RUG: Turbo LLM for Rust Unit Test Generation

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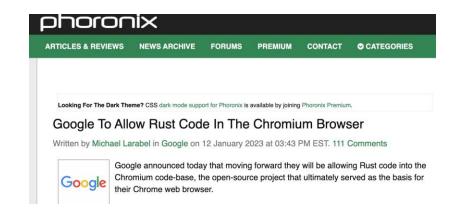
Content

- Motivating
- Challenge & Insights
- Solution
 - \circ LLM
 - $\circ \ \textbf{Fuzzing}$
- Evaluation

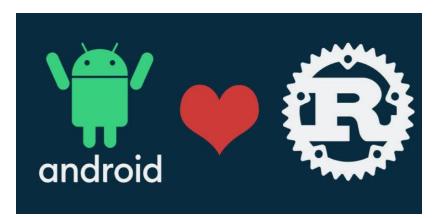


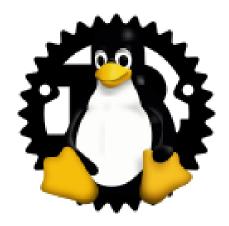
Rust's Adoption is very Fast

• From DARPA/Microsoft/Linux/Google: use Rust to ensure memory safety









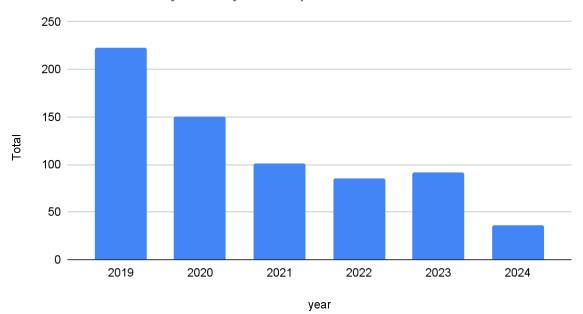


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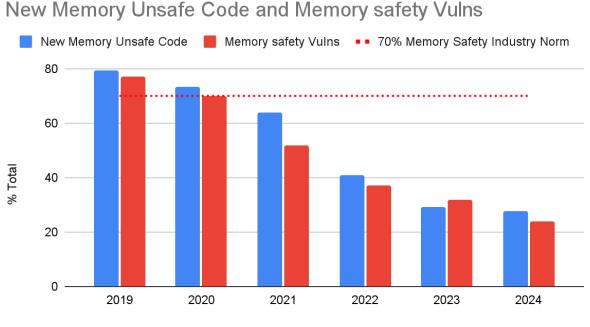
Picture: from chrome/windows/android/Rust-for-linux homepage

From Android's Practice

- AOSP starts to use Rust in 2019
- The total number of memory safety errors starts to drop even with unsafe Rust



Number of Memory Safety Vulns per Year



year



Picture: Google Online Security Blog: Eliminating Memory Safety Vulnerabilities at the Source

Rust Unit Testing

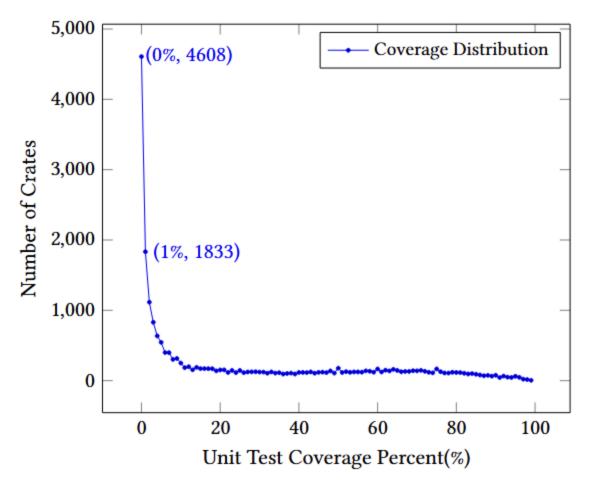
- Unit test is a type of software test that focuses on testing individual units or components of a program in isolation.
- Rust has a good support to unit test:
 - Annotations #[test] to mark a region as test
 - Temporally break encapsulation when testing in the same file
 - Provide driver build for all the tests:
 - cargo test run all tests in the target repo



