Cyber Security Landscape in Today's Technology Scenario

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Department of Computer Science and Engineering

Indian Institute of Technology Guwahati

Workshop on Cyber Security in the Era of Emerging Technologies

IIT Guwahati · 7 May 2026

About Me

Assistant Professor, Dept. of CSE, IIT Guwahati

Previously Staff Engineer at **Qualcomm Product Security Initiative, Hyderabad**

Research: Software & system security, program analysis, fuzzing

Current focus: **AI for security** and software security analysis

Software runs the world.

Software runs the world.

Finance. Healthcare. Defence. Infrastructure. Communication.

The Scale of Modern System Software

Linux Kernel: **36.9 million** lines of C, 4,037 contributors[1]

Chromium: **36.2 million** lines of C++, 2,109 contributors[2]

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70% of security issues are memory safety bugs[3]

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Real-World Impact

Heartbleed (2014): OpenSSL buffer over-read. Leaked private keys worldwide.[1]

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One insecure line can compromise **millions** of systems.

Manual code review at this scale is practically impossible.

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What Is Software Security?

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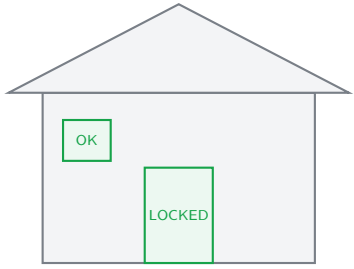
- Security depends on assumptions:
  - Define the **threat model**
  - Attacker capabilities: local, remote, insider
  - Assets being protected

Vulnerability = A Flaw in Software



Your Software

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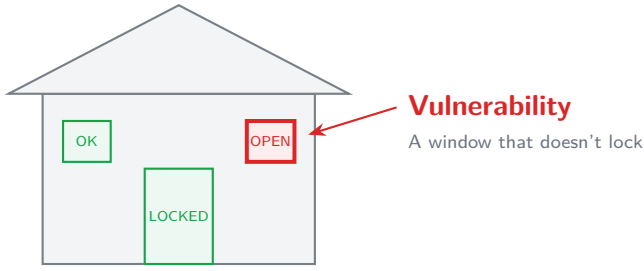

A **weakness** in software that *could* be exploited to cause harm.

Unintentional. But attackers hunt for exactly these.

Common Vulnerability Classes

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- **Buffer overflow**: writing data beyond allocated memory.
- **Race condition**: two threads clash over a shared resource.
- **Logic error**: code does the wrong thing "correctly".
- Also includes: use-after-free, null pointer dereference, integer overflow, TOCTOU.
- Pattern-based tools catch the first two. **Logic errors** require *reasoning*.

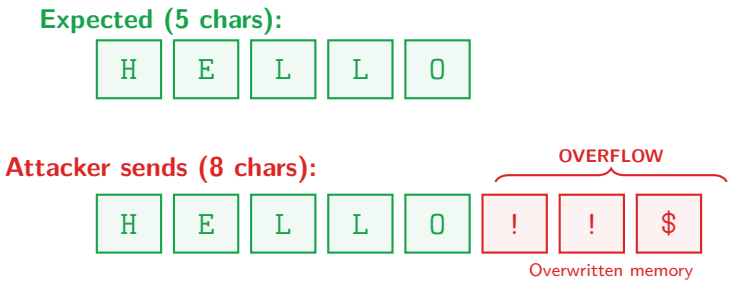
Buffer Overflow

The classic

Expected (5 chars):

Buffer Overflow

The classic



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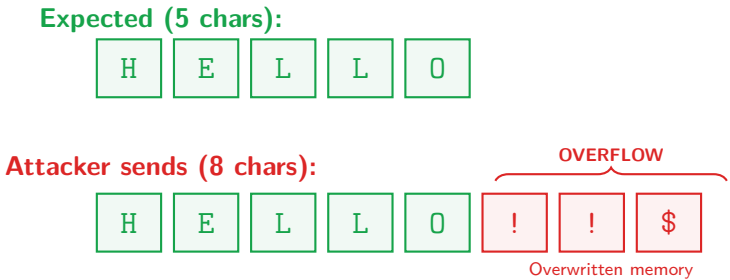

Data spills past its boundary → attacker can **inject code**.

`strcpy(buffer, input)` with no bounds check.

Vulnerability → Exploit → Impact

Vulnerability

The flaw

The vulnerability is the **unlocked window**.

