Counterexample Guided Program Repair Using Large Language Models and MaxSAT-based Fault Localization

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IIIA Seminars, IIIA, CSIC

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and

$$\forall (t^i_{in}, t^i_{out}) \in T \ : \ P_f(t^i_{in}) = t^i_{out}$$

Motivation

```c
int main(){ //finds max of 3 nums
   int f,s,t;
   scanf("%d%d%d",&f,&s,&t);
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LLMs for code (LLMCs)

- GRANITE and CODEGEMMA **cannot fix** the buggy program within 90 secs;
- Even if we provide this assignment's **description and IO tests**.
- Suggesting a correct implementation, **both LLMs copy the correct code**, ignoring instructions not to do so.

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- Symbolic approaches demand an **excessive amount of time to produce an answer**;
- LLMs, while fast, **often produce incorrect fixes**.

Program Sketches

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1: Program sketch with holes.

```
1  int main(){
2     int f,s,t;
3     scanf("%d%d%d",&f,&s,&t);
4     @ HOLE 1 @
5        printf("%d",f);
6     else if (s > f && s >= t)
7        printf("%d",s);
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- Combines the strengths of **Formal Methods (FM) and LLM-based approaches**;
- Uses **MaxSAT-based fault localization to rigorously identify buggy lines**, which can then be highlighted in the LLM prompt;
- For instance, **instructing both LLMs to complete the previous sketch allows them to fix the buggy program** in a single interaction;

MaxSAT-Based Fault Localization

- **FM24** - CFaults: Model-Based Diagnosis for Fault Localization in C with Multiple Test Cases.

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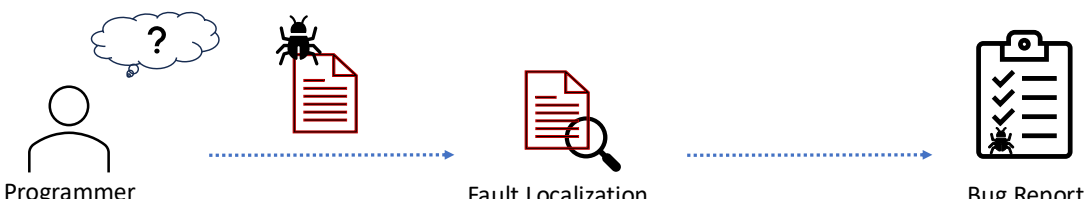
- In 2024, the estimated global cost of Crowdstrike's error that hit Microsoft systems, is 5.4 Billion US$ [The Guardian UK, 2024].

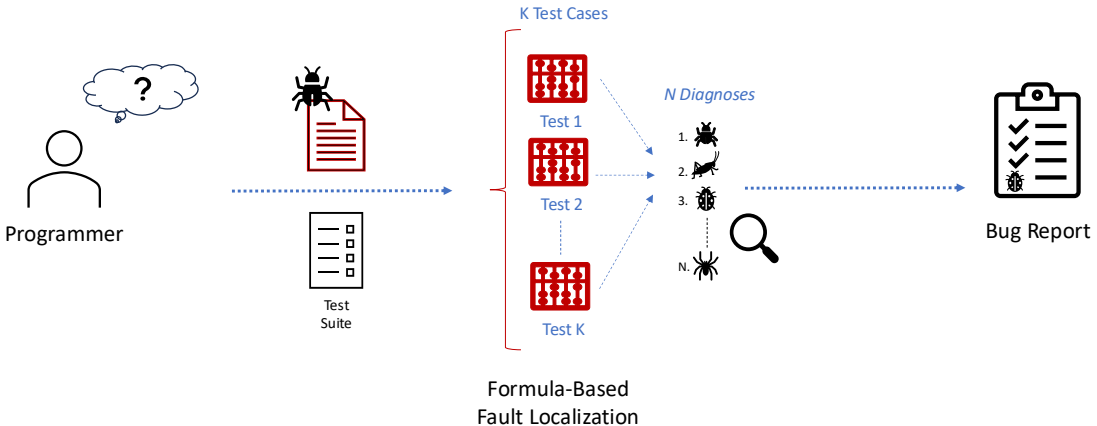
Fault Localization

- Given a buggy program, *fault localization (FL)* involves identifying locations in the program that could cause a faulty behaviour (bug).



