Efficient Incremental Dynamic Invariant Detection

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MIT CSAIL

Dynamic invariant detection

- Program analysis that generalizes over observed runtime values to hypothesize program properties
- The result is a set of likely invariants per program point
  - Entry to function `binary_search(int[] list, int val)`
    - `list` is sorted
    - `list` ≠ null
    - `val` ∈ `list`
  - Exit from function `square(int a)`
    - `return` = `a` · `a`
  - Class `Stack`
    - `this.top` = `this.stack`[`this.top_stack`-1]
    - `this.stack`[`this.top_stack`..] = null

Uses of dynamic invariant detection

- Verifying safety properties [Vaziri 98] [Nimmer 02]
- Automatic theorem proving [Win 02]
- Identifying refactoring opportunities [Kataoka 01]
- Predicate abstraction [Dodoo 02]
- Generating test cases [Xie 03] [Gupta 03]
- Selecting and prioritizing test cases [Harder 03]
- Explaining test failures [Groce 03]
- Predicting incompatibilities in component upgrades [McCamant 03]
- Error detection [Raz 02] [Hangal 02] [Pytlik 03] [Mariani 04] [Brun 04]
- Error isolation [Xie 02] [Liblit 03]
- Choosing modalities [Lin 04]

Goals of this research

- Handle moderate to large programs
- Produce useful and expressive program properties
  - Rich set of derived variables
    - array references: `a[i]`, `a[i..]`, `a[..i]`
    - pre-state variables: at exit, `orig(x)` stands for the value at entry
  - Rich invariant grammar
    - unary, binary, and ternary invariants
    - invariants over pointers, integers, floats, strings and arrays

Outline

- Approaches to invariant detection
  - Simple incremental algorithm
  - Simple incremental algorithm scales poorly
  - Many invariants are redundant
  - Multiple pass approach
  - Multi-pass scales poorly to large data sets
- Optimized incremental algorithm
- Complications
- Results

Simple incremental algorithm

- Hypothesize each invariant in the grammar
  - Over each set of variables
  - At each program point
- Check observed values for each variable (sample) at each invariant
  - Discard invariants that are falsified
- The remaining invariants are true over the sample data
- Examples
  - DIDUCE [Hangal 02] - checks 1 invariant over each variable
  - Carrot [Pytlik 03] - checks 2 unary and 4 binary invariants
  - Daikon version 1

Simple incremental algorithm scales poorly

- Ternary derived variables (eg, A[i..j])
  - V = the number of source program variables (at a program point)
  - $V_D = O(V^3)$
- Ternary invariants
  - $I = O(V_D^3) = O(V^9)$
- The number of possible invariants in modest test cases ranged from 460 million to 750 million

Many invariants are redundant

- Many invariants are implied by other invariants
- Examples
  - $(x = y) \wedge \text{odd}(x) \Rightarrow \text{odd}(y)$
  - $(x = 5) \wedge (y = 6) \Rightarrow (x < y)$
  - $(x < y) \Rightarrow (x \geq y)$
  - $(x \geq y)$ at class `Stack` $\Rightarrow$ $(x \geq y)$ at method `Stack.top()`

Multiple pass approach

- Processes the input data multiple times
- Early passes check simple invariants
- Later passes check more complex invariants only if they are not redundant
  - Constants are checked first and removed
  - Equality is checked next. Only one member of an equal set need be checked in following passes
- The multi-pass approach doesn't create or check invariants implied by earlier passes (saving both time and space)
- Example: Daikon version 2

Multi-pass scales poorly to large data sets

- Even modest traces require gigabytes of space
- Possible solutions have drawbacks
  - May be too large to store in memory
  - File I/O is expensive and disks may be insufficient for larger traces
  - Running the target program multiple times is often not acceptable
    - Program has side effects
    - Program depends on its environment
    - Program uses expensive resources (such as human attention)
    - Program doesn’t terminate

