Thinking Outside the Sink

How Tree-of-AST Redefines the Boundaries of Dataflow Analysis

Alexander Zyuzin

Ruikai Peng

CONTENTS

1 PICTURE WORTH 1000 WORDS...

saylese 16.10.2024, 16:46 **My teacher**

i have a student who's very interested in security stuff and he's looking for a mentor for a project he's working on (idk what i it is). https://retr0.blog/ would you be interested in discussing with him? i don't think he would expect much time from you

> **Retr0's Register**
>
> Retr0's Threat Research

greyroad 16.10.2024, 18:28 **Me**

«I've had the incredibleopportunity to identify 22 CVEs,»

Does he need a mentor for stealing nuclear codes?

I mean sure

WHAT IS THE ALGORITHMIC PART OF OUR SOLUTION?

THE PAPER I'VE READ

Tree of Thoughts: Deliberate Problem Solving with Large Language Models

Shunyu Yao Princeton University
Dian Yu Google DeepMind
Jeffrey Zhao Google DeepMind
Izhak Shafran Google DeepMind
Thomas L. Griffiths Princeton University
Yuan Cao Google DeepMind
Karthik Narasimhan Princeton University

Abstract

Language models are increasingly being deployed for general problem solving across a wide range of tasks, but are still confined to token-level, left-to-right decision-making processes during inference. This means they can fall short in tasks that require exploration, strategic lookahead, or where initial decisions play a pivotal role. To surmount these challenges, we introduce a new framework for language model inference, "Tree of Thoughts" (ToT), which generalizes over the popular "Chain of Thought" approach to prompting language models, and enables exploration over coherent units of text ("thoughts") that serve as intermediate steps toward problem solving. ToT allows LMs to perform deliberate decision making by considering multiple different reasoning paths and self-evaluating choices to decide the next course of action, as well as looking ahead or backtracking when necessary to make global choices. Our experiments show that ToT significantly enhances language models' problem-solving abilities on three novel tasks requiring non-trivial planning or search: Game of 24, Creative Writing, and Mini Crosswords. For instance, in Game of 24, while GPT-4 with chain-of-thought prompting only solved 4% of tasks, our method achieved a success rate of 74%. Code repo with all prompts: https://github.com/princeton-nlp/tree-of-thought-llm.

1 Introduction

Originally designed to generate text, scaled-up versions of language models (LMs) such as GPT [25, 26, 1, 23] and PaLM [5] have been shown to be increasingly capable of performing an ever wider range of tasks requiring mathematical, symbolic, commonsense, and knowledge reasoning. It's perhaps surprising that underlying all this progress is still the original autoregressive mechanism for generating text, which makes token-level decisions one by one and in a left-to-right fashion. Is such a simple mechanism sufficient for a LM to be built toward a general problem solver? If not, what problems would challenge the current paradigm, and what should be alternative mechanisms?

The literature on human cognition provides some clues to answer these questions. Research on "dual process" models suggests that people have two modes in which they engage with decisions – a fast, automatic, unconscious mode ("System 1") and a slow, deliberate, conscious mode ("System 2") [30, 31, 16, 15]. These two modes have previously been connected to a variety of mathematical models used in machine learning. For example, research on reinforcement learning in humans and other animals has explored the circumstances under which they engage in associative "model free" learning or more deliberative "model based" planning [7]. The simple associative token-level choices of LMs are also reminiscent of "System 1", and thus might benefit from augmentation by a more deliberate "System 2" planning process that (1) maintains and explores diverse alternatives for current

37th Conference on Neural Information Processing Systems (NeurIPS 2023).

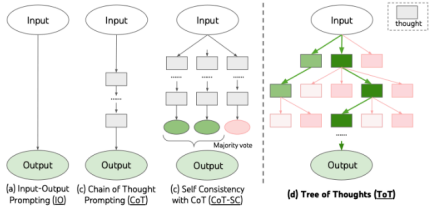


Figure 1: Schematic illustrating various approaches to problem solving with LLMs. Each rectangle box represents a *thought*, which is a coherent language sequence that serves as an intermediate step toward problem solving. See concrete examples of how thoughts are generated, evaluated, and searched in Figures 2,4,6.

choices instead of just picking one, and (2) evaluates its current status and actively looks ahead or backtracks to make more global decisions.

To design such a planning process, we return to the origins of artificial intelligence (and cognitive science), drawing inspiration from the planning processes explored by Newell, Shaw, and Simon starting in the 1950s [21, 22]. Newell and colleagues characterized problem solving [21] as search through a combinatorial problem space, represented as a tree. We thus propose the Tree of Thoughts (ToT) framework for general problem solving with language models. As Figure 1 illustrates, while existing methods (detailed below) sample continuous language sequences for problem solving, ToT actively maintains a tree of thoughts, where each *thought* is a coherent language sequence that serves as an intermediate step toward problem solving (Table 1). Such a high-level semantic unit allows the LM to self-evaluate the progress different intermediate thoughts make towards solving the problem through a deliberate reasoning process that is also instantiated in language (Figures 2,4,6). This implementation of search heuristics via LM self-evaluation and deliberation is novel, as previous search heuristics are either programmed or learned. Finally, we combine this language-based capability to generate and evaluate diverse thoughts with search algorithms, such as breadth-first search (BFS) or depth-first search (DFS), which allow systematic exploration of the tree of thoughts with lookahead and backtracking.

Empirically, we propose three new problems that challenge existing LM inference methods even with the state-of-the-art language model, GPT-4 [23]: Game of 24, Creative Writing, and Crosswords (Table 1). These tasks require deductive, mathematical, commonsense, lexical reasoning abilities, and a way to incorporate systematic planning or search. We show ToT obtains superior results on all three tasks by being general and flexible enough to support different levels of thoughts, different ways to generate and evaluate thoughts, and different search algorithms that adapt to the nature of different problems. We also analyze how such choices affect model performances via systematic ablations and discuss future directions to better train and use LMs.

2 Background

We first formalize some existing methods that use large language models for problem-solving, which our approach is inspired by and later compared with. We use p_θ to denote a pre-trained LM with parameters θ, and **lowercase letters** $x, y, z, s, \cdots$ **to denote a language sequence**, i.e. $x = (x[1], \cdots, x[n])$ where each $x[i]$ is a token, so that $p_\theta(x) = \prod_{i=1}^{n} p_\theta(x[i] | x[1...i])$. We use uppercase letters $S, \cdots$ to denote a collection of language sequences.

Input-output (IO) prompting is the most common way to turn a problem input x into output y with LM: $y \sim p_\theta(y|\texttt{prompt}_{IO}(x))$, where $\texttt{prompt}_{IO}(x)$ wraps input x with task instructions and/or few-shot input-output examples. For simplicity, let us denote $p_\theta^{\texttt{prompt}}(\texttt{output} \mid \texttt{input}) = p_\theta(\texttt{output} \mid \texttt{prompt(input)})$, so that IO prompting can be formulated as $y \sim p_\theta^{IO}(y|x)$.

TREE-OF-THOUGHT

Goal:

Make 24 using four given numbers and basic math operations

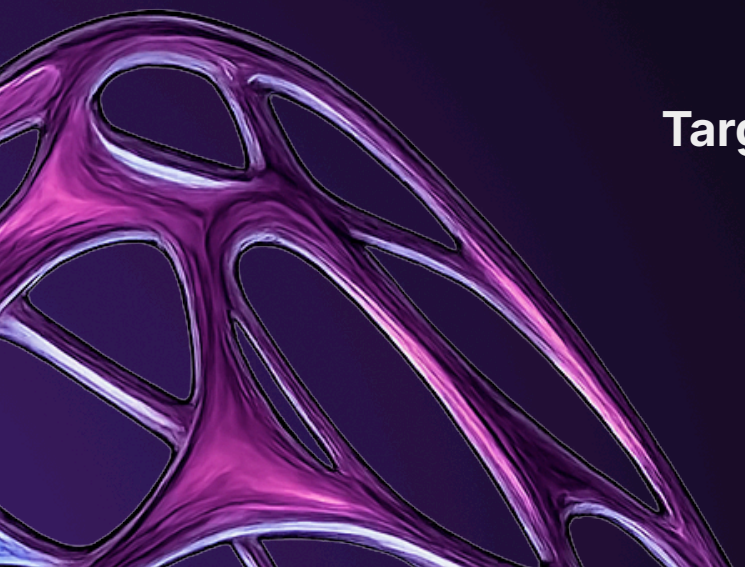
Rules:

Given: 4 numbers (e.g., 8, 3, 8, 3)