Formula-Based Fault Localization (FBFL)

- FBFL methods encode the localization problem into **several optimization problems** to identify a minimal set of bugs (diagnoses).



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FBFL tools especially for programs with multiple faults:

- **do not ensure a minimal diagnosis** across all failing tests (e.g., BugAssist);
- may produce an overwhelming number of **redundant diagnoses** (e.g., SNIPER).

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- We leverage MaxSAT and the theory of *Model-Based Diagnosis (MBD)* [Reiter et al., 1987], **integrating all failing test cases simultaneously**;
- We implement this MBD approach in a publicly available tool called CFaults.

Partial Maximum Satisfiability (MaxSAT)

Hard:	$h_1 : (v_1 \vee v_2)$	$h_2 : (\neg v_2 \vee v_3)$
Soft:	$s_1 : (\neg v_1)$	$s_2 : (\neg v_3)$

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Soft:	$s_1 : (\neg v_1)$	$s_2 : (\neg v_3)$
Possible Solution:	$\neg v_1 \ \vee \ v_2 \ \vee \ v_3$	$\text{cost} = 1$

Figure 1: Example of a partial MaxSAT formula.

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- Each component in $\mathcal{C}$ can be declared **healthy** or **unhealthy**.
- For each component $c \in \mathcal{C}$, $h(c) = 0$ **if** c **is unhealthy, otherwise,** $h(c) = 1$.
- $\mathcal{P}$ is described by a CNF formula, where $\mathcal{F}_c$ denotes the encoding of component c:

$$\mathcal{P} \triangleq \bigwedge\nolimits_{c \in \mathcal{C}} (h(c) \implies \mathcal{F}_c)$$

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- In our work, **the failing test cases represent the set of observations**.
- A system $\mathcal{P}$ is considered **faulty if there exists an inconsistency with a given observation o when all components are declared healthy**:

$$\mathcal{P} \wedge o \wedge \bigwedge\nolimits_{c \in \mathcal{C}} h(c) \vDash \bot$$

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  - is **redundant** if it is not subset-minimal [Ignatiev et al., 2019].

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- This encoding enables enumerating subset **minimal diagnoses, considering a single observation**;

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- Given a MaxSAT solution, **the set of unhealthy components ($h(c) = 0$), corresponds to a subset-minimal aggregated diagnosis**.
- This diagnosis makes the system **consistent with all observations**, as follows:

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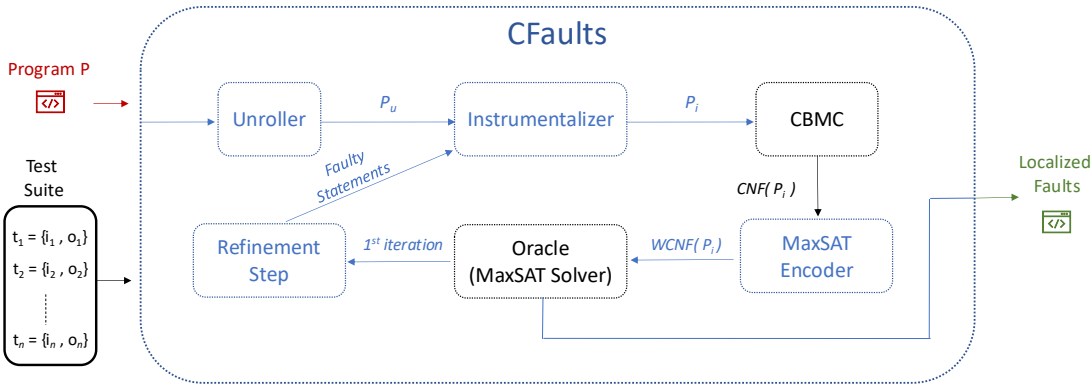
CFaults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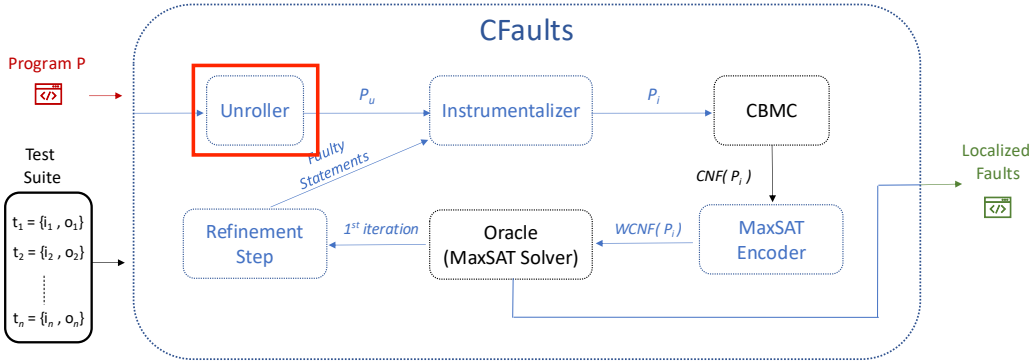
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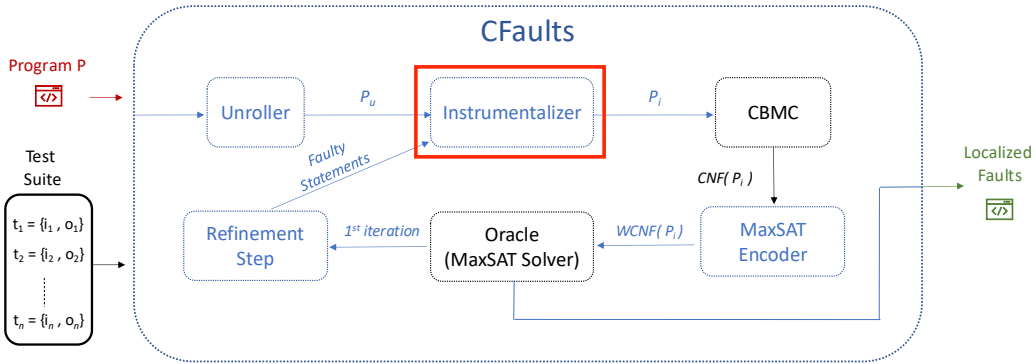
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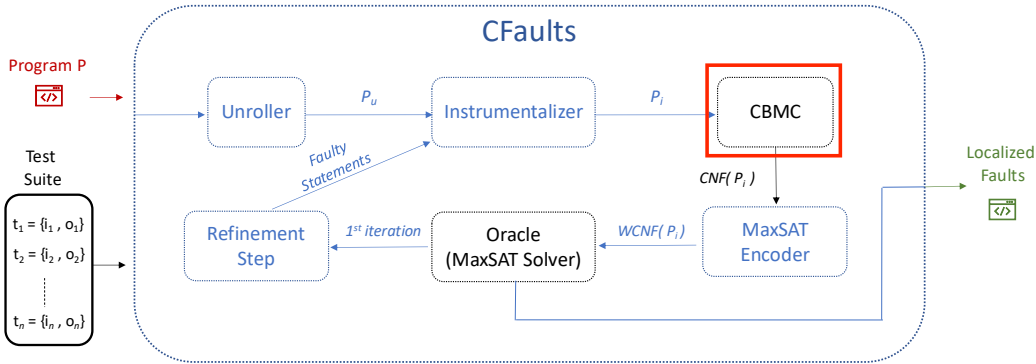
