

# Next Steps in LLM-Supported Java Verification

1st International Workshop on Neuro-Symbolic Software Engineering

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May 3, 2025

- Large Language Models have seen tremendous success in recent years
- GitHub Copilot & Co show: LLMs can generate code
- But can they **specify code?**



```
/*@ normal behavior
  @ ensures (\forall int j; j >= 0 && j < a.length; \result >= a[j]);
  @ ensures a.length > 0
         ==> (\exists int j; j >= 0 && j < a.length; \result == a[j]);
  0*/
public static /*@ pure */ int max(int[] a) {
    if (a.length == 0) return 0;
    int max = a[0], i = 1;
    /*@
      @*/
    while (i < a.length) {</pre>
        if (a[i] > max) max = a[i]:
        ++i:
    return max:
  May 3, 2025 S. Teuber and B. Beckert - Next Steps in LLM-Supported Java Verification 4 □ ▶ 4 🗇 ▶ 4 🖹 ▶ 📳 = 🕬 ९ 🕒
```

#### **Verification requires Loop Invariant**

- Holds before first loop iteration
- Preserved by loop iteration
- Implies post condition

#### Additionally:

- Loop Variant
- Assignable Heap Variables



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public static /*@ pure */ int max(int[] a) {
   if (a.length == 0) return 0;
   int max = a[0], i = 1;
   /*@ loop_invariant 0 <= i && i <= a.length;</pre>
     0 loop invariant (\forall int k; 0 <= k && k < i; max >= a[k]);
     @ loop_invariant (\exists int k: 0 \le k \&\& k \le i: max == a[k]);
     @ decreases a.length - i;
     @ assignable max. i:
     @*/
   while (i < a.length) {</pre>
       if (a[i] > max) max = a[i]:
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   }
   return max:
```



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#### Let's ask ChatGPT:

Do you know JML, the Java Modeling Language?

Yes, I am familiar with JML (Java Modeling Language). JML is a formal specification language for Java programs. [...] JML is typically used in conjunction with formal verification tools, such as ESC/Java or **KeY**, to check that the code meets its specifications.



## The Program Verifier KeY

Deductive verification

100% Java Card

Java Modeling Language (JML)

#### Numerous Case Studies:

- TimSort (OpenJDK)
- LinkedList (OpenJDK)
- Super Scalar Sample Sort



Modular Reasoning

collaboration of KIT, TU Darmstadt, Chalmers University

Ahrendt u. a. 2016





## **Java Modelling Language**

- Specification Language for Java
- Design by Contract Paradigm
- Rich set of possible first-order annotations:
  - Hoare-Style pre- and post-conditions
  - Invariants
  - Asserts
  - Class-Invariants
- Supported by numerous tools for Java verification

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     ensures (\forall int j;j >= 0 && j <
     ensures a.length > 0
         ==> (\exists int j;j >= 0 && j <
  @*/
public static /*@ pure */ int max(int[] a)
    if (a.length == 0) return 0;
    int max = a[0], i = 1;
    /*@ loop_invariant 0 <= i && i <= a.1
      0 loop_invariant (\forall int k; 0
      0 loop_invariant (\exists int k; 0
         decreases a.length - i;
      @ assignable max, i;
      @*/
    while (i < a.length) {</pre>
        if (a[i] > max) max = a[i];
        ++i:
   return max:
```

### LLMs for Deductive Java Verification

#### Large Language Models

- May produce output that is not correct
- "Reasoning" is **not rigorous**
- **Inconsistent Answers**



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- Lack "common sense"
- Symbolic techniques: Not good at "quessing" annotations from context



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- Symbolic techniques:
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Objective: An Intersymbolic Al approach to Program Verification

Combine LLMs and Deductive Verification so that weaknesses cancel out



Java Program (partially annotated)

```
//@ ensures \result == -2*x;
int f(int x) {
    return g(-x);
}

int g(int x) {
    return x+x;
}
```



