

AI x Smart Contract :
靜態分析工具做不到的，交給 Prompt Engineering !

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Agenda



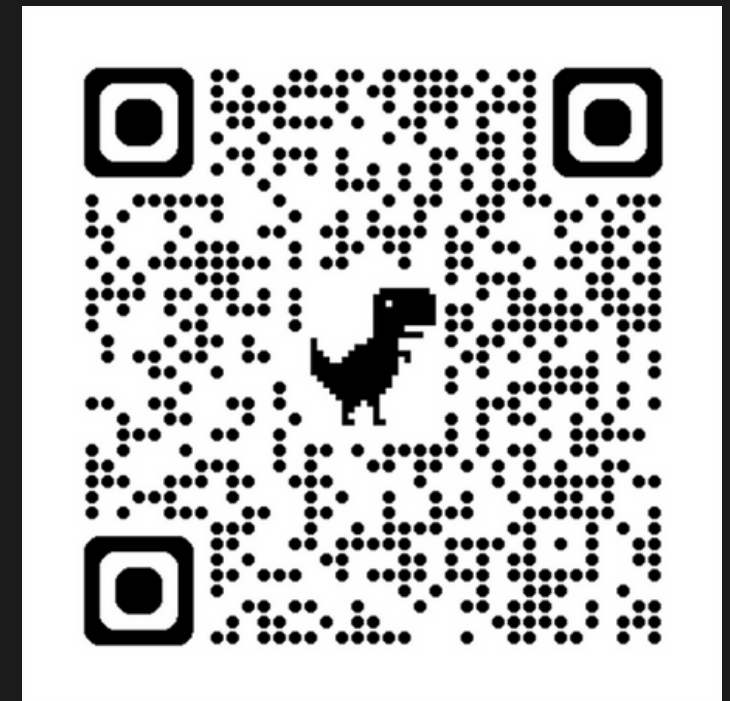
- Background - From Static Analysis to AI-based Auditing
- Methodology - Prompting LLMs to Think Like An Auditor
- Conclusion - Future Work & Takeaway

Bastet: Let's Build a Safer Web3 Together!



DEFIHACKLABS
Let's make web3 more secure!

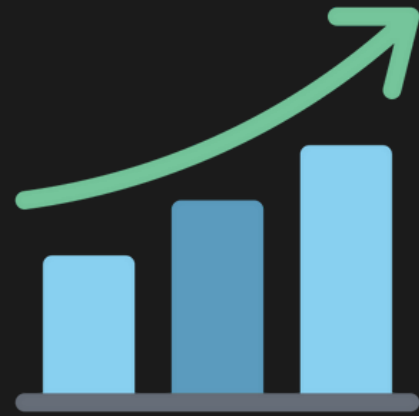
- **Bastet** is a dataset of DeFi smart contract vulnerabilities, paired with an AI-driven detection process.
- We're building tools to enhance vulnerability detection and optimize security lifecycle management.



Background



Importance of Smart Contract Security



Rapid Market Growth

\$232M → \$1.98B by 2034

([Statifacts](#), 2024)



Security Breaches in 2024

\$2.01B lost in 410 attacks

([Slowmist](#), 2024)

Security as a Core Requirement.

The expanding DeFi landscape is driving stronger demand for robust smart contract protection.

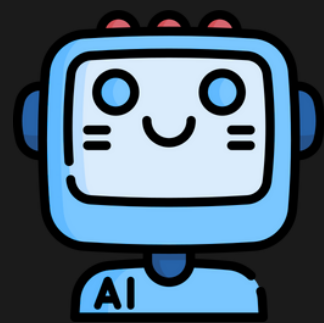
Limitations of Static Analysis Tools

- Rules - AST or Regex.
- Lack of Customization - Not perfectly align with the specific needs.
- High False Positives - Flags harmless code with limited context.
- Limited Scope - Fails to capture full contract logic beyond single functions.



Advantages of LLM

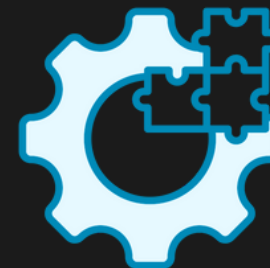
- Rules - Prompt
- Easy Adjustment - Easily adapts to new code and patterns.
- Cross-language - Works across languages, no tool lock-in.
- Contextual & Semantic Awareness - LLMs capture semantic patterns beyond the reach of static analysis tools.



