

PoC_{GEN}: Generating Proof-of-Concept Exploits for Vulnerabilities in Npm Packages

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Security vulnerabilities in software packages are a significant concern for developers and users alike. Patching these vulnerabilities in a timely manner is crucial to restoring the integrity and security of software systems. However, previous work has shown that vulnerability reports often lack proof-of-concept (PoC) exploits, which are essential for fixing the vulnerability, testing patches, and avoiding regressions. Creating a PoC exploit is challenging because vulnerability reports are informal and often incomplete, and because it requires a detailed understanding of how inputs passed to potentially vulnerable APIs may reach security-relevant sinks. In this paper, we present PoC_{GEN}, a novel approach to autonomously generate and validate PoC exploits for vulnerabilities in npm packages. The approach is the first to address this task by combining the complementary strengths of large language models (LLMs), e.g., to understand informal vulnerability reports, with static analysis, e.g., to identify taint paths, and dynamic analysis, e.g., to validate generated exploits. PoC_{GEN} successfully generates exploits for 77% of the vulnerabilities in the SecBench.js dataset. This success rate significantly outperforms a recent baseline (by 45 absolute percentage points), while imposing an average cost of only \$0.02 per generated exploit. Moreover, PoC_{GEN} generates six successful exploits for recent real-world vulnerabilities, five of which are now included in their respective vulnerability reports.

Additional Key Words and Phrases: Vulnerability, Exploit Generation, Large Language Models

ACM Reference Format:

Deniz Simsek, Aryaz Eghbali, and Michael Pradel. 2025. PoC_{GEN}: Generating Proof-of-Concept Exploits for Vulnerabilities in Npm Packages. 1, 1 (September 2025), 21 pages. <https://doi.org/10.1145/nnnnnnnnnnnnnn>

1 Introduction

Security vulnerabilities pose a major threat to software and users alike, with the number of reported vulnerabilities increasing each year. In 2024 alone, over 40,000 CVEs were disclosed, an increase of 38% over the previous year [1]. As software ecosystems become more complex and interdependent, mitigating vulnerabilities becomes increasingly challenging. This holds particularly for Node.js and its package manager, npm, which form the backbone of the JavaScript and TypeScript ecosystem. With millions of packages and a dense network of dependencies, the npm ecosystem is susceptible to a wide range of security risks [52], including transitive vulnerabilities, where a single vulnerable package can propagate security risks across thousands of applications [45].

When a vulnerability is discovered, it is typically reported to the developers of the affected package, who are then expected to create a patch to fix the issue. Once the vulnerable software is fixed, or some time has passed from the initial vulnerability report, the vulnerability report is published

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ACM XXXX-XXXX/2025/9-ART

<https://doi.org/10.1145/nnnnnnnnnnnnnn>

Fig. 1. CVE-2024-36751 report with no PoC exploit in the report.

¹ An issue in parse-uri v1.0.9 allows attackers to cause a Regular expression Denial of Service (ReDoS) via a crafted URL.

as a Common Vulnerabilities and Exposures (CVE) entry. The process of fixing vulnerabilities is often facilitated by a proof-of-concept (PoC) exploit, which demonstrates how the vulnerability can be exploited in practice. Moreover, PoC exploits are useful for testing the patch and preventing regressions in the future. However, many vulnerability reports lack a PoC exploit [19], and even many CVE reports do not have any PoC exploit. For example, in the SecBench.js [3] dataset, only 179 out of 560 CVEs contain a PoC exploit in the report. Furthermore, the publicly available exploits are not reliable, and in some cases are malicious themselves [43].

As a real-world example, consider the vulnerability CVE-2024-36751 in the “parse-uri” package shown in Fig. 1. The vulnerability report informally describes the problem, but it does not contain an executable code example to reproduce it, i.e., there is no PoC exploit. PoC exploits are useful for preventing regressions and identifying partial or ineffective fixes that fail to resolve the underlying vulnerability. The process of creating PoC exploits is often time-consuming and requires a deep understanding of the codebase, the vulnerability, and the underlying technology [3]. Particularly in the case of Fig. 1, the vulnerability description does not mention which function is vulnerable, and does not provide any information about the input that triggers the vulnerability.

One way to address the challenge of generating a PoC exploit that is missing in a given vulnerability report is to leverage the capabilities of large language models (LLMs). LLMs have demonstrated their effectiveness in various software engineering tasks, including code completion [13], test generation[25, 34], program repair [6, 20, 21, 41, 47], and repository setup [7]. They are especially good candidates because of their ability to understand natural language and other informal, imprecise, and vague information provided in vulnerability reports. Moreover, with their understanding of different vulnerability types, LLMs can generate payloads for exploits in a targeted manner. However, LLMs alone may not be sufficient to generate successful PoC exploits, as they lack the necessary context about the codebase, such as implementation details of the vulnerable code, and have only a limited ability to reason about the behavior of the code.

Another way to generate PoC exploits is to deploy traditional testing and analysis techniques, such as fuzzing [9] and symbolic execution [31]. The currently most effective such technique is a recent approach called *Explode.js* [31], which uses taint analysis, a set of exploit templates, and symbolic execution to produce exploits that trigger vulnerabilities in npm packages. *Explode.js* has been shown to generate PoC exploits for 182 out of 560 vulnerabilities (32%) in the SecBench.js dataset, which is helpful, but still leaves many vulnerabilities without a PoC exploit. We attribute this gap to the fact that *Explode.js* uses traditional program testing and analysis techniques only, but leverages neither the information provided in vulnerability reports nor the capabilities of LLMs.

This paper addresses these limitations by presenting PoC_{GEN}, a novel approach for generating PoC exploits from informal vulnerability reports. PoC_{GEN} is the first to address this problem by combining LLMs with static and dynamic program analysis. The approach takes as input an informal description of a vulnerability, as found in CVE reports, as well as the vulnerable code base, and automatically generates an executable JavaScript file that demonstrates how to exploit the vulnerability. PoC_{GEN} consists of four, iteratively executed components: (i) understanding the vulnerability and extracting source-level information, (ii) generating a candidate exploit, (iii) validating the exploit, and if necessary, (iv) refining the prompt to obtain an improved exploit. These

Fig. 2. PoC_{GEN}-generated PoC exploit for CVE-2024-36751.

```

1 async function exploit() {
2   const parseuri = require("parse-uri");
3   // This input is designed to cause excessive backtracking in the regex
4   const craftedInput = 'http://example.com/' + 'a'.repeat(30000) + '?key=value';
5   const result = await parseuri(craftedInput);
6 }
7 await exploit();

```

components use a combination of LLM prompting and static and dynamic analysis techniques: Component (i) uses dynamic analysis to explore the package’s exported functions, prompts the LLM with the given vulnerability report to identify potentially vulnerable functions, and queries a static taint analysis to extract taint paths. Component (ii) generates a candidate exploit using an LLM. Component (iii) executes and validates the candidate exploit against a dynamic analysis-based test oracle. If the candidate exploit is not valid, PoC_{GEN} uses component (iv) and refines the prompt using a set of refiners that provide static or dynamic information to component (ii) where the LLM attempts again to generate a valid exploit. This process continues until either a valid exploit is generated or until exceeding the computational budget.