Unit testing status of Rust

• Crates.io is like npm/maven/pip, serves as the dependency manager in Rust

- As of Dec 2024, serves 164k crates, and more than 96B downloads
- We evaluate the top 30K popular crates
 - 60% crates have less than 10% test coverage
 - 16% crates doesn't have any tests



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Why unit test is difficult

- Unit test requires to build a minimal context to trigger the target function, it's not easy to implement in some cases
 - Rust is applied for low-level systems: embedding device, OS driver...
- Developers are tired of writing unit tests:
 - E.g. 3 conditions + 2 loops to test

```
pub fn unfill(text: &str) -> (String, Options<'_>) {
    let prefix_chars: &[_] = &[' ', '-', '+', '*', '>', '#', '/'];
```

<pre>let mut options = Options::new(0);</pre>
<pre>for (idx, line) in text.lines().enumerate() {</pre>
<pre>options.width = std::cmp::max(options.width, display_width(line));</pre>
<pre>let without_prefix = line.trim_start_matches(prefix_chars);</pre>
<pre>let prefix = &line[line.len() - without_prefix.len()];</pre>
if idx == 0 {
<pre>options.initial_indent = prefix;</pre>
<pre>} else if idx == 1 {</pre>
options.subsequent indent = prefix:
<pre>} else if idx > 1 {</pre>
<pre>for ((idx, x), y) in prefix.char_indices().zip(options.subsequent_indent.chars()) {</pre>
if x != y {
<pre>options.subsequent_indent = &prefix[idx];</pre>
break;
}
}
<pre>if prefix.len() < options.subsequent_indent.len() {</pre>
<pre>options.subsequent_indent = prefix;</pre>
}
}
}

Insight: LLM + Fuzzing

- Chain-of-thought is proven to be effective for LLM reasoning
 - => RUG uses type dependencies to automatically apply chain of thought
- The result of each subproblem needs to be verified, otherwise the error will accumulate
 - => RUG verifies the result for each subproblem, ensuring the final correctness
- The LLM isn't good at exploring program paths
 - => RUG leverages fuzzing as post-processor to extend the testing coverage



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Semantic Aware Decomposition

- Challenge: to build the testing context, LLM is expected to correctly built all its necessary dependents in one shot, leading to errors
- Semantic aware decomposition: Type has dependencies, RUG automatically decomposes the context building into sub-problems

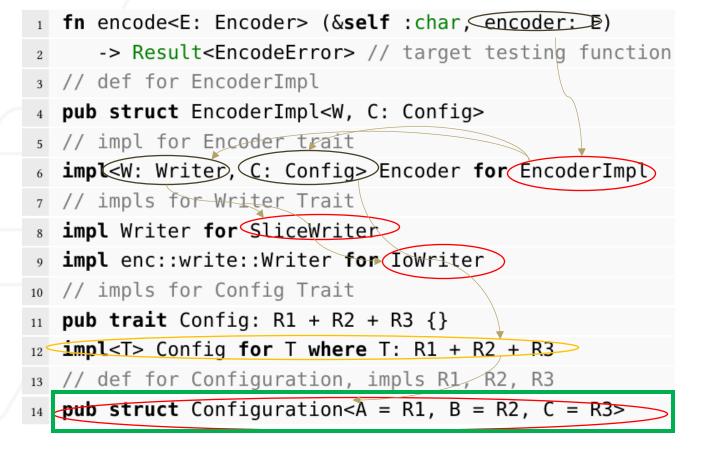
```
1 fn encode<E: Encoder> (&self :char, encoder: E)
```