Java Program
(partially annotated)

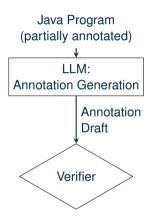
↓

LLM:
Annotation Generation

```
//@ ensures \result == -2*x;
int f(int x) {
    return g(-x);
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int g(int x) {
    return x+x;
}
```

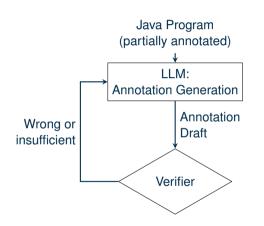




```
//@ ensures \result == -2*x;
int f(int x) {
    return g(-x);
}

//@ ensures x == 2 ==> \result == 4;
int g(int x) {
    return x+x;
}
```

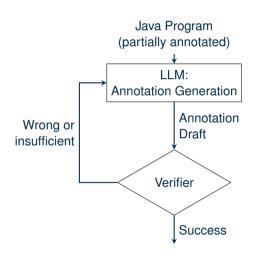




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Annotated File





Curation of a first, small benchmark set: KeY repository and old exercise sheets



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#### **Benchmark Categories:**

 Generate top-level contract for isolated method (Java ⇒ JML)



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#### **Benchmark Categories:**

- Generate top-level contract for isolated method (Java ⇒ JML)
- Generate auxilliary annotations for given toplevel spec
  - $(Java+JML \Rightarrow JML)$
  - Loop invariant (given method contract)
  - Contract of callee-method (given caller contract)



## **Evaluation Benchmark: Features**

	Isolated Methods	Sub-Methods	Invariants	Total	
No. of benchmarks	36	27	14	77	
JML features					
Quantifiers	32	24	14	70	91%
Non-empty assignable	24	17	11	52	68%
Reference to pre-state (\old)	18	11	8	37	48%
(Pure) Method calls in spec	10	7	7	24	31%
Java features					
Arrays	30	23	13	66	86%
Field access	11	7	3	21	27%



Curation of a first, small benchmark set: KeY repository and old exercise sheets

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		$\mu \pm \sigma$ of success rate (%)		
Category	Instances	GPT 3.5	GPT 4o	
		( <i>n</i> = 10)	(n = 3)	
Isolated Method	36	52.2 ± 4.3	$\textbf{62.0} \pm \textbf{1.6}$	
Submethods	14	$19.3 \pm 12.1$	$\textbf{40.5} \pm \textbf{4.1}$	
Invariants	27	$37.0 \pm 7.4$	$\textbf{67.9} \pm \textbf{5.7}$	



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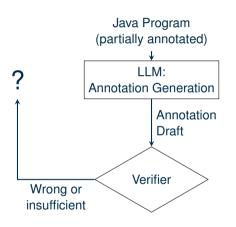
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No elaborate prompt engineering yet!

Objective: Evaluate baseline performance

Not enough benchmarks





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#### What steps to take?



We can provide feedback on failed proof attempts, but **does this benefit** the specification generation?



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**Concrete Counterexamples** Via bounded model checking



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#### **Concrete Counterexamples** Via bounded model checking

The provided invariant does not hold for the following instantiations of variables:

```
k = 0
a = [0, 0, 0]
i = 1
```

You're right; we still need to refine the loop invariant to handle the specific case where the array length is odd. In such cases, the middle element should remain unchanged.