To generate a PoC exploit for the ReDoS vulnerability in Fig. 1, the main challenge is to construct a payload that, when passed to the vulnerable function, triggers a security-relevant action. The goal of ReDoS is to exploit the regular expression engine’s backtracking behavior, leading to excessive resource consumption. After analyzing the codebase for potential vulnerable functions, PoC_{GEN} identifies that there is a default exported function, and extracts some usage examples from the codebase as well. In its first attempt, PoC_{GEN} generates an exploit that passes a crafted input string designed to trigger the ReDoS vulnerability. However, this payload is invalid as it does not cause the expected backtracking behavior. Once PoC_{GEN} executes the initial candidate exploit, it realizes that the exploit does not work, and by reasoning about the vulnerability, the code, and runtime information, the LLM comes up with a new payload. After multiple refinements, PoC_{GEN} generates a new exploit that triggers the ReDoS vulnerability, as shown in Fig. 2.

We evaluate PoC_{GEN} on SecBench.js, a benchmark of vulnerable npm packages with path traversal, prototype pollution, command injection, code injection, and ReDoS vulnerabilities. Our results show that PoC_{GEN} successfully generates exploits for 432 out of 560 vulnerabilities (77%), outperforming the previous state of the art [31] by 45 absolute percentage points. When measuring the costs due to LLM usage, we find that PoC_{GEN} incurs an average cost of only \$0.02 per vulnerability, which is reasonably low for adoption in practice. To further validate the practical usefulness of PoC_{GEN}, we use it to generate PoC exploits for six recent real-world vulnerabilities that previously lacked a PoC exploit in their reports. Five of the six generated exploits have been accepted and added to their respective vulnerability reports, and the remaining one is still pending.

We envision the approach to be useful for developers and security researchers. By using PoC_{GEN}, developers of npm packages can generate PoC exploits for vulnerability reports they receive to help them understand the vulnerability and how to address it. They can also use the PoC exploits to test their patches and even add them to their test suites as regression tests. Moreover, security researchers can automate reporting vulnerabilities to downstream packages, by automating the PoC exploit generation process.

In summary, this paper makes the following contributions:

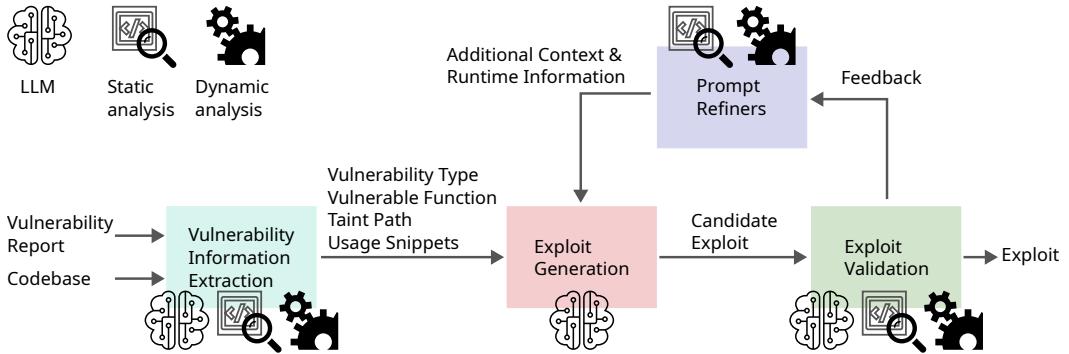


Fig. 3. Overview of PoCGen.

- A novel approach to autonomously generate and validate PoC exploits for vulnerabilities in npm packages by combining LLMs with static and dynamic analysis.
- Empirical evidence of the effectiveness of PoCGen on 560 real-world vulnerabilities, covering five common vulnerability types, as well as its utility for augmenting vulnerability reports that were previously missing PoC exploits.
- We share our code and data to foster future research (Section 6).

2 Approach

2.1 Overview

Figure 3 provides an overview of PoCGen. The approach consists of four main components, which combine LLM prompting, static analysis, and dynamic analysis. PoCGen takes as input a vulnerability report, which is an informal description of the vulnerability, and the codebase of the vulnerable package. Vulnerability reports originate from several sources, such as vulnerability databases (e.g., the CVE database, GitHub Security Advisories, and Snyk), bug and issue trackers, or security mailing lists.

The first step of PoCGen (Section 2.2) is to extract information about the vulnerability and the codebase. This step is necessary because the natural language description in a vulnerability report is often vague and does not provide enough information to directly generate a PoC exploit. The approach extracts the vulnerability type, the likely vulnerable function, taint paths to vulnerable sinks, and usage examples.

In the second step (Section 2.3), PoCGen uses the extracted information to generate a candidate exploit. To this end, the approach compiles all the available information into a prompt that asks the LLM to generate a PoC exploit.

Once the LLM generates a candidate exploit, the third step of PoCGen (Section 2.4) executes and validates the candidate exploit. The approach uses multiple validation mechanisms, including a set of runtime checkers that are specific to each vulnerability type. For example, for command injection vulnerabilities, the validation checks whether a specific command is executed after running the candidate exploit, while for prototype pollution vulnerabilities, it checks whether a specific property is added to the global object.

In case the candidate exploit is successfully validated, PoCGen returns it to the user and the approach terminates. Otherwise, the fourth step of the approach (Section 2.5) refines the exploit generation prompt by adding additional context based on static analysis and the runtime information

obtained during exploit generation. This process continues until either finding a valid exploit or exhausting the computational budget.

2.2 Vulnerability Information Extraction

In this component, PoCGEN extracts four pieces of information from the vulnerability report and the codebase to provide as context to the exploit generation component.

