Automated Error Diagnosis Using Abductive Inference

Işıl Dillig, Tom Dillig
College of William & Mary

Alex Aiken
Stanford University

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- If answer is no, there are two possibilities:
  - Either the program is indeed buggy
  - Or report is a false alarm

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- But manually classifying error reports is time-consuming and error-prone.
- Furthermore, user must redo all the reasoning the tool performed just to discover where it became stuck.
- Very painful process for most users of static analysis tools!

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A new technique for semi-automating error report classification when automated program verification fails

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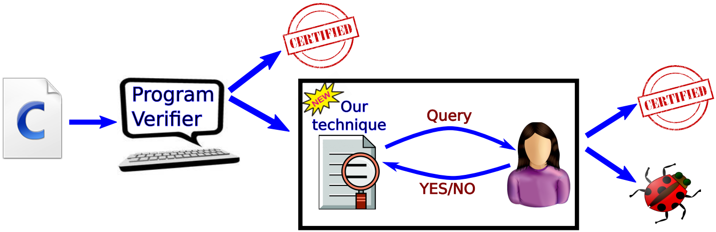

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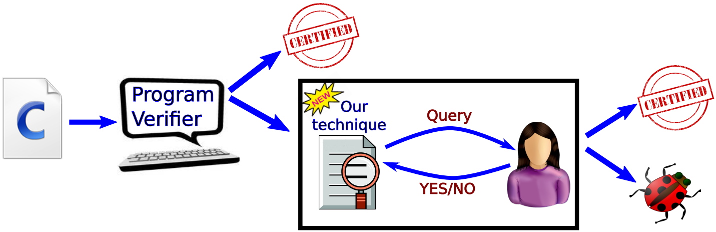

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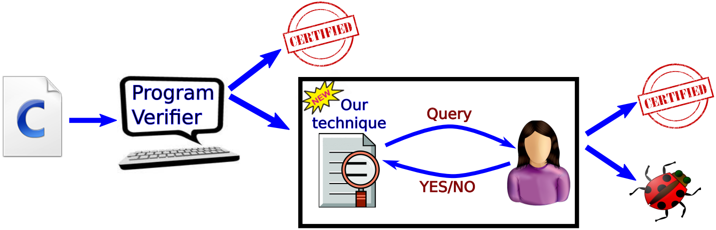

- Allows verifier to interact with user by asking small, relevant queries until report is classified as real bug or false positive
- Queries capture only the information verifier is missing $\Rightarrow$ user contributes facts verifier could not decide on its own
- Answering queries much easier than classifying error report

Key Ideas

Key Idea #1: Analysis makes explicit not only facts it knows, but also facts it does not know

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Key Ideas

Key Idea #1: Analysis makes explicit not only facts it knows, but also facts it does not know

- Sources of imprecision/incompleteness in static analysis represented using abstraction variables
- For example, if value of variable is unknown after a loop, represent this unknown value using abstraction variable
- This representation allows analysis to be "introspective" and reason about what facts it could be missing

Key Ideas, cont.

Key Idea #2: Abductive inference

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- Given known facts F and desired outcome O, abductive inference finds simple explanatory hypothesis E such that

$$F \land E \models O \quad \text{and} \quad \mathrm{SAT}(F \land E)$$

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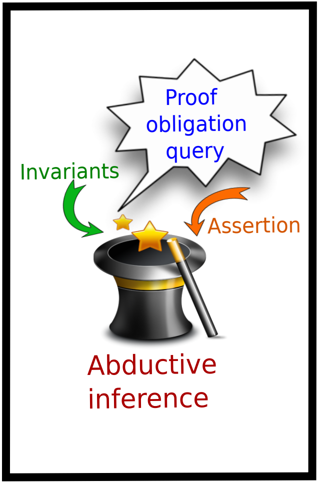
- We use abductive inference to generate simple explanations that either guarantee that program is error-free or definitely buggy
- These abductive explanations are presented as queries to user