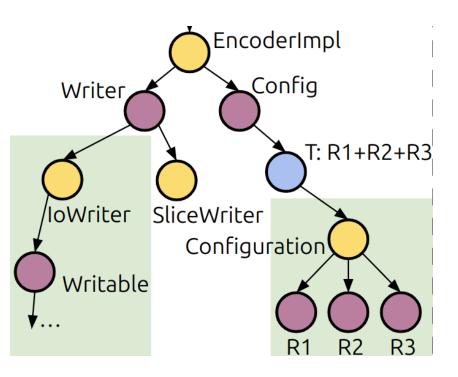
- -> Result<EncodeError> // target testing function
- 3 // def for EncoderImpl
- 4 pub struct EncoderImpl<W, C: Config>
- 5 // impl for Encoder trait
- 6 impl<W: Writer, C: Config> Encoder for EncoderImpl
- 7 // impls for Writer Trait
- 8 impl Writer for SliceWriter
- 9 impl enc::write::Writer for IoWriter
- 10 // impls for Config Trait

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- 11 pub trait Config: R1 + R2 + R3 {}
- impl<T> Config for T where T: R1 + R2 + R3
- 13 // def for Configuration, impls R1, R2, R3
- 14 pub struct Configuration<A = R1, B = R2, C = R3>







- Build type dependency graph as G = {E, V}, V denotes type entities and E denotes dependency relations, G is directed
- Divide the context generation into sub-problems and resolve them individually
- Rely on static analysis to guide and verify the LLM output



Pros and Corner Cases

- Semantic Aware Decomposition
 - We minimize the context for each iteration (only the direct dependent instances in the green square)
 - We verify the result of each iteration output to ensure the correctness
 - We memorize the result based on type and saves tokens in project scope
- Corner Cases:
 - Cycles: we will randomly decide the order and use natural language description of the dependencies as context
 - LLM failed in the middle: we will mark the node as unfinished and continue, using natural language description of dependencies
 - Candidate selection: our evaluation shows its influence is limited for different strategies



Fuzzing as post-processing

- Fuzzers are efficient to explore different paths in few seconds
- We build a harness transformation program based on Rustc to convert the generated tests into fuzzing harnesses
- To control the number of unit tests, we propose a greedy selection and ranking algorithm to select the fuzzing inputs



Evaluation

- How efficient is our approach compared with traditonal Rust/unit testing tools?
- How efficient is our problem division compared with other LLM based tools?
- How efficient is fuzzing?
- Can RUG be applied in real-world software development?



https://github.com/cxworks/rug



RUG vs Synthesizing Tools

- RustyUnit: SBST in Rust
- SyRust: SAT based Rust synthesizer
- RUG: using GPT-3.5

Crate	Func	Region	Func	Region		
	Rust	yUnit	RUG			
gamie	55.54%	30.79%	68.67%	72.24%		
humantime	45.55%	26.67%	50.33%	64.92%		
lsd	32.58%	40.23%	37.66%	43.98%		
quick-xml	17.38%	24.61%	54.5%	62.76%		
tight	24.70%	30.27%	32.24%	36.90%		
time	75.26%	70.78%	68.13%	56.94%		
mean	37.23%	37.23% 34.70%		54.84%		
	SyF	Rust	RUG			
data-structure	26.11%	31.19%	52.10%	56.03%		
encoding	30.69%	28.51%	55.47%	48.54%		
mean	28.40%	30.65%	53.79%	52.28%		



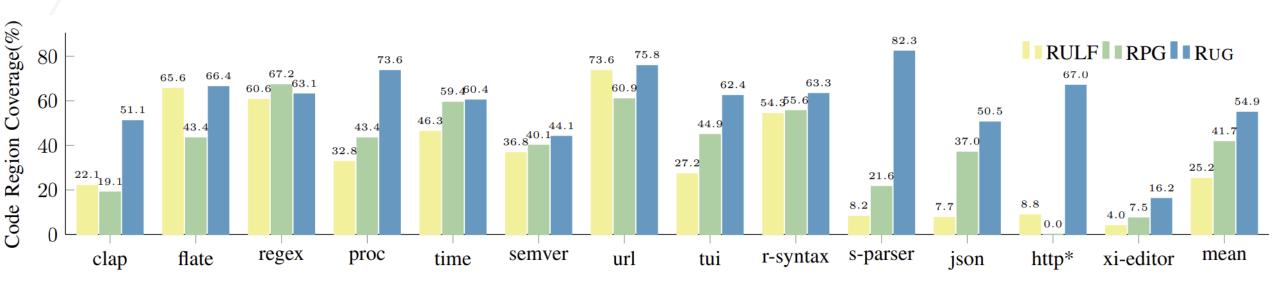
RUG vs Synthesizing Tools

- RustyUnit: SBST in Rust
- SyRust: SAT based Rust synthesizer
- RUG: using GPT-3.5
- RUG out-performs both tools for 20.14% and 21.63%