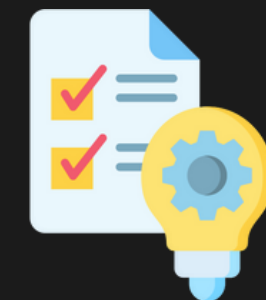
LLM



Code & **Prompt**



Tokenization &
Embedding



Context-aware Reasoning

How Do LLMs “Understand” Code?



Pretrained on
Massive Code Datasets



Tokenization &
Embedding to Capture the
Meaning & relationships



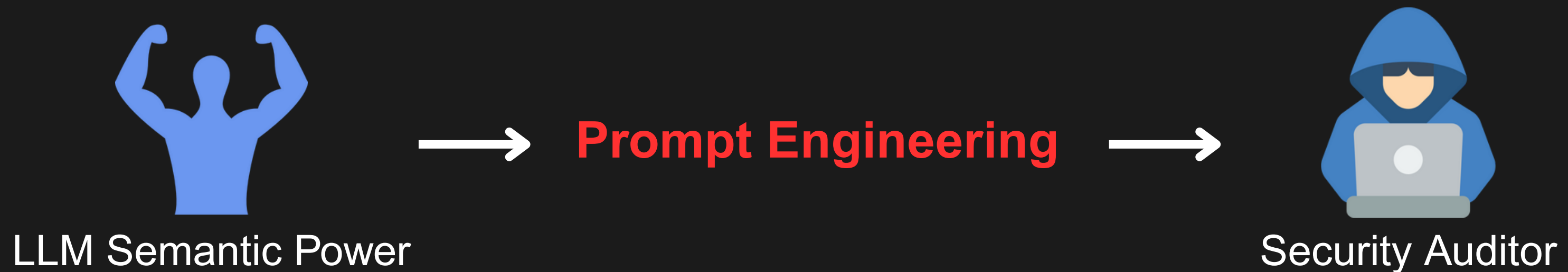
Self-Attention
Enables Context
Awareness

LLMs don't truly understand code; instead, they generate outputs by statistically predicting the most probable next token based on their training data.

LLMs “Understand”. But Can They Audit?



- LLMs are generalists - Without task-specific guidance, they may hallucinate or misinterpret code logic.
- **Prompt engineering bridges the gap between understanding and auditing.**



Why Prompt Engineering Over Fine-tuning



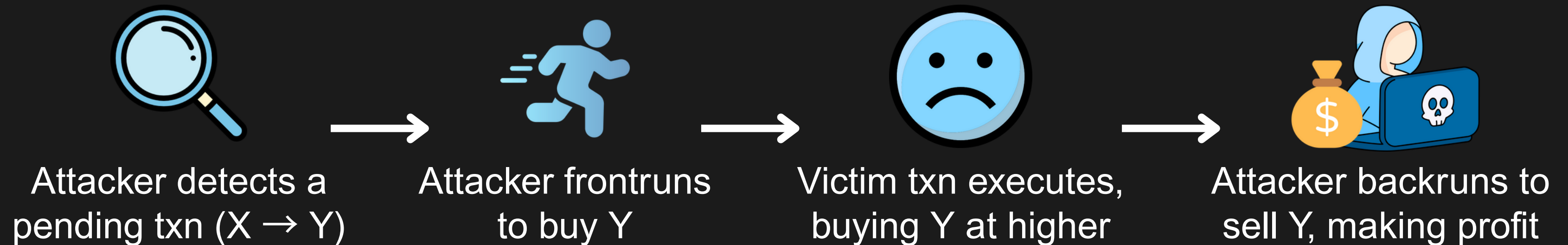
	Prompt Engineering	Fine-tuning
Cost	Low - no training needed	High - training required
Experiment	Fast - prompts can be tested and iterated quickly	Slow - testing requires time-consuming retraining
Flexibility	High - fine-grained control with prompt adjustments	Low - retraining needed for new tasks or changes

Methodology



Vulnerability: `slippage_min_amount`

- Swap functions must allow users to specify a minimum amount they want to receive, and this variable shouldn't be hardcoded or unused.
- If not followed, users are vulnerable to sandwich attacks, leading to poor trade execution and fewer tokens received.