2.2.1 Vulnerability Type. First, PoCGEN identifies the type of vulnerability. This is crucial to our approach as the type of vulnerability determines the goal of the exploit and how it should be validated. To do this, we prompt the LLM with the vulnerability report and ask it to identify the type of vulnerability. As the vulnerability report is written in natural language, and the description is informal, an LLM is a suitable tool to extract information from it. We provide the LLM with a list of possible vulnerability types, which are the five vulnerability types that we support in our approach, namely, path traversal, prototype pollution, command injection, code injection, and Regular Expression Denial of Service (ReDoS). PoCGEN prompts the LLM to select the most relevant vulnerability type from the list.

2.2.2 Vulnerable Function. In our approach and throughout this paper, we refer to the function that is accessible to an attacker and is the entry point for the exploit as the *vulnerable function*. Finding the vulnerable function is helpful for generating the PoC exploit, as it provides information about the input types and possible values, and potentially the vulnerable execution path of the function. To identify the vulnerable function, we first load the package and dynamically extract all the functions that it exports. We then prompt the LLM with the vulnerability report and ask it to identify the vulnerable function from the extracted functions. Since the vulnerability report can be vague, and multiple functions can be candidates for the vulnerable function, we prompt the LLM to rank the functions based on their likelihood of being the vulnerable function. This ranked list of candidate functions is the input to the next step which is to extract taint paths.

2.2.3 Taint Path Extraction. To generate a successful PoC exploit, it is crucial to understand whether and how the input to the vulnerable function flows through the code and reaches the sensitive operations, commonly referred to as vulnerable sinks. Taint analysis is a technique that tracks the flow of data through the code by marking a certain input as tainted and propagating this taint through the code. Moreover, to narrow down the search space for the vulnerable function, PoCGEN attempts to extract a taint path from each of the candidate functions identified in the previous step to a vulnerable sink. If no taint path is found for a candidate function, that function is not considered for exploit generation.

In our approach we define a taint path as a sequence of source code lines starting with the signature line in the definition of the vulnerable function, and ending with a vulnerable sink. Any lines of code that propagate the taint are also included in the taint path. To provide more context to the LLM, for each line in the taint path, we include three lines before and after it as additional context. If these context windows overlap, we merge them to avoid duplication.

We use the static taint analysis provided by CodeQL¹. For each vulnerability type, we use the vulnerable sinks and taint propagation rules specified in the JavaScript security library of CodeQL².

From the vulnerable functions obtained in the previous step, in the order of their ranking, in batches of 50 functions, PoCGEN queries the static taint analysis to extract at least one taint path, which is also used to pinpoint the vulnerable function. The taint analysis of CodeQL is designed for

¹<https://codeql.github.com/>

²The module semmle.javascript.security

industry-level security analysis, which requires high precision and few false positives. This means that the taint analysis may not find all taint paths.

Hence, if the first taint tracking attempt does not find any taint paths, our approach retries the taint analysis with our own extended set of taint propagation rules and vulnerable sinks. If the extended taint analysis is also unsuccessful, PoCGEN switches to a combination of static and dynamic taint analysis. First, it prompts the LLM to generate an exploit for the vulnerable function. Then, it executes the generated exploit and runs the static taint analysis on the functions that are executed during the exploit. If any of the executed functions have a taint path to a vulnerable sink, the approach uses this taint path as the taint path for the vulnerable function.

If PoCEN still do not find a taint path, it proceeds to the next batch of candidate functions from the ranking and repeats the process. If the approach exhausts all candidate functions without finding any taint paths, it considers the exploit generation attempt as failed and does not move to further steps of the approach.

The output of this phase is a sequence of code snippets interleaved with natural language explanations of how the code propagates the taint, shown in Fig. 4, with multiple sections if the taint path spans multiple files. In each section, there is a header specifying the file, followed by the taint path and its additional context from that file. The taint path lines are also marked by a comment at the end of the line.

The package djv in Fig. 4, which is a JSON schema validator, had a code injection vulnerability (CVE-2020-28464). The vulnerable function `import` takes a JSON string as input, parses it, and then calls the `restore` function with each of the attributes of the parsed object. In the `restore` function, a new function is dynamically created where the body of the function comes from the parsed JSON string. As shown in Fig. 4, a malicious input (e.g., JSON string containing arbitrary JavaScript code) to the `import` function, flows through to the `restore` function, and is used as the body of a dynamically created function, which is a code injection vulnerability.

2.2.4 Usage Snippets. To help the LLM generate a valid exploit, PoCEN extracts usage examples of the vulnerable function from the codebase. These examples allow the LLM to understand the function signature, and any setup that is required to call the function. We extract usage snippets both from the source code and from the documentation of the package. The usage snippets from the source code are extracted from test files using static analysis, by finding all the call sites of the vulnerable function. For the usage snippets from the documentation, we first extract all code pieces in the documentation, wrapped in triple backticks ("```"), and then we prompt an LLM to determine if they are usage examples of the vulnerable function. If they are, we also prompt the LLM to summarize them.

2.3 Exploit Generation

PoCEN assembles a prompt for the LLM to generate the PoC exploit. Figure 6 shows the prompt template that we use for generating the exploit. The prompt starts with naming the vulnerable function (as `vulnerableFunction`) and the vulnerability type (as `vulnerabilityType`), which are extracted in the previous phase, followed by a description of the vulnerability (as `vulnerabilityDescription`), which is the text of the vulnerability report. Then, we provide the example usages of the vulnerable function (as `usageSnippets`), which are extracted from the codebase in the previous step.

Next, the prompt describes how the generated exploit should look like by providing the skeleton of the exploit code (as `exploitSkeleton`), and also providing exploits of similar vulnerabilities (as `similarExploits`). The skeleton of the exploit code, is a fixed template that contains the definition of the exploit function, its call, and loading the vulnerable function from the vulnerable package. To extract similar exploits, our approach uses BM25 to find the three most similar vulnerability

Fig. 4. Example of a taint path extracted by PoC_{GEN} from the package d_{jv} with code injection vulnerability (CVE-2020-28464).

```

1 Vulnerable method `import` of class `Environment` located in djv/lib/djv.js:
2 ````js
3 import(config) { // tainted: "config"
4   const item=JSON.parse(config) // tainted: "config"
5   let restoreData=item // tainted: "item"
6   if (item.name && item.fn && item.schema) {
7     restoreData={
8       [item.name]: item,
9     }
10   }
11   Object.keys(restoreData).forEach((key)=>{ // tainted: "restoreData"
12     const {name, schema, fn: source}=restoreData[key] // tainted: "restoreData"
13     const fn=restore(source, schema, this.options) // tainted: "source"
14     this.resolved[name]={
15       name,
16       schema,
17     }
18   }
19 Call to `restore`:
20 ````js
21 function restore(source, schema, {inner}={}) { // tainted: "source"
22   const tpl=new Function("schema", source)(schema) // tainted: "source"
23   if (!inner) {
24   ````
```