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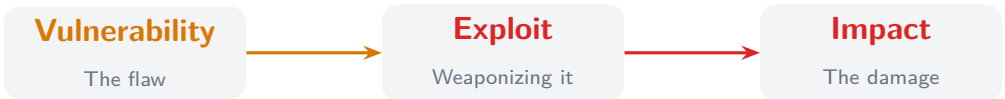

The vulnerability is the **unlocked window**.

The exploit is the **burglar climbing through**.

The impact is **everything they steal**.

Zero-Day Vulnerability

Nobody knows

Zero-Day Vulnerability

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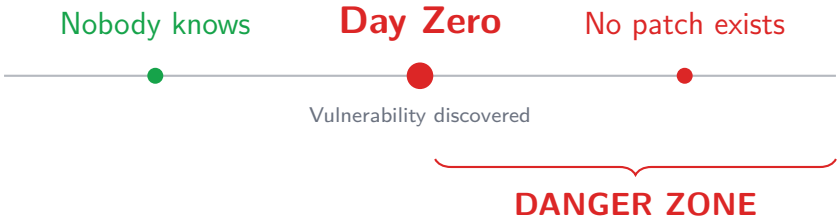

A vulnerability **unknown to defenders**.

Zero time to prepare. Zero patches available.

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How do we find bugs at scale?

Automated Code Analysis

Dynamic analysis: run the code, observe behavior at runtime

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Hybrid analysis: combine both

Each has trade-offs: false positives vs. missed bugs vs. scalability.

Fuzzing

Automated vulnerability discovery

Input Generator

Wu, **Nongpoh**, et al., "Fine-grained Coverage-based Fuzzing," ACM TOSEM 2024

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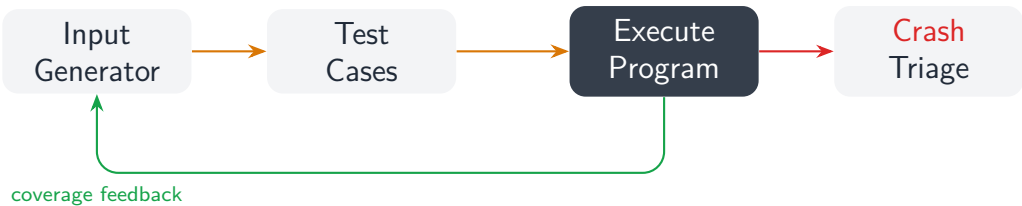

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Limitations of Traditional Tools

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False positives: static analysis flags theoretical issues

No semantics: tools don't understand *intent* or business logic

Auth bypasses, logic errors, design flaws all require *reasoning*.

What if we had something that could reason about code like a human?

A new player. . .

A new player...

Large Language Models

A new player...

Large Language Models

Can they do what human security researchers do?

LLMs Can Find Real Zero-Days

- **Google Big Sleep** (2024): first LLM-found zero-day in SQLite[1]

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- **CyberGym / UC Berkeley** (ICLR 2026): agents found **35 zero-days**[5]

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Agentic LLM-based vulnerability research is emerging as a new category of security tooling.

The Needle-in-the-Haystack Problem

"Find all vulnerabilities" produces breadth-first **hallucination**.

Devansh, "Needle in the Haystack: LLMs for Vulnerability Research," Mar 2026

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Every success used: threat model + thin slice + **tool-based verification**.

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LLM Alone vs. LLM + Analysis Tools

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Generic CWE checklists

Hallucinated exploits

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Tools give the LLM **ground truth**. Without them, you get plausible fiction.

DARPA AI Cyber Challenge (AIxCC)

- **AIxCC**: DARPA competition on autonomous vulnerability discovery and patching.
- Goal: build AI systems that can find vulnerabilities, generate exploits, and repair software automatically.
- Systems operated continuously on real-world open-source software at machine speed.

Source: darpa.mil/research/programs/ai-cyber-challenge

AIxCC: Autonomous Security Pipelines

- AIxCC systems combined: LLM agents, program analysis, symbolic execution, fuzzing, automated patch validation.
- Final competition: autonomous systems competed to discover and patch vulnerabilities faster than other teams.

AIxCC marked a transition from isolated tools to **autonomous AI-driven security pipelines**.