Crate	Func	Region	Func	Region						
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gamie	55.54%	30.79%	68.67%	72.24%						
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lsd	32. RI	IG improv	es Rustvl	Unit <mark>%</mark>						
quick-xml		17. RUG improves RustyUnit %								
tight	$\frac{17.}{24.}$ coverage by 20.14% $\frac{\%}{\%}$									
time	75.									
mean	37.23%	34.70%	49.96%	54.84%						
	SyF	Rust	RUG							
data-structure	26.1	21 10 2								
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	coverage by 21.63%									
	orgia									
				Tech						

RUG vs Fuzzing based Testing

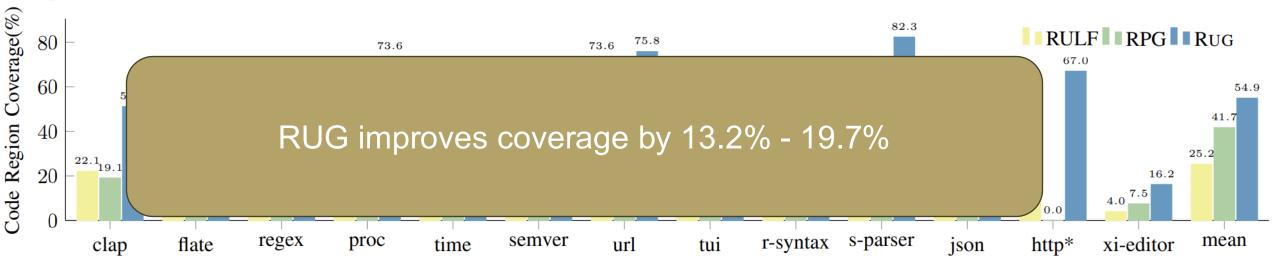
- RULF: type dependency based fuzzing harness generator for Rust
- RPG: improved RULF with harness selection algorithm
- RUG achieves 54.9% code coverage, while RULF as 25.2% and RPG has 41.7%





RUG vs Fuzzing based Testing

- RULF: type dependency based fuzzing harness generator for Rust
- RPG: improved RULF with harness selection algorithm
- RUG: using GPT-3.5
- RUG achieves 54.9% code coverage, while RULF as 25.2% and RPG has 41.7%



RUG vs LLM Approach

- Base: RUG improves baseline for 21.81% in GPT-3.5 and 10.20% in GPT-4
- Sensitivity test of RUG for: GPT model/fuzzing/problem decomposition