Use: +, −, ×, ÷ and parentheses

Must: Use each number exactly once

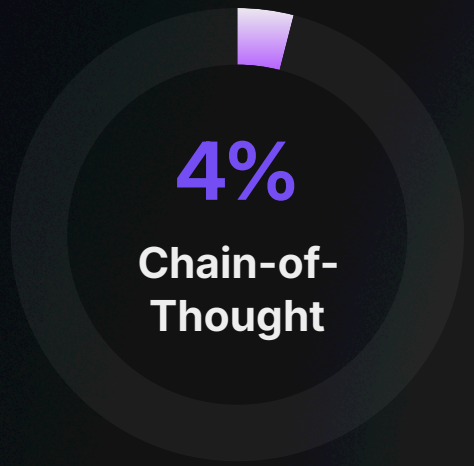
Target: Final result = 24

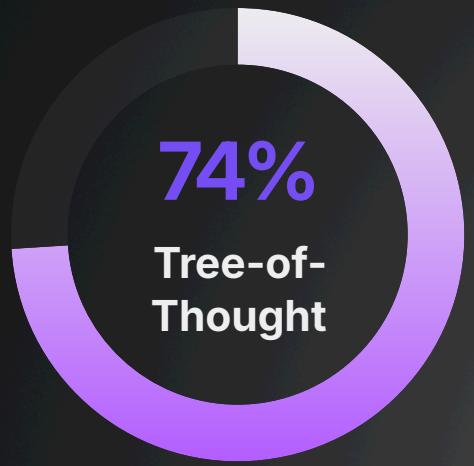


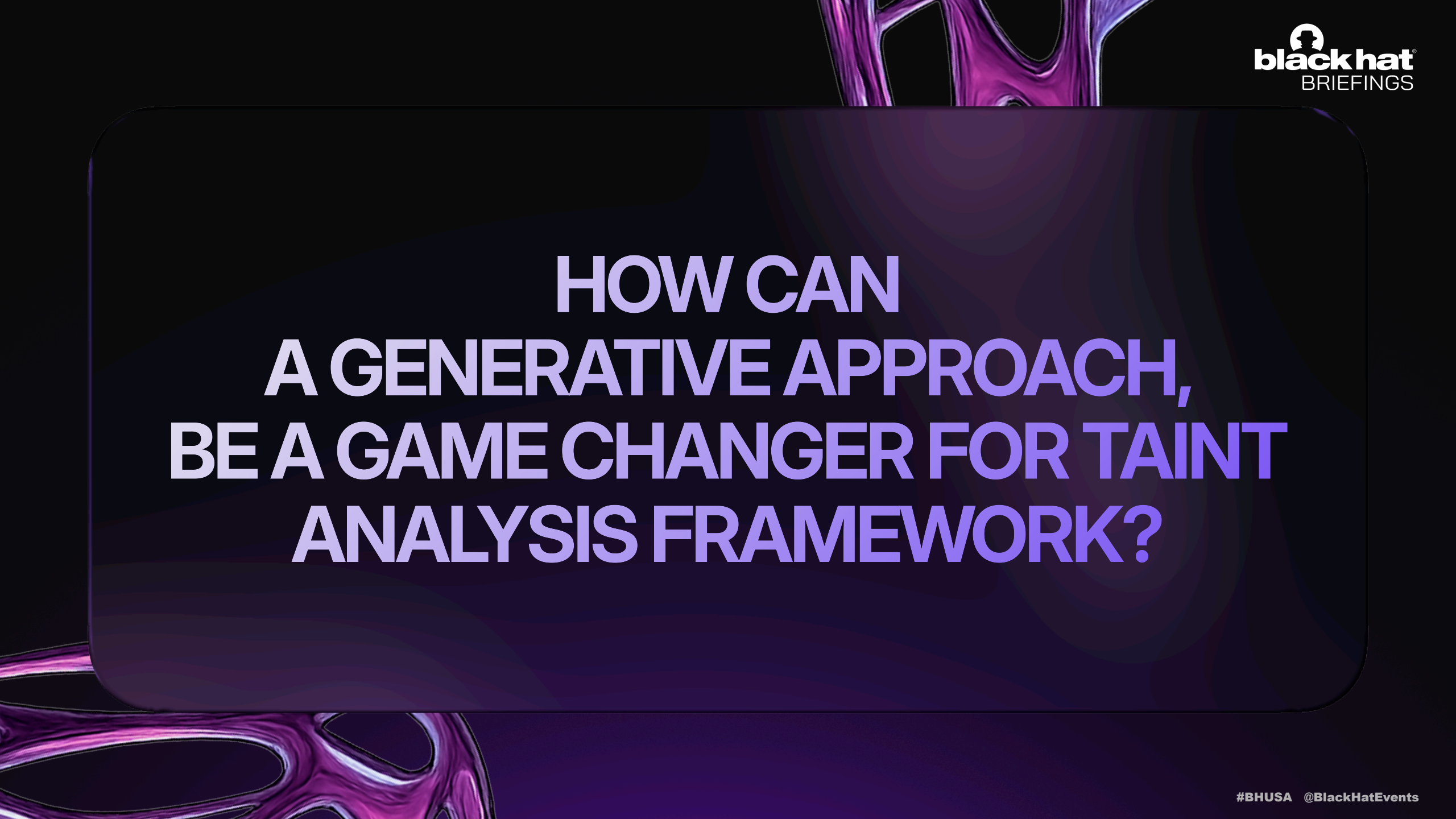
WHY IT'S SO CHALLENGING FOR AI?

1. Huge search space of combinations
2. Early mistakes lead to dead ends
3. Requires strategic planning & backtracking

RESULTS





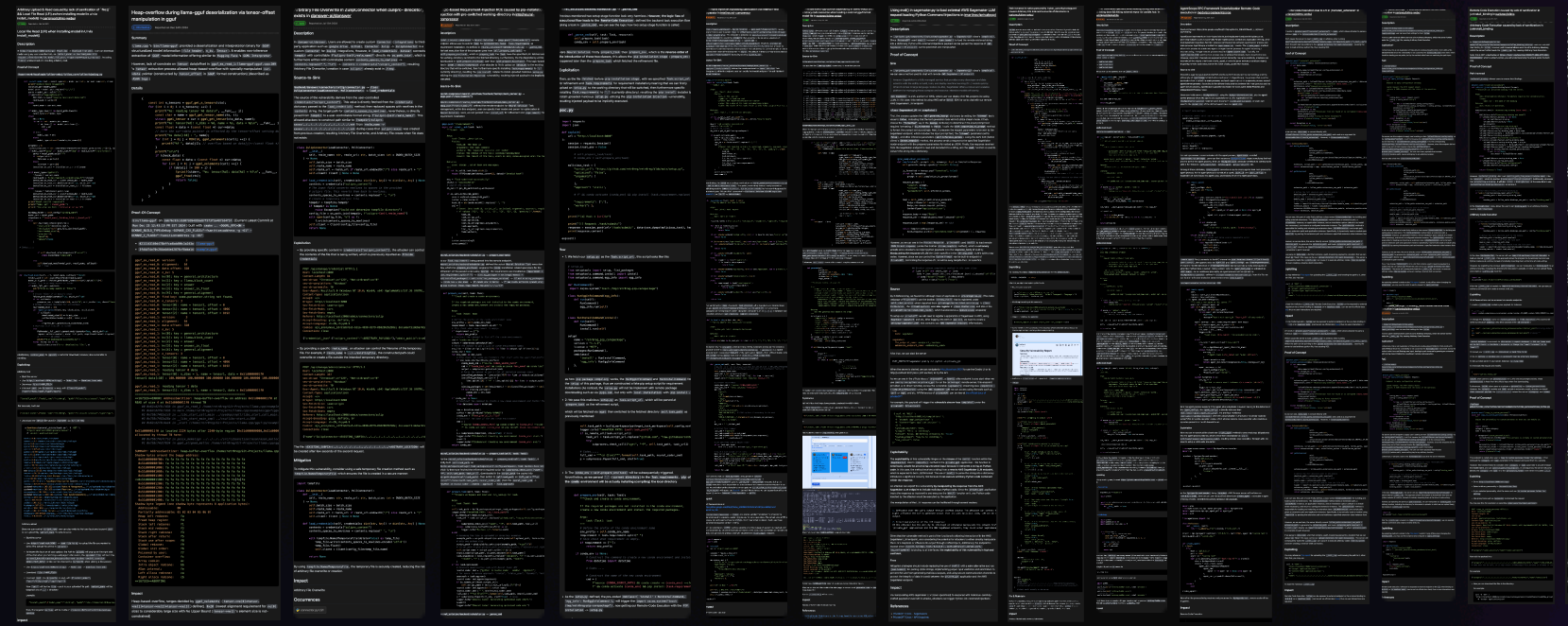

HOW CAN
A GENERATIVE APPROACH,
BE A GAME CHANGER FOR TAINT
ANALYSIS FRAMEWORK?

INSPIRATION: HUNTR STORY

51 report

18 CVEs

Transformers, Tensorflow, Llama.cpp...



- Heap-overflow during llama-gguf deserialization via tensor-offset manipulation in GGUF
- Llama.cpp (GGML) RPC Heap Overflow to Remote-Code Execution in GGML
- AgentScope RPC Framework Deserialization Remote-Code execution in modelscope/agentscope in modelscope/ag...
- Remote-Code Exeution via dynamic module importing | Arbitray File Overwrite | Pip Injection at "/api/tools" in com...
- LFIs at "/api/download" in composiohq/composio
- RPC Framework arbitrary file exposure in modelscope/agentscope
- AgentScope RPC Framework Deserialization Remote-Code execution in modelscope/agentscope
- workflowdag -> sanitize_node_data Remote-code execution in modelscope/agentscope
- Path traversal in '/read-examples' in modelscope/agentscope
- Local file inclusion via "/api/file" in modelscope/agentscope
- Arbitrary File Overwrite in ZulipConnector when zuliprc- direcetory exists in danswer-ai/danswer
- Command Injection Bypass via escaped \xa0 in intel/neural-compressor
- Vulnerable pdfjs-dist imported in Gradio Guides results JavaScript injection in gradio-app/gradio

- Logic-based Requirement-injection RCE caused by pip-installation injection with pre-switched working-directory in i...
- Denial-of-Service due to unlimited Task.workers in intel/neural-compressor
- REDACTED in intel/neural-compressor
- Command injection bypassing sanitization via Internal Field Separator in intel/neural-compressor
- SQL injection at /task/submit/ in intel/neural-compressor
- Symlink-Based Model Theft & File leakage during extracting in deepjavalibrary/djl
- Invalid fix on previous published Unrestricted File Upload Path On Windows in lightning-ai/pytorch-lightning
- Vulnerable llama-cpp-python dependency in lollms-webui allow arbitrary code execution when loading a external g...
- Using eval() in sagemaker.py to load external AWS Sagemaker LLM request leading Python Command injections in i...
- /api/create-project's 'project_name' is vulnerable to path traversal in stitionai/devika
- LFI in '/api/get-browser-snapshot' in stitionai/devika
- Lack of limitation on config editing resulting Arbitrary File Leakage / File Writing in stitionai/devika
- Arbitrary Folder/File leakages via Path Traversals in "/api/download-project" in stitionai/devika
- Chat is vulnerable to Stored XSS in stitionai/devika
- Path traversal in native personality 'cyber_security/codeguard' causes Arbitrary File leak and overwrite of directori...
- SSRF in 'scrape_and_save' allow the use of arbitrary scheme/protocol in parisneo/lollms-webui
- Path Traversal in 'save_settings' bypassing existing patches causing RCEs in parisneo/lollms-webui