`slippage_min_amount` Example 1

```
function addLiquidity(  
    IERC20 tokenA,  
    IERC20 tokenB,  
    uint256 amountADesired,  
    uint256 amountBDesired,  
    uint256, // amountAMin = unused  
    uint256, // amountBMin = unused  
    address to,  
    uint256 deadline  
) external override returns (uint256 liquidity) {  
    return
```

```
        addLiquidity(  
            tokenA,  
            tokenB,  
            amountADesired,  
            amountBDesired,  
            to,  
            deadline
```

); did not use `amountAMin` & `amountBMin`

```
}
```

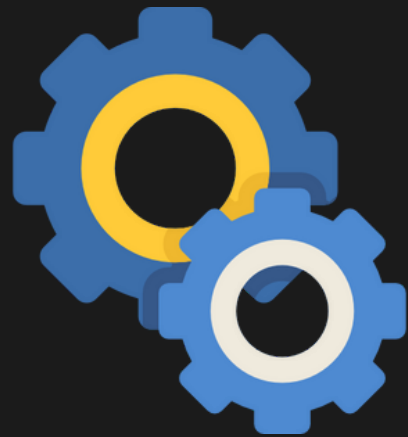
`slippage_min_amount` Example 2

```
if (amountOut > currentBalance) {  
    ICurveSwap(CVX_CRV_CRV_CURVE_POOL).exchange(  
        _CRV_INDEX,  
        _CVX_CRV_INDEX,  
        currentBalance,  
        0  
    );  
    `min amount out` set to 0 (hardcoded).
```

Why static analysis tools can't detect it well



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Let's make web3 more secure!



