Beware of the Unexpected:

Bimodal Taint Analysis

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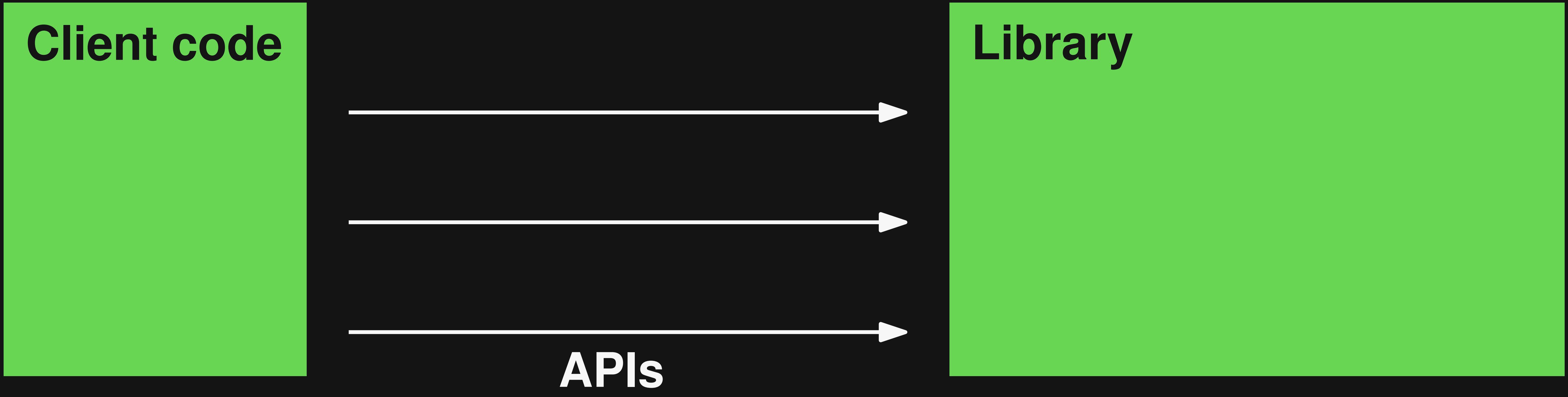
Motivation

- **Static analysis: Only as good as its specs**
- **E.g., taint analysis**
  - Need policy that specifies insecure source-sink pairs
  - Problematic flow if both
    - data flows from source to sink and
    - the flow is unexpected by developers

Example: Command Injection

Want: **Untrusted data does not flow to `exec()`**

(Otherwise, command injection vulnerability)



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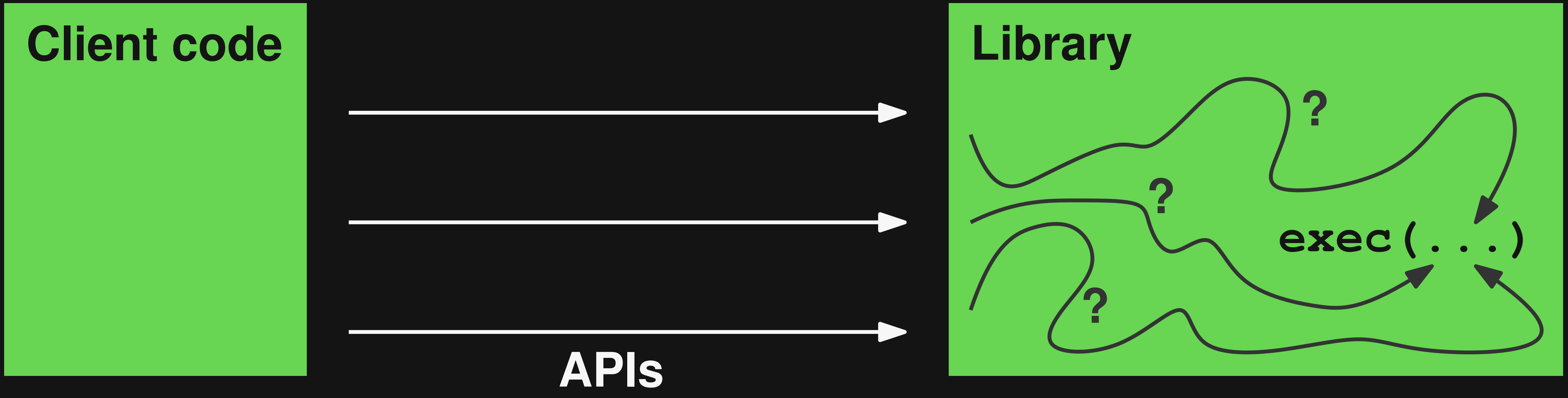

