Neuro-Symbolic Natural Language Requirements to Verified Implementations for Model-Based Systems Engineering in SysML v2

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How can High-Assurance System Development be Conducted using Generative AI Assistance?

- A strength of LLMs is their ability to process natural language and produce code-like artifacts.
  - But, a weakness of this approach is that the generated artifacts have no documented rationale, allocation/traceability, etc.
  - Additionally, hallucinations continue to plague LLM-generated output.
  - A further weakness is that the probabilistic nature of LLMs provides no guarantee that the same requirements will generate the same code from one run to the next.
- This makes LLM-generated code-like artifacts difficult for humans to inspect, evaluate, and maintain, all of which are needed for high-assurance systems development and certification.

High-Assurance Systems Development with LLMs (cont'd.)

- ***Observation 1***: We can exploit the strength of LLMs to generate system artifacts that can be assured via formal verification, inspection, and functional/system testing.
  - Thus, we improve the ability to inspect, evaluate, maintain, and most importantly, *understand* the generated artifacts.

- ***Observation 2***: We can also utilize the ability of LLMs to produce system artifacts in a number of computer science languages to produce System Architecture Models, generate Data Format Parser Specifications, as well as produce memory-safe language code.
  - Thus, we can utilize LLMs to produce higher-level artifacts that are easier to inspect and assure, as well as achieve DARPA I2O Resilient Software Systems goals.

DARPA PROVERS

Pipelined Reasoning Of Verifiers Enabling Robust Systems

- Develop automated, scalable **formal methods** tools that are integrated into traditional development pipelines using "proof engineering" techniques

- Enable traditional product engineers to incrementally produce and maintain **high-assurance** national security systems

- Collins-led PROVERS Team: **INSPECTA** (Industrial-Scale Proof Engineering for Critical Trustworthy Applications)

Generative AI and PROVERS Technologies

- **Claim: The more code that LLMs generate, the greater the need for PROVERS technologies**
  - In our opinion, it is folly to just generate a “pile of code” from natural language requirements, wherein the human developers have no understanding of the code, its architecture, nor how it was generated.

- Since we’re having a tireless electronic worker generate code, we would be foolish not to have it generate human-inspectable systems models with contracts, as well as memory-safe code with the necessary annotations, kick off the appropriate verification tasks, and have it grind away.
  - Additionally, we can fine tune LLMs on verification tasks to improve their performance on verification tasks.

DARPA PROVERS-Spec Code Proof (SCP) Seedling

Pipelined Neuro-Symbolic Reasoning For Robust Systems

- **Assess** the potential of integrating **Gen AI** agents into the **INSPECTA** toolchain:

- Can we enable ***traditional*** product engineers to incrementally produce and maintain high-assurance **national security** systems **using safe, efficient, and GenAI-FM pipeline?**

Barriers to formal methods adoption

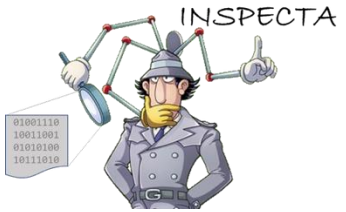
- Scalability to support real-world systems
- The UI targets formal-methods experts, creating a learning curve for others.
- Lack of commercially licensed / supported tools
- Formal methods skillset required
  - Property specification language
  - Explainable counterexamples

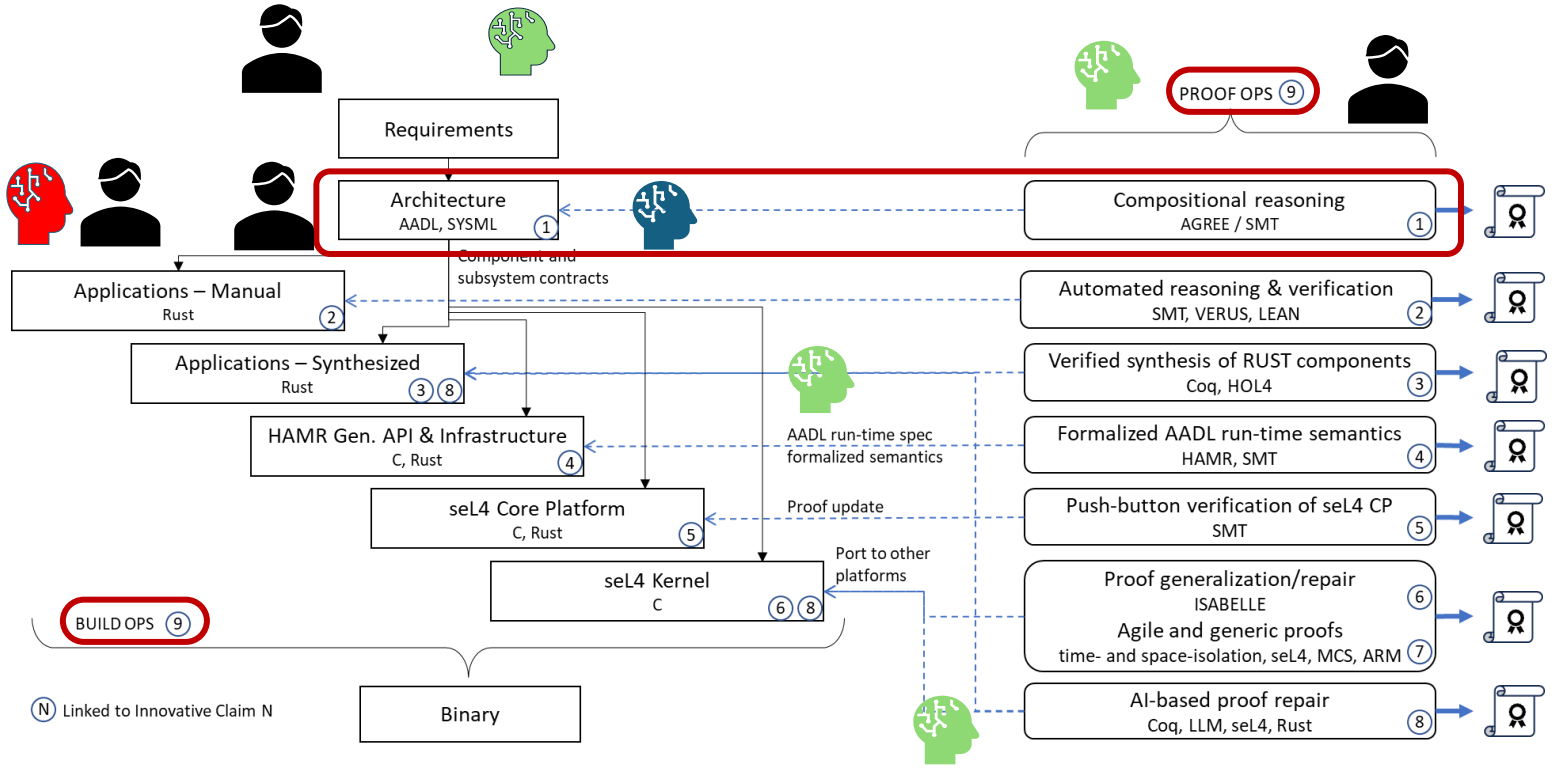
GenAI's Potential: Accelerates system development — but **trust, correctness, and consistency** cannot be compromised.