Here's the corrected code:

<wrong invariant>

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- Pass on parser errors
- Pass on information on open proof branches



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Focus: Auxilliary Specifications
Sampling (pass@N) vs. Feedback
10 rounds with GPT 40



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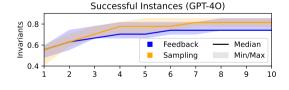
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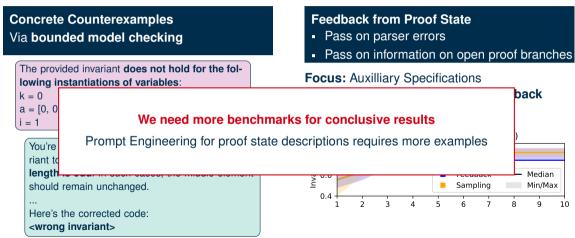
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**Focus:** Auxilliary Specifications Sampling (pass@N) vs. Feedback 10 rounds with GPT 40





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## Feedback vs. Sampling

## What is the right metric?

#### **Classic Verification**

Two verification techniques:

(A)5 iterations, 2 seconds CPU time/iteration

(B)3 iterations, 4 seconds CPU time/iteration

 $\Rightarrow$  (A) is better

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⇒ (A) is better

API usage hides computational cost!



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API usage **hides** computational cost!

#### What we know:

Computational cost increases with token count

- Initial Query: I tokens
- LLM Output: O tokens
- Feedback: F tokens

**Sampling:**  $n(I + O) \in \mathcal{O}(n)$  tokens

**Feedback:**  $n(I + O) + \frac{n(n-1)}{2}(O + F) \in \mathcal{O}(n^2)$  tokens



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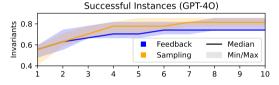
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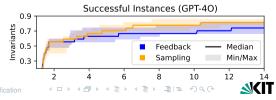
**Feedback:**  $n(I + O) + \frac{n(n-1)}{2}(O + F) \in \mathcal{O}(n^2)$  tokens

#### Another evaluation:

#### Iteration based:



#### Token based:



### **Related Work**

This is a rapidly growing research field



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• A lot of work on **Dafny** (e.g. due to DafnyBench)

Loughridge u. a. 2025



#### This is a **rapidly** growing research field

- A lot of work on **Dafny** (e.g. due to DafnyBench)
- AUTOSPEC for C and ACSL with Frama C
  - Beyond filling the gap:
     Strategy for generating all method/invariant annotations
  - No proof state feedback for individual annotations
  - Also use ChatGPT API

Loughridge u. a. 2025 Wen u. a. 2024



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Loughridge u. a. 2025

AUTOSPEC for C and ACSL with Frama C

Wen II a 2024

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- Joint generation of code and specification

Sun II a 2024

- No soundness guarantees
- Empirically: Consistency between code and spec helps



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AUTOSPEC for C and ACSL with Frama C Wen II a 2024

 Beyond filling the gap: Strategy for generating all method/invariant annotations

- No proof state feedback for individual annotations
- Also use ChatGPT API
- Joint generation of code and specification
  - No soundness guarantees
  - Empirically: Consistency between code and spec helps
- Dataset for JML via GitHub scraping

Sun II a 2024

Greiner II a 2024





### Conclusion

- OpenAl's models are surprisingly good at JML
- Foundation Models:
  - Make effective usage of ML for niche languages like JML possible
  - Cannot solve all data problems (we still need well-curated benchmark sets)
- Iteration helps, but feedback not (yet)

#### **Open Questions**

- Effective Feedback from the verifier's proof state
- Prompt Engineering in the presence of "perfect checkers"
   Sampling may not be that bad afterall?
- What is a fair comparison between an LLM approach and a "classic" approach?



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### References II

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# Demo (Backup) Back to Slides

## **Example: Find the Maximum**

```
/*@ normal behavior
  @ ensures (\forall int j; j \ge 0 && j < a.length; \result >= a[j]);
  @ ensures a.length > 0 ==>
  @ (\exists int j; j \ge 0 && j < a.length; \result == a[j]);
  a */
public static /*@ pure */ int max(int[] a) {
    if (a.length == 0) return 0;
    int max = a[0], i = 1;
    while (i < a.length) {
        if (a[i] > max) max = a[i];
        ++i:
    return max;
```