Outline

- Approaches to invariant detection
- Optimized incremental algorithm
  - Optimized incremental algorithm concept
  - Constants
  - Equality sets
  - Program point and variable hierarchy
  - program point and variable hierarchy
  - Suppression
- Complications
- Results

Optimized incremental algorithm concept

- Same processing model as the simple incremental algorithm
- Redundant invariants are not instantiated or checked
  - Many invariants are implied by others
  - As long as the antecedents are true, the consequent need be neither instantiated nor checked
- An invariant must be created when its antecedent is falsified
  - $(x = y) \wedge \text{odd}(x) \;\Rightarrow\; \text{odd}(y)$
  - If a sample is seen where $x \neq y$, the odd(y) invariant must be created
  - The new invariant must be true over all *past* samples (which are no longer available)
  - The new invariant must be checked over future samples

Constants

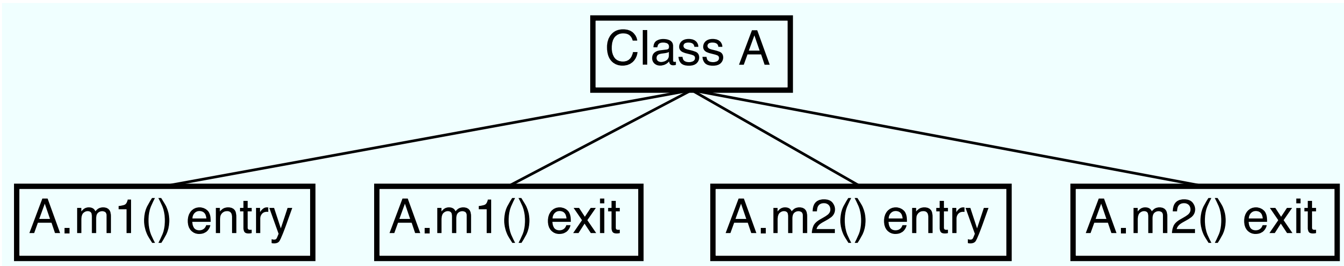
- Invariants over (only) constant variables are redundant
  - $(x = 5) \Rightarrow \text{odd}(x)$
  - $(x = 5) \wedge (y = 6) \Rightarrow x < y$
- All variables are initially constant
- Invariants are not instantiated *between* constants
- When (*var* = constant) is falsified
  - Invariants are instantiated between it and all remaining constants
  - Invariants which are not true over the constant values are discarded

Equality sets

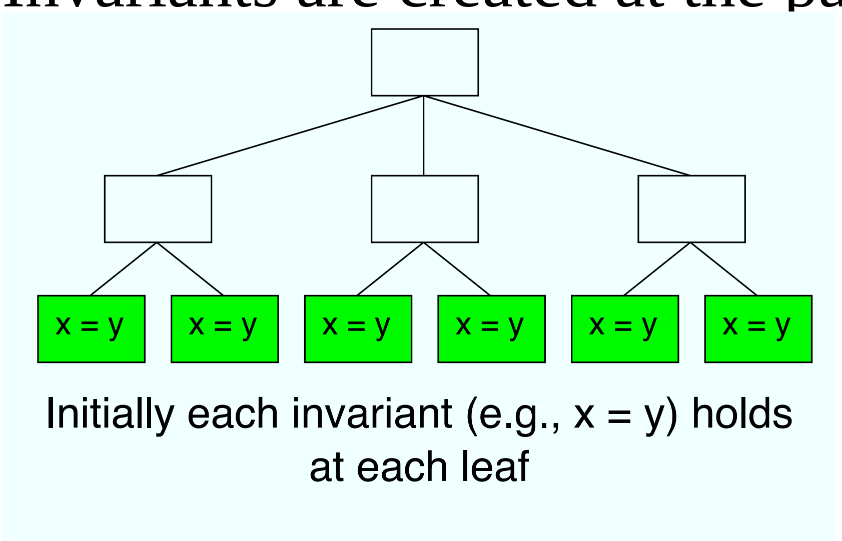
- If two or more variables are equal, any invariant true over one variable is true over all of them
  - $(x = y)$ and $f(x) \Rightarrow f(y)$
- Initially, all variables are placed in a single equality set
- One variable (the leader) represents the set
- Invariants are instantiated only between leaders
- When ($var1 = var2$) is falsified
  - The set is split into two or more equality sets
  - Invariants over each old leader are copied to each new leader