Fig. 5. Example of extracted usage snippets for the vulnerable function setPath in the doc-path package.

```

1 const path = require('doc-path');
2 let document = {
3   Make: 'Nissan',
4   Features: [ { feature: 'A/C' } ]
5 };
6 console.log(path.setPath(document, 'Color.Interior', 'Tan'));
7 /* {
8   Make: 'Nissan',
9   Features: [ { feature: 'A/C' } ]
10  Color: { Interior: 'Tan' }
11 } */
12 console.log(path.setPath(document, 'StockNumber', '34567'));
13 /* {
14   Make: 'Nissan',
15   Features: [ { feature: 'A/C' } ]
16   Color: { Interior: 'Tan' },
17   StockNumber: '34567'
18 } */
19 console.log(path.setPath(document, 'Features.cost', '$0 (Standard)' ));
20 /* {
21   Make: 'Nissan',
22   Features: [ { feature: 'A/C', cost: '$0 (Standard)' } ]
23   Color: { Interior: 'Tan' },
24   StockNumber: '34567'
25 } */
```

Fig. 6. Prompt template for the first round of exploit generation.

```

1 `{{vulnerableFunction}}` is vulnerable to {{vulnerabilityType}}.
2 ## Vulnerability Description:
3 ``
4 {{vulnerabilityDescription}}
5 ``
6 {{> usageSnippets }}
7 {{> exploitSkeleton }}
8 ## Task:
9 Create an exploit that uses the {{vulnerabilityType}} in `{{vulnerableFunction}}` to
10 {{vulnerabilityTrigger}}.
11 Respond with the full exploit code and explain why it works.
12 If there is an exception thrown, do not try to handle it and pass it on.
13 Enclose the exploit code in backticks and define the exploit within a function named `exploit`.
14 ## Source code:
15 {{taintPathSnippets}}

```

descriptions from the SecBench.js dataset to the current vulnerability report, and provides their exploits as examples.

After providing the context, the prompt specifies the task to the LLM, which is to create an exploit that uses the vulnerability in the vulnerable function to trigger a security-relevant action (as `vulnerabilityTrigger`). This action is specifically defined for each vulnerability type, to facilitate the validation of the generated exploit. Finally, the prompt provides the taint path snippets (as `taintPathSnippets`), which are extracted in the previous step.

2.4 Exploit Validation

For each vulnerability type, PoCgen uses a specific validation mechanism to check whether the generated exploit is valid. These mechanisms are inspired by the validation checks in SecBench.js [3].

2.4.1 Path Traversal. The goal of path traversal exploits is to access a file in the root directory. In the validators of SecBench.js this was implemented as being able to read a flag file in the root directory. However, this would render exploits for vulnerabilities that perform other file operations invalid. To mitigate this, we consider all file system operations during runtime, and check the normalized path of the accessed file. If the normalized path is evaluated to `flag.txt` in a directory above the current directory, the exploit is considered valid.

2.4.2 Prototype Pollution. In the case of prototype pollution vulnerabilities, the goal of the exploit is to add a property named `exploited` to the global `Object.prototype` object. However, this does not always guarantee that the exploit is valid, as the property can be added to the object without exploiting the vulnerability. To filter out such cases, we also check if an assignment of the form `*[__proto__|prototype].exploited = *` is present in the exploit code. If such an assignment exists and the property is set, the exploit is considered invalid.

2.4.3 Command Injection. For command injection vulnerabilities, the goal of the exploit is to execute the command `/usr/bin/genpoc`. This command writes a file to the file system, which is then checked by the validation checker.

2.4.4 Code Injection. For code injection vulnerabilities, the goal of the exploit is to call the built-in `process.seteuid` function, with parameter 42. This indicates that the exploit was able to access the

process module. Access to this module implies the ability to execute arbitrary code in the context of the Node.js process. To ensure that the exploit uses the vulnerable function, we statically check whether there is a direct call to `process.seteuid(42)` in the exploit code. If there is, we consider the exploit as invalid, as it does not exploit the vulnerable function.

2.4.5 ReDoS. For ReDoS vulnerabilities, the goal of the exploit is to cause a denial of service by taking a long time to execute. We hook the string and regex functions in the V8 engine to measure the time these functions take. If the execution time of a function exceeds 1,500 milliseconds, we consider the exploit as valid.

2.4.6 Sanity Checks. In addition to the vulnerability-specific validation checks, PoCGEN performs a set of sanity checks to validate that the exploit is achieved through the vulnerable function. After the checks mentioned above, PoCGEN searches the stack trace for a call to the vulnerable function. If there is no such call, the exploit is considered invalid.

As a last step in the validation process of any vulnerability type, we prompt the LLM to check whether the exploit actually triggers the vulnerability described in the report. This is done to filter out any invalid exploits that passed the previous validation checks.

2.5 Prompt Refinement

After the validation step, if the exploit is not valid, PoCGEN refines the prompt to generate a new candidate exploit. PoCGEN uses a set of refiners that provide static or dynamic information to the LLM to help it generate a valid exploit.

2.5.1 Context Refiners. The first set of refiners are the *context refiners*, which provide additional context to the LLM to help it generate a valid exploit. Since the taint path only contains the taint propagation lines, checks on taint values are not included in the taint path. Therefore, the LLM might not have the information about the checks that are in place to prevent the vulnerability from being exploited. To address this, we provide a *body refiner*, which provides the full body of any function that has at least one line of code in the taint path.

However, there can be checks that happen via function calls that are not in the taint path. To address this, we also provide a *missing declaration refiner*, which provides the LLM with the ability to ask for definitions of variables and functions in the taint path, through the function calling format of OpenAI's API. The LLM can output a list of identifiers for which it needs their definitions, and PoCGEN will provide the definitions of these identifiers in the prompt using the V8's API, which itself uses a combination of static and dynamic analyses.

2.5.2 Runtime Refiners. The second set of refiners are *runtime refiners*, which add information about the execution to the prompt. The refiners in this category are the *error refiner*, the *coverage refiner*, the *debugger refiner*, and the vulnerability-specific refiners.

Since the exploit generated by the LLM can have runtime errors, for example from a wrong API usage, the *error refiner* provides the LLM with the error message that was thrown during the execution of the candidate exploit.

The *coverage refiner* provides the LLM with the coverage information of the candidate exploit, as markings in comments at the end of each line in the taint path. This information is useful for the LLM to understand which parts of the code were not executed. If the vulnerable sink was not executed, the information provided by this refiner can help the LLM to generate a new exploit that reaches the vulnerable sink.