Various Functions
Related to Swap



Naming Variations of
Slippage Parameter
Across Protocols



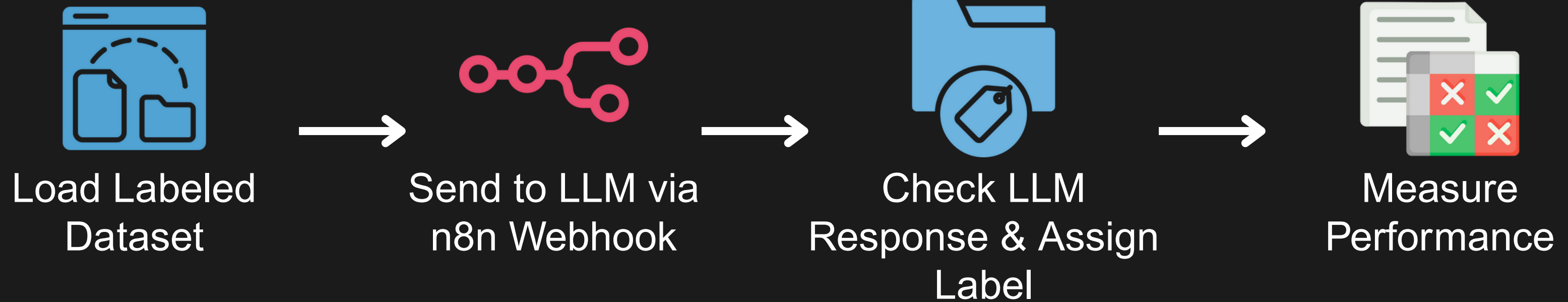
Cross-language
Detection Limitation

Dataset for `slippage_min_amount`

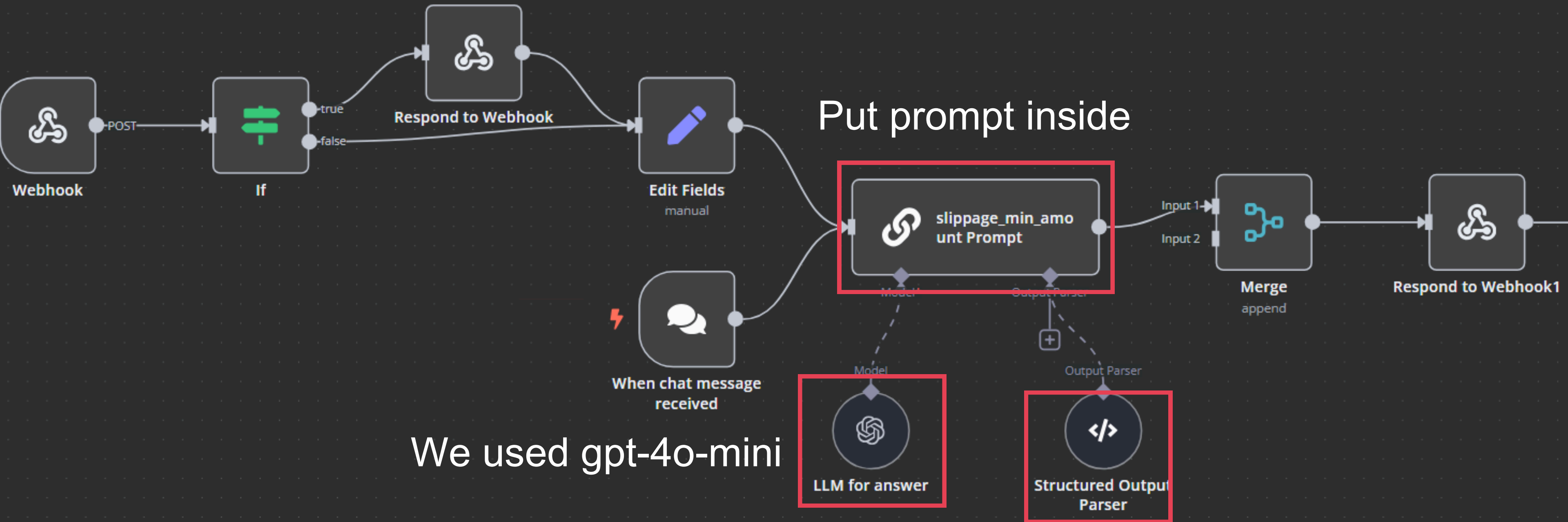
Positive Data (vuln) =  **code4rena** + On-chain Contracts = 29

Negative Data (no vuln) = Secure Contracts (e.g., OZ, top protocols) = 29

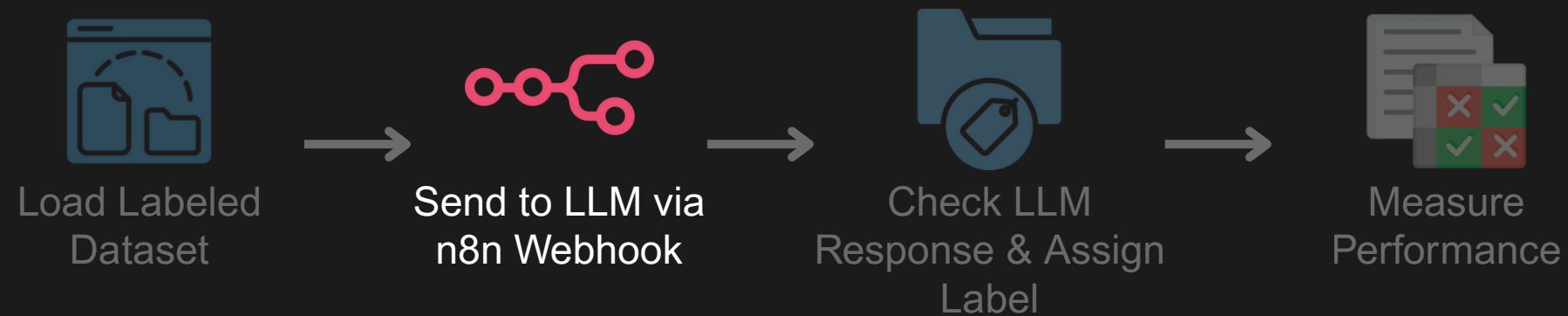
Evaluation Workflow



n8n Workflow



Fix LLM's output



Output Parser

- To convert LLM's output into structured and usable data, we designed a JSON output parser.
- Each JSON object corresponds to a single detected vulnerability in the LLM's final array output.

```
{  
  "summary": "...",  
  "severity": ["high", "medium", "low"],  
  "vulnerability_details": {  
    "function_name": "...",  
    "description": "..."  
  },  
  "code_snippet": [...],  
  "recommendation": "..."  
}
```

Evaluation Method & Output

- Evaluation Method - If output = `[]`, predict 0 (safe), else 1 (vulnerable).
- Metrics - Confusion Matrix.