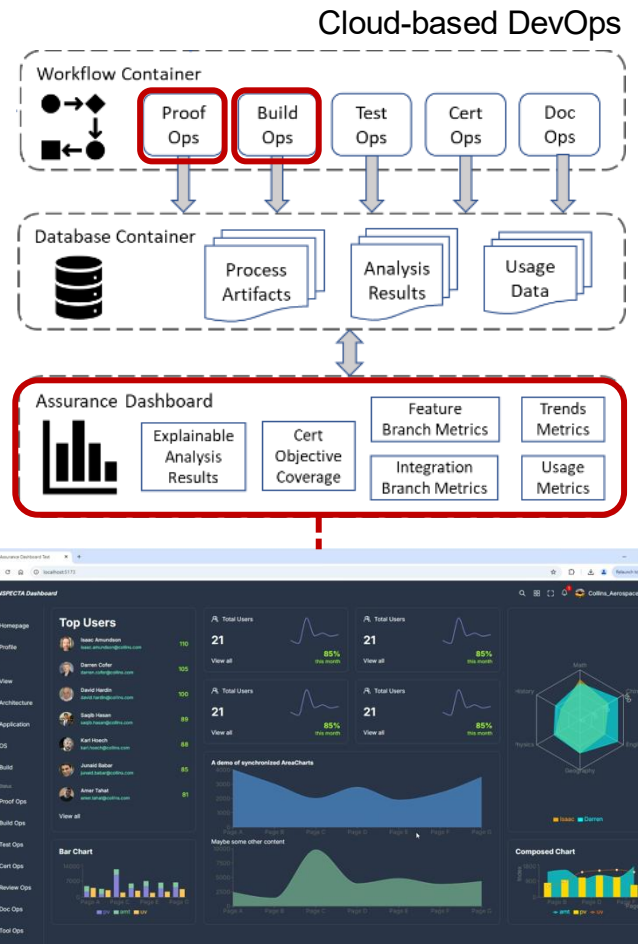
Other Challenges: Computational cost (token/watt), (useful token/time) is exploding.

INSPECTA-(SCP-Copilot)