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Expected → No need to warn developer

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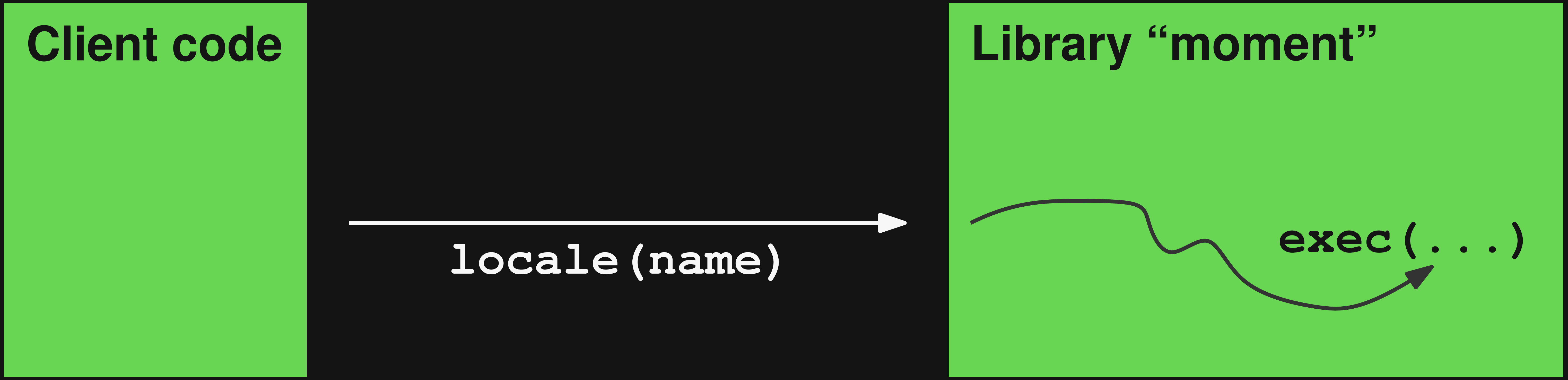