Program point and variable hierarchy

- Relationship between program points



- Samples are only processed at the leaves of the hierarchy
- Invariants are created at the parent *iff* it is true at each child



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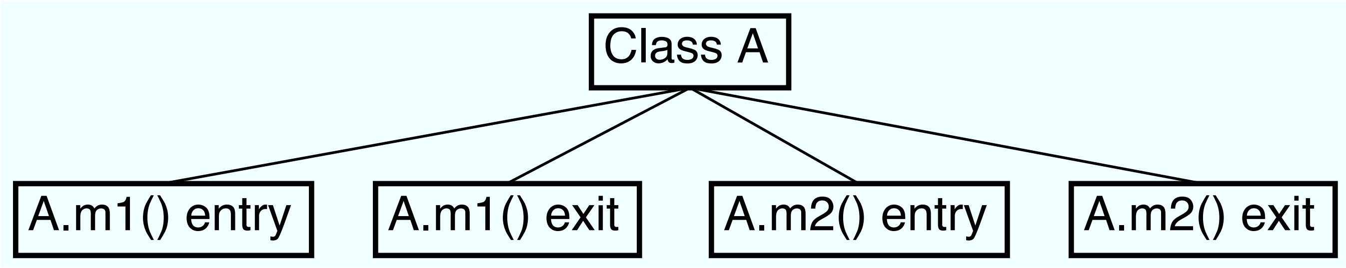

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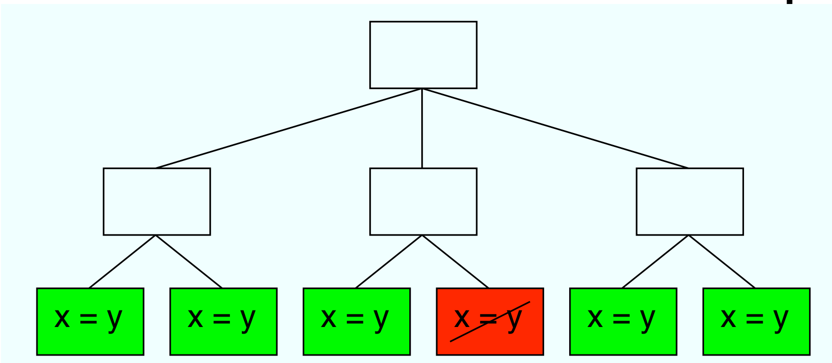

After processing the invariant was falsified at one program point (red)

program point and variable hierarchy

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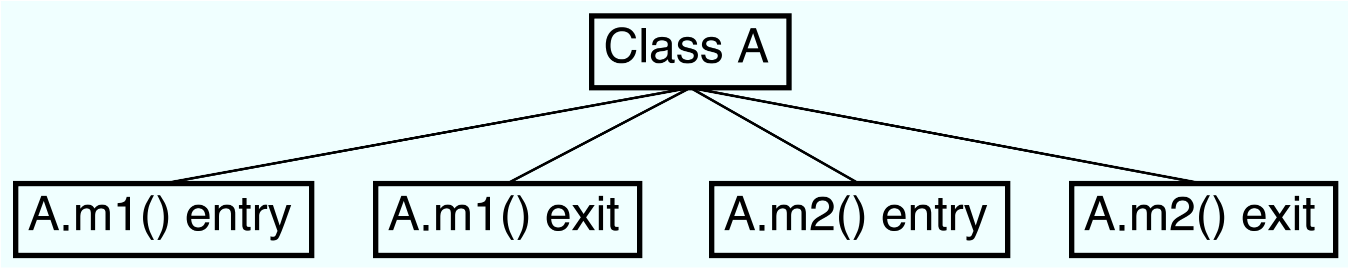