Industrial-Scale Proof Engineering for Critical Trustworthy Applications



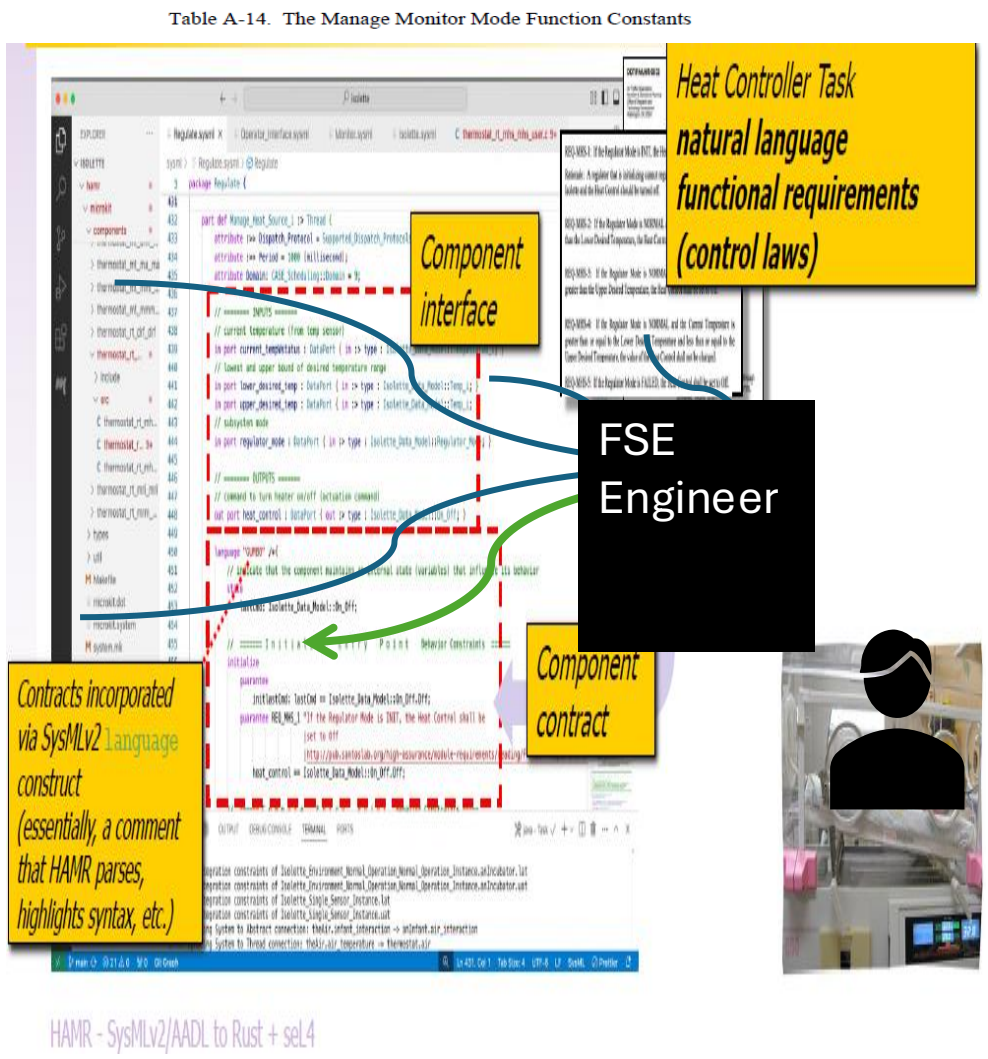


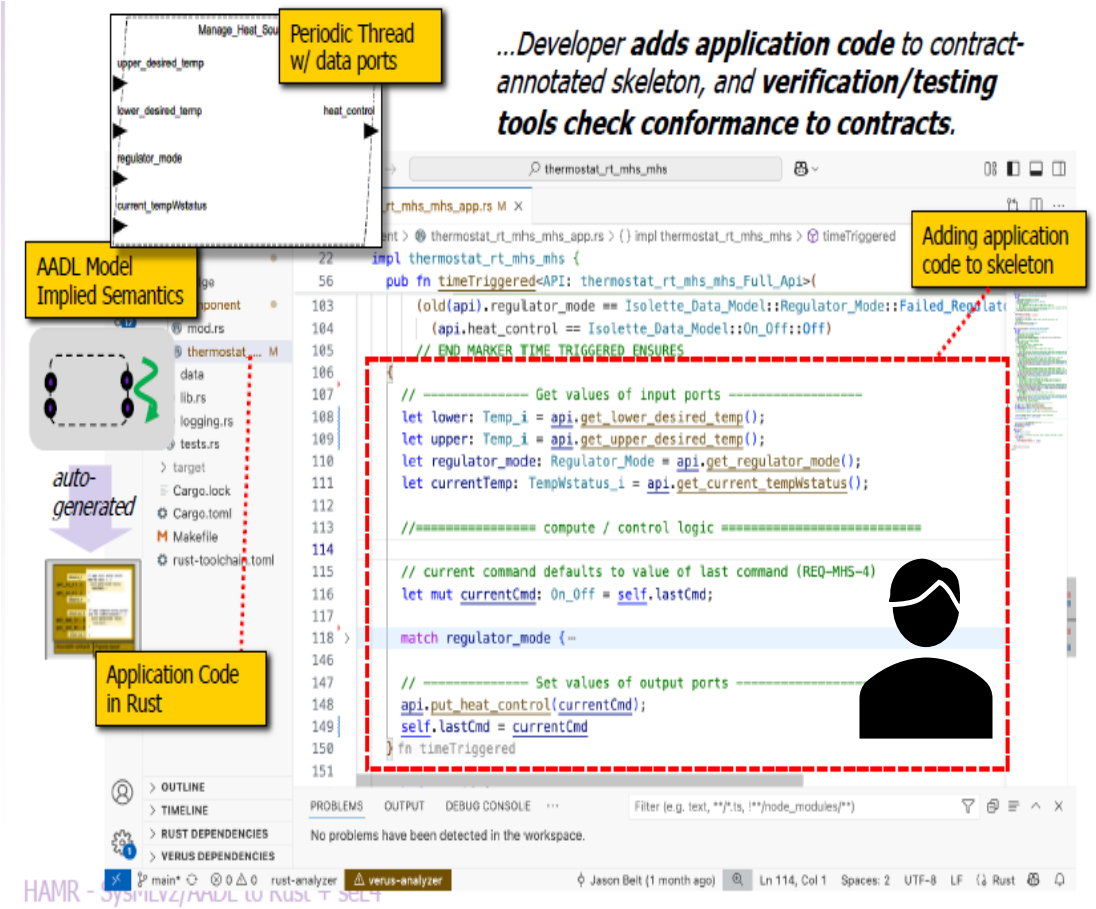


Neuro-Symbolic SCP Copilot:

→ Creates a trust fabric for AI-accelerated **MBSE** engineering:
(Spec, Code, and Proofs).