Proof Obligation via Abductive Inference

- Input: invariants computed by verifier and assertion to discharge



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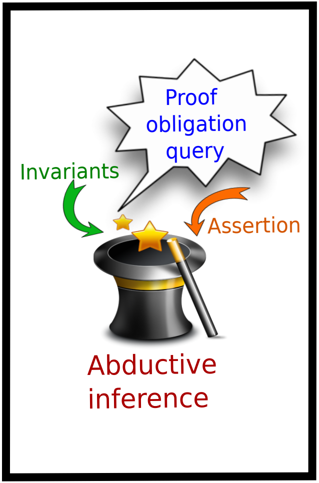

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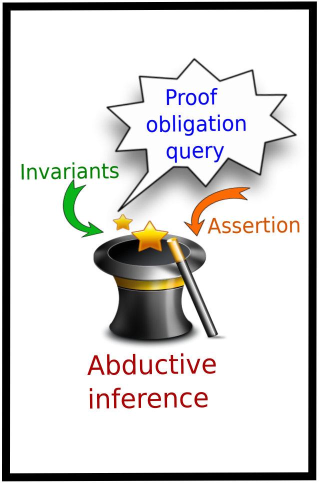

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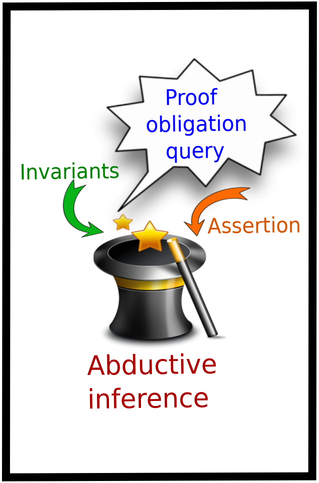

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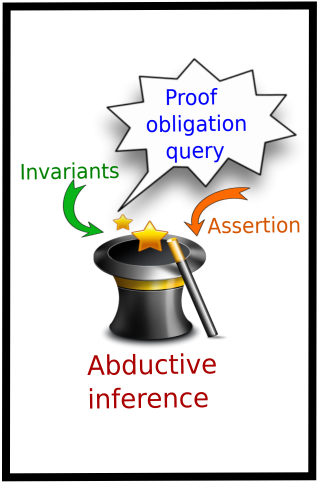
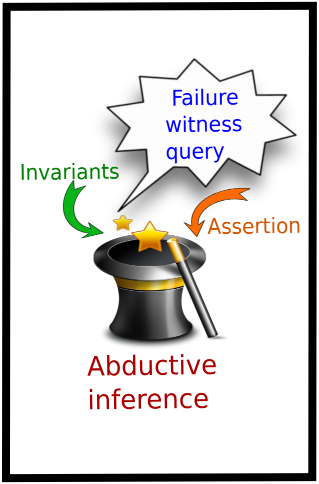
- If Γ is invariant, report is false alarm



Failure Witnesses

- Proof obligation query used to show report is false alarm



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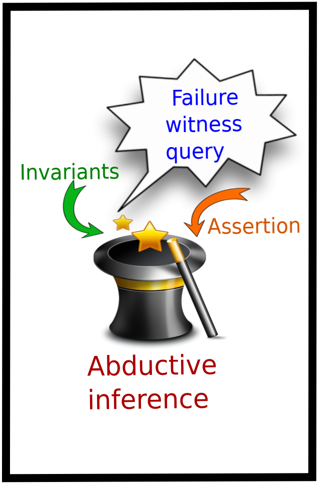

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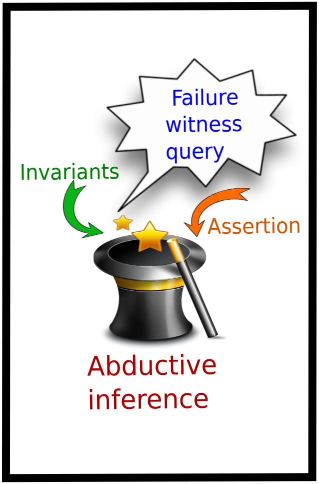

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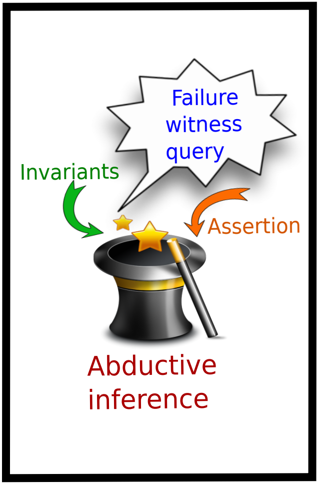
- If Δ can hold in some program execution, then report is real bug!