- Command injection in 'run_xtts_api_server' when starting xtts services in parisneo/lollms-webui
- Python Command injections when loading config files when listing && listing docs && listing external repos via 'pad...
- Path traversal in '/switch_personal_path' cause sensitive configs leakage && Arbitrary Upload & Overwrites in paris...
- RCE when loading HuggingFace Hub 'tools' in 'src/transformers/tools/base.py' -> 'load_tool' in huggingface/transfo...
- 'collector/utils/url/index.js' sanitization on IP in 'isInvalidIp' can by bypassed in mintplex-labs/anything-llm
- Remote Code Execution due to LFI in '/reinstall_extension' in parisneo/lollms-webui
- Remote Code Execution due to LFI in '/install_extension' in parisneo/lollms-webui
- LFI in '/save_settings' -> extensions causes Remote Code Execution in parisneo/lollms-webui
- LFI in '/save_settings' -> binding_name causes Remote Code Execution in parisneo/lollms-webui
- Remote Code Execution due to the lack of sanitization of key 'extensions' in parisneo/lollms-webui
- Remote Code Execution when switching bindings due to lack of sanitization of binding name in parisneo/lollms-web...
- Remote Code Execution caused by lack of sanitization in /uninstall_binding in parisneo/lollms
- Remote Code Execution caused by an path traversal due to the lack of path sanitization in reinstall_binding in paris...
- Local File Read (LFI) when "Copy to custom personas folder for editing" in parisneo/lollms-webui
- SSRF when installing model in UI via install_model() in parisneo/lollms-webui
- Arbitrary Upload & Read casued by lack of sanitization of 'file://' && Local File Read (LFI) awhen installing model in ...
- Two Path Traversal leading Remote Code Execution in parisneo/lollms-webui

- LFI in '/save_settings' -> binding_name causes Remote Code Execution in parisneo/lollms-webui
- Remote Code Execution due to the lack of sanitization of key 'extensions' in parisneo/lollms-webui
- Remote Code Execution when switching bindings due to lack of sanitization of binding name in parisneo/lo
- Remote Code Execution caused by lack of sanitization in /uninstall_binding in parisneo/lollms
- Remote Code Execution caused by an path traversal due to the lack of path sanitization in reinstall_binding
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- Arbitrary Upload & Read casued by lack of sanitization of 'file://' && Local File Read (LFI) awhen installing m
- Two Path Traversal leading Remote Code Execution in parisneo/lollms-webui
- SSRF add_webpage() when fetching weblink for discussions via scrape_and_save() in parisneo/lollms-web
- Using eval() in sagemaker.py to load external AWS Sagemaker LLM request leading Python Command Inje
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- Insecure and deprecated function mktemp() in tensorflow/tensorflow
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- Transformers has a Deserialization of Untrusted Data vulnerability in huggingface/transformers
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INSPIRATION: HUNTR STORY

The first thing you do with a target, you run Bandit to see static point-of-interest:

Code Search, SAST tell us where the sinks are
- There are **tons** of them!
- We spend **hours** tracking them to their sources.

e.g., modelscope/agentscope:

8 sinks identified per SAST (Bandit) scan

→

...4 of them reachable

→

... within only 2 of them exploitable

WHAT IS TAINT ANALYSIS. SINK? SOURCE?

Disney WHERE'S MY WATER?

"Sink"
The place where meets usually indicate dangerous (e.g. eval, memcpy, pickle)

"Source":
The input of data (e.g., endpoint, argv, file)

WHEN YOU THINK IT UPSIDE-DOWN, IT'S MUCH MORE SIMPLE.

Why?

- It's too ***easy*** to identify sinks
- Avoids False positive & prioritize
- ***Context relevance***
  - Potential Context
  - State Recovery
    - Complexity of conditional flow (path explosion of executions)

SOURCE-TO-SINK

SINK-TO-SOURCE

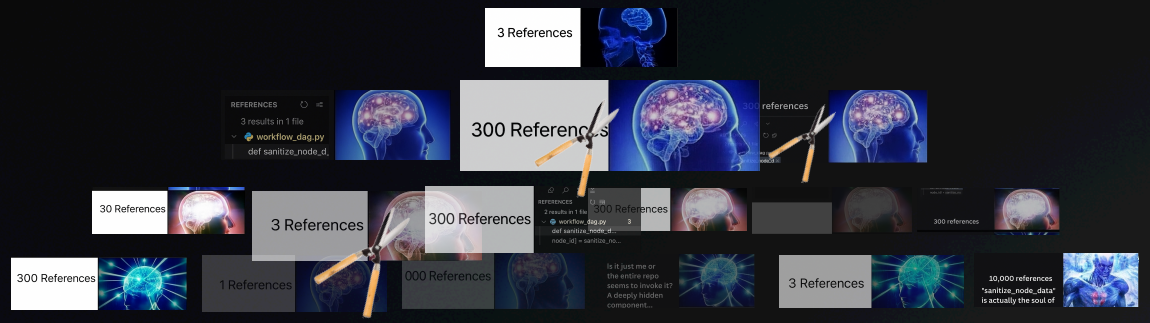
ESSENCE OF THE TASKS STATEFUL-NESS, PRUNING?

The **Pruning** Process:
- Cut off unrelated / low-valued branches, to focus on the biggest fruit

Statefulness:
- **dependency** of relationship **between** each nodes (states).
(Directed acyclic graph)

State-Recovery
- Recovering future states with both past states and potential states as contextual information,

TREE-OF-*STATES*?




```python
def sanitize_node_data(raw_info: dict) -> dict:
    copied_info = copy.deepcopy(raw_info)
    for key, value in copied_info["data"].get("args", {}).items():
        raw_info["data"]["args"][key]
            = eval(value)
```

```python
def build_dag(config: dict) -> ASDiGraph:
    for node_id, node_info in config.items():
        config[node_id] = sanitize_node_data(node_info)
```

```python
def start_workflow(config: dict) -> None:
    dag = build_dag(config)
```

```python
def compile_workflow(config: dict,
compiled_filename: str = "main.py") -> None:
    dag = build_dag(config)
    dag.compile(compiled_filename)
```

```python
def _convert_to_py(  # type: ignore[no-untyped-def]
    content: str,
    **kwargs,
) -> Tuple:
    from agentscope.web.workstation.workflow_dag import build_dag
    try:
        cfg = json.loads(content)
        return "True", build_dag(cfg).compile(**kwargs)
```

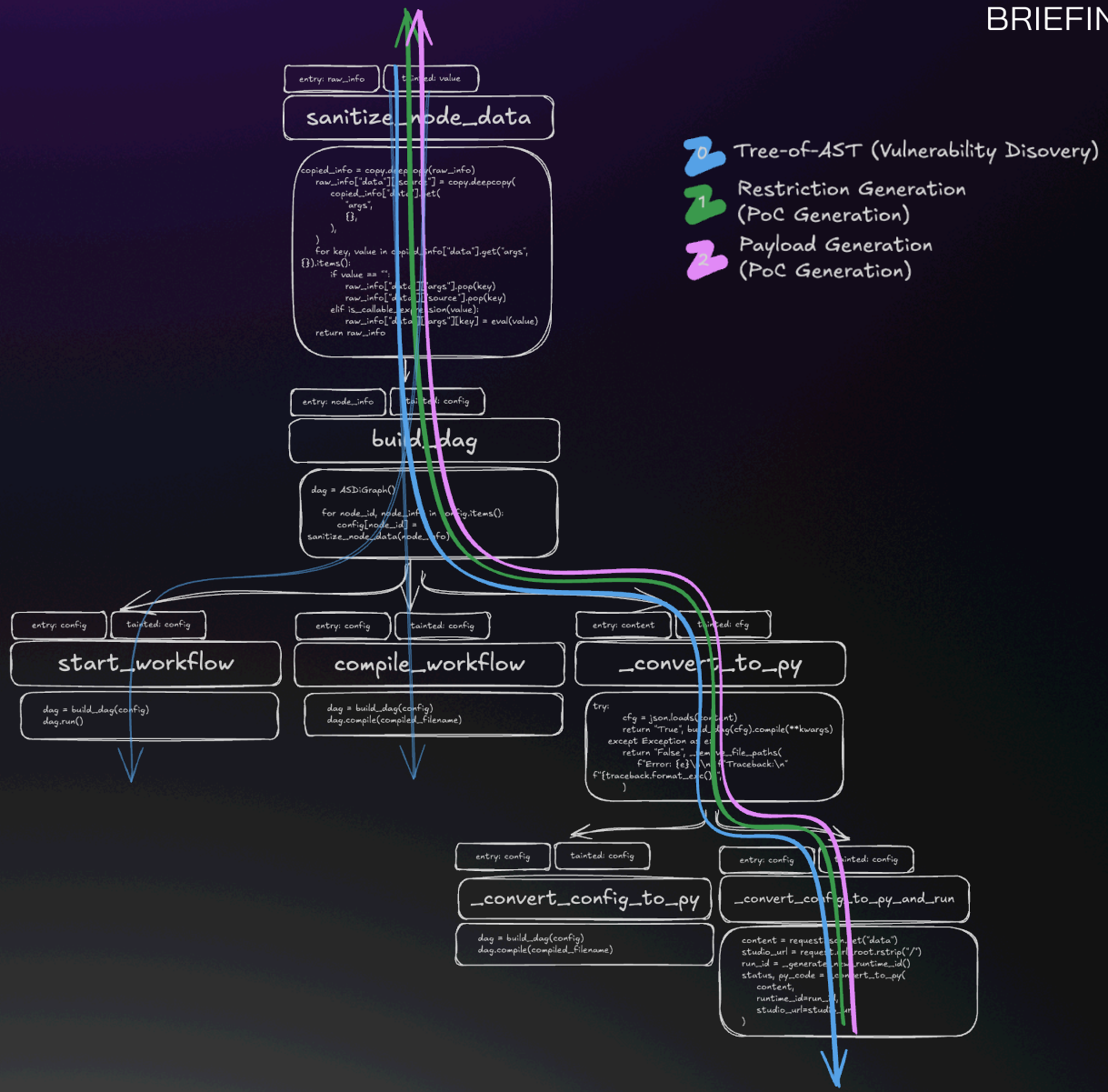
```python
@_app.route("/convert-to-py", methods=["POST"])
def _convert_config_to_py() -> Response:
    content = request.json.get("data")
    status, py_code = _convert_to_py(content)
```

SINK-TO-SOURCE?