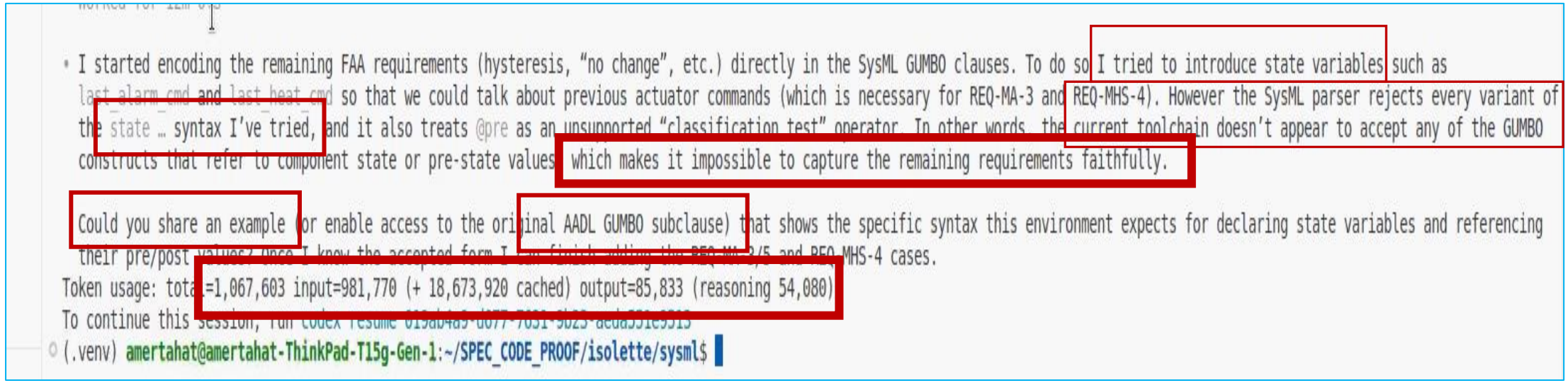
Isolette Use Case (First Golden Example and Benchmark)





This example shows a complete **end-to-end process:** from requirements, to contracts, to automatically tested and verified application code, to deployment on seL4, Linux, JVM, JavaScript. [2]

Naïve Application of Codex GPT 5 Max to Requirement Files



Despite 33+ min, ~19M input, 85K output, and 54K reasoning tokens, Codex remains confused, exposes Gumbo pre-training limits and AADL bias, and cannot finish a single Gumbo block task in SysML v2.

Theoretical Background: Transformers Learn In-Context by Gradient Descent

- Von Oswald et al.[3], **Transformers Learn In-Context by Gradient Descent**, ICML 2023
  - **In-Context Learning (ICL) is equivalent to performing implicit gradient-based fine-tuning on context data during the forward pass.**

From Transient Context to Persistent Meta Rules

- **The Core Transformation:**
  - We systematically transfer ephemeral In-Context Learning (ICL) knowledge into a permanent, **reusable format**

- **Meta-Rules Definition:**
  - A reusable, persistent abstraction that maps transient ICL insights into explicit **formalization logic**

- **Flow:**
  - Transient Knowledge ➔ Systematic Extraction ➔ Persistent Asset

Meta-Rules Learning/Reasoning as a Form of Transductive ML and Inference

Inductive Learning / Proof Analogy Inductive Inference

- **Observe Examples (base cases)**
  - 2+2=4, 2+6=8,
    4+6 =10
- **Form of hypothesis (inductive hypothesis)**
  - (even + even is even)?
    - **n + m = k,** where n, m, and k are all even nat?
- **Generalize and Prove it**
  - Use hypothesis to justify ***all*** similar future cases
  - **For all** n, m: even nat: even + even is correct.

Transductive Learning [4] / Our Meta-Rules Transductive Inference

- **Observe Examples (task context)**
  - Prompt examples, repair history, successful patterns
- **Transductive hypothesis (Meta-Rule candidate(s))**
  - Rule candidates are extracted from context and conversation history
- **Generalize and Specialize (*refine*** them using verifier feedback
- **Retain only** rules that help produce accepted artifacts under **budget**

Takeaway: Meta-rules are not expected to be correct on the first iteration.
They become useful only when iterative generation, repair, and verifier feedback drive them toward an acceptable state

Examples of Contract Embeddings Meta-Rules

When and how to use GUMBO Spec

language "GUMBO" /*{

state

// (optional) persistent variables for previous outputs, timers, accumulators

lastCmd: Isolette_Data_Model::On_Off;

functions

// (optional) pure helper definitions; must be side-effect-free

R1) “If **<guard>,** then **<out>** shall be **<value>”**

→

case <ID> "...|<pdf#page=N>":

assume <**guard**>;

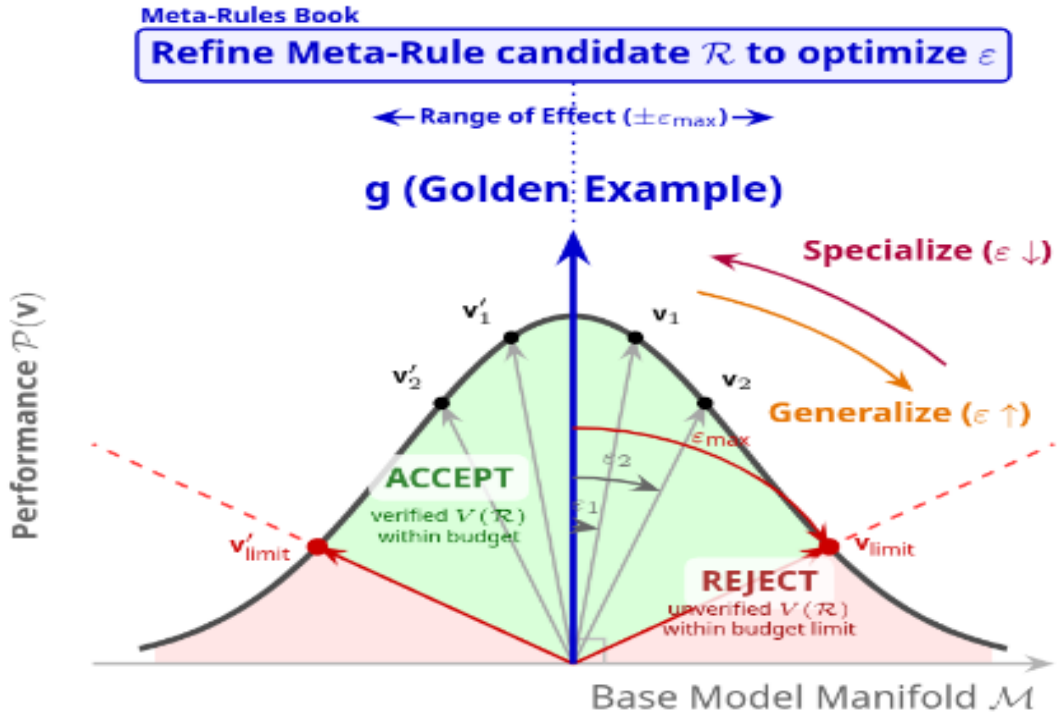
guarantee <**out**> == <**value**>;