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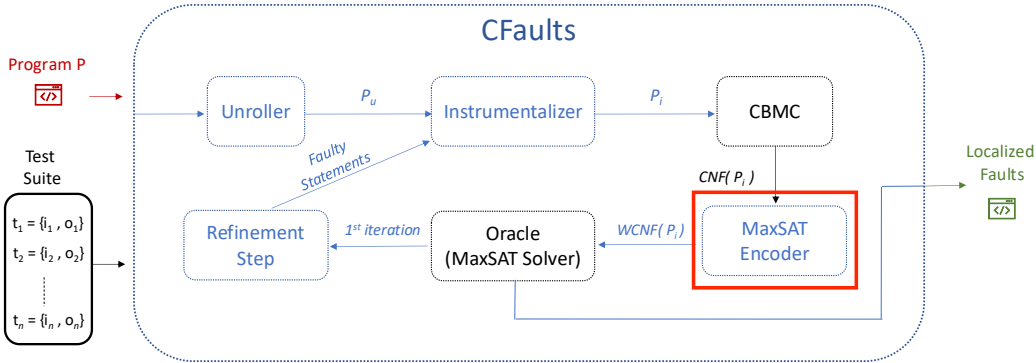
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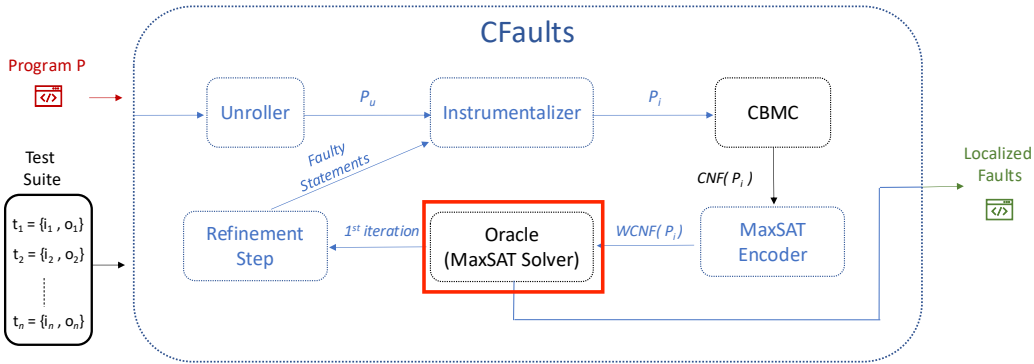
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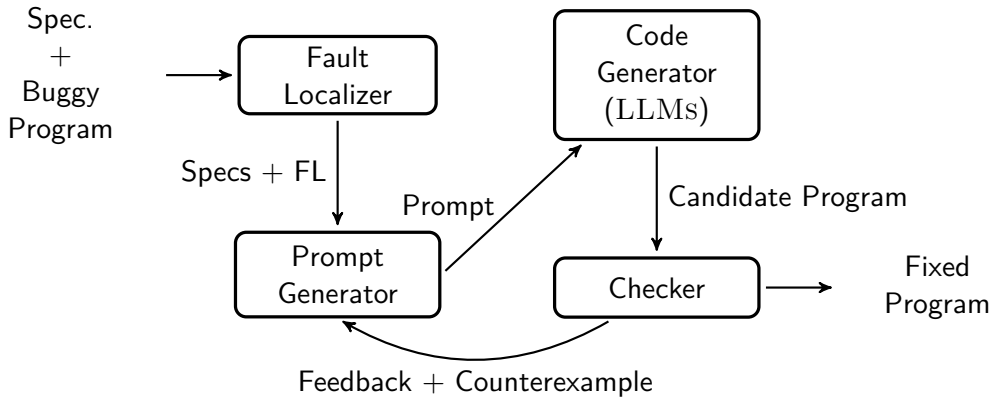
Counterexample Guided Program Repair