Source: darpa.mil/research/programs/ai-cyber-challenge

ATLANTIS

DARPA AIxCC Winner: Team Atlanta, Taesoo Kim[1]

Target

C/C++, Java

[1] ATLANTIS: AIxCC Finalist System Report, arXiv 2025

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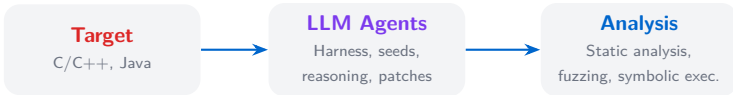

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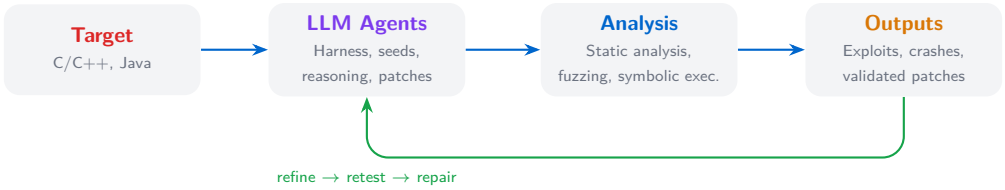

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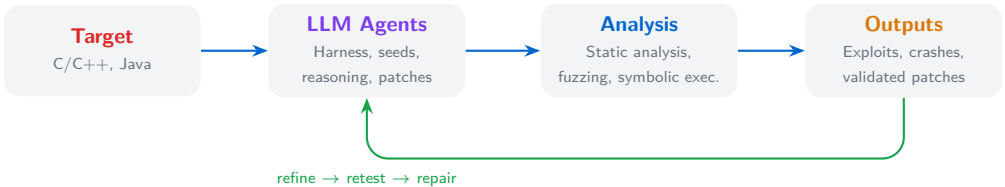

ATLANTIS combines **LLM reasoning** with automated program analysis and fuzzing.

LLMs generate harnesses, inputs, hypotheses, and patches; the analysis infrastructure validates every result.

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The LLM generates and refines hypotheses. The analysis infrastructure provides **ground truth**.

The Shrinking Window

2018

771 days[1]

disclosure → exploit

[1] zerodayclock.com

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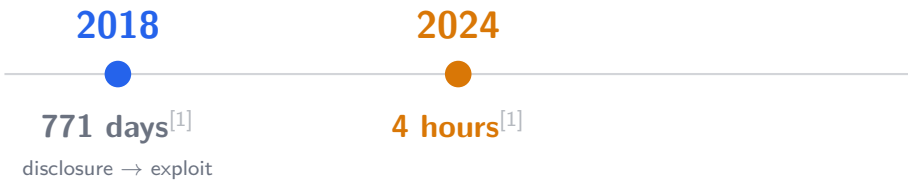

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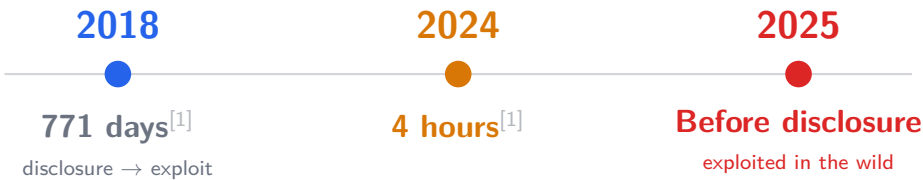

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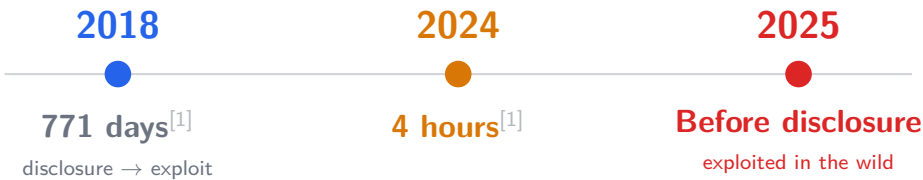

"AI can reverse-engineer a patch and generate a working exploit in minutes."

: Sergej Epp, Zero Day Clock

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The Global Cybersecurity Landscape

89% increase in AI-enabled attacks (2025)[1]

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- Many governments, financial institutions, and critical infrastructure operators lack access to state-of-the-art AI security tooling.
- The gap is especially visible across parts of the **Asia-Pacific** region, including **India**.

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- LLMs alone may hallucinate findings that are plausible but unverifiable.
- **LLM + fuzzing + program analysis** enables discovery of verified and exploitable vulnerabilities.
- Hybrid systems such as ATLANTIS demonstrated autonomous vulnerability discovery and repair at AIxCC scale.

Thank You

Questions?