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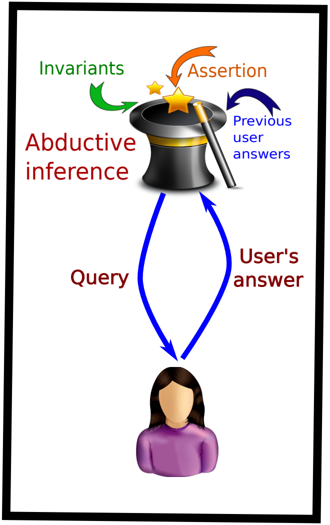

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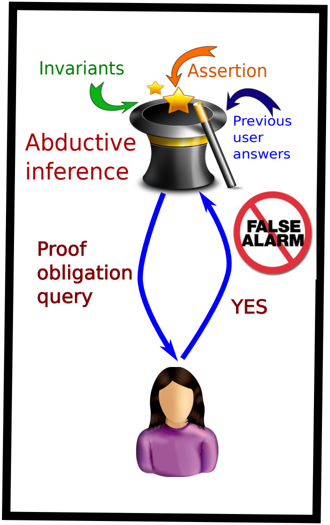

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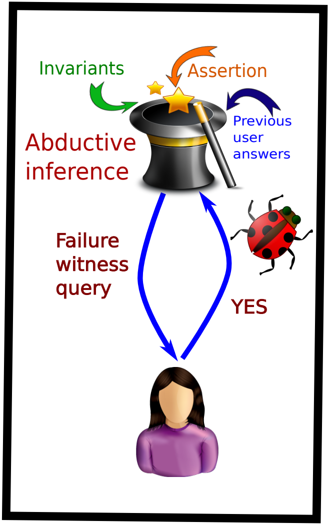

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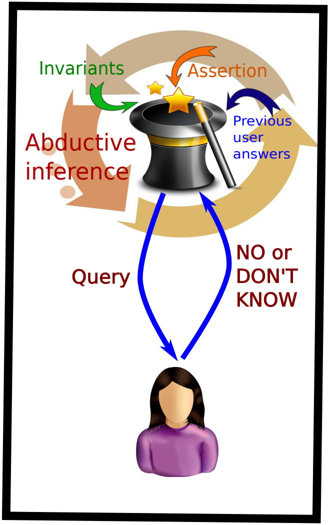

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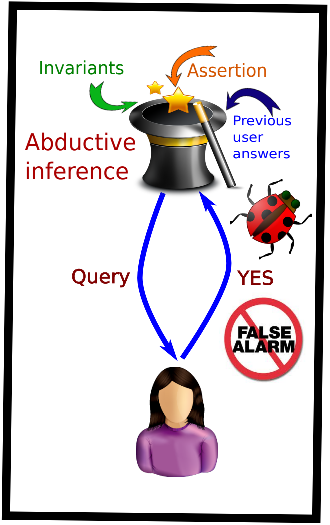
- Interaction continues until report is classified as real bug or false alarm



Example

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- Suppose a verification tool reports potential error for this example

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- First, perform symbolic value flow analysis, representing each unknown value as an abstraction variable α
- Since precise values of `i` and `j` are unknown after loop, represent their values using α_i and α_j
- Similarly, represent unknown value of `x` as abstraction variable α_x

Example, cont.