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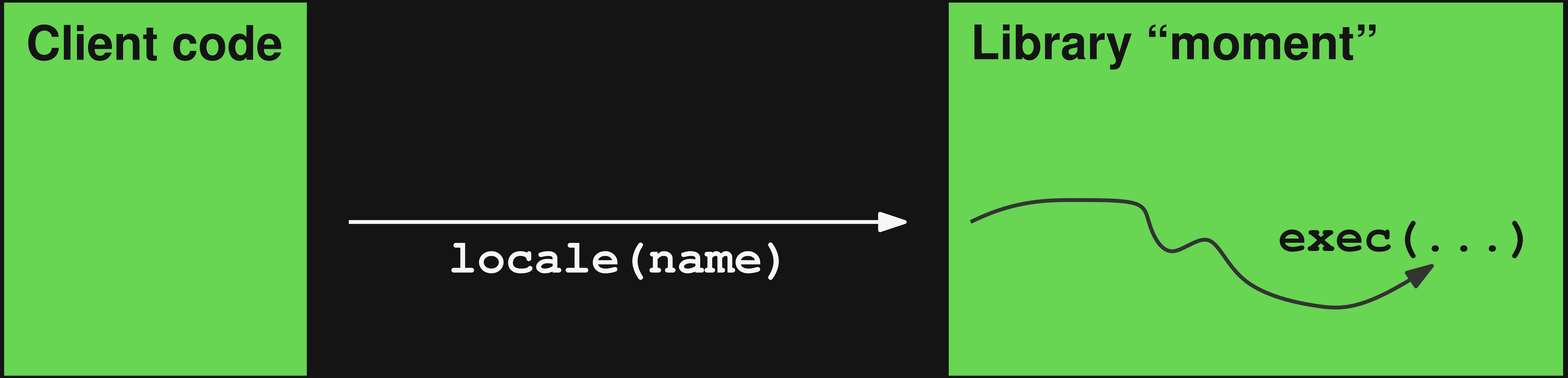
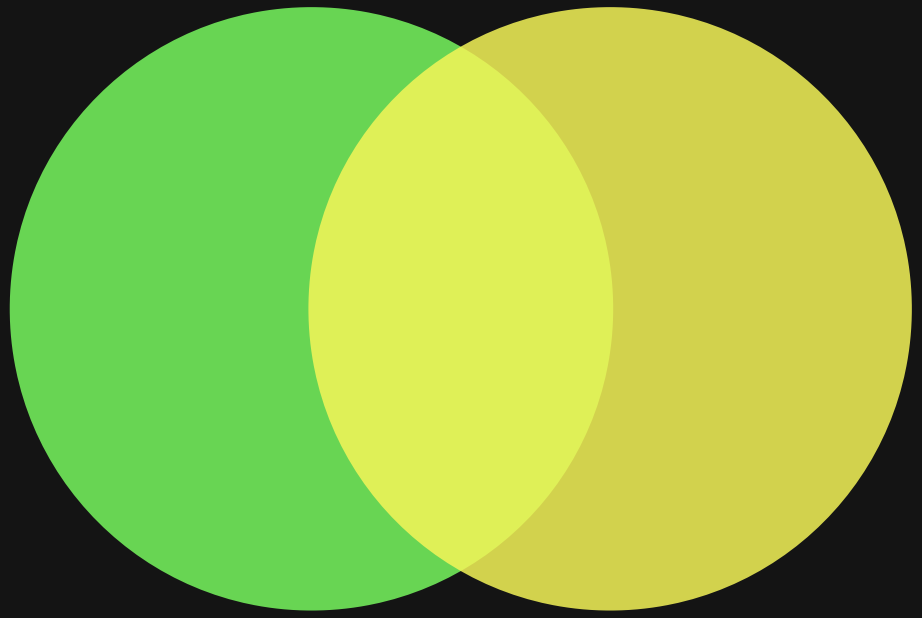


Unexpected → Should warn developer

This Talk

Bimodal program analysis

Program analysis:
Reason about PL semantics



Machine learning:
Reason about NL embedded in code

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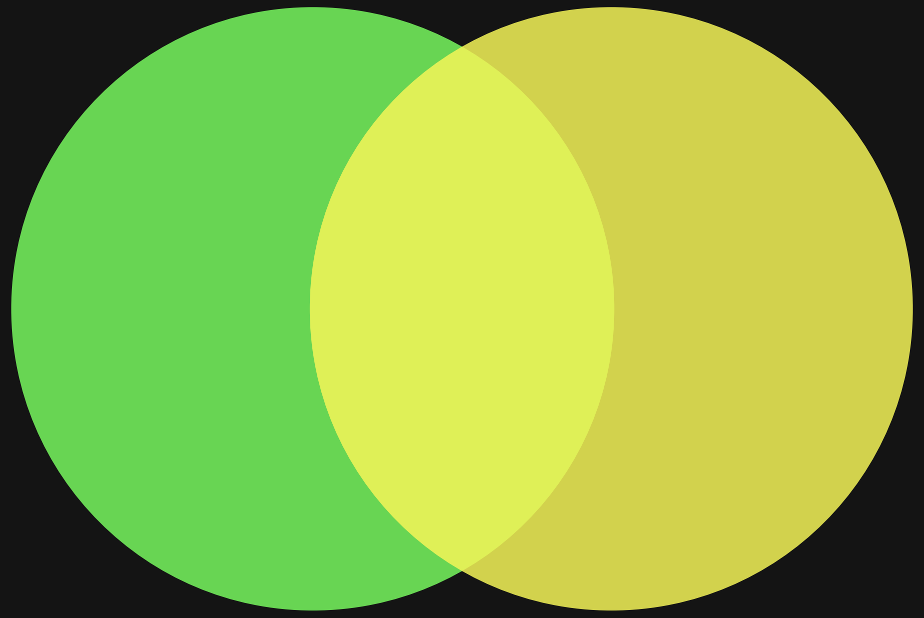