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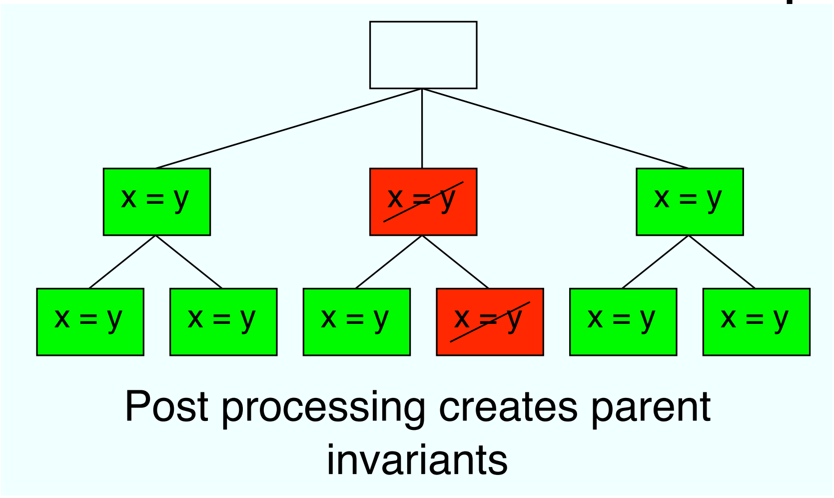

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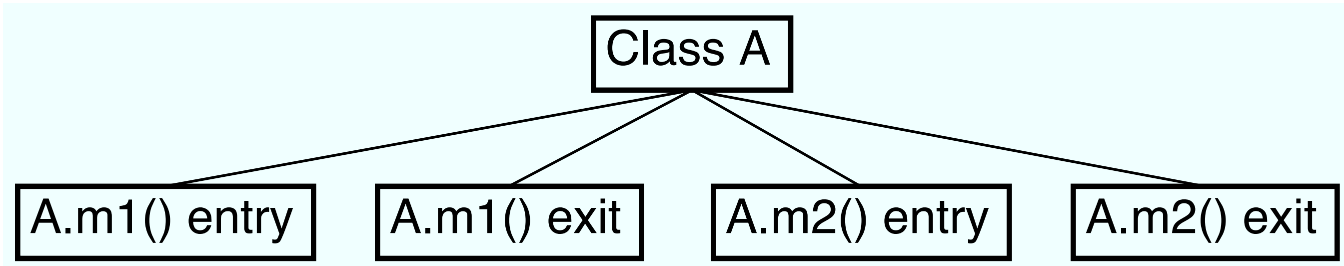

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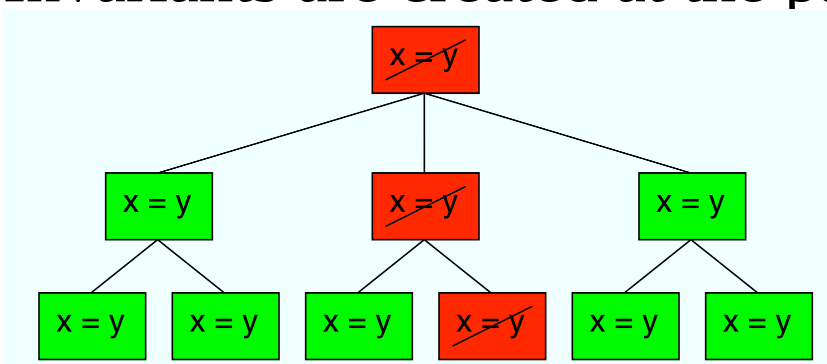