	Actually Vulnerable	Actually Safe
Predicted Vulnerable	True Positive	False Positive
Predicted Safe	False Negative	True Negative

```
+-----+-----+
| Metric | Value |
+=====+=====+
| True Positive | 28 |
+-----+-----+
| True Negative | 0 |
+-----+-----+
| False Positive | 29 |
+-----+-----+
| False Negative | 1 |
+-----+-----+
accuracy: 0.4827586206896552
precision: 0.49122807017543857
recall: 0.9655172413793104
f1: 0.6511627906976745
```

Evaluation Method & Output

- Performance Indicators
 - Accuracy - Overall correctness.
 - Precision - Correctness of positive predictions.
 - Recall - Coverage of actual positives.
 - F1 Score - Average of precision and recall.

```
+-----+-----+
| Metric      | Value |
+=====+=====+
| True Positive | 28 |
+-----+-----+
| True Negative | 0 |
+-----+-----+
| False Positive | 29 |
+-----+-----+
| False Negative | 1 |
+-----+-----+
accuracy: 0.4827586206896552
precision: 0.49122807017543857
recall: 0.9655172413793104
f1: 0.6511627906976745
```

Prompt Ver. 1 - Listing

- Outline common patterns that cause this vulnerability.
- checklist:
 - should not be set to 0.
 - should not be unused.
 - should not be hardcoded.