Machine learning:
Reason about NL embedded in code

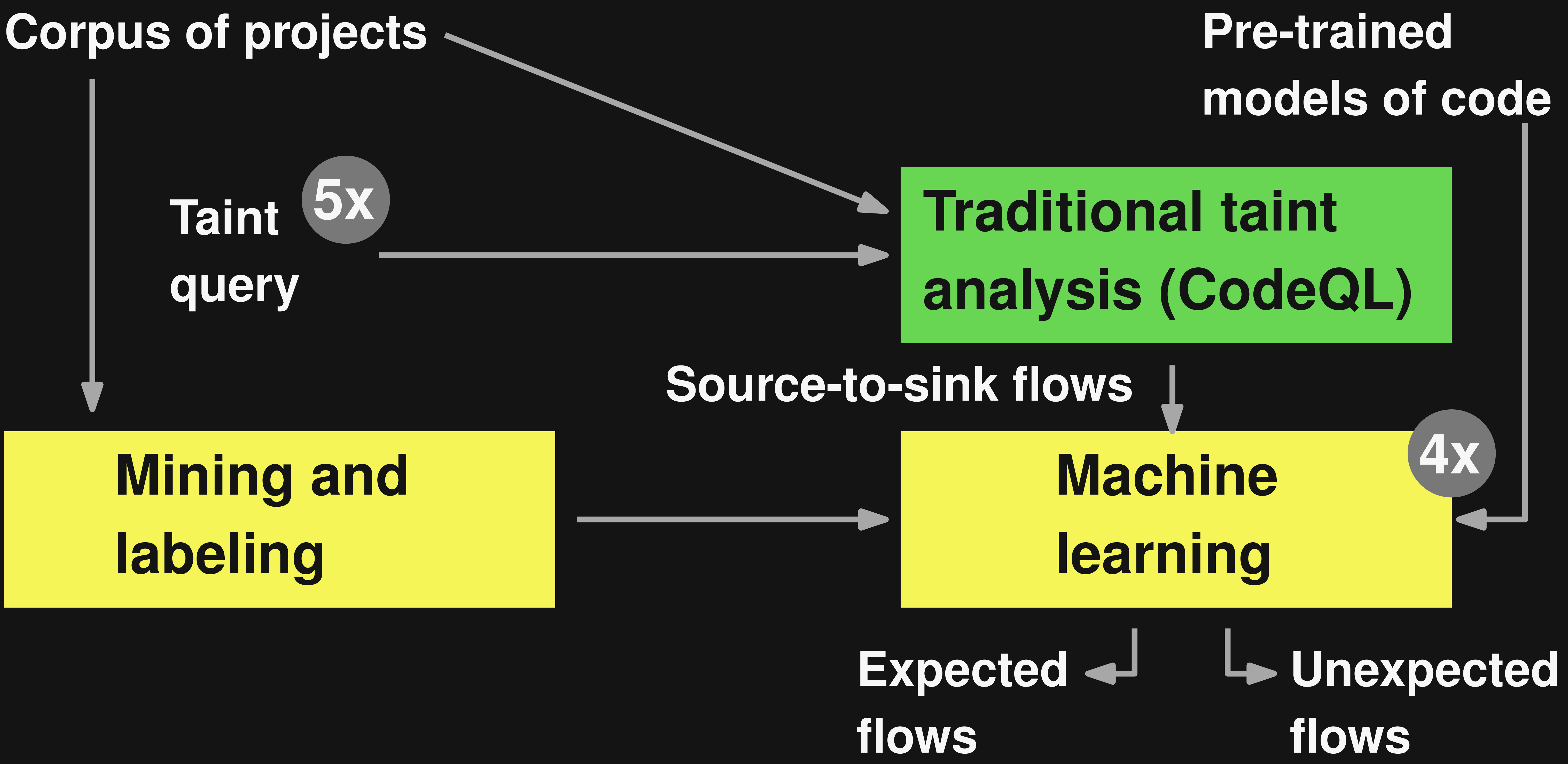
Overapproximate relevant flows

Taint analysis

Identify unexpected flows

Fluffy = Flagging unexpected flows for better security

Overview