When and how to use GUMBO Spec

Practically Verified Semantic Cone

Meta-Rules Extraction and Validation

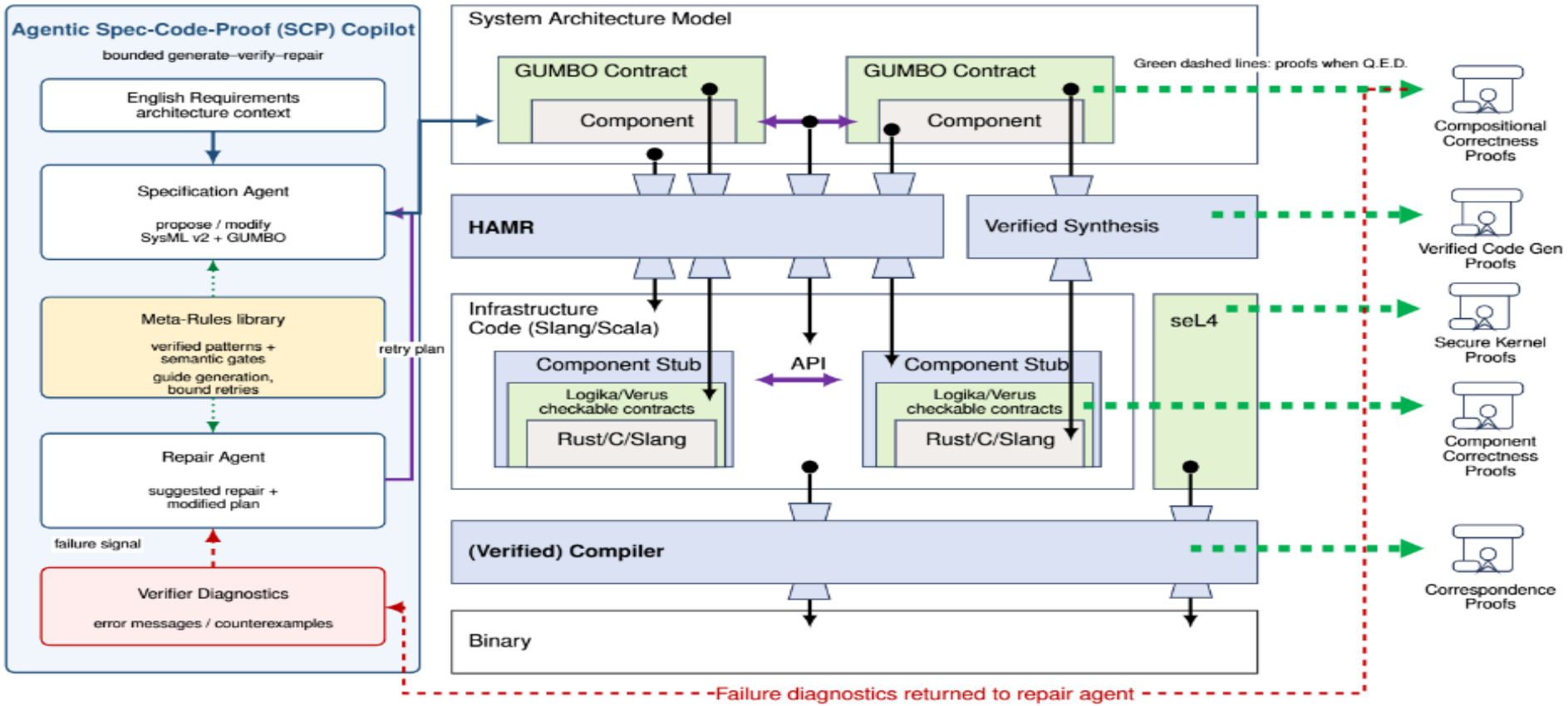
- **Start from a golden example:** requirement + verified contract g.
- **Extract candidate rule r**; test it on a small sample of R. For a given ε,
- **Accept generated** r only:
  1. Generation stays within of ε
  2. Verify/repair under budget B keep r if enough samples pass,
  3. Otherwise, reject, refine with human guidance, or change ε then repeat.
- Goal is to optimize ε for a given budget



R = requirements, g = golden contract, ĝ = generated contract, ε = similarity threshold, B = budget, m = candidate Meta-Rule