vuln description



checklist

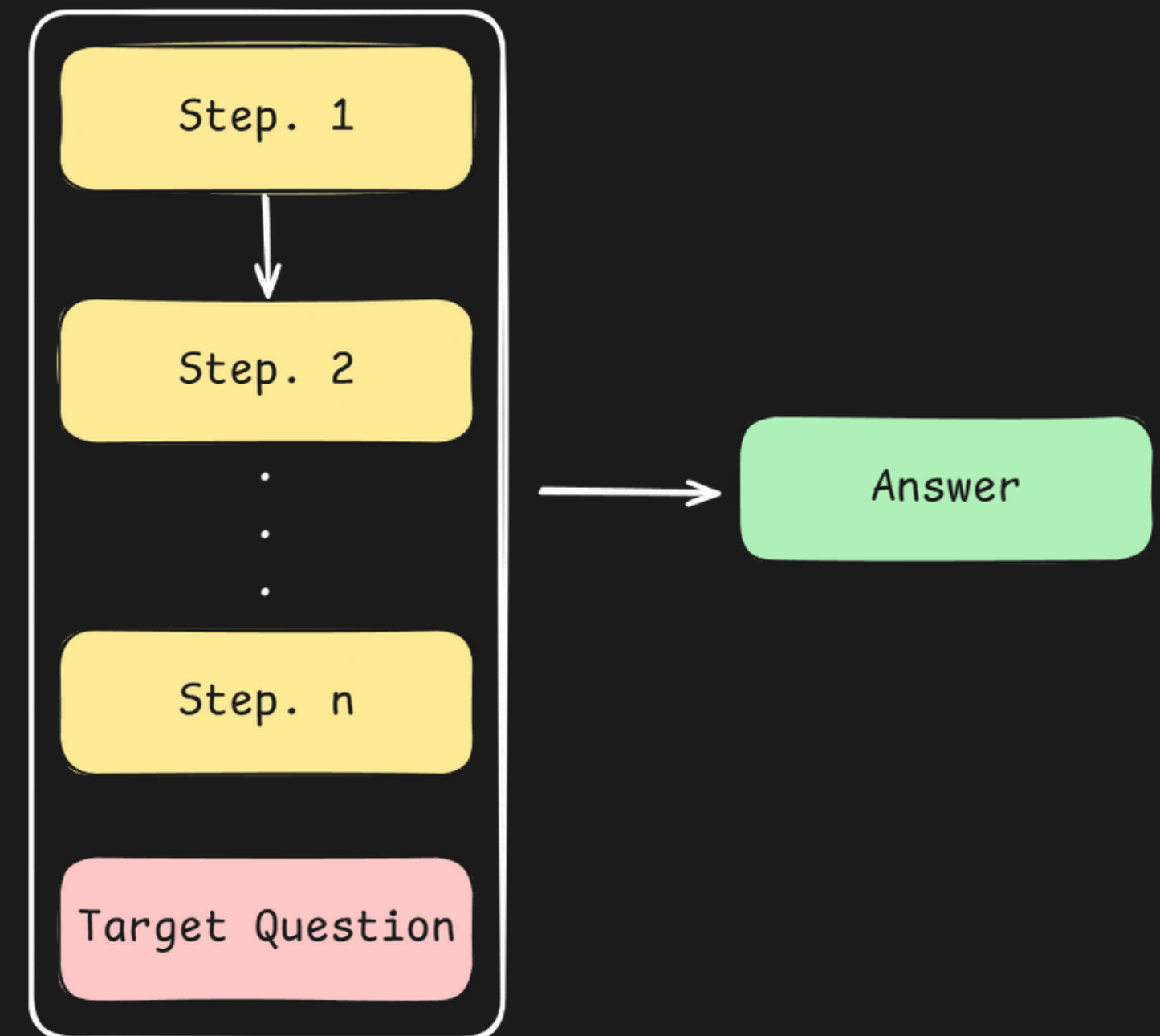
Observation

- High Recall, Poor Precision - Flags many safe functions by mistake.
- Overgeneralization - Matches risky-looking patterns without checking if they're actually unsafe.
- Lack of Reasoning - Matches patterns without applying deeper logic or understanding the code's intent.

```
+-----+-----+
| Metric      | Value |
+=====+=====+
| True Positive | 28 |
+-----+-----+
| True Negative | 0 |
+-----+-----+
| False Positive | 29 |
+-----+-----+
| False Negative | 1 |
+-----+-----+
accuracy: 0.4827586206896552
precision: 0.49122807017543857
recall: 0.9655172413793104
f1: 0.6511627906976745
```


Prompt Engineering Technique - CoT

- Chain-of-Thought
- Breaks down reasoning into explicit, step-by-step explanations.
- Mimics human(auditor) thinking by laying out how each part leads to the next.
- Helps identify where reasoning might go wrong, making the model's logic more transparent and interpretable.



Prompt Ver. 2 - CoT

1. Identification - Find out function involving swap-related actions.
2. Extraction - Spot parameters related to slippage protection in these functions.
3. Validation - Assess use of slippage parameters. (unused? hardcoded?)
4. Confirmation - Verify actual vulnerability.

vuln description



CoT

Observation

- Lower false positives, but not enough.
- More Explainable Output - Step-by-step thinking improves clarity and makes results easier to audit.
- Steps Not Followed - Steps are sometimes skipped, merged, or misinterpreted.

```
+-----+-----+
| Metric      | Value |
+=====+=====+
| True Positive | 27 |
+-----+-----+
| True Negative | 9 |
+-----+-----+
| False Positive | 20 |
+-----+-----+
| False Negative | 2 |
+-----+-----+

accuracy: 0.6206896551724138
precision: 0.574468085106383
recall: 0.9310344827586207
f1: 0.7105263157894737
```

Prompt Engineering Technique - Few-shot



- Giving the model a few examples to help it learn how to perform a task.
- Each example shows input + desired output, helping the model generalize to new cases.
- Typical number of examples: 2 ~ 5.