Fig. 7. Algorithm for the refinement loop.

```

1 prompts ← PriorityQueue{ (0, getSeedPrompt())}
2 usedRefiners ← {}
3 seenExploits ← {}
4 while prompts ≠ {} and |usedRefiners| < 30 do
5   prompt ← top(prompts)
6   prompts ← prompts \ {prompt}
7   prompts ← prompts ∪ {prompts with more info}
8   exploit ← generateExploit(prompt)      // via LLM
9   if exploit ∉ seenExploits then
10     result ← runAndValidate(exploit)
11     if result.success then
12       return exploit
13     endif
14     correctlyUsedInfo ← getCorrectlyUsedInfo(prompt, result) // Information in the prompt that
15     ↪ the LLM used correctly
16     prompts ← prompts ∪ {
17       result.taintSteps + result.newErrors,
18       prompt + result.errors - correctlyUsedInfo
19     })
20     usedRefiners ← usedRefiners ∪ {used refiners}
21     seenExploits ← seenExploits ∪ {exploit}
22   endif
23 endwhile
24 return failure

```

The *debugger refiner* provides the LLM with a debugger-like tool. The LLM can output a list of expressions, for which it needs the runtime values. Using the Inspector API of Node.js³, PoCGen evaluates these expressions during the execution of the exploit. These values are provided as comments in their respective lines of the taint path in the prompt.

There are cases where the LLM generates an exploit that reaches the vulnerable sink, but the exploit fails the validation checks due to a wrong input. For path traversal, command injection, and code injection vulnerabilities, we provide specific refiners that hook into the vulnerable sinks and provide the runtime values passed to these functions. This form of feedback allows the LLM to understand how the input it generated is transformed, which can help it generate a valid exploit in the next iteration. For path traversal vulnerabilities, the refiner provides the values passed to the file system functions, like `fs.readFile` and `fs.open`. For command injection vulnerabilities, it provides the values passed to the `spawn` function. Finally, in case of code injection vulnerabilities, the refiner provides the values passed to the most common sink functions, like the `Function` constructor.

2.5.3 Combining Refiners. Based on the different refiners described above, PoCGen implements a refinement loop that iteratively improves prompts until a valid exploit is generated or the budget is exhausted. Figure 7 shows the algorithm for the refinement loop. In every refinement attempt, PoCGen chooses one refiner from the front of a priority queue. Initially a seed prompt is in the priority queue. Each time the approach uses a refiner, it assigns a score based on the number of new errors the respective exploit causes, and the number of steps from the taint path it covers. It then adds the refined prompt to the priority queue with the score. Moreover, if a refinement generates a prompt that is already used, PoCGen does not query the LLM again, and moves to the next refiner. To keep the prompts concise, in each refinement, PoCGen removes parts of the prompt

³<https://nodejs.org/api/inspector.html>

that the LLM has correctly used in the previous attempts. For example, if the exploit generated in the previous step uses the vulnerable function correctly, PoC_{GEN} removes the usage snippets from the prompt. The refinement process continues until either a valid exploit is generated, or the computational budget is exhausted.

3 Evaluation

We evaluate PoC_{GEN} on 560 vulnerabilities in npm packages to answer the following research questions:

- RQ1: How effective is PoC_{GEN} in generating PoC exploits?
- RQ2: How much does each component of PoC_{GEN} contribute to the overall effectiveness?
- RQ3: How much does it cost to generate PoC exploits in terms of money and time?
- RQ4: How useful is PoC_{GEN} in augmenting real-world vulnerability reports with exploits?
- RQ5: What are the characteristics of vulnerabilities that affect the success of PoC_{GEN}?

3.1 Experimental Setup

3.1.1 Dataset. We use the SecBench.js dataset [3] to evaluate PoC_{GEN}. The dataset contains 600 vulnerable npm packages with code injection, command injection, prototype pollution, path traversal, and ReDoS vulnerabilities. We exclude packages that have been removed from the npm registry. This leaves us with a total of 560 vulnerabilities to evaluate our approach.

3.1.2 Implementation and Configuration. We run all experiments on an Ubuntu 22.04 machine with Intel Zeon(R) Silver 4214 CPU, with 256 GB of RAM. The experimental setup uses Node.js version 22.11.0, running on a modified V8 engine that throws an error if a configurable backtracking limit is exceeded. For static taint analysis, we use CodeQL version 2.20.4.

As the LLM, we use OpenAI's gpt-4o-mini-2024-07-18 model through the OpenAI API. We use a system prompt that assigns the role of a security researcher specialized in creating exploits for the identified security class to the LLM. This is done to reduce refusals to generate exploits by the LLM for safety reasons. For each vulnerability, we allocate a time budget of one hour, a token budget of 300k input tokens, and 100k output tokens. The maximum refinement budget is set to 30 iterations.

3.1.3 Baselines. We compare PoC_{GEN} against two baselines: Explode.js [31] and an LLM-based agent using the AutoGPT framework⁴. Explode.js is a state-of-the-art approach for generating PoC exploits. It first uses a static dataflow analysis to detect which exported functions reach a vulnerable sink, which is then used to create an exploit template. Then, using symbolic execution, it generates symbolic inputs to exploit the vulnerability. Finally, it uses an SMT solver to generate concrete inputs that trigger the vulnerability.

Since PoC_{GEN} is the first LLM-based PoC exploit generator, we implement an LLM-based agent using the AutoGPT framework as a second baseline. Recently, LLM-based agents have shown great promise in software engineering tasks, such as resolving issues [44], repairing bugs [5], and executing arbitrary projects [7]. The AutoGPT agent can use tools to traverse the codebase, such as navigating the file system, reading and writing files, and executing shell commands, by default. We also add two tools to allow direct execution of a JavaScript code piece or a JavaScript file for this agent.