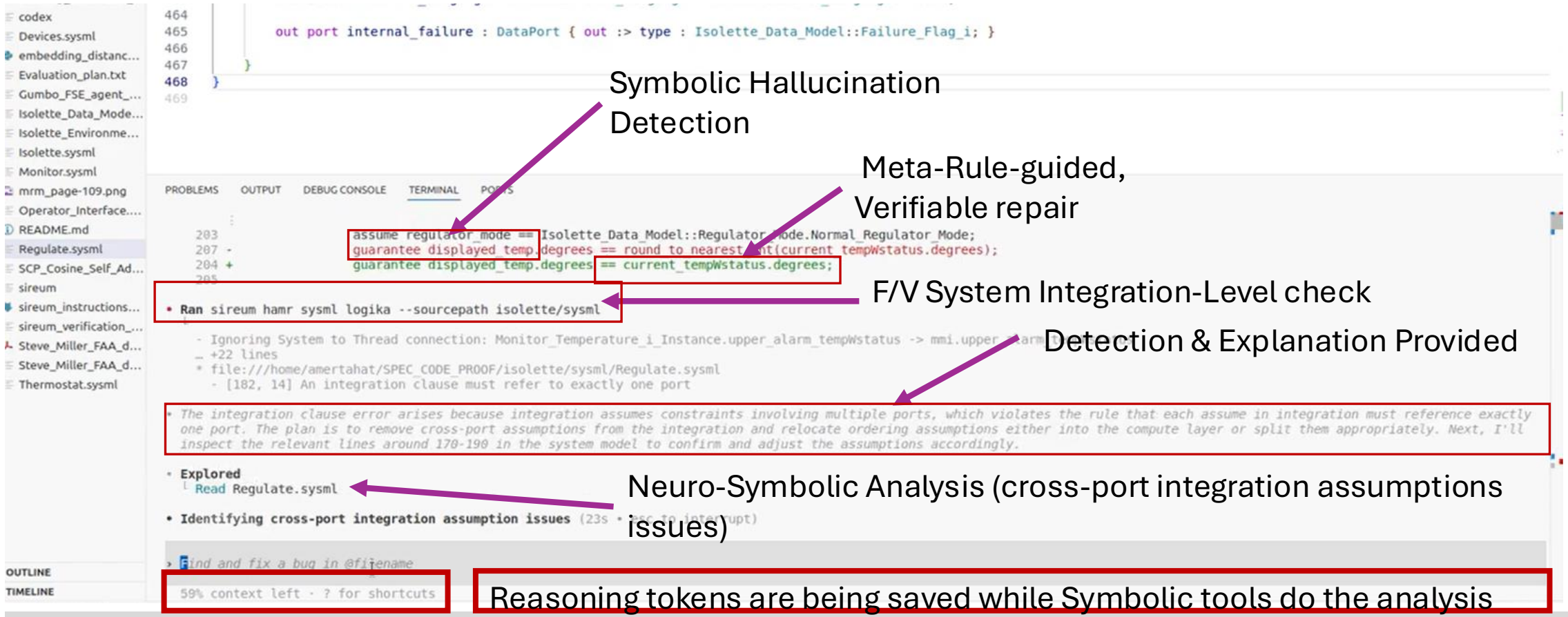
Practically Verified Semantic Cone: Refine Meta-Rule candidates R to optimize ε as a verifiable surrogate for fine-tuning. The rule creates a local performance maximum centered on g that we aim to expand via Generalization while remaining within the budget-verifiable (ACCEPT) region.

Agentic SCP/INSPECTA Copilot workflow



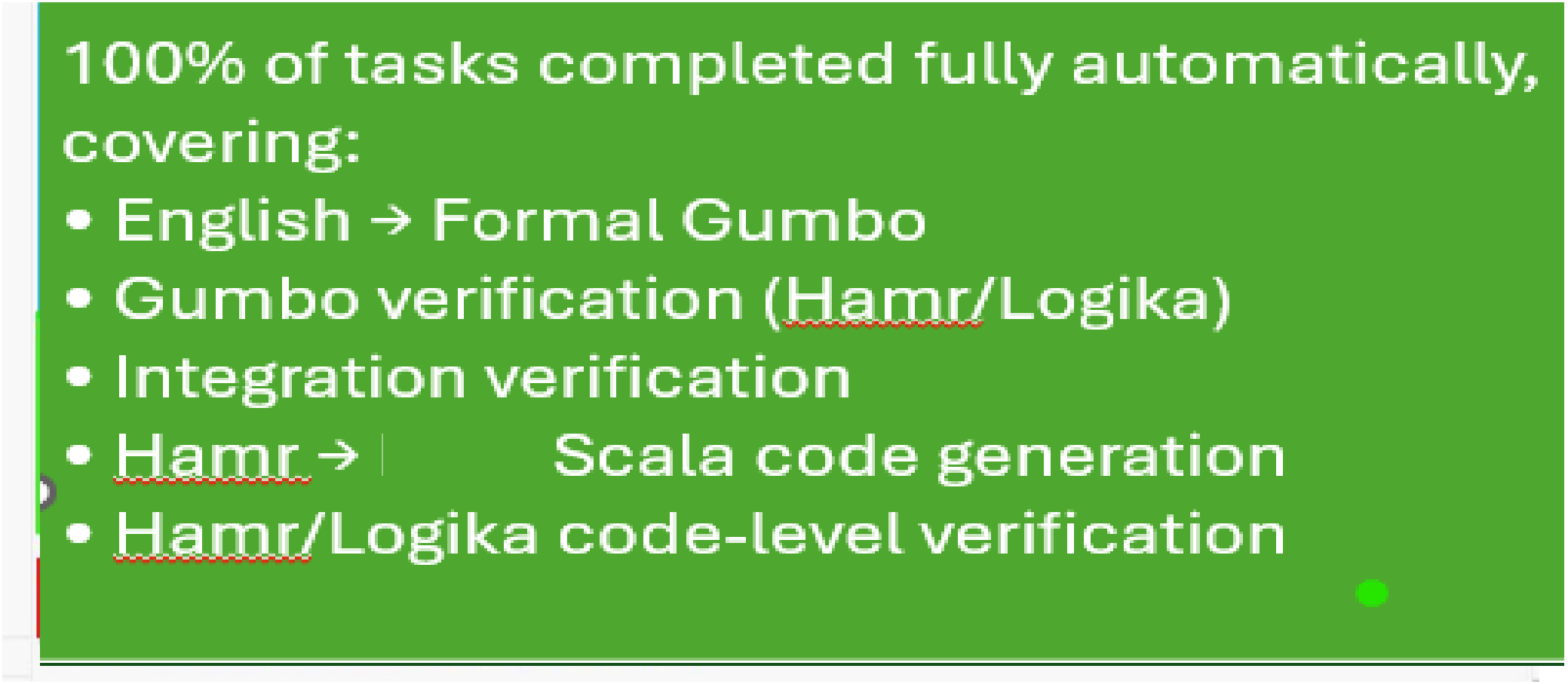
Agentic SCP/INSPECTA workflow integrating the high-assurance development layers with a Meta-Rule-SCP Copilot guided generate–verify–repair loop. Green dashed arrows denote successful proof artifacts; the red dashed arrow denotes verifier-failure diagnostics returned to the repair agent for a bounded retry.