Post processing creates parent invariants

Suppression

- An invariant can be suppressed if it is logically implied by some set of other invariants. For example:
  - $(x = y) \wedge (z = 1) \;\Rightarrow\; x = y \cdot z$
  - $(x = z) \wedge (y = 1) \;\Rightarrow\; x = y \cdot z$
- Other optimizations are special cases of suppression
- Goals
  - Instantiate/check only non-redundant invariants
  - Use *no* storage for a non-instantiated invariants
- When an antecedent is falsified
  - Each invariant that might be suppressed is checked
  - If a suppression held before the antecedent was falsified, but no suppression holds after, the invariant is instantiated

Outline

- Approaches to invariant detection
- Optimized incremental algorithm
- Complications
  - Missing variables
  - Optimizations interact
- Results

Missing variables

- Suppose a is null. What do we do with the invariant $a.b > x$?
- One choice is to falsify the invariant
  - The invariant is thus: $(a \neq \text{null}) \wedge (a.b > x)$
  - Problem: interesting invariants are lost
- Alternative is to retain the invariant
  - The invariant is thus: $(a \neq \text{null}) \Rightarrow (a.b > x)$
  - Problem: difficult to implement
- Optimizations must take missing into account
  - Constants must never be missing
  - Members of an equality set must have identical missing attributes
  - Suppressions can't assume transitivity
    - $(x > a.b) \wedge (a.b > y) \not\Rightarrow (x > y)$
    - $((a \neq \text{null}) \Rightarrow (x > a.b)) \wedge ((a \neq \text{null}) \Rightarrow (a.b > y))$
      $\Rightarrow (a \neq \text{null}) \Rightarrow (x > y)$

Optimizations interact

- When checking to see if an invariant is no longer suppressed, uninstantiated invariants must be considered.
- Creating parent invariants using the program point hierarchy
  - Suppression optimizations must be undone
  - Constant and equality set information must be merged
  - Different equalities in different children require special processing
  - Uninstantiated invariants between constants must be considered

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- Approaches to invariant detection
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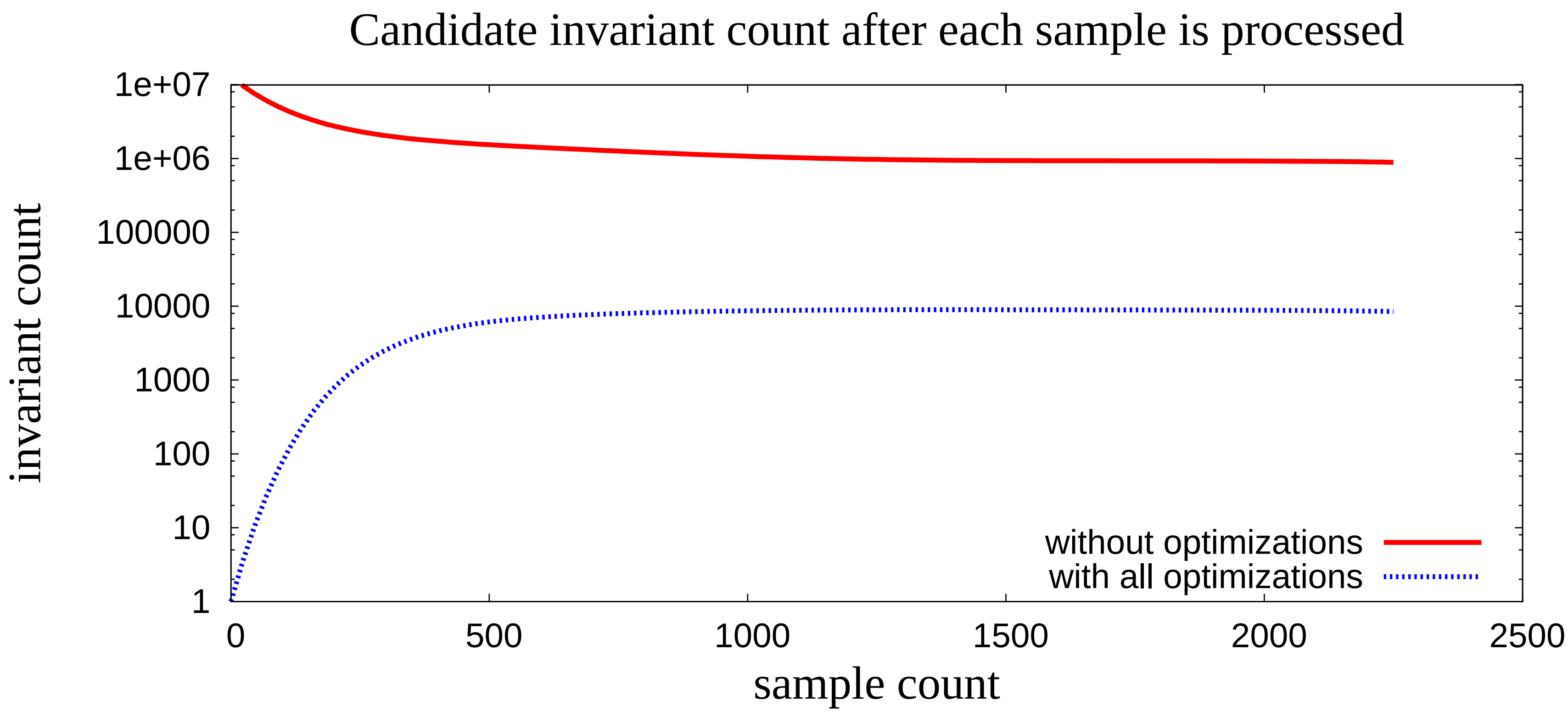
  - Optimizations are effective
  - Real programs can be processed
  - Performance comparison on the Daikon utilities
  - Contributions