⁴We use the open-source version of AutoGPT, now called AutoGPT Classic, which is available at <https://github.com/Significant-Gravitas/AutoGPT/tree/793d056d81ca1c1a21538ddef13c4e6d7d0d254/classic>

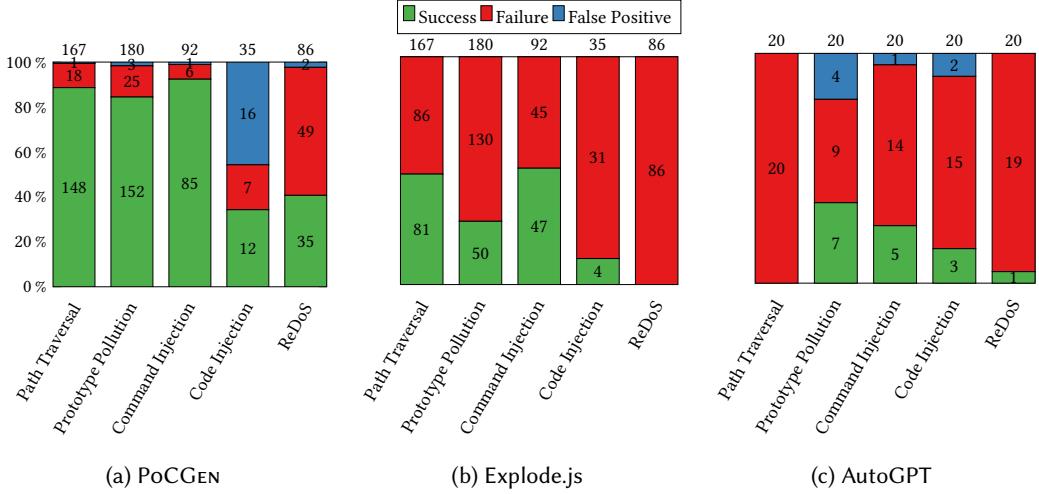


Fig. 8. Effectiveness of PoC_{GEN}, Explode.js, and AutoGPT on SecBench.js.

3.2 RQ1: Effectiveness

We evaluate the effectiveness of PoC_{GEN} in generating PoC exploits for vulnerabilities in SecBench.js as done in previous work [31]. We measure the success rate of our approach and compare it to the baselines. We also report the number of failed attempts, and the number of false positives, which are exploits that pass the validator, but do not trigger the vulnerability through the vulnerable function. For each PoC exploit that PoC_{GEN} generates, one of the authors manually inspects it to determine whether it is a false positive or a successful exploit.

In our experiments, we run PoC_{GEN} on all 560 vulnerabilities in SecBench.js, and use the reported results of Explode.js⁵ on the same set of vulnerabilities. However, since agentic approaches are slower and more expensive, we limit the number of vulnerabilities evaluated with our agentic baseline approach to 100. We randomly sample 20 vulnerabilities from each of the five vulnerability types in SecBench.js, and run AutoGPT on them.

Figure 8 shows the effectiveness of PoC_{GEN}, Explode.js, and AutoGPT on the SecBench.js dataset. PoC_{GEN} successfully generates PoC exploits for 432 out of 560 vulnerabilities, which is 77% of the vulnerabilities. Explode.js successfully generates PoC exploits for 182 out of 560 vulnerabilities, which is 32% of the vulnerabilities. AutoGPT generates successful PoC exploits for 16 out of the 100 vulnerabilities. For the same set of 100 vulnerabilities, PoC_{GEN} generates PoC exploits for 63 vulnerabilities. The results show that PoC_{GEN} outperforms Explode.js by 45 and AutoGPT by 47 absolute percentage points.

When comparing the performance of PoC_{GEN} on different vulnerability types, we find that PoC_{GEN} performs best on path traversal, prototype pollution, and command injections, with success rates of above 83%. Explode.js also performs best on these vulnerability types, with success rates between 50% and 60%. Since Explode.js does not support ReDoS vulnerabilities, its success rate on ReDoS vulnerabilities is 0%. AutoGPT performs best on prototype pollution and command injection, with success rates of 35% and 25%, respectively. AutoGPT performs worst on path traversal, with no successful PoC exploits.

⁵<https://github.com/formalsec/explode-js/blob/71ec17fe90f29e236b01b8cad02685344f8aff10/bench/explode-vulcan-secbench-results.csv>

Table 1. The effect of each component of PoC_{GEN} on successfully generating PoC exploits.

Configuration	Valid Exploits	Success Rate
PoC_{GEN}	432	77%
noTaintPath	149	27%
noUsageSnippet	196	39%
noFewShot	402	72%
noDebugger	417	74%
noErrorRefiner	407	73%

A closer comparison of the sets of vulnerabilities covered by each approach reveals that PoC_{GEN} generates PoC exploits for 158 vulnerabilities where Explode.js fails. Moreover, PoC_{GEN} generates exploits for all vulnerabilities that AutoGPT generates PoC exploits for. In contrast, Explode.js generates PoC exploits for only two command injection vulnerabilities that are not handled by PoC_{GEN}. For one of these cases, the vulnerability can be exploited with a simple payload. But, our validator requires the execution of the command `/usr/bin/genpoc`, and our prompts direct the LLM to generate an input that executes this command. Therefore, the exploit becomes much more complex, and the LLM is not able to generate it. The other case is a vulnerable function that implements the functionality to kill processes. Our generated payload causes the running bash process to be killed, which does not allow the execution of the rest of the command. The LLM is also not able to fix this after the refinements.

PoC_{GEN} uses multiple approaches to reduce the number of false positives, i.e., exploits that pass the validation and LLM checks, but do not correctly trigger the vulnerability. As a result, it only generates 23 false positive PoC exploits, which amounts to just 5% of the successful exploits generated.

3.3 RQ2: Ablation Study

To evaluate the impact of each component on the effectiveness of PoC_{GEN}, we perform an ablation study on the SecBench.js dataset. We evaluate the following configurations of PoC_{GEN} to measure the impact of each component on the success rate of generating PoC exploits.

- PoC_{GEN}: The complete PoC_{GEN} approach with all components.
- noTaintPath: PoC_{GEN} without the taint path analysis, described in Section 2.2.3. In this configuration, no taint analysis is done, which means the approach does not utilize taint paths to find the vulnerable source, the LLM prompt does not contain the taint path, and also both of the context refiners, i.e., the body refiner and the missing declaration refiner, that depend on the taint path are not used.
- noFewShot: PoC_{GEN} without the few-shot examples of exploits of similar vulnerabilities (Section 2.3).
- noUsageSnippet: PoC_{GEN} without the usage snippet examples (Section 2.2.4).
- noDebuggerRefiner: PoC_{GEN} without the debugger refiner (Section 2.5.2).
- noErrorRefiner: PoC_{GEN} without the error refiner (Section 2.5.2).

The success rates of these configurations on SecBench.js are shown in Table 1. These results show that all components contribute to PoC_{GEN}'s overall performance, with the taint analysis having the highest impact, followed by the usage snippet examples.