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- Perform symbolic value propagation to represent z's value in terms of α's and function inputs
- If flag is zero, z $= 1 + \alpha_i + \alpha_j$
- If flag is non-zero, z $= \alpha_x + \alpha_i + \alpha_j$
- Thus, condition under which assertion succeeds is:

$$\phi = \begin{array}{l} (1 + \alpha_i + \alpha_j > 2 * n \wedge \neg flag) \vee \\ (\alpha_x + \alpha_i + \alpha_j > 2 * n \wedge flag) \end{array}$$

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- And that `i` is greater than `n` after loop: $\alpha_i > n$
- Finally, since `n` is unsigned, $n \geq 0$
- Putting this all together, we know the invariants:

$$\mathcal{I} = \alpha_x \geq 0 \land \alpha_i > 0 \land n \geq 0$$

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- To classify error report, we solve two abductive inference problems.

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- To classify error report, we solve two abductive inference problems.
- First, find proof obligation Γ s.t:

$$\Gamma \land \mathcal{I} \models \phi$$

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- Solution computed by our technique is:

$$\Gamma = \; \alpha_j \geq n$$

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- Next, solve another abductive inf. problem to compute failure witness Δ:

$$\Delta \land \mathcal{I} \models \neg\phi$$

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$$\Delta = \;\neg flag \wedge \alpha_i + \alpha_j < 0$$

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- Next, we compare Γ and Δ to decide which one is more promising:

$$\Gamma = \alpha_j \geq n \quad \Delta = \neg \mathit{flag} \wedge \alpha_i + \alpha_j < 0$$

Example, cont.

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void foo(int flag,
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  int k = 1;
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  if(flag) k = x;

  int i=0, j=0;
  while(i<=n)
  {
    i++;
    j+=i;
  }
 Query: Is j>=n invariant?
  int z = k+i+j;
  assert(z>2*n);
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- Next, we compare Γ and Δ to decide which one is more promising:

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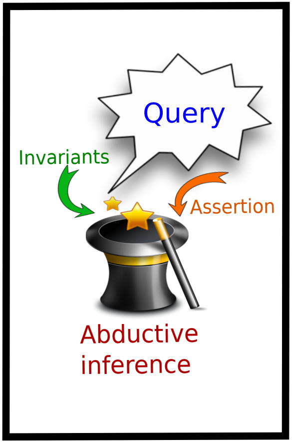
- In this case, easy to show `j >= n` is invariant
- Thus, we classify report as false alarm
- Easier to answer this query than to manually classify error report

Computing Abductive Explanations

- Abduction is useful, but how do we compute these explanations?



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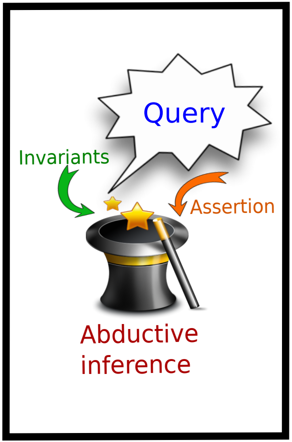

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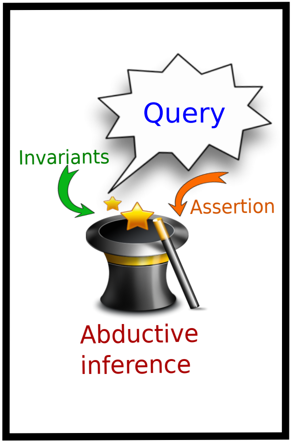

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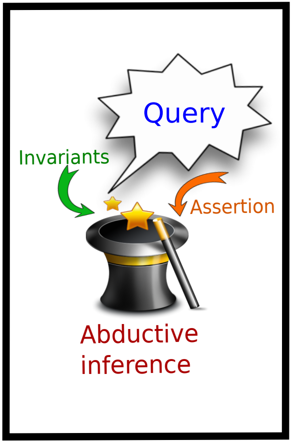