## Example: Find the Maximum (1st try)

```
Given the following Java class:
[ ... ]
Please provide a loop invariant for the loop construct with the comment
'//Add invariant here' of the method 'max'. Beware this annotation has to be
a loop invariant. A loop invariant typically has the following structure:
[Template: loop_invariant, decreases, assignable]
```

```
Based on the method 'max', the goal is to find the maximum element in the given array 'a'. [...]

/*@ loop_invariant 0 <= i && i <= a.length;
@ loop_invariant (\forall int k; 0 <= k && k < i; max >= a[k]);
@ decreases a.length - i;
@ assignable i, max;
@ */
```

Problem: max not required to be in the array



## Example: Find the Maximum (2nd try)

```
The provided JML does not solve the task. [...] some proof goals were not
closed:
[...]
During verification, the following proof branches could not be closed:
Normal Execution ( a != null)
Please fix the JML loop invariant.
```

```
Let's refine the loop invariant [...]
/*@ loop invariant a != null;
  @ loop_invariant 0 <= i && i <= a.length;
  @ loop_invariant (\forall int k; 0 <= k && k < i; max
      >= a[k]);
  @ decreases a.length - i;
  @ assignable i. max:
  a * /
```

**Problem:** same (only added a != null)



## Example: Find the Maximum (3rd try)

[Same message]

Invariant that is strong enough to prove the post-condition.

**Problem:** Invariant is not inductive (because of i > 0)



# Example: Find the Maximum (4th try)

[Same message]

```
Let's ensure that the JML loop invariant comprehensively captures [...]
/*@ loop_invariant a != null;
  @ loop invariant 0 <= i && i <= a.length;
  @ loop_invariant (\forall int k; 0 <= k && k < i; max
      >= a[k]);
  @ loop_invariant
  @ \exists int m; m >= 0 && m < i && max == a[m];</pre>
  @ decreases a.length - i;
  @ assignable i, max;
  a */
```

Correct invariant

```
Syntax error: ACSL \exists ... vs. JML (\exists ...)
```



# Example: Find the Maximum (5th try)

The provided code is not valid JML.

[...]

Error during JML parsing: Failed to parse JML fragment: Encountered unexpected token: "\exists" "\exists" at line 4, column 20.

Was expecting one of: [...]

[unfortunately still fails]



# **Example: Find the Maximum (restart)**

## Second Attempt...

[Same initial question]

```
In the given 'max' method, the loop is responsible for [...]

/*@ loop_invariant 0 <= i && i <= a.length;
@ loop_invariant (\forall int k; 0 <= k && k < i; max >= a[k]);
@ decreases a.length - i;
@ assignable max, i;
@*/
```

**Problem:** max not required to be in array.

[Same feedback]





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# More Difficult Example: Rotate an Array

```
public static void rotate(int[] a, int len) {
    int[] b = new int[a.length];
    int i = 0:
   /*@ [...] @*/
    for (i = 0; i < len; i++) {
        b[i] = a[a.length - len + i];
    /*@ [...] @*/
    for (i = len; i < a.length; i++) {
       b[i] = a[i - len]:
    /*@ [...] @*/
    for (i = 0; i < a.length; i++) {
        a[i] = b[i]:
```



# More Difficult Example: Rotate an Array Correct specification generated by GPT 4o



# Demo (Backup) Back to Slides



### **Evaluation: Isolated Methods**

Category	# Benchmarks	$\mu \pm \sigma$ of success rate (%)	
		GPT 3.5	GPT 40
		(n = 10)	(n = 3)
Isolated Method	36	$52.2 \pm 4.3$	$\textbf{62.0} \pm \textbf{1.6}$

Success criterion: KeY proves code satisfies generated spec

Manual Inspection: Spec adequately specifies code behavior

Sometimes incomplete

#### Repetition/Feedback helps

- 75% of benchmarks successful (over 10 runs, GPT 3.5)
- Feedback from the verifier can help