To better understand the contribution of iteratively refining the prompts, we also measure the number of refinement attempts required to generate a valid PoC exploit. Iterative attempts for

generating PoC exploits have a significant impact on the performance of PoCGEN. Only 36% of the successful PoC exploits are generated in the first attempt, and 51% are generated within two to ten refinements. On average, successful PoC exploits are generated after 3.92 rounds of refinement.

3.4 RQ3: Costs

To evaluate the costs of PoCGEN, we measure the time and token usage of the approach. On average, each PoC exploit generation attempt takes 11 minutes. Since successful attempts stop earlier than failing attempts, which require running the refiners, the successful runs complete on average in 7 minutes. A significant portion of this time is spent on the LLM calls, which take 41% of the execution time. Using a faster LLM model, or running a local open-source LLM, could significantly reduce this time. The second-largest portion of the overall time is spent on the taint analysis done by CodeQL, which takes 21% of the overall time, on average.

We measure the number of tokens sent to and received from the LLM. On average, for each attempt to generate an exploit, PoCGEN sends 61,234 tokens to the LLM and receives 17,750 tokens in response. With the current price of the OpenAI API (as of September 2025), this costs \$0.02 per exploit generation attempt. For the successful attempts, this cost is even lower, with only \$0.008 per vulnerability, on average.

3.5 RQ4: Augmenting Real-World Vulnerability Reports

To further evaluate the usefulness and generalizability of PoCGEN, we use it to augment several recent vulnerability reports that were lacking a PoC exploit. To this end, we select vulnerabilities reported on the GitHub Security Advisories database that match one of our five vulnerability types. To avoid any bias towards vulnerabilities that may be already known to the LLM, we only select vulnerabilities that were reported after the knowledge cutoff date of gpt-4o-mini, which is October 1, 2023. PoCGEN generates valid PoC exploits for six such vulnerabilities. For each of them, we have created a pull request to add the generated PoC exploit to the vulnerability reports. For five of the six cases, these have been accepted and have been added to their corresponding vulnerability reports. The remaining pull request is still under review.

For example, the popular package `tar-fs`, with over 25 million weekly downloads, had a path traversal vulnerability (CVE-2024-12905) reported on March 27, 2025. This vulnerability affected three version ranges of this package, and before running PoCGEN, there were no public PoC exploits for this vulnerability. PoCGEN generates a valid PoC exploit for this vulnerability, which is shown in Fig. 9. To generate this exploit, PoCGEN uses eight refinement attempts, which include the error refiner and the debugger refiner.

Another example is our motivating example shown in Fig. 1. This vulnerability, reported on January 16, 2025 as CVE-2024-36751, is a regular expression denial of service (ReDoS) vulnerability in the `parse-uri` package. As shown in Fig. 2, PoCGEN successfully generates a PoC exploit, which is now part of the vulnerability report on GitHub Security Advisories database.

3.6 RQ5: Qualitative Analysis

To better understand the strengths and limitations of PoCGEN, we present examples of successful and unsuccessful attempts by PoCGEN to generate PoC exploits.

3.6.1 Successful Example: CVE-2023-26127. The vulnerability report CVE-2023-26127 describes a command injection vulnerability in the `n158` package. This vulnerability is due to not sanitizing the input, which then flows to the `exec` function of `shelljs`. However, the input is first passed to a `copy` function, as shown in Fig. 10. This means that if the `seedPath` is set to a value where the corresponding path does not exist, the exploit fails before reaching the vulnerable sink. This

```

1 const tarfs = require("tar-fs");
2 const fs = require("fs");
3 const path = require("path");
4
5 async function exploit() {
6     // Create a writable stream to extract the tar content
7     const extractStream = tarfs.extract('/', {
8         // We can ignore the file type checks to allow the extraction of the malicious file
9         ignore: (name) => false,
10    });
11
12     // Create a tar stream
13     const tarStream = tarfs.pack().on('error', (err) => {
14         throw err;
15    });
16
17     // Append the malicious entry to the tar stream
18     tarStream.entry({ name: '/flag.txt', mode: 0o644 }, Buffer.from('This is a flag!'));
19
20     // Finalize the tar stream
21     tarStream.finalize();
22
23     // Pipe the tar stream into the extract stream
24     tarStream.pipe(extractStream);
25 }
26
27 // Call the exploit function
28 exploit();

```

Fig. 9. PoC exploit generated by PoCGen for CVE-2024-12905 in the tar-fs package.

Fig. 10. Example of a command injection vulnerability in the n158 package.

```

1 module.exports = function (seedPath, targetPath) {
2     fsExtra.copySync(seedPath, targetPath);
3     shell.exec('sh -c \'cd '+targetPath+' && npm install\'');
4     shell.exec('sh -c \'cd '+targetPath+' && npm start\'');
5 }

```

constraint is not easy to capture with symbolic execution, as attempted by Explode.js [31], but using execution feedback and an LLM, PoCGen is able to generate a working exploit.

In the first round of exploit generation, PoCGen generates an exploit that calls `initProject("someSeedPath", "targetPath; /usr/bin/genpoc")`. After the execution of this exploit, the runtime feedback shows that there was a runtime error happening at the `fsExtra.copySync` function, which is due to the fact that no directory called "someSeedPath" exists. The LLM then naively tries to fix this by changing "someSeedPath" to "/path/to/valid/seed", which results in the same error. It takes multiple refinements until the LLM requests the definition of `shelljs`, which allows the reasoning part of the response to understand that it needs to create the directory for a successful exploit. This results in the final exploit shown in Fig. 11.

3.6.2 Unsuccessful Example: GHSA-3486-rvxc-hrrj. The vulnerability report GHSA-3486-rvxc-hrrj describes a command injection vulnerability in the gitblame package. The package exports one

Fig. 11. Example of a successful PoC exploit generation by PoC_{GEN}.

```

1 async function exploit() {
2   const initProject = require("n158/src/cli/initProject");
3   const seedPath = "/path/to/valid/seed";
4   const targetPath = "targetPath; /usr/bin/genpoc";
5   const fs = require('fs');
6   if (!fs.existsSync(seedPath)) {
7     fs.mkdirSync(seedPath, { recursive: true });
8   }
9   const result = await initProject(seedPath, targetPath);
10 }
11 await exploit();

```

Fig. 12. Example of a command injection vulnerability in the gitblame package.

```

1 module.exports = function (file, cb) {
2   var dirname = path.dirname(file);
3   var filename = path.basename(file);
4   exec('git blame ' + filename, { cwd: dirname}, ...

```

function, which takes a file path as an argument and after some processing passes it to exec. The relevant parts of the source code are shown in Fig. 12.