TREE-OF-AST

1. **Diffuse** taint graph from on the **sink**
2. Traverse ***sink-to-source***
   - **vote** if current state is **source**
     - ***vote*** & ***value*** *next parrallel states for most possible* ***source****-leading* ***node***
       - *depth,* ***lookaheads***
       - ***rewind****, stateful-task*

PAYLOAD GENERATION



1. **Reverse** traverse *source-to-sink*
   - Nested-restriction tags to **semantically** describe the **constrains** from the slice.
     - Make up for the part we deliberately neglacted
     - *"Intuition"* for solvers in a *pruned-and-limited* **slice**

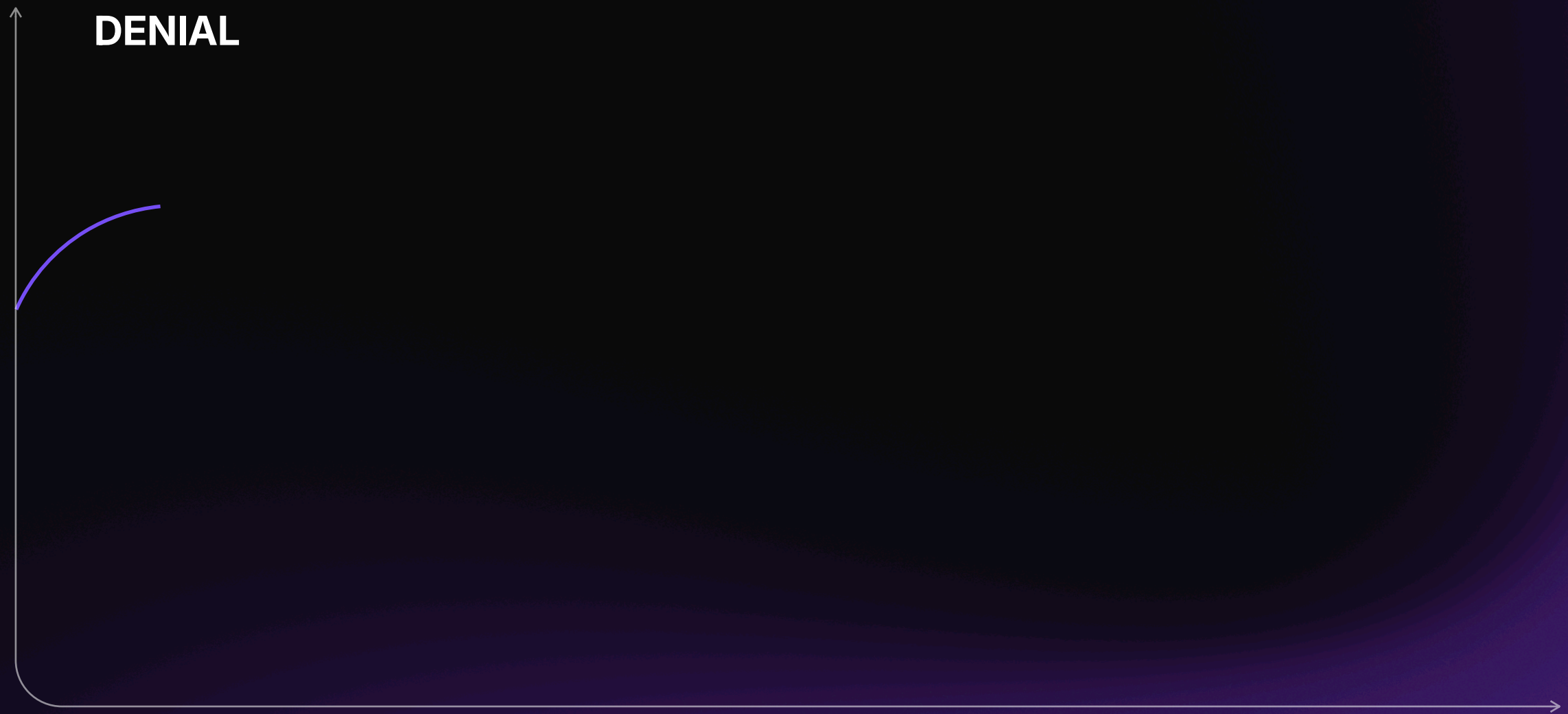
2. Traverse *source-to-sink* **again**
   - Constraints with **SMT* Solvers for model-generations, linearly **solving** the constrains into payloads


black hat
BRIEFINGS
Technical side
of our approach
#BHUSA @BlackHatEvents

THE PROBLEM WE NEED TO SOLVE:

INTERNAL PROGRAM REPRESENTATION

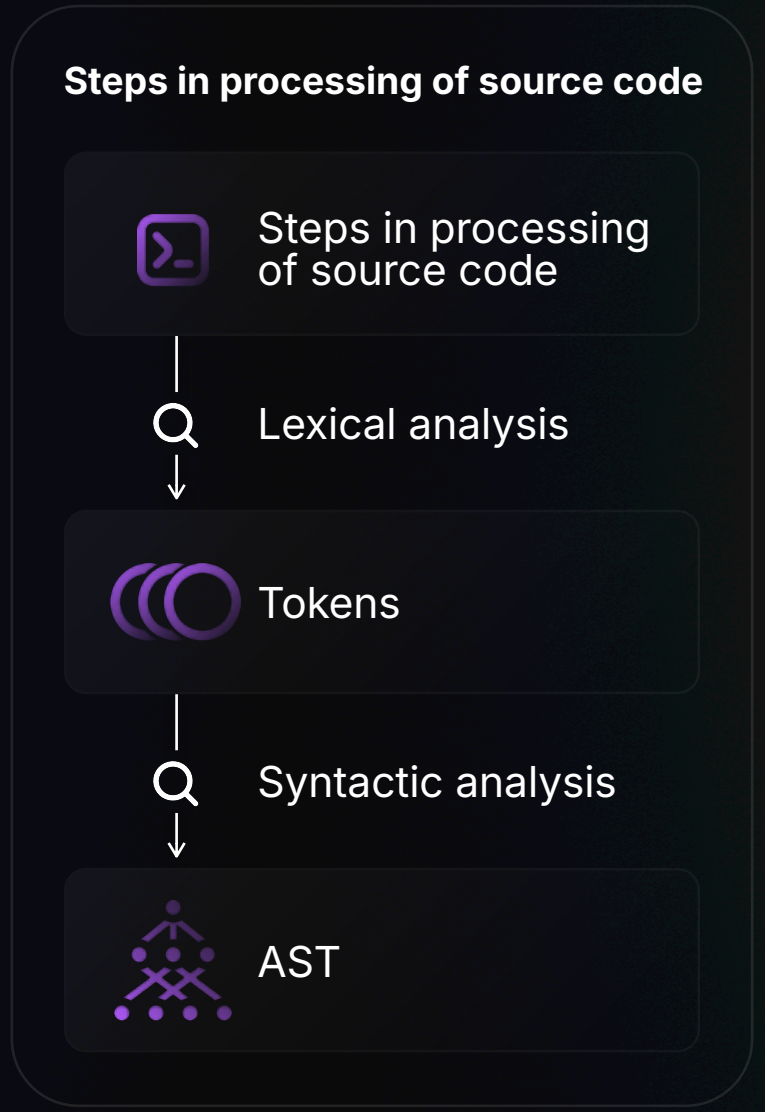
STAGES OF PROBLEM ACCEPTANCE



FIRST STEP: AST

An Abstract Syntax Tree

- Code Structure as Data
- Foundation for Security Analysis




```
        ]
      )
  )
body=[
  Expr(
    value=
      Call(
        func=
          Attribute(
            value=
              Call(
                func=
                  Attribute(
                    value=
                      Attribute(
                        value=
                          Name(
                            id='_RunTable'
                            ctx=
                              Load(
                              )
                          )
                        attr='query'
                        ctx=
                          Load(
                          )
                      )
                    attr='filter_by'
                    ctx=
                      Load(
                      )
                  )
```

AST OR NO AST?

Intuitively (as simple result):

```
>>> print(ast.dump(ast.parse('a if b else c', mode='eval'), indent=4))
Expression(
    body=IfExp(
        test=Name(id='b', ctx=Load()),
        body=Name(id='a', ctx=Load()),
        orelse=Name(id='c', ctx=Load())))
```

AST OR NO AST?