Optimizations are effective

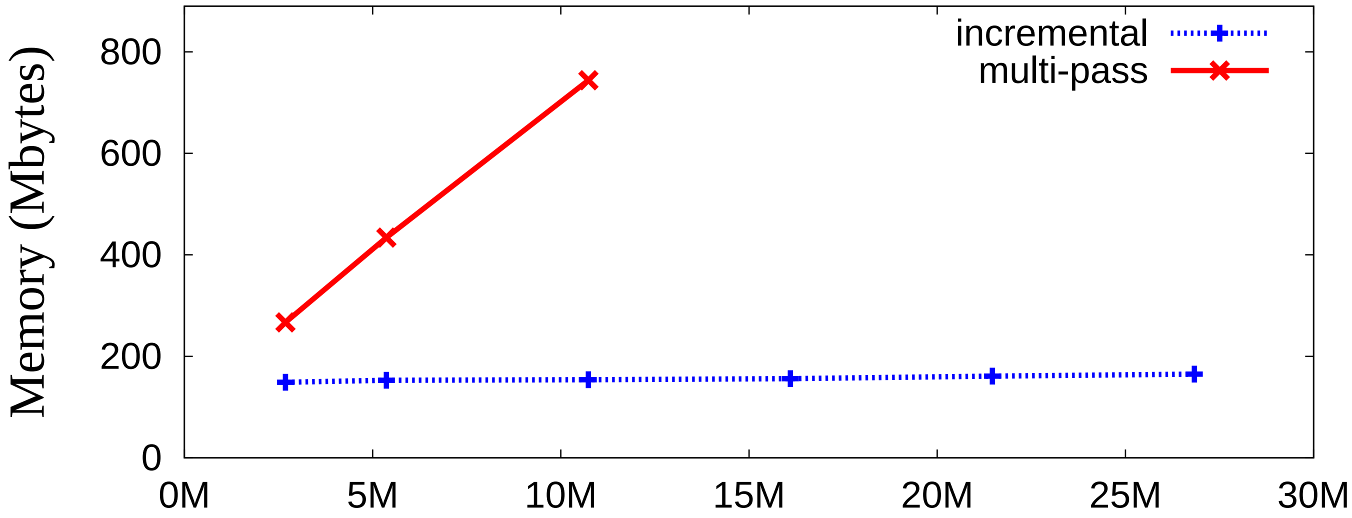


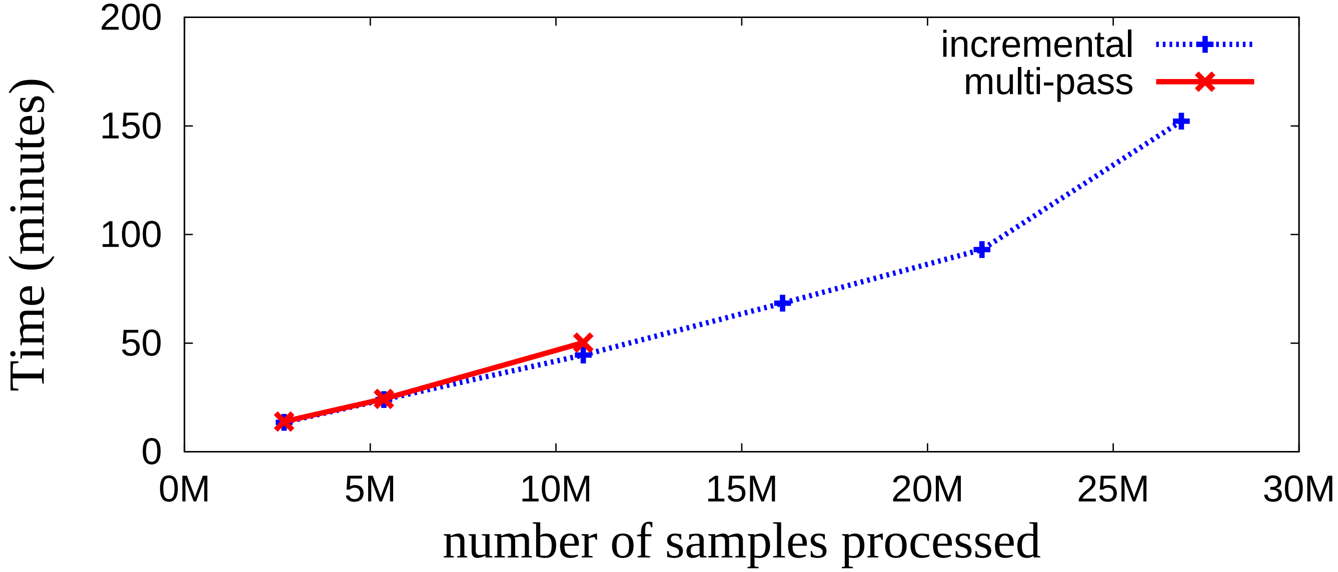
- 100 times fewer invariants with the optimizations

Real programs can be processed

- The optimized algorithm can process non-trivial programs in a reasonable amount of time and space
- The multi-pass and simple incremental approaches cannot process our experiments
- Experiments
    - Flex lexical analyzer
        - 391 program points averaging 275 variables each
        - 232,000 samples (9.2 Gbytes of data)
        - Processing time of 4 hours
        - Max memory use of 750 Mbytes
    - Daikon utilities
        - 1593 program points averaging 60 variables each
        - 26 million samples (11.5 Gbytes of data)
        - Processing time of 1.5 hours
        - Max memory use of 150 Mbytes

Performance comparison on the Daikon utilities





Contributions

- Effective optimizations in an incremental context
  - Redundant invariants are neither instantiated or checked
  - When antecedents are falsified, the optimization is undone and invariants that are no longer redundant are created
- Result is usable in a wide variety of contexts
  - Handles non-trivial programs
  - Supports a rich set of derived variables and invariants
  - Supports on-line operation