PoC_{GEN} is not able to generate a working exploit for this vulnerability. The reason is that our validator requires the execution of the command /usr/bin/genpoc. However, the split by path.basename and path.dirname does not allow passing of payloads with "/" to reach the sink without change. This means that our approach is limited by the constraints imposed by the validator. Even with multiple refinements, PoC_{GEN} is unable to generate a working exploit, although the exploit for this vulnerability in SecBench.js has the simple payload "& touch gitblame".

4 Threats to Validity

One threat to internal validity is the LLM's potential to recall exploits from its training data. To mitigate this, we use the same LLM for the AutoGPT baseline, which we would expect to perform similarly well as PoC_{GEN} if the results were simply due to memorization. Another threat is that the labeling process of false positive PoC exploits is done manually, which can introduce human bias. To reduce the effects of this bias, we devise a set of objective criteria. For example, prototype pollution cases where the Object.prototype is part of an assignment or a function call are considered false positives. A threat to external validity is that our evaluation is limited to five vulnerability types. However, these vulnerability types correspond to the five most common threat classes in server-side JavaScript [3]. Adapting the approach to other vulnerability types would require adapting our prompts, the sinks used by the taint analysis, and the validators. Our approach is implemented for JavaScript and the npm ecosystem, which may limit its applicability to other programming languages and ecosystems. We believe that the core ideas of PoC_{GEN}, i.e., how to combine LLMs with program analysis techniques, could be adapted to other contexts, but leave this for future work.

5 Related Work

Vulnerability Detection. Greybox fuzzing [4, 46], applied to source code [36] or binaries [15], is a common approach for vulnerability detection. To evaluate fuzzing, techniques for reverting fixes [50] and benchmarking methodologies [23, 26] have been proposed. Learning-based vulnerability detection includes neural classification [11, 16, 28], graph neural networks [27, 39], and combinations of LLMs with static analysis. Similar to our work, the latter leverages CodeQL to identify taint flows [29]. To support learning-based detection, datasets from commit histories [51] and large-scale vulnerability generation approaches [32, 33] have been introduced. Vulnerability detection is orthogonal to our work, as we assume vulnerabilities are already described in a report but lack an exploit.

Detecting and Exploiting Node.js Vulnerabilities. The closest work to PoCGEN is Explode.js [31], which finds vulnerabilities and generates PoC exploits for npm packages. Explode.js uses static dataflow analysis to extract the sequence of function calls required to propagate attacker input to a vulnerable sink. It then applies symbolic execution and constraint solving to generate a PoC exploit. However, Explode.js does not model external functions and libraries during symbolic execution, which limits its effectiveness, as the npm ecosystem heavily relies on small, reusable packages. PoCGEN addresses this limitation by leveraging LLMs to generate exploits and by incorporating runtime feedback. LLMs, trained on large code corpora, can better predict the behavior of external functions and reason about inputs that exercise specific program paths.

Other approaches have used symbolic execution to generate exploits for vulnerabilities. FAST [22] applies bi-directional dataflow analysis to detect taint paths efficiently, enabling scalable vulnerability detection. It generates exploits by concretizing symbolic path constraints once a vulnerability is found. Node-Medic [10] and Node-Medic-FINE [9] combine dynamic taint analysis with symbolic execution to detect and generate exploits for Node.js packages. Node-Medic-FINE further incorporates fuzzing to generate inputs and explore additional execution paths. All three approaches are outperformed by Explode.js [31], which we therefore use as a baseline in our evaluation.

Test Generation for Security Vulnerabilities. Zhang et al. [48] and Gao et al. [17] use LLMs to generate unit tests for Java vulnerabilities given a PoC exploit. Their goal is to encourage developers to update vulnerable dependencies and prevent supply chain attacks. In contrast, our work generates code that directly exploits a vulnerable package, rather than exploiting it through a third-party dependency.

LLM-Assisted Attacks. Recent work has explored the potential of LLMs for attacking vulnerable software. PENTESTGPT [14] uses LLMs for penetration testing. Xu et al. [42] developed an LLM agent with command-line access to exploit vulnerabilities in Linux and Windows applications. Charan et al. [12] investigated using LLMs to generate payloads for exploiting vulnerabilities.

Vulnerability Mitigation and Repair. Mitigating vulnerabilities can involve removing unused dependencies [24] or reducing the privileges of vulnerable code [40]. Repairing vulnerabilities can be achieved by fine-tuning LLMs to find fixes [2], using LLM agents [49], or applying generative adversarial networks (GANs) [18].

JavaScript and Npm Ecosystem Security. The npm ecosystem faces various security issues, such as injection attacks [38], ReDoS [37], and malicious packages [35]. Several empirical studies have analyzed npm from a security perspective, including vulnerability propagation [30, 52] and how developers address vulnerabilities [45]. Householder et al. [19] found that most vulnerability reports lack a public PoC exploit for at least one year. Yadmani et al. [43] further showed that many PoC exploits on GitHub are themselves malicious. These findings motivate our work on automated

PoC exploit generation. To support further research, Bhuiyan et al. [3] introduced the SecBench.js dataset, and Brito et al. [8] created the VulcaN dataset.

6 Conclusion

This paper presents PoCGen, an LLM-based approach to automatically generate proof-of-concept exploits for vulnerabilities in npm packages. PoCGen extracts information from the vulnerability report and the codebase to generate a PoC exploit using an LLM. The generated PoC exploits are validated using a set of runtime checkers, and the prompt is refined using static and dynamic information to generate a valid exploit. We evaluated PoCGen on a dataset of 560 vulnerabilities in npm packages. PoCGen generates PoC exploits for 77% of these vulnerabilities, outperforming the state-of-the-art approaches Explode.js and AutoGPT by 35 and 47 absolute percentage points, respectively.

By automating the generation of PoC exploits, PoCGen enables developers and security teams to more rapidly understand and address vulnerabilities, reducing the time between vulnerability disclosure and patch deployment. This automation also improves regression testing, as the generated PoC exploits can be directly used to verify the effectiveness of fixes and to prevent vulnerabilities from reappearing in the future. For security researchers, PoCGen provides an automated way to evaluate the effectiveness of existing mitigation strategies across large sets of vulnerabilities. Furthermore, PoCGen can improve the quality of existing vulnerability reports, including those that are poorly documented or lack existing exploits. Finally, automated PoC generation can facilitate responsible vulnerability disclosure by providing clear, actionable evidence to affected parties, encouraging timely remediation.

Data Availability

The source code of PoCGen, the new dataset, and all experiment scripts are available at <https://github.com/sola-st/PoCGen>.

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