Intuitively (as simple result):

```
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Expression(
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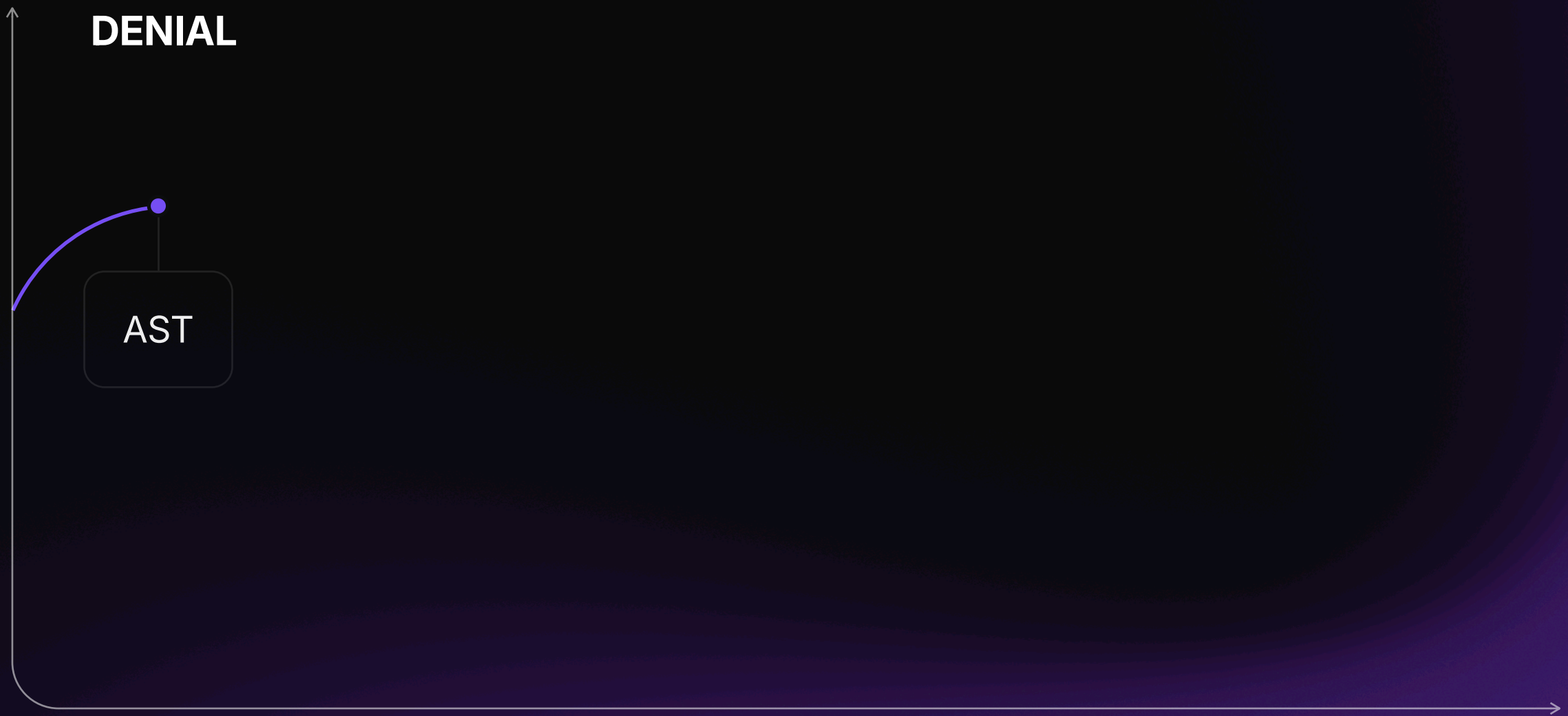
STAGES OF PROBLEM ACCEPTANCE



PROBLEMS OF ASTS

Note: ASTs remain useful for static analysis despite these challenges

LANGUAGE-SPECIFIC PARSING

Must implement custom parser for each language

CROSS-FILE ANALYSIS

SCOPE RESOLUTION

IMPORT HANDLING

COMPLEXITY VS. BENEFIT

PROBLEMS OF ASTS

Note: ASTs remain useful for static analysis despite these challenges

LANGUAGE-SPECIFIC PARSING

CROSS-FILE ANALYSIS

Tracking definitions and usage across files (e.g., function in a.py used in b.py)

SCOPE RESOLUTION

IMPORT HANDLING

COMPLEXITY VS. BENEFIT

PROBLEMS OF ASTS

Note: ASTs remain useful for static analysis despite these challenges

LANGUAGE-SPECIFIC PARSING

CROSS-FILE ANALYSIS

SCOPE RESOLUTION

Managing variable shadowing and name conflicts

IMPORT HANDLING

COMPLEXITY VS. BENEFIT

PROBLEMS OF ASTS