- **AAAI 2025** - Counterexample Guided APR Using MaxSAT-based Fault Localization.

Counterexample Guided Automated Repair



Prompt Example without Fault Localization

````
Fix all semantic bugs in the buggy program
below. Modify the code as little as possible.
Do not provide any explanation.

### Problem Description ###
Write a program that determines and
prints the largest of three integers
given by the user.

### Test Suite
#input:
6 2 1
#output:
6
// The other input-output tests

# Reference Implementation
(Do not copy this program) <c> #
```c
int main(){
  // Reference Implementation
}
```

### Buggy Program <c> ###
```c
int main(){
  // Buggy program from Listing 1
}
```

### Fixed Program <c> ###
```c
````
````

Prompt with Fault Localization (Sketches)

Complete all the '@ HOLES N @' in the incomplete program below.
Modify the code as little as possible.
Do not provide any explanation.

Problem Description
Write a program that determines and prints the largest of three integers given by the user.

Test Suite
#input:
6 2 1
#output:
6
// The other input-output tests

Reference Implementation
(Do not copy this program) <c> #
```c
int main(){
  // Reference Implementation
}
```

Incomplete Program <c>

```c
int main(){
  // Buggy program from Listing 1
}
```

Complete Program <c>
```c
```

Experimental Results

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- **Evaluation Benchmark:** C-PACK-IPAS, a set of twenty-five IPAS, comprising **1431 faulty programs**;

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- Experiments were conducted using a memory limit of **10GB**, and a timeout of **90s**.

LLM-Driven APR with CFaults

	Prompt Configurations				
LLMs	**De-TS**	**De-TS-CE**	**Sk_De-TS**	**Sk_De-TS-CE**	**Portfolio (All Configurations)**
CodeGemma	597 (41.7%)	606 (42.3%)	682 (47.7%)	**688 (48.1%)**	823 (57.5%)
CodeLlama	492 (34.4%)	500 (34.9%)	**573 (40.0%)**	561 (39.2%)	712 (49.8%)
Gemma	496 (34.7%)	492 (34.4%)	532 (37.2%)	**534 (37.3%)**	670 (46.8%)
Granite	626 (43.7%)	624 (43.6%)	**691 (48.3%)**	681 (47.6%)	846 (59.1%)
Llama3	564 (39.4%)	590 (41.2%)	578 (40.4%)	**591 (41.3%)**	851 (59.5%)
Phi3	494 (34.5%)	489 (34.2%)	**547 (38.2%)**	535 (37.4%)	621 (43.4%)
Portfolio (All LLMs)	842 (58.8%)	846 (59.1%)	900 (62.9%)	**907 (63.4%)**	1013 (70.8%)
Verifix	90 (6.3%)				
Clara	495 (34.6%)				

Table 1: The number of programs fixed by each LLM under various configurations. Mapping abbreviations to configuration names: **De** - IPA *Description*, **TS** - *Test Suite*, **CE** - *Counterexample*, **SK** - *Sketches*.

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- Incorporating **FL-based Sketches allows LLMs to repair more programs**;
- Including **a reference implementation allows for more repaired programs but with less efficient fixes** (see our paper);
- Our CEGIS approach **significantly improves the accuracy of LLM-driven APR across various configurations**;

Takeaway Message

- We tackle the APR problem using an **LLM-Driven Counterexample Guided Inductive Synthesis (CEGIS) approach** [Solar-Lezama et al., 2006];

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Takeaway Message

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- We employ **MaxSAT-based Fault Localization to guide and minimize LLMs' patches** to incorrect programs by feeding them bug-free program sketches;
- With our approach **all six evaluated LLMs fix more programs and produce smaller patches** than other configurations and symbolic tools;
- Our code is available on GitHub and on Zenodo.

Thank you!

https://cs.ox.ac.uk/people/pedro.orvalho

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