Precise and Compact Modular Procedure Summaries for Heap Manipulating Programs

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Our Goal



Goal:

Perform a precise flowand context- sensitive pointer analysis that is modular and bottom-up

Advantages of Modular Pointer Analysis

- Reuse of results: Same summary can be reused in any context
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 - ⇒ Allows local reasoning
- Natural parallelization: Functions that do not have caller-callee relationship can be independently analyzed



Unfortunately performing a modular pointer analysis is difficult!

⇒ particularly if we want to perform strong updates to memory locations!

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f(int** a, int **b,
  int *p, int *q)
{
  *a = p;
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  **a = 3;
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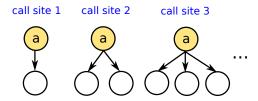
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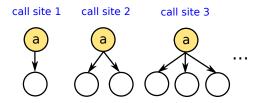
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- Although f is conditional and loop-free, it may have very different effects at different call sites
- Example: After a call to f, value of *p may be 3, 4, or remain its initial value
 - ... depending on points-to facts at call site!

One difficulty: An argument a to a function f may have different number of points-to targets at different call sites of f

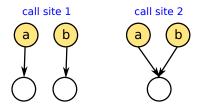


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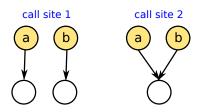


⇒ Unknown number of points-to targets at call sites

Another difficulty: Different aliasing patterns between arguments may exist at different call sites



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⇒ Aliasing patterns exponential in number of locations

Overview of Our Approach



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- To allow strong updates, ensure that locations represented by two distinct variables stand for disjoint set of locations
- Enforce disjointness by symbolically representing all possible aliasing relations on function entry

Location Constants vs. Variables

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- Location Constants: Model memory allocations, NULL, locations of stack variables etc.
- Location Variables: Range over the unknown location constants pointed to by arguments at function entry

Simple Example



 ν ranges over abstract memory locations at call sites of foo

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In this context, ν stands for location constants loc_1 and loc_2

Strong Updates to Location Variables



If ν_1 and ν_2 are two distinct location variables in ${\bf f}$, we can only apply strong updates to them in ${\bf f}$ if:

$$\gamma(\nu_1) \cap \gamma(\nu_2) = \emptyset$$

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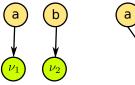
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Why?

If ν_1 and ν_2 may represent an overlapping set of locations, updates to ν_1 may affect updates to ν_2

Enforcing Disjointness: Naive Solution

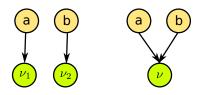
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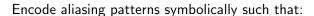


Problem:

Number of alias patterns = nth Bell number (n= # of argument-reachable locations)

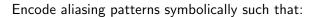
Encode aliasing patterns symbolically such that:





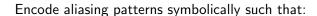


 Number of location variables, n, is the number of argument-reachable locations



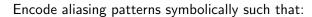


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⇒ Since we precisely account for all aliasing patterns in any context, it is safe to apply strong updates to (non-summary) location variables

Construction of the Initial Points-to Graph

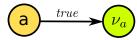
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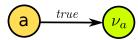


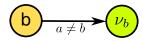


 ν_a represents points-to targets of a in any calling context

Construction of the Initial Points-to Graph

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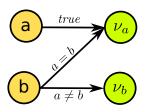




 ν_b represents points-to targets of b only in those contexts where a and b do not alias

Construction of the Initial Points-to Graph

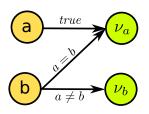
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Construction of the Initial Points-to Graph

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 ν_a also represents points-to targets of b in those contexts where a and b alias

Observe: Construction enforces that $\gamma(\nu_a) \cap \gamma(\nu_b) = \emptyset$

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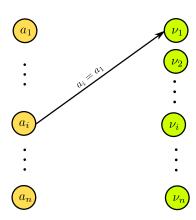




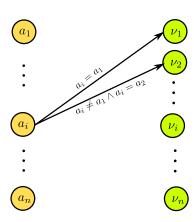




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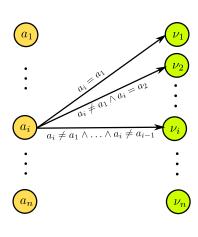


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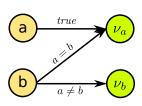
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- Each a_i points to ν_k with $k \leq i$ under constraint:

$$\bigwedge_{i < k} a_i \neq a_j \land a_i = a_k$$

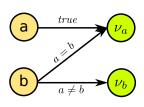


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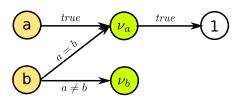
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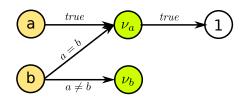
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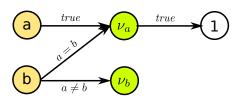


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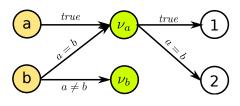


Observe: *b has value 1 if a and b alias

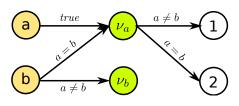
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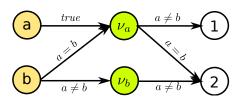
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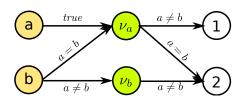
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Observe: *a has value 1 if a and b do not alias and value 2 otherwise

Experiments

- Analyzed 4 large open-source C and C++ applications:
 - OpenSSH
 - LiteSQL
 - Inkscape Widgets
 - DigiKam

First Experiment

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- Goal: Assess importance of strong updates at call sites
- Checked for various memory safety properties, such as buffer overruns, null dereferences, accessing deleted memory, . . .
- Compared false positive rates of new analysis with analysis that only performs weak updates at call sites

Comparison of False Positives



Weak updates at call sites:
 98.2% false positive rate

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- Weak updates at call sites:
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- Strong updates using this technique:
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- Weak updates at call sites:
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- Strong updates using this technique:
 26.3% false positive rate
 - ⇒ Modular analysis that cannot apply strong updates too imprecise!

Comparison of Running Times



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- Strong updates using this technique:
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 - ⇒ More precise actually analysis runs faster

Analysis can be parallelized



• Also ran this analysis on 8 CPUs

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- Average speed-up over 1 CPU:
 4.2× speedup

Second Experiment

• Goal: Assess scalability of summary-based analysis

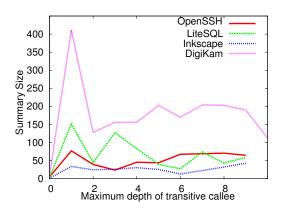
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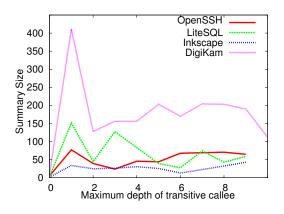
Second Experiment

- Goal: Assess scalability of summary-based analysis
- Explored growth of heap summaries vs. depth of call chain
- Measured summary size as the number of points-to edges weighted according to the size of the edge constraints

Results



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Local reasoning by focusing only on externally-visible side effects

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- Technique capable of performing strong updates at call sites
- Demonstrated practicality of technique for verifying memory safety on four applications

Thanks!



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