Biabduction (and Related Problems)  
in Array Separation Logic*

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University of Vienna, 14 Mar 2017

## *Compositional proofs in separation logic (1)*

- Separation logic is based on **Hoare triples**  $\{A\} C \{B\}$ , where  $C$  is a program and  $A, B$  are formulas.

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- Its **compositional** nature, the key to scalable analysis, is supported by two main pillars.
- The first pillar is the soundness of the following **frame rule**:

$$\frac{\{A\} C \{B\}}{\{A * F\} C \{B * F\}} \text{ (Frame)}$$

where the **separating conjunction**  $*$  is read, intuitively, as “*and separately in memory*”.

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- Terms  $t$ , pure formulas  $\Pi$  and spatial formulas  $F$  given by:

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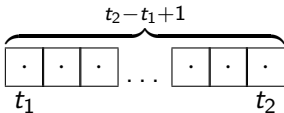
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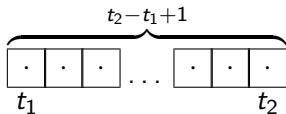


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- We also allow **linear arithmetic** in the pure part.

## *Semantics of ASL*

- **Stacks** are  $s : \text{Var} \rightarrow \text{Val}$ ; **heaps** are  $h : \text{Loc} \rightarrow_{\text{fin}} \text{Val}$ ;  $\circ$  is union of **domain-disjoint** heaps;  $e$  is the **empty** heap.

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$$s, h \models F_1 * F_2 \Leftrightarrow h = h_1 \circ h_2 \text{ and } s, h_1 \models F_1 \text{ and } s, h_2 \models F_2$$

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## *Motivating example*

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**Spatially minimal**, and **incomparable**, solutions include:

$$X := a = c \wedge b = d : \text{emp} \quad \text{and} \quad Y := \text{emp}$$

$$X := d < a : \text{array}(c, d) \quad \text{and} \quad Y := \text{array}(a, b)$$

$$X := a < c \wedge b < d : \text{emp} \quad \text{and} \quad Y := \text{array}(a, c - 1) * \text{array}(b + 1, d)$$

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- Thus the problem is in NP.

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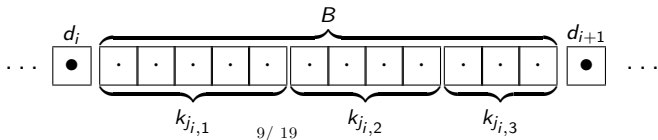
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## *Biabduction*

**Biabduction problem for ASL.** *Given satisfiable symbolic heaps  $A$  and  $B$ , find symbolic heaps  $X$  and  $Y$  such that  $A * X$  is satisfiable and  $A * X \models B * Y$ .*



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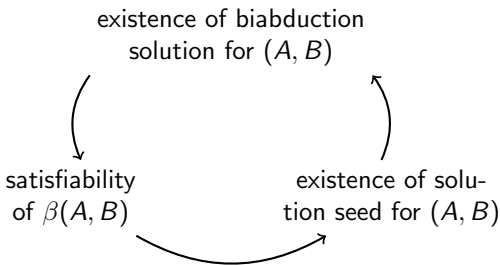
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- For a solution to exist, we need to know that
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- For a solution to exist, we need to know that
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- This can be coded up as a Presburger formula  $\beta(A, B)$ , using the  $\gamma(-)$  encoding of satisfiability.

## *Solution seeds*

- Write  $\mathcal{T}_{A,B}$  for the set of all terms in  $A$  and  $B$ . A **solution seed** for  $(A, B)$  is a pure formula  $\Delta = \bigwedge_{i \in I} \delta_i$  such that:



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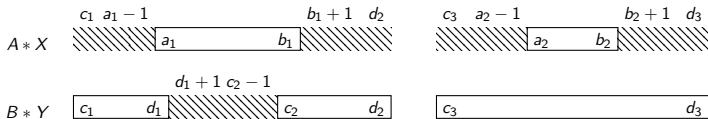


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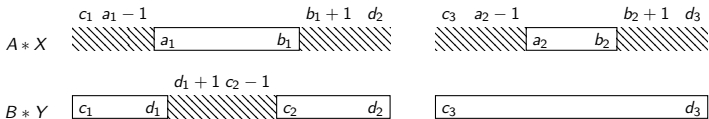
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- We have to be a little careful about the pointer / array distinction though.

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- (Given  $G$ , we define  $A_G$  to encode a 3-colouring of the leaves, and  $B_G$  to encode a 3-colouring of  $G$ .)



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- Due to item 3, we can't allow  $\exists$  over R-values in pointers.



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- I suspect the upper bound is closer to the “true complexity”.

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- Extension of ASL with more expressive features (e.g. combine with list segments?).

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- Indeed, biabduction is NP-complete, climbing higher when  $\exists$  quantifiers are added.
- We also establish decision procedures and complexity bounds for **satisfiability** and **entailment**.

# Thanks for listening!

**Paper available on arXiv:**

arXiv:1607.01993