Note: ASTs remain useful for static analysis despite these challenges

LANGUAGE-SPECIFIC PARSING

CROSS-FILE ANALYSIS

SCOPE RESOLUTION

IMPORT HANDLING

Resolving module dependencies and import paths

COMPLEXITY VS. BENEFIT

PROBLEMS OF ASTS

Note: ASTs remain useful for static analysis despite these challenges

LANGUAGE-SPECIFIC PARSING

CROSS-FILE ANALYSIS

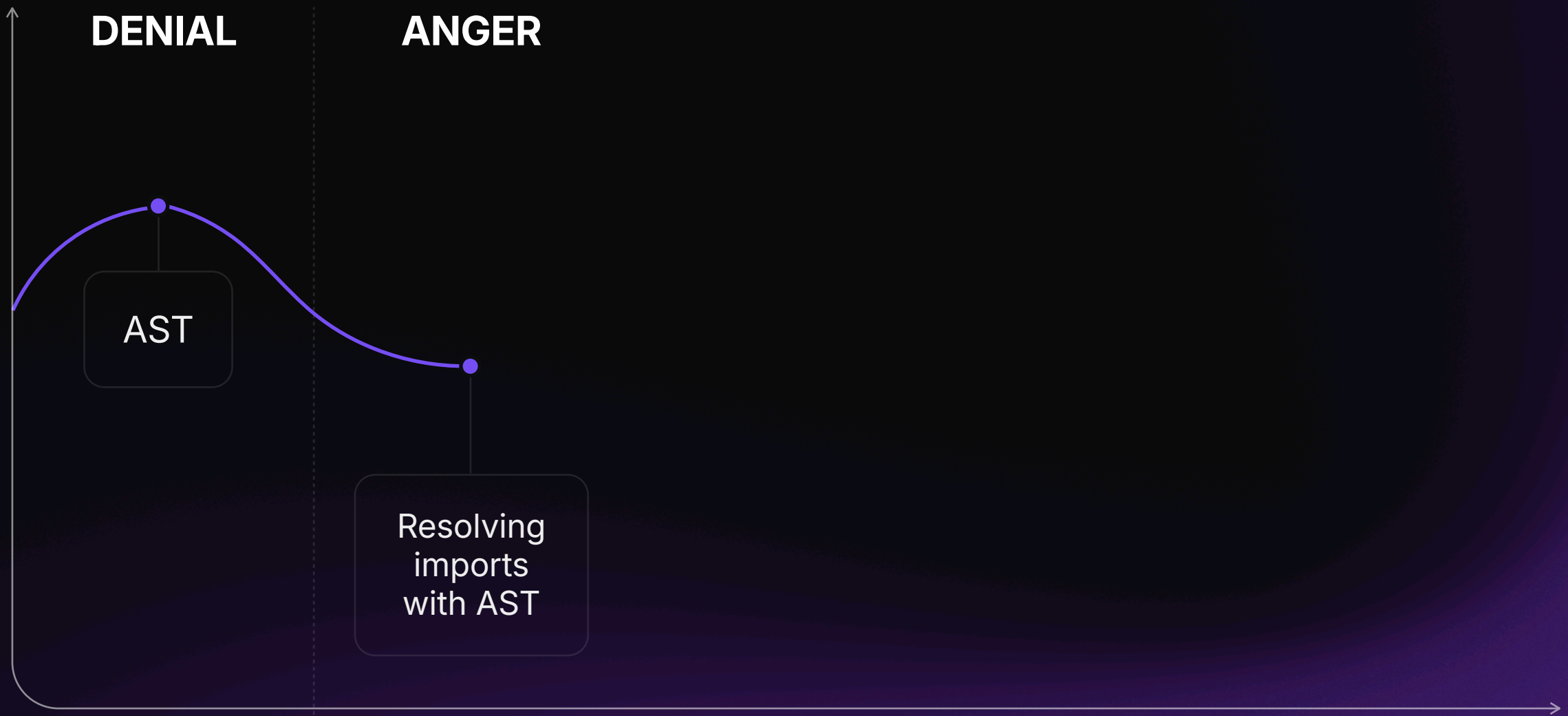
SCOPE RESOLUTION

IMPORT HANDLING

COMPLEXITY VS. BENEFIT

High implementation effort for basic static analysis tasks

STAGES OF PROBLEM ACCEPTANCE



Stack graphs are an open source framework

THE SOLUTION? STACK GRAPHS!

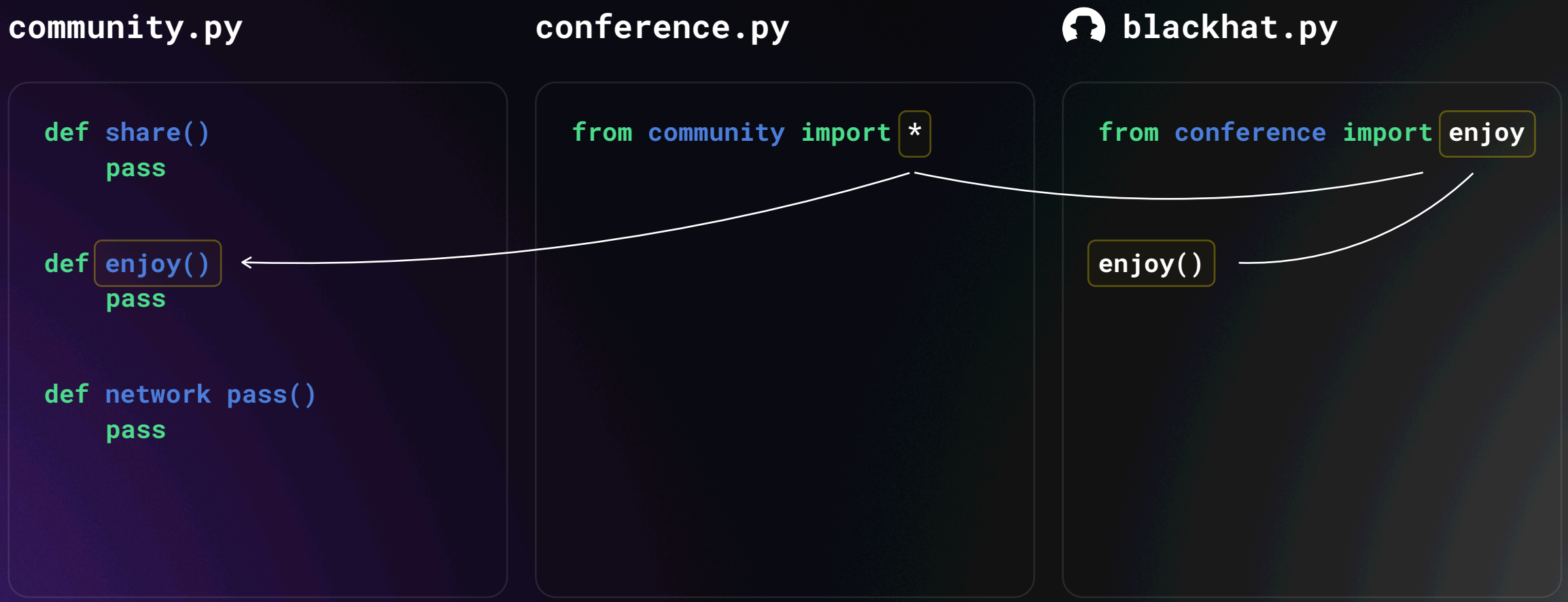
for precise

code navigation

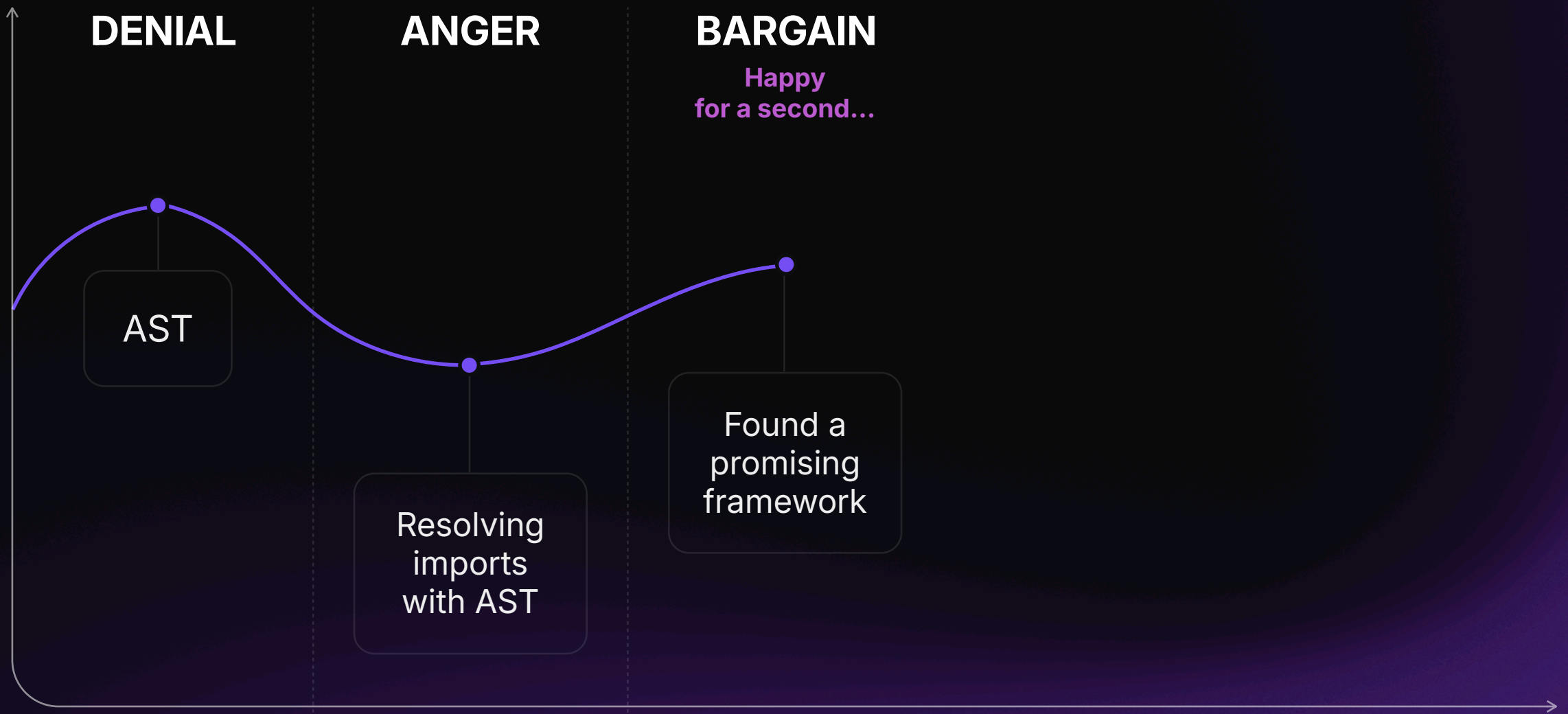
THE SOLUTION? STACK GRAPHS!

, which allows to represent how symbols flow through a program.

WHAT IS SYMBOL RESOLUTION?



STAGES OF PROBLEM ACCEPTANCE



HOW DO THEY WORK? SIMPLIFIED

stack-graphs Public

Tree-sitter

Tells you "there's a function called **foo** here and a call to **foo** there"