Example 1
input + output

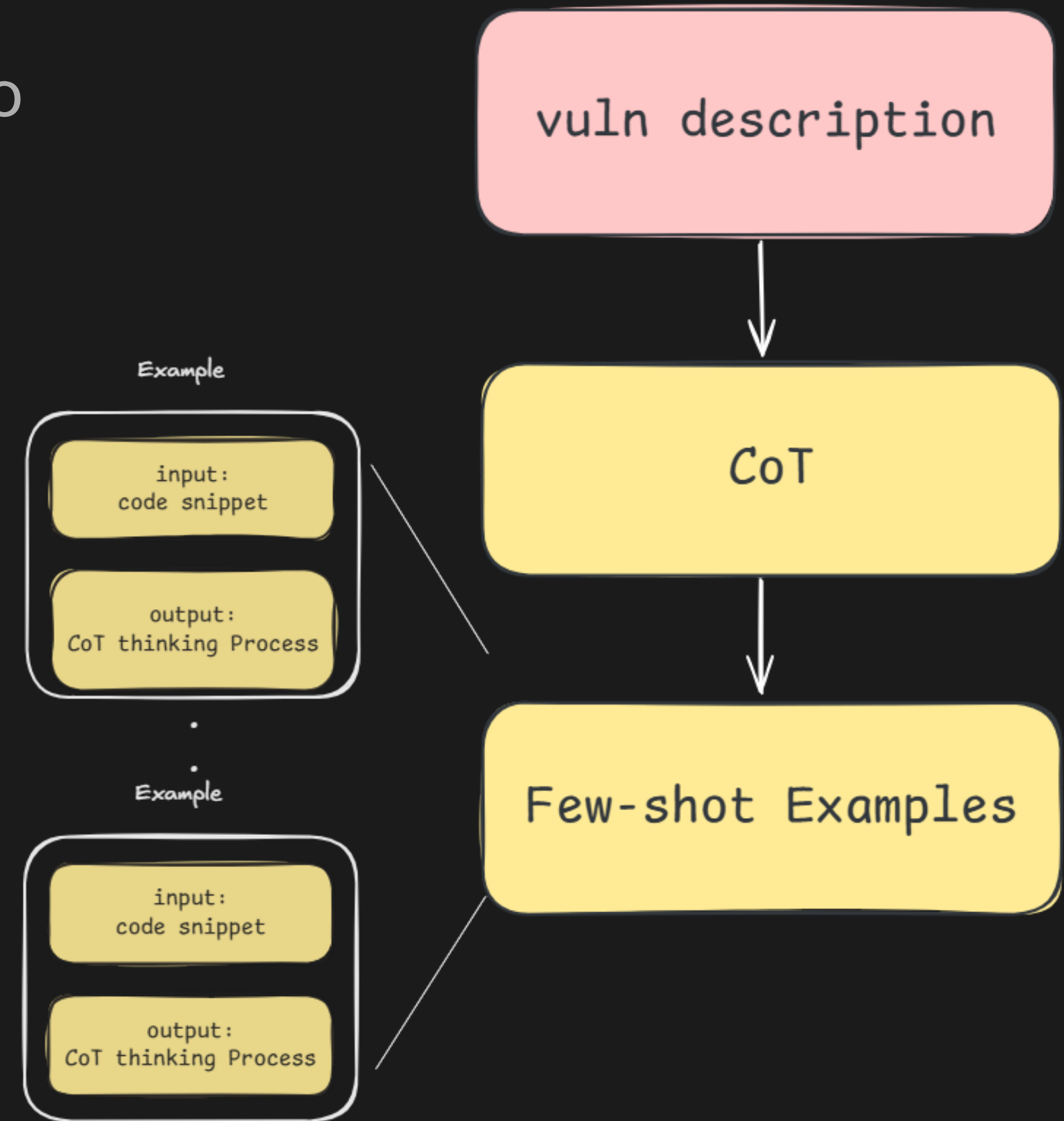
Example 2
input + output

⋮

Example n
input + output

Prompt Ver. 3 - CoT + Few-Shot

- Besides CoT, provide several examples to illustrate how it works in practice.
- Example input - Code snippet.
- Example output - CoT thinking process.
- 3 positive + 2 negative examples.



Observation

- Significantly Lower False Positives - With a slight rise in false negatives. A worthwhile tradeoff in most audit scenarios.
- Strong Alignment with Desired Behavior - Examples enhance the CoT, guiding LLM to reason consistently and stay on track.

```
+-----+-----+
| Metric      | Value |
+=====+=====+
| True Positive | 24 |
+-----+-----+
| True Negative | 22 |
+-----+-----+
| False Positive | 7 |
+-----+-----+
| False Negative | 5 |
+-----+-----+
accuracy: 0.7931034482758621
precision: 0.7741935483870968
recall: 0.8275862068965517
f1: 0.8
```

Other Vulnerabilities Explored

- Reentrancy
- Liquidation - No Incentive to Liquidate Small Positions
- Liquidation - DoS
- Liquidation - Accounting Error

Conclusion



Future Works

- Establish Clear Evaluation Standards - Develop more rigorous, fine-grained methods to evaluate prompt performance.
- Expand Dataset Scale - ~4,400 cases labeled with data mutation; more contributors needed for labeling.
- Refine Prompt Engineering - Test diverse prompt techniques and sharing results with the community.
- Explore More Vulnerabilities - Leverage **Bastet** across a wider range of attack vectors, and promote knowledge sharing with the community.

Takeaway



- Static analysis tools are limited by rule-based approaches.
- LLMs offer flexible, cross-language, and semantically aware analysis that better handles complex code.
- Prompt engineering guides LLMs to perform context-aware and logic-aware auditing.
- Prompt engineering requires iterative experimentation and refinement.
- Rapid AI advancement makes LLM-based auditing increasingly powerful and easier to apply.

Join Us - Shape the DeFi Security with **Bastet**

- **Bastet** is a dataset of DeFi smart contract vulnerabilities, paired with an AI-driven detection process.
- We're building tools to enhance vulnerability detection and optimize security lifecycle management.
- Whether you're from blockchain or AI, your contribution can shape the future of DeFi security. We're building a safer Web3 and need your expertise to get there.