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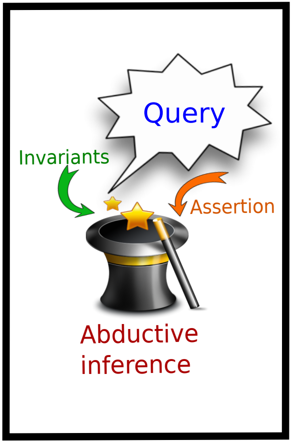
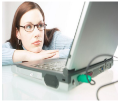
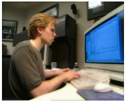


Use minimum satisfying assignments and quantifier elimination to compute simple and general explanations

Experimental Evaluation

- Performed user study to evaluate new technique

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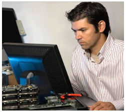
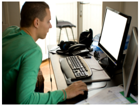


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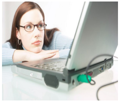
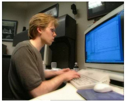

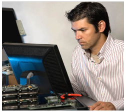
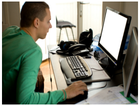


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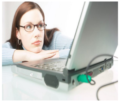
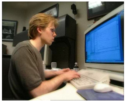

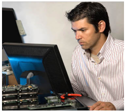
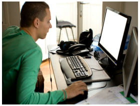


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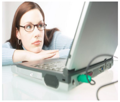
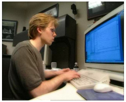

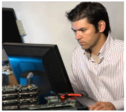
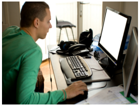


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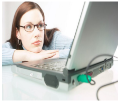
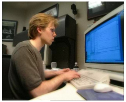

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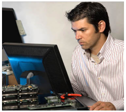
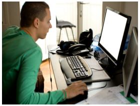


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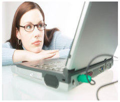
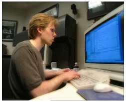
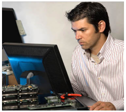
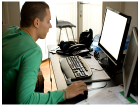
- Based on answers to queries, report classified automatically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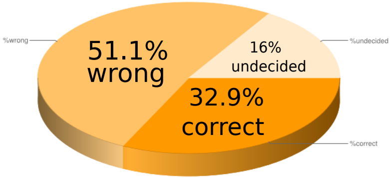

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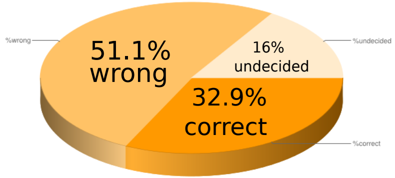

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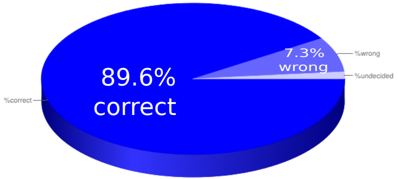

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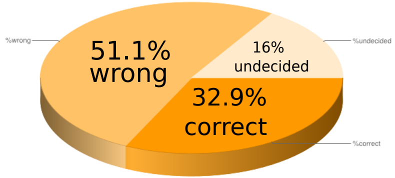

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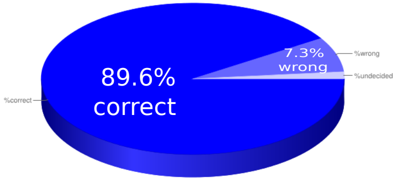

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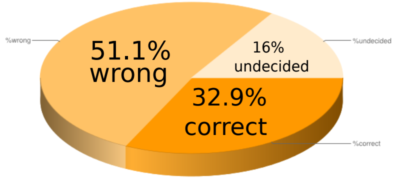

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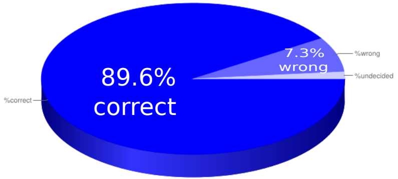

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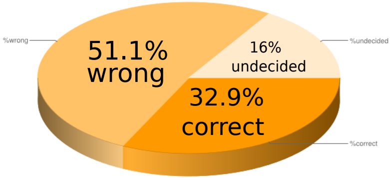
Manual Classification



