Step-by-Step Vulnerability Detection using Large Language Models

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Motivation

- Vulnerability detection is a very critical task for systems security.
- Current analysis techniques suffer from the trade-off between coverage and accuracy.
- ML-based* analysis tools are non-robust, black-box and unreliable to use in real-world [1].
- LLMs* demonstrate revolutionizing capabilities for programming language-related tasks but they are also studied in a *black-box fashion* for both vulnerability detection and its repair.
- Security experts follow a step-by-step approach for vulnerability detection. Can using the same approach help LLMs performing better at the vulnerability detection task?

Objective

Design a framework to emulate step-by-step reasoning process of a human security expert using LLMs, to efficiently detect vulnerabilities in source code.

Methodology

- Our approach uses few-shot in-context learning to guide LLMs to follow a step-by-step human-like reasoning model for vulnerability detection.
- We make sure that the model first generates chain-of-thought reasoning [5] and then makes a decision based on that reasoning (as shown in Figure 1 and 3b).

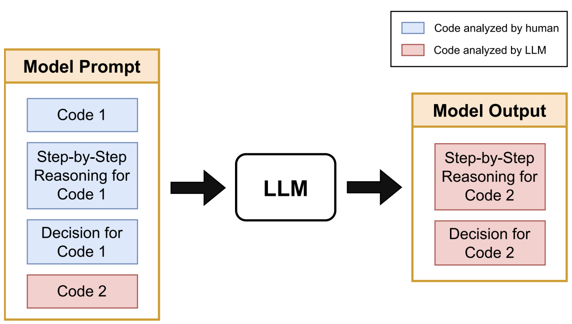


Figure 1. Overview of our few-shot in-context learning approach for vulnerability detection using LLMs.

* ML = Machine Learning
LLM = Large Language Model

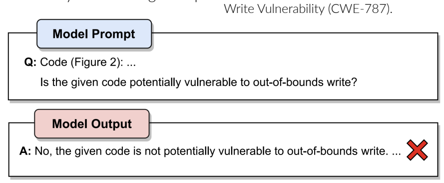
Visualizing the Process of Vulnerability Detection

In this experiment, we study the behavior of an LLM when it is asked to detect a vulnerability in two different scenarios. First, when it is asked to give a direct answer (Figure 3a); and second, when it is first asked to perform human-expert like reasoning and then make a decision (Figure 3b).

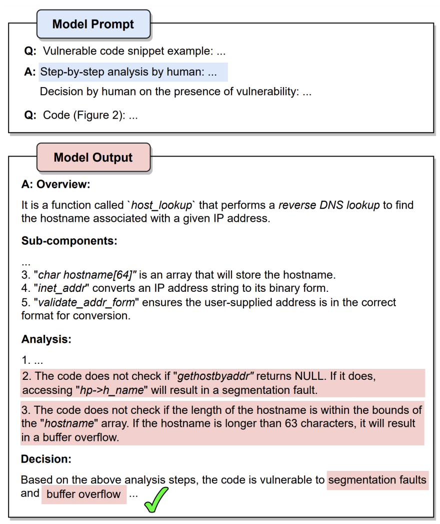
We choose GPT-3.5 as an LLM and a code snippet (shown in Figure 2) containing an out-of-bound write vulnerability as a running example.

```c
void host_lookup(char *user_supplied_addr){
    struct hostent *hp;
    in_addr_t *addr;
    char hostname[64];
    in_addr_t inet_addr(const char *cp);

    /*routine that ensures user_supplied_addr
    is in the right format for conversion */

    validate_addr_form(user_supplied_addr);
    addr = inet_addr(user_supplied_addr);
    hp = gethostbyaddr( addr, sizeof(struct in_addr), AF_INET);
    strcpy(hostname, hp->h_name);
}
```

Figure 2. Code Snippet from the MITRE Out-of-Bound Write Vulnerability (CWE-787).



(a) Standard Prompting.



(b) Step-by-Step Reason Prompting.

Figure 3. Vulnerability Analysis using GPT-3.5

Evaluation

- Figure 3 shows that step-by-step reasoning guides the LLM to detect the (CWE-787) vulnerability.
- To systematically evaluate this approach, we create our own diverse synthetic dataset based on a subset of the MITRE 2022 top 25 most dangerous vulnerabilities.
- For each vulnerability we create vulnerable examples and their patches with varying levels of complexity.
- We use the 'gpt-3.5-turbo-16k' chat API to compare our approach with SoTA tools (Table 1).

Tool/Model	Description	Size	F1	Precision
cppcheck, infer, flawfinder	Combination of SoTA static analysis (SA) tools for C/C++	-	0.49	0.53
UniXcoder	RoBERTa-based model fine-tuned for defect detection in C/C++	126M	0.33	0.25
CodeT5+	LLM specifically pre-trained for progamming langauges-related tasks, including C/C++	16B	0.46	0.54
GPT-3.5	GPT-3.5 without reasoning	175B	0.48	0.50
Our approach with GPT-3.5	GPT-3.5 with step-by-step reasoning	175B	**0.70**	**0.72**

Table 1. Evaluation of different vulnerability analysis techniques on our dataset.

Takeaways

- Following a human-like step-by-step reasoning approach helps LLMs to efficiently analyze code and detect vulnerabilities.
- Our approach provides an explanation for the detected vulnerabilities, which helps user to better contextualize them and to find their root cause.
- Systematic evaluation of this approach on real-world datasets is still required to determine its reliability in real-world use cases.

References

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