1. Builds CST
2. Consistent API across languages
3. Understands the grammar but not the meaning

HOW DO THEY WORK? SIMPLIFIED

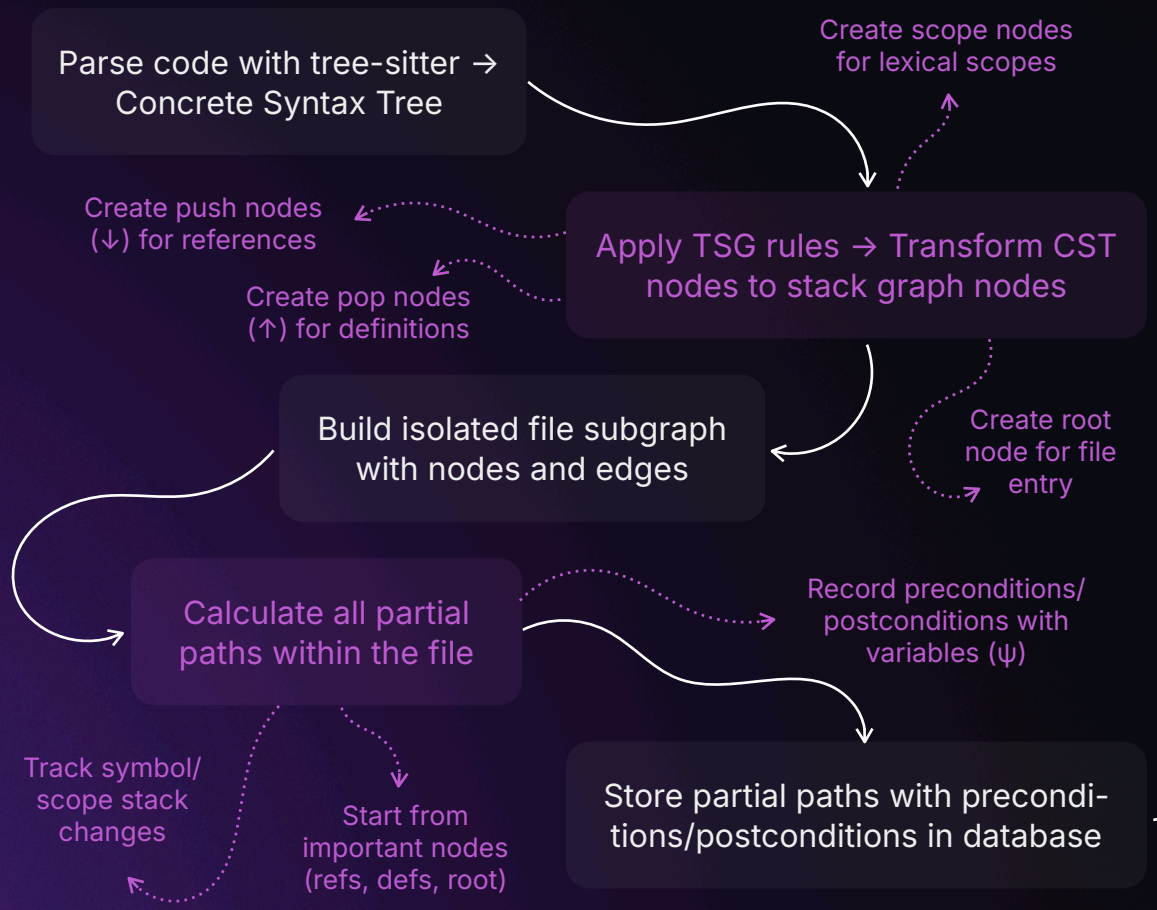
stack-graphs Public

Tell you "this specific call to foo resolves to that specific definition of foo based on the language's scoping rules"

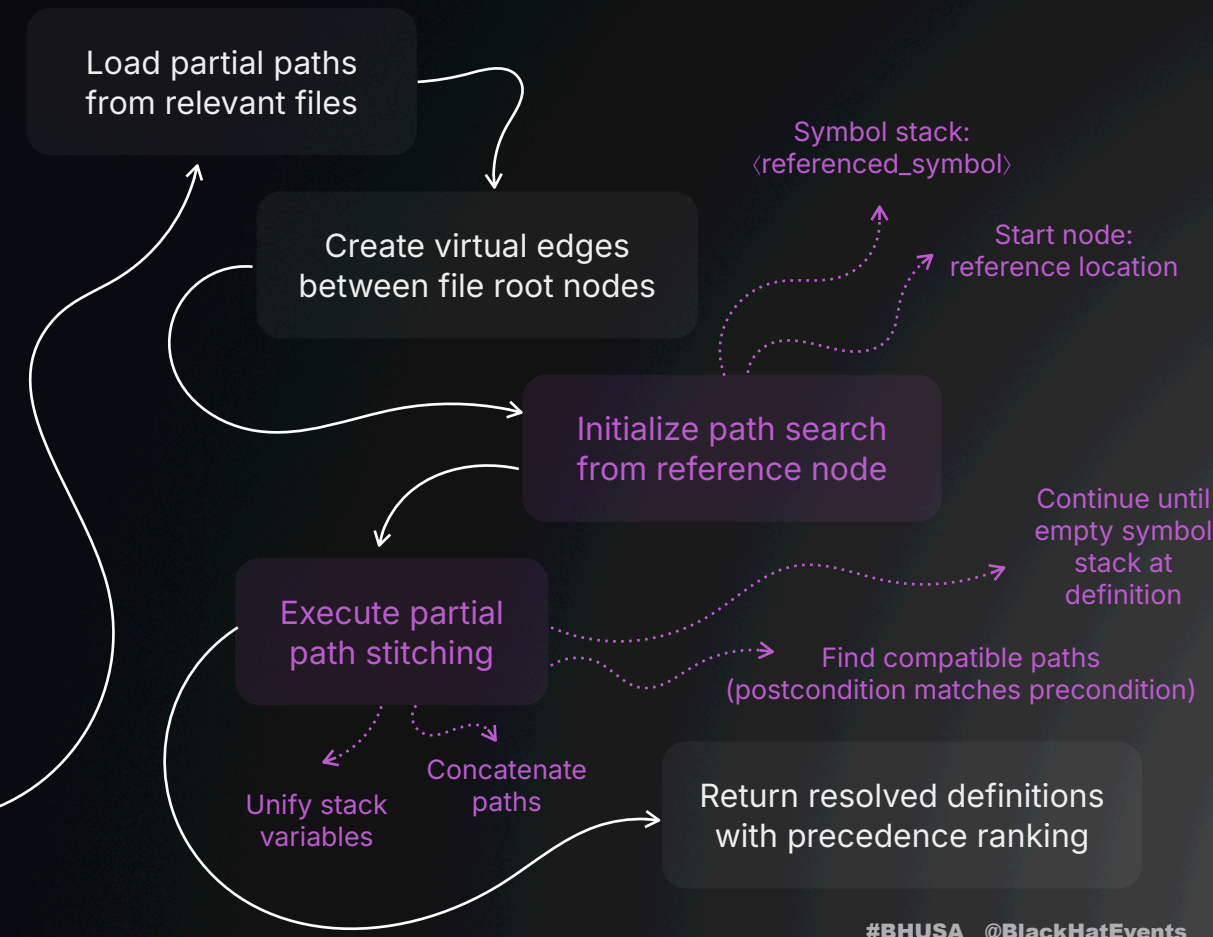
1. Apply language-specific rules (TSGs) to understand how names resolve
3. Understand imports, scope rules, and visibility modifiers
4. Resolve references across files based on actual language semantics
3. Build a graph structure that represents all possible name resolution paths

HOW DO THEY WORK? ACTUAL

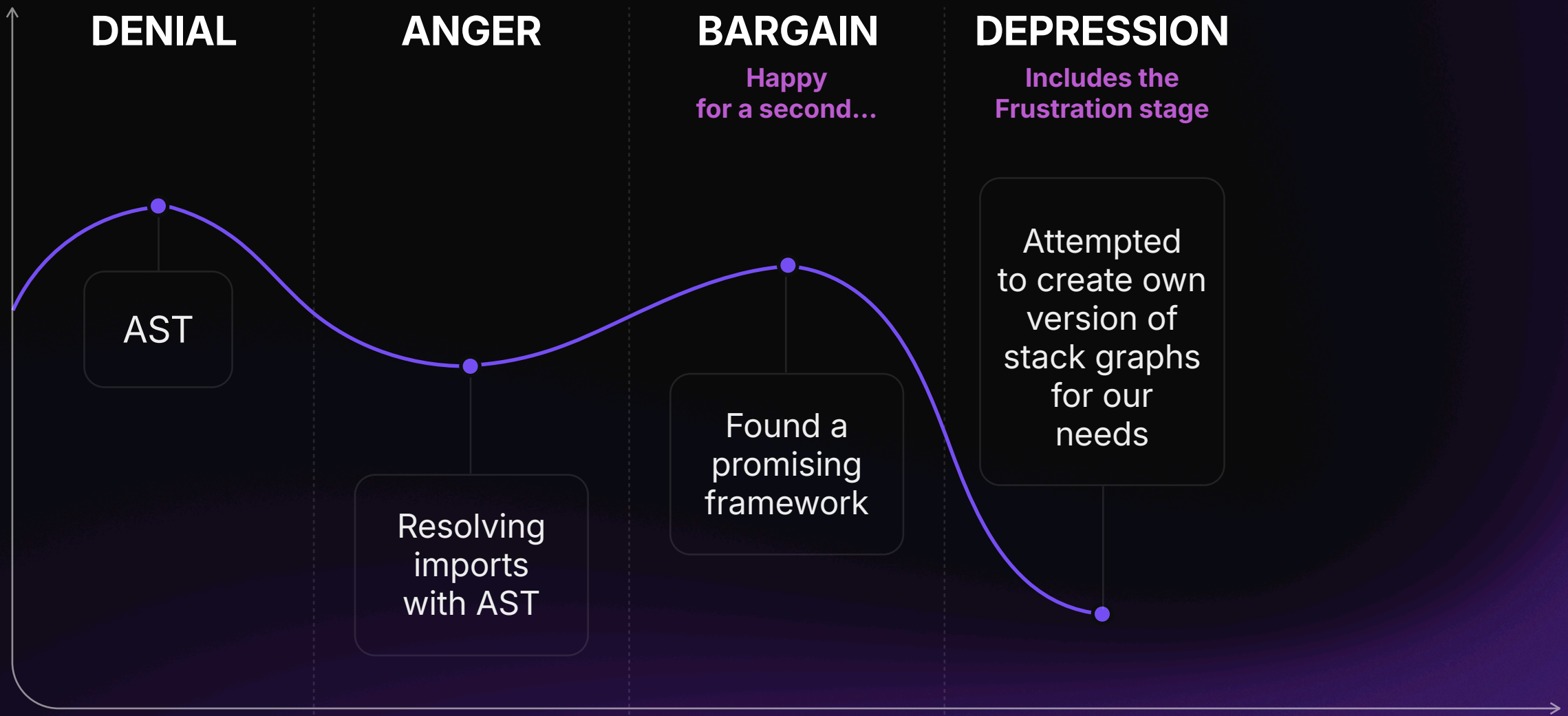
Phase I. Index-Time (Per File)



Phase II. Query-Time (Cross-File)



STAGES OF PROBLEM ACCEPTANCE



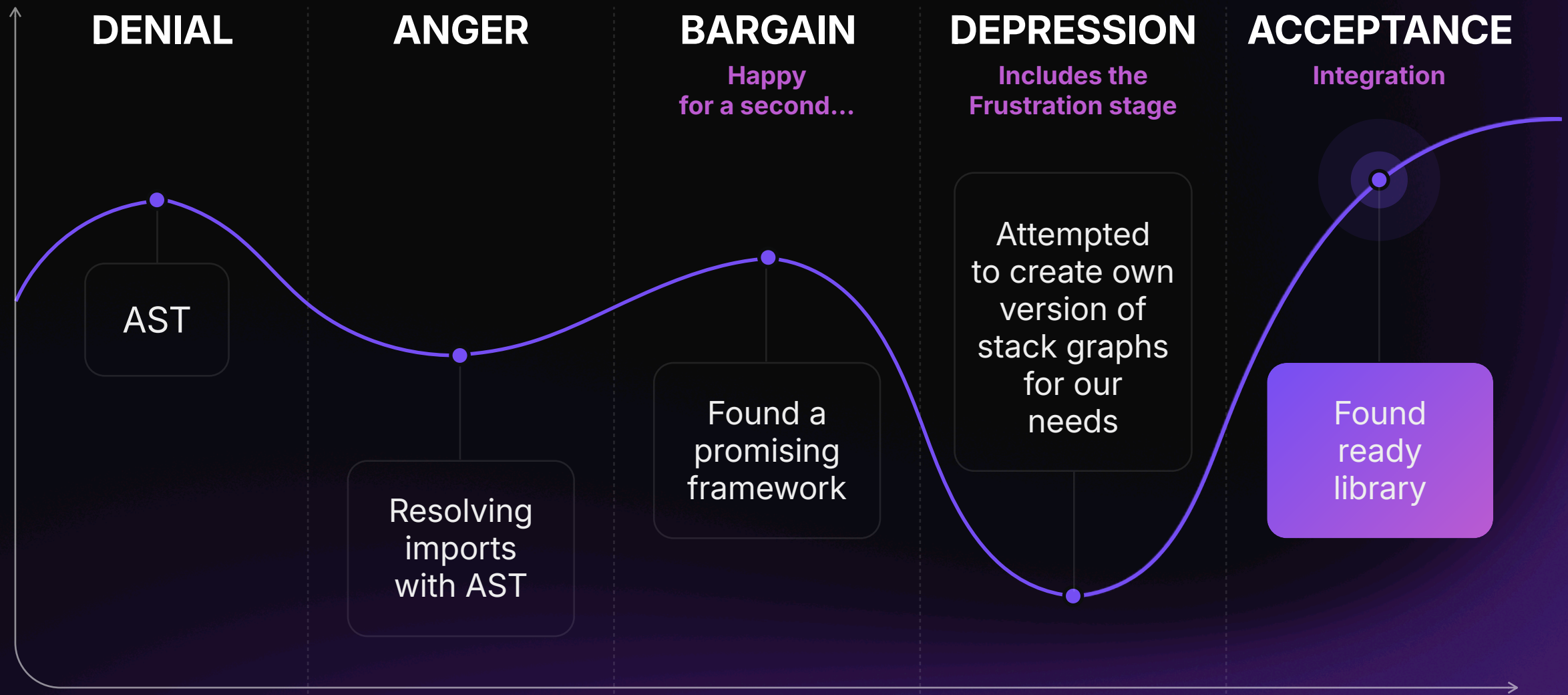
SO WHAT ARE WE EVENTUALLY USING?

After quite some time, we've found a working Stack Graphs library, and it all simplified to...