Crate Name	Tests		GPT	-3.5			Human				
(Downloads)	ac/rej	E	Base RUG		Base		RUG		Newly API	Test	
	acrej	w/o	w. fuzzing	w/o	w. fuzzing	w/o	w. fuzzing	w/o	w. fuzzing	Cov Rate	Coverage
bincode(49M)	4/0	1.57%	1.57%	22.92%	23.91%	16.63%	18.79%	44.67%	47.91%	74.11%	64.58%
chrono(128M)	22/13	37.88%	44.07%	47.2%	58.29%	54.04%	59.24%	56.90%	62.67%	73.05%	76.66%
hashes(266M)	P (7)	43.84%	43.84%	68.28%	68.28%	57.71%	57.71%	68.96%	85.16%	61.41%	85.17%
humantime(98M)	P (5)	63.09%	64.40%	67.02%	75.39%	74.08%	75.92%	74.61%	80.37%	40.00%	79.32%
itoa(221M)	1/0	26.00%	26.00%	82.00%	96.00%	96.00%	98.00%	100.00%	100.00%	83.33%	86.00%
json(203M)	-	28.10%	35.69%	44.60%	52.07%	62.26%	67.00%	70.25%	70.49%	47.33%	72.36%
mio(145M)	-	20.47%	20.47%	25.20%	25.20%	26.77%	26.77%	33.86%	33.86%	38.89%	24.19%
nom(114M)	6/1/ P (14)	25.81%	25.81%	39.93%	40.04%	51.13%	51.17%	53.84%	53.87%	28.64%	76.20%
num-traits(185M)	-	36.02%	36.47%	43.20%	43.95%	46.94%	46.94%	47.23%	47.98%	90.36%	50.58%
demangle(93M)	P (14)	21.32%	21.62%	21.83%	65.99%	20.00%	74.82%	26.60%	76.55%	18.75%	72.25%
crc32fast(104M)	-	62.35%	64.71%	70.59%	71.76%	87.06%	88.24%	87.06%	88.24%	92.86%	68.24%
ryu(185M)	0/3	52.51%	95.28%	61.65%	97.64%	76.40%	99.42%	81.72%	99.42%	100.00%	87.85%
semver(168M)	18/0	61.40%	62.96%	62.54%	73.36%	72.36%	74.64%	74.22%	76.50%	95.24%	84.33%
textwrap(134M)	1/0	88.84%	92.56%	90.15%	94.31%	92.78%	94.75%	92.56%	94.97%	83.34%	87.53%
time(200M)	P (3)	33.08%	35.06%	48.98%	51.72%	55.34%	55.34%	79.89%	79.89%	66.06%	96.48%
toml(125M)	-	32.43%	37.06%	47.28%	49.02%	59.58%	64.40%	38.90%	38.90%	25.14%	70.81%
uuid(108M)	1/0	58.66%	64.44%	69.30%	77.20%	73.86%	75.08%	75.68%	76.60%	88.89%	61.40%
mean	-	40.79%	45.41%	53.69%	62.60%	60.17%	66.37%	65.11%	71.37%	65.14%	73.18%
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Evaluation on real world development

- We run the project's original test and compare with RUG, find the coverage differences
- For the untested regions, we submit RUG's tests as Pull Request to the project
 - 113 tests submitted: 53 merged/17 rejected/43 pending for response

#[test]

fn test_unfill_consecutive_different_prefix() { let (text, options) = unfill("foo\n*\n/"); assert_eq!(text, "foo * /");

```
pub fn untill(text: &str) -> (String, Options<'_>) {
    let prefix_chars: &[_] = &[' ', '-', '+', '*', '>', '#', '/'];
```

```
let mut options = Options::new(0);
for (idx, line) in text.lines().enumerate() {
    options.width = std::cmp::max(options.width, display_width(line));
    let without_prefix = line.trim_start_matches(prefix_chars);
    let prefix = &line[..line.len() - without_prefix.len()];
```

```
if idx == 0 {
    options.initial_indent = prefix;
} else if idx == 1 {
    options.subsequent_indent = prefix;
} else if idx > 1 {
    for ((idx, x), y) in prefix.char_indices().zip(options.subsequent_indent.chars()) {
        if x != y {
            options.subsequent_indent = &prefix[..idx];
            break;
        }
    }
    if prefix.len() < options.subsequent_indent.len() {
        options.subsequent indent = prefix;
    }
}</pre>
```

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Evaluation on real world development

- We run the project's original test and compare with RUG, find the coverage differences
- For the untested regions, we submit RUG's tests as Pull Request to the project
 - 113 tests submitted: 53 merged/17 rejected/43 pending for response
- RUG received positive feedback



pub fn unfill(text: &str) -> (String, Options<'_>) {
 let prefix_chars: &[_] = &[' ', '-', '+', '*', '>', '#', '/'];



Conclusion

- RUG leverages program analysis to guide LLM for Rust unit test generation and address the concerns of compiling errors
- RUG can help developers to build uncovered tests and achieves a coverage comparable with experienced human efforts