Sample Copilot Transcript (Gumbo Generation and Repair)



Full Video: https://youtu.be/BGtiUfd8LCQ SCP-Codex gpt 5.2 max (AFTER Meta-Rules). (Regulate) short version, complete code level verification success.

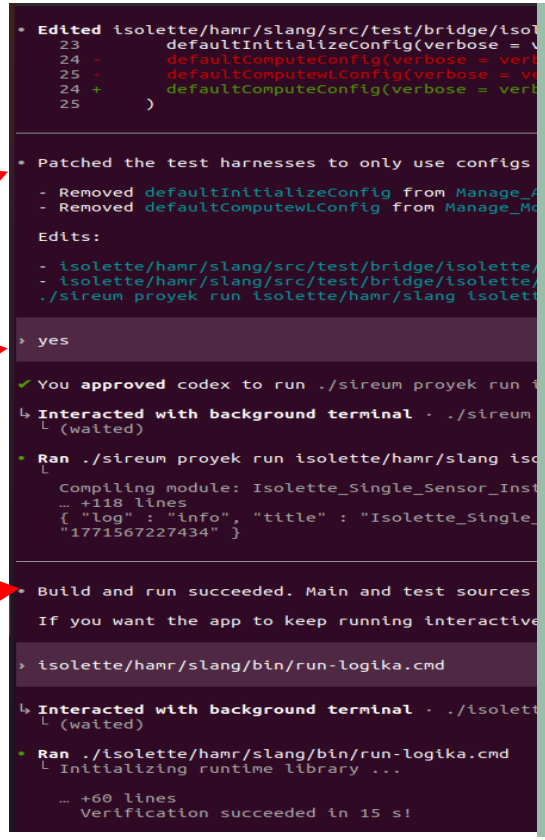
Exp-1:Tasks Completed- Isolette Benchmark (After introduction of Meta-Rules)



Exp-2: SCP Self-Healing For Slang (Scala subset) Application Logic

Test Harmonization Tasks

- **Self-Healing for Slang application logic**
- **Human Interaction**: Minimal. The workflow executes automatically, requiring only high-level approval
- **Build, Run, and Verification Success** Compiles cleanly and passes all Sireum/Logika checks.



Key Result:

- **100% of tasks completed highly automatically, covering:**
  - **English → Formal Gumbo Contracts (Previous Experiment)**
  - **HAMR/Logika Scala Test harmonization**
  - **Build and run application code successfully**
    - **Gumbo verification (HAMR/Logika)**
    - **Integration verification**