```python
def index_directory(self, dir_path: str):
    """
    Index a directory of code files to build the stack graph.
    :param dir_path: Absolute path to the directory containing code files.
    """
    abs_dir = os.path.abspath(dir_path)
    self.indexer.index_all([abs_dir])
    print(f"Indexed directory: {abs_dir}")
```

```python
def query_definitions(self, file_path: str, line: int, column: int) -> list[Position]:
    """
    Query dataflow: Find all definitions that reach a reference at the given position.
    This is a basic reaching-definitions dataflow analysis.
    :param file_path: Absolute path to the file.
    :param line: 0-indexed line number.
    :param column: 0-indexed column number.
    :return: List of Position objects for definitions.
    """
    position = Position(path=os.path.abspath(file_path), line=line, column=column)
    results = self.querier.definitions(position)
    return results
```

STAGES OF PROBLEM ACCEPTANCE

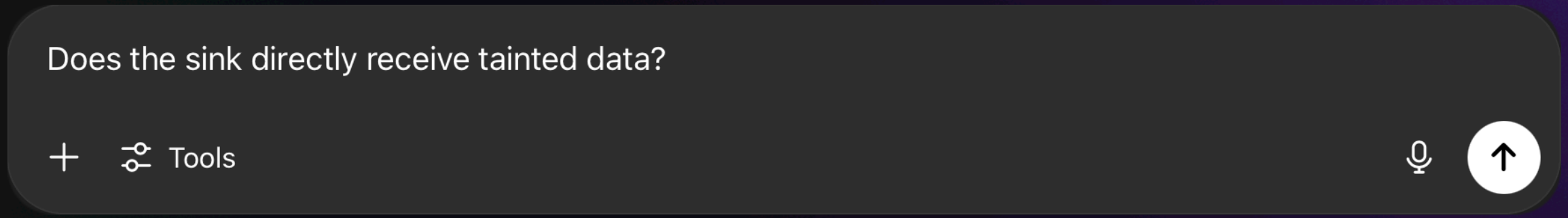


MORE INTERESTING STUFF

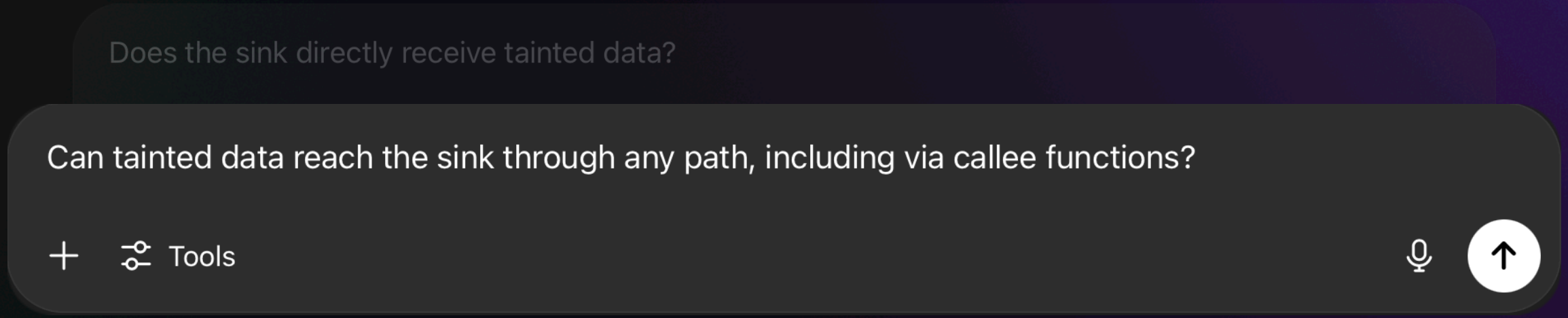
OUR SOLUTIONS, APPROACHES & OTHER OBSERVATIONS

TRIED AND TRUE, YET OFTEN OVERLOOKED

Instead of asking this...



TRIED AND TRUE, YET OFTEN OVERLOOKED



↑

Try asking this

THREE REPRESENTATIVE CASES

Code Pattern	Description	Argument Tracking	Parameter-Based Tainting	Traditional Sink Trace
`sink(caller.param)`	Direct taint flow from caller parameter	Yes	Yes	Yes
`sink(callee())`	Taint originates from callee function	No	Yes	No
`sink(callee(caller.param))`	Tainted parameter passed through callee	Yes	Yes	No

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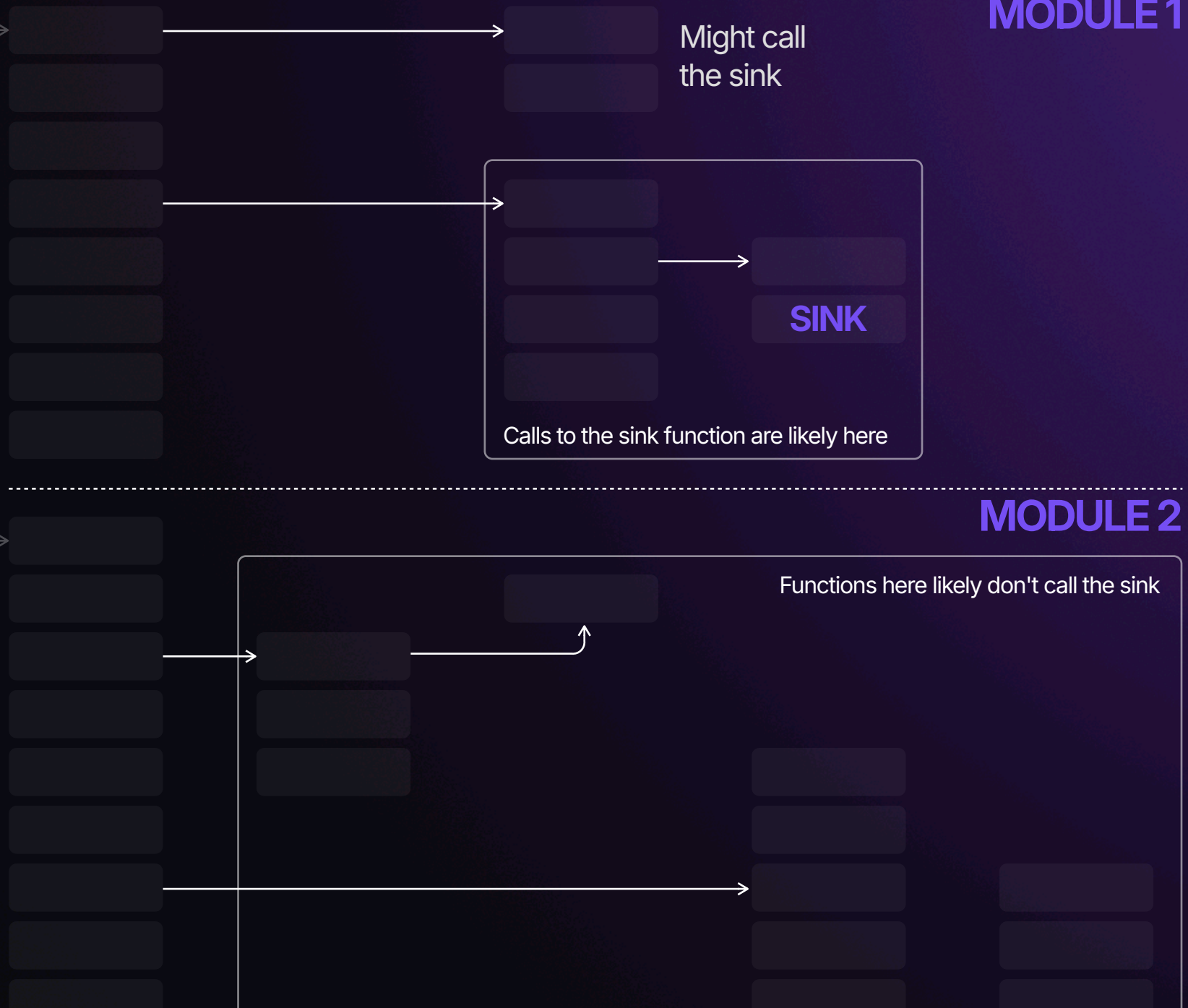
HOW TO AVOID FREEZES ON LARGE PROJECTS?



black hat BRIEFINGS

HOW DO WE USE LMS?

We use LangChain

01 LLM makes decisions on (1) Input Source Detection, (2) Path Selection, and (3) Backtracking

02 Implements chain lookahead analysis

03 Voting algorithms are implemented

04 Similar voting results are getting re-weighted with smarter models.


WHAT ARE
THE RESULTS?

HOW IS OUR APPROACH DIFFERENT (AS A DATAFLOW ENGINE)?

01 It doesn't require the entry point specification to analyze the program.

02 It uses LMs, but doesn't just send the code over and ask "Is there a vulnerability?"

03 Designed specifically for large projects that span across many files, modules, repositories.

WHAT HAVE WE (RE) DISCOVERED?

CVE-2022-29216
TENSORFLOW

Code injection via eval

190k stars on Github

CVE-2023-40581
YT-DLP

Command injection via subprocess.call

119k stars on Github

CVE-2019-14904
ANSIBLE

Code injection via os.system

63k stars on Github

WHAT IS THE PROBLEM WITH MEASURING THE PERFORMANCE?

CONCLUSIONS (AKA BLACK HAT SOUND BYTES)

Automating strategic decisions with LLMs to optimize human work automation

Replacing traditional security analysis (fuzzing, static/dynamic) with AI-powered approaches

Rethinking problems from first principles rather than iterating on existing solutions

The sink is just the end. What matters is how we got there.

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retr0@retr0.blog

RESOURCES

 / Blog https://github.blog/open-source/introducing-stack-graphs/

 https://pypi.org/project/stack-graphs-python-bindings/

 https://arxiv.org/pdf/2305.10601

 https://apps.apple.com/us/app/wheres-my-water/id449735650

INTERESTING FACTS ABOUT OUR PROJECT

We are called Tree-of-AST, but we don’t actually use AST that much...

01

We re-wrote the project from 0 at least 3 times

02

Different versions of the project have different codebase sizes, varying from 1000 to 12 000+ lines of code

03