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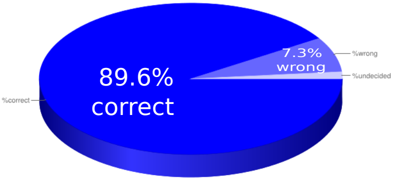

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- Using new technique, programmers take 55 seconds on average

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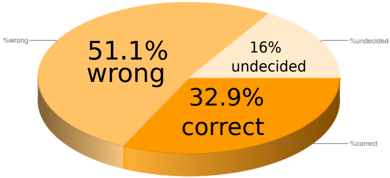

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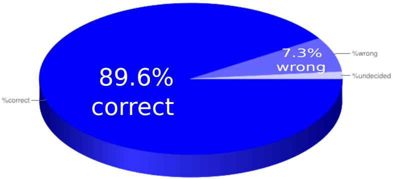
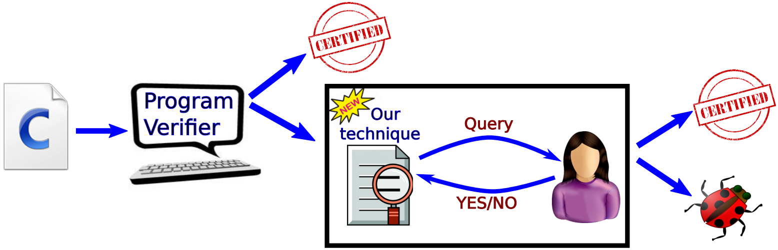


Summary



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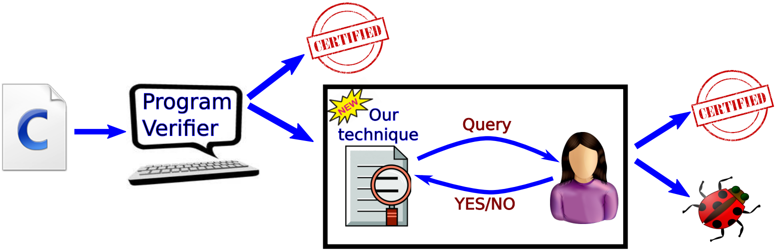
Summary



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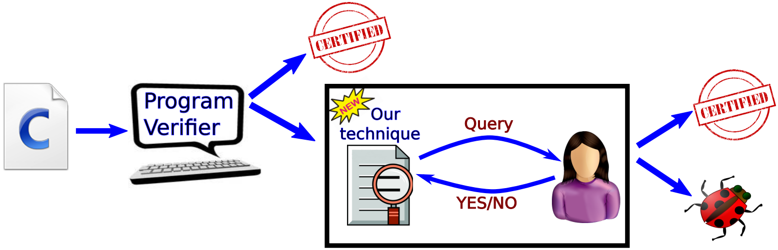

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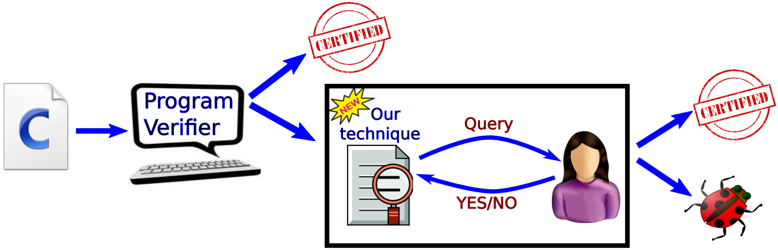

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- Interacts with user until report is classified as bug/false alarm
- User study shows technique dramatically improves classification speed and accuracy

Related Work:

- Ball, T., Naik, M., Rajamani, S.: From Symptom to Cause: Localizing Errors in Counterexample Traces. POPL 2003
- Jose, M., Majumdar, R.: Cause Clue Clauses: Error Localization using Maximum Satisfiability. PLDI 2011
- Groce, A.: Error Explanation with Distance Metrics. TACAS 2004
- Dillig, I., Dillig, T., McMillan, K., Aiken, A.: Minimum Satisfying Assignments for SMT. CAV 2012.