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Pre-trained
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Taint
5x
query
Traditional taint
analysis (CodeQL)
Source-to-sink flows
Mining and
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Machine
learning
4x
Expected
flows
Unexpected
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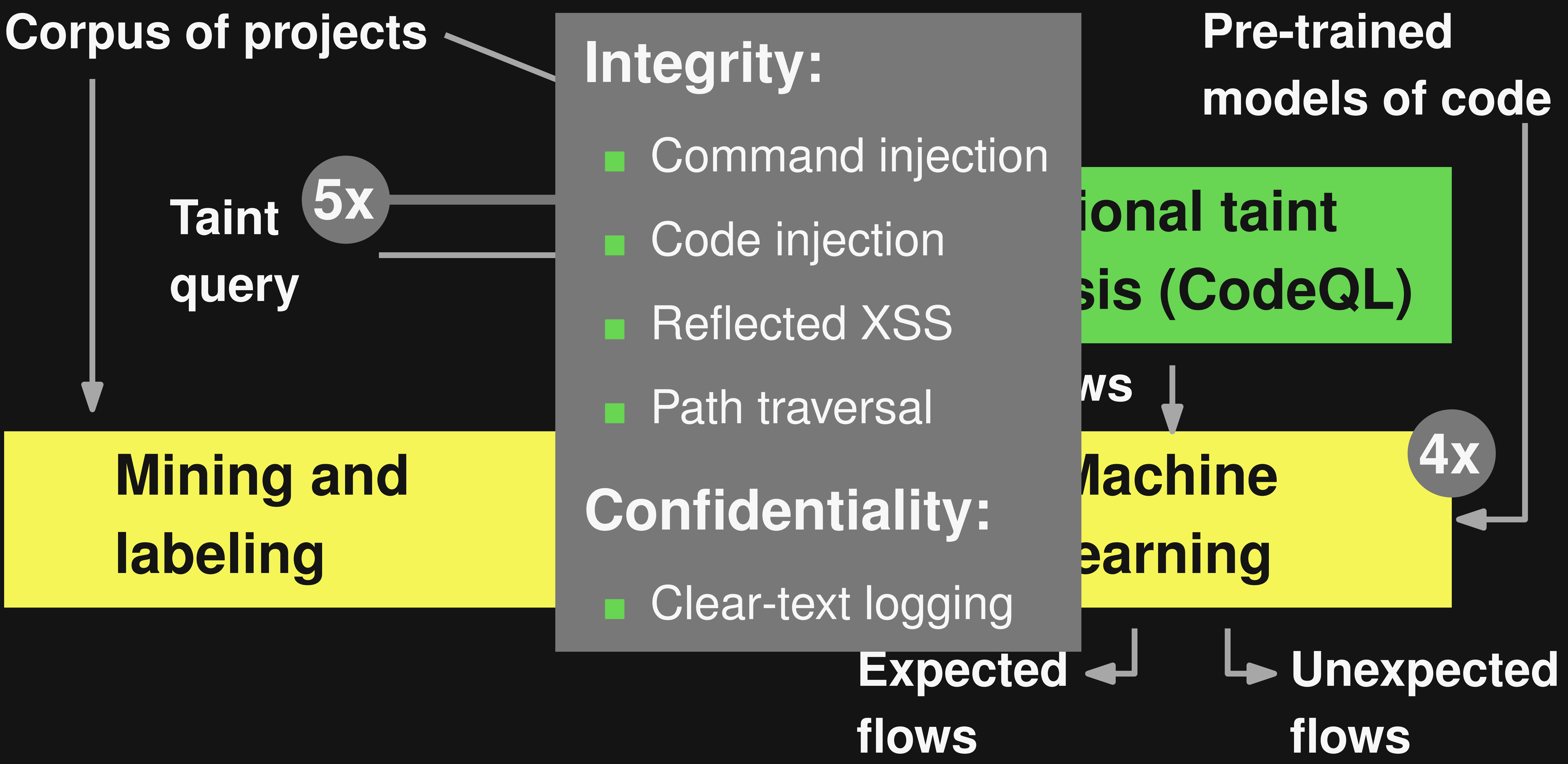
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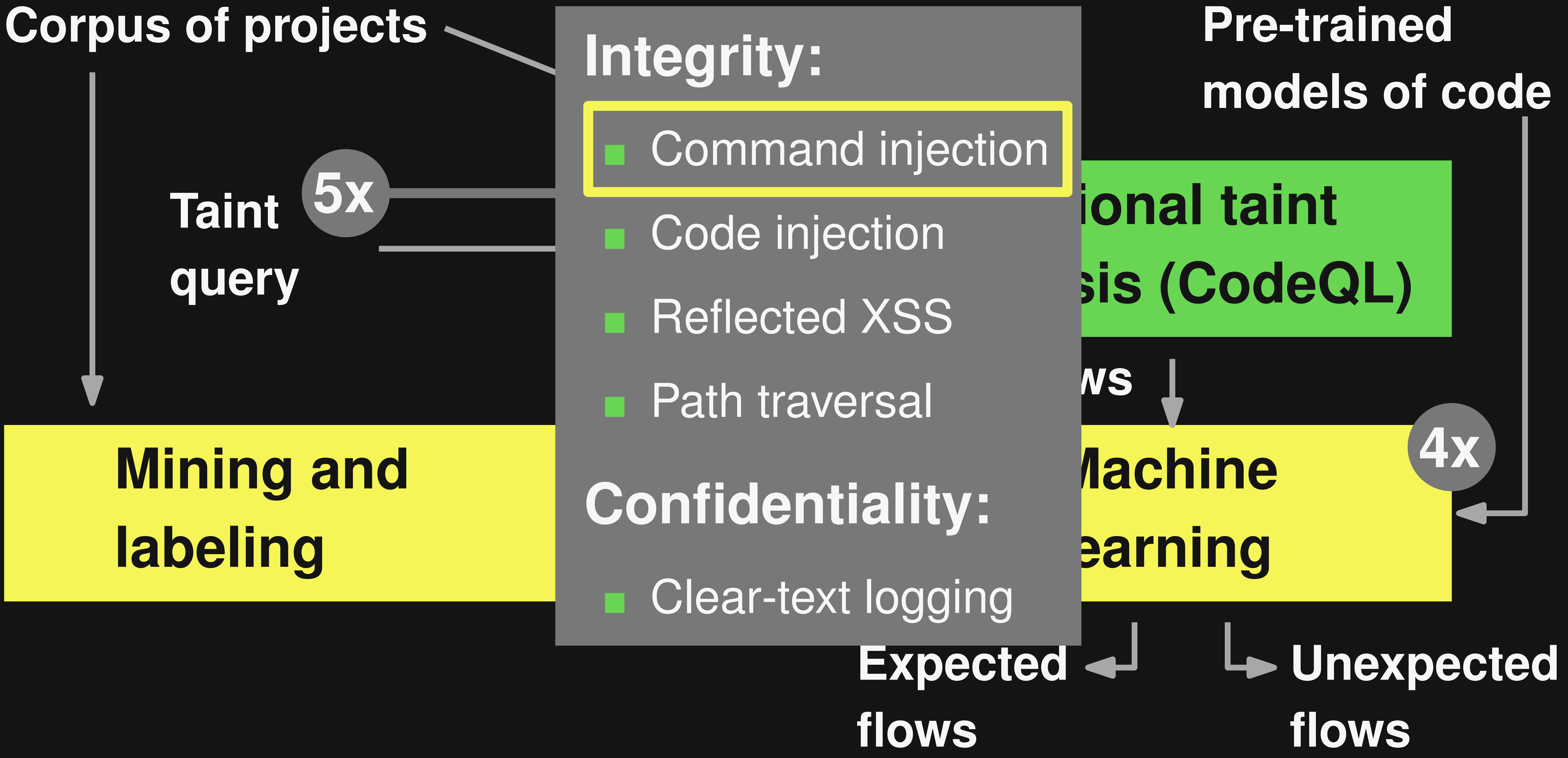