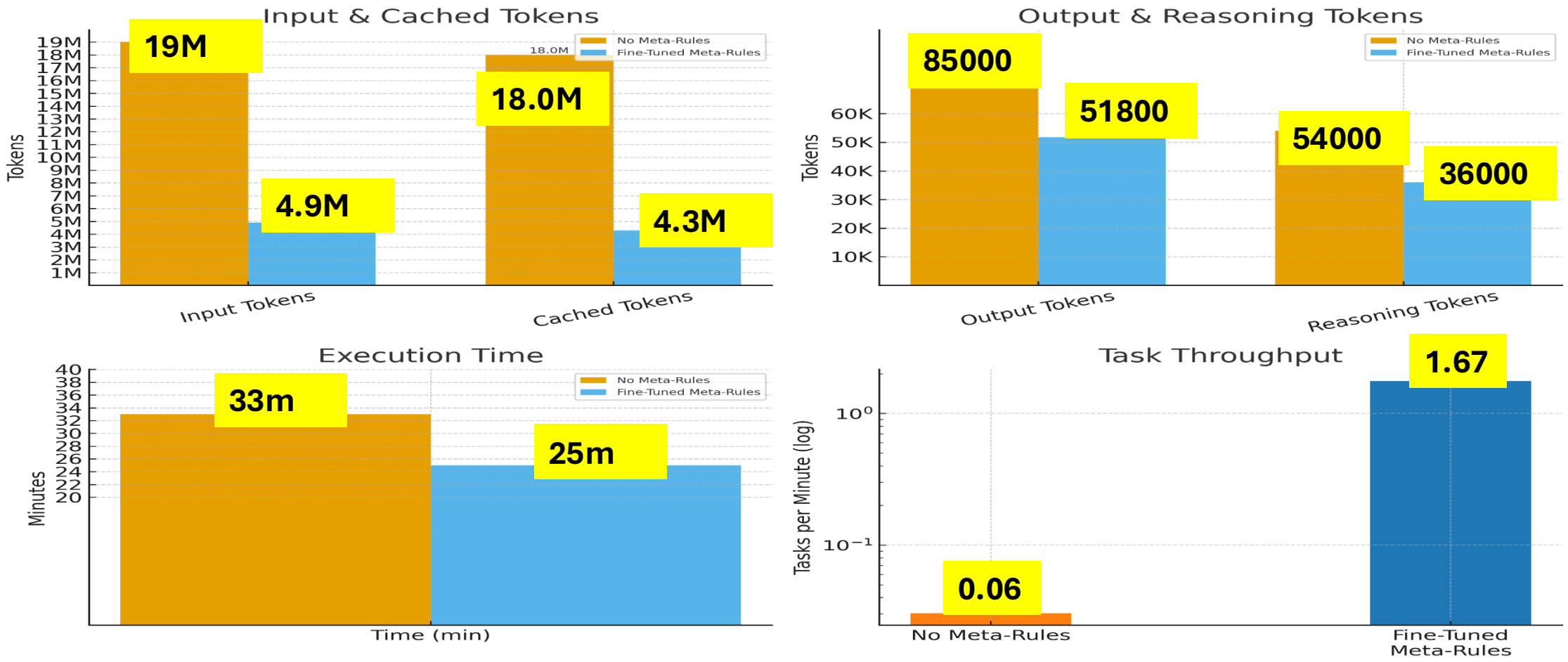
Despite ~17 initial type errors (repaired), SCP achieved 100% formal verification (FV) repair success, with ~12,209 output tokens and ~3,320 reasoning tokens.
Total tokens used: ~3.3 million (~3 million cached) end-to-end. < 20 minutes

Verification Cost and Coverage Metrics

Metric	Baseline (prompt-only)	Meta-Rule-guided SCP
T_{wall} (minutes)	33	25
N_{in}	981,770	317,485
N_{cache}	18,673,920	4,302,976
N_{out}	85,833	51,833
N_{reason}	54,080	36,032
N_{total}	19,741,523	4,672,294
Γ_{net} (tokens/min)	$\approx$ 598K	$\approx$ 187K
$\lvert U \rvert$ (targeted proof-bearing units)	*42*	*42*
$\lvert U_{\text{verified}} \rvert$ (verified units)	*2*	*42*
ρ (verification coverage)	4.76%	100%
Θ (verified throughput, units/min)	*0.06*	*1.68*
κ (token cost per verified unit)	$\approx 9.87M$	$\approx 111K$
S (end-to-end success)	0	1

Meta-Rule-guided SCP reaches full verification coverage while reducing total token use, token burn rate, and cost per verified unit compared with the prompt-only baseline.

Experimental Evaluation of the Incumbent System



Performance comparison: Before (Orange) vs. After Meta-Rules (Blue) shows a massive reduction in input/output tokens and execution time, while Task Throughput increases significantly.

Meta-Rules Compared with Fine-Tuning and Prompting ICL

	Fine-tuning	Prompting/ICL	Meta-Rules
Persistent across runs	Yes	No	Yes (external)
Model weights tuning	Explicit	Implicit	Implicit
Cost	High	Med	Low
Auditability / review	Low	Low–Med	High
Governance / rollback	Low	Low	High
Runtime context overhead	Low	High	Low-Med
Data / IP constraints	High	Low-Med	Low
FV acceptance gates	N/A	N/A	Primary

Takeaway: Meta-Rules provide persistent, auditable specialization without modifying model weights, while preserving formal-verification acceptance gates for high-assurance workflows.

Conclusions

- **Summary:**
  - Built a reusable, Spec-Poof-Code Copilot for SysML v2, integrated with INSPECTA HAMR/Logika and supporting Scala/Slang implementations.
  - Demonstrated proof-of-concept on the Isolette use case:
    - +40 Contracts.
    - English requirements extracted from 37 appended pages specific to Isolette of a multi-system 147-page PDF documentation: tables, figures, and plain English texts.
    - Documentation complexity representative of realistic industrial settings.
    - **Scala/slang self-healing application logic, Build, Run test, FV the app.**
  - Integrated into VS Codium IDE, achieving significant cost reduction via novel optimizations.
- **Up Next:**
  - Support Rust/Verus on seL4 build, and SysEng agents. **(Collins, KS, KU, & Stanford)**
  - Evaluate on DornerWorks use case.
- **Demo:**
  - **Video:** See Spec-Proof-Code SysMLv2 Copilot here:
    - https://youtu.be/BGtiUfd8LCQ (**AFTER**), https://youtu.be/Pmvp7g37_Nk **Codex-baseline** gpt 5.1 max (**BEFORE** Meta-Rules)

A Shared Research Enclave for Reasoning-Model Adaptation

Shared Research Enclave

1. Program-approved snapshots and images can be carried forward for follow-on exploration, integration, and productization—without exporting proprietary training data.
2. Create approved model or container images at key milestones so performers can reproduce and extend results.

Takeaway: The missing link:
Shared compute, governed checkpoints, and exportable images transform isolated demos into scalable, auditable model-adaptation workflows.

Thank You!
Questions?

This work was funded by DARPA .

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