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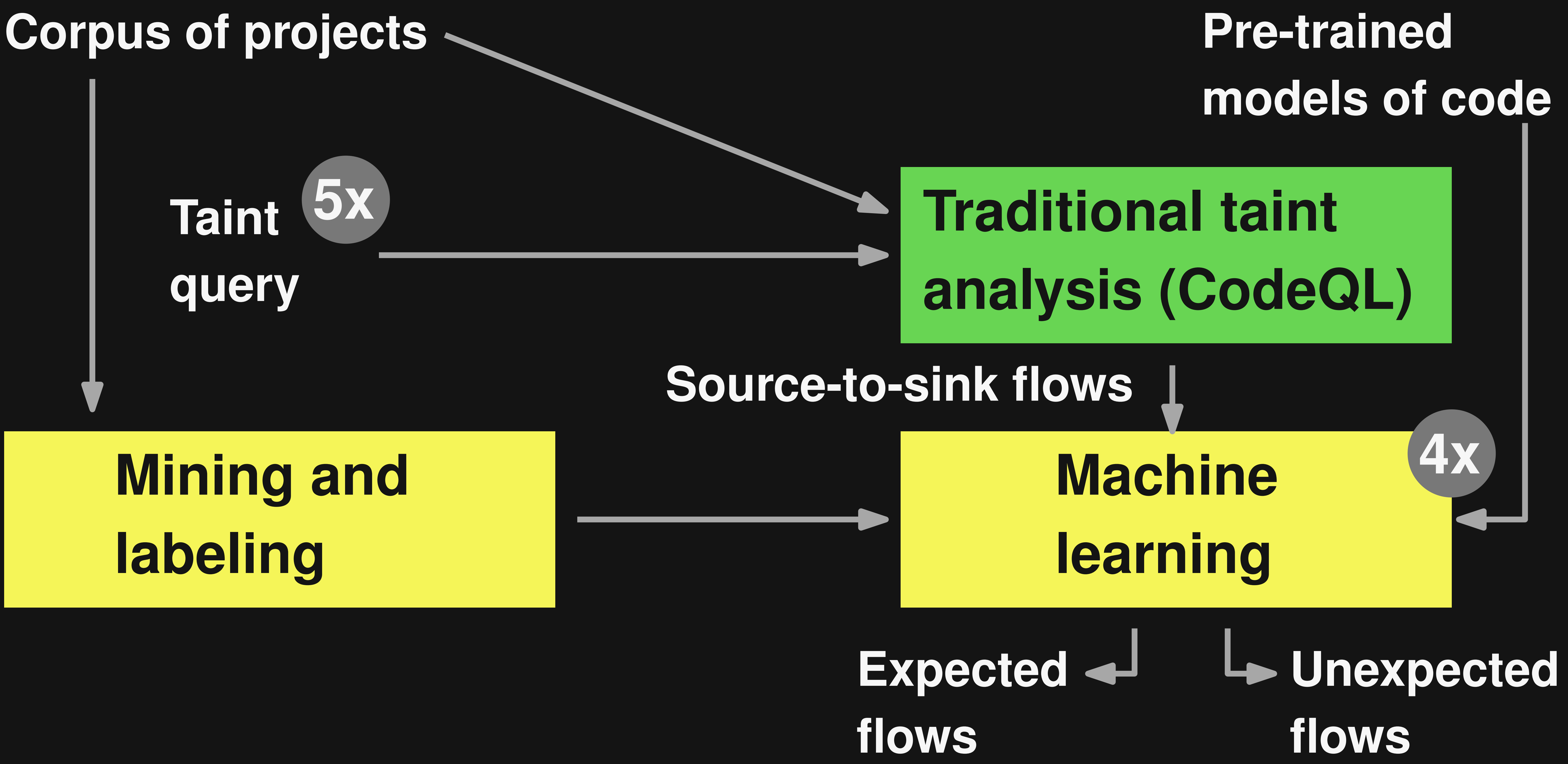

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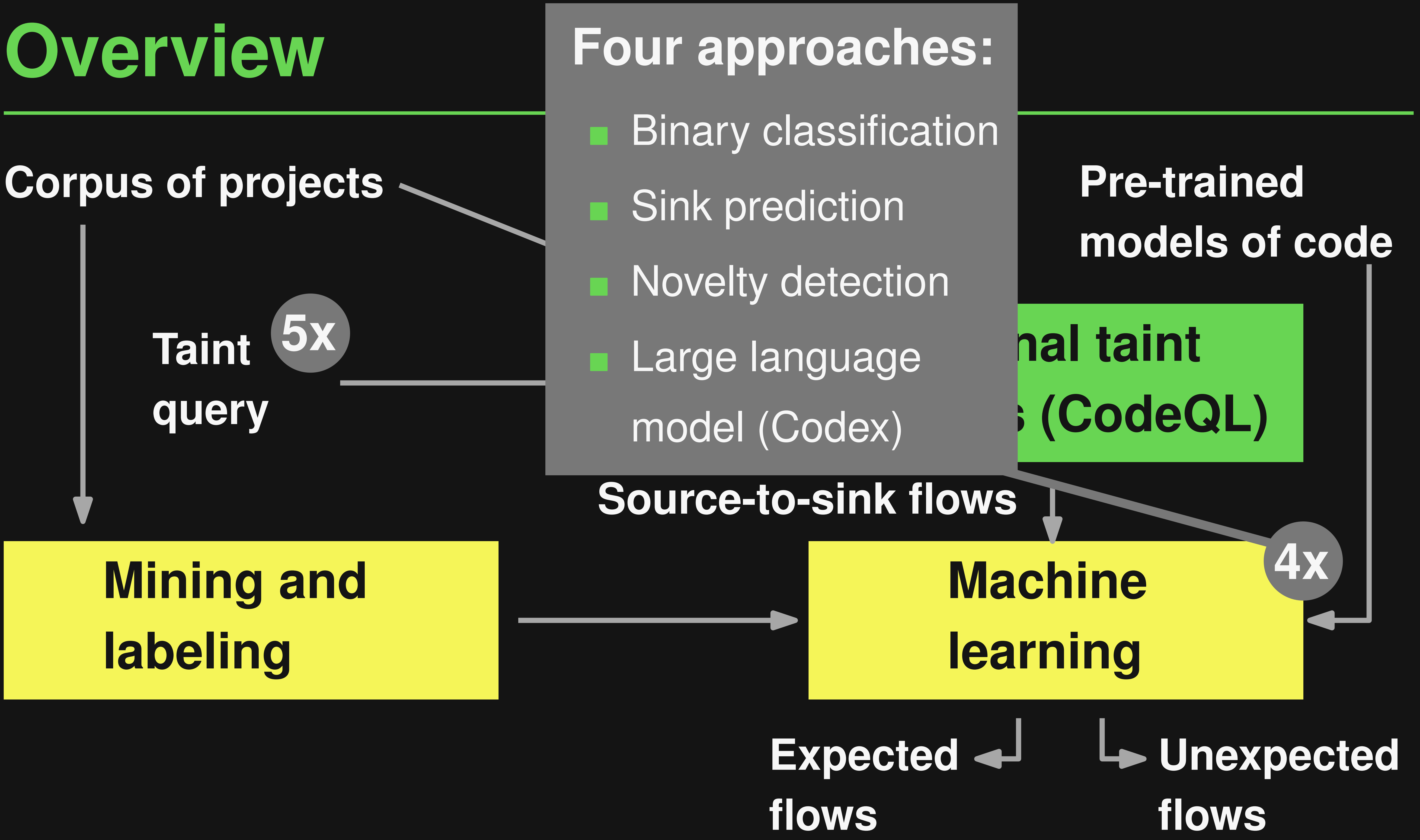
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Binary classification
Sink prediction
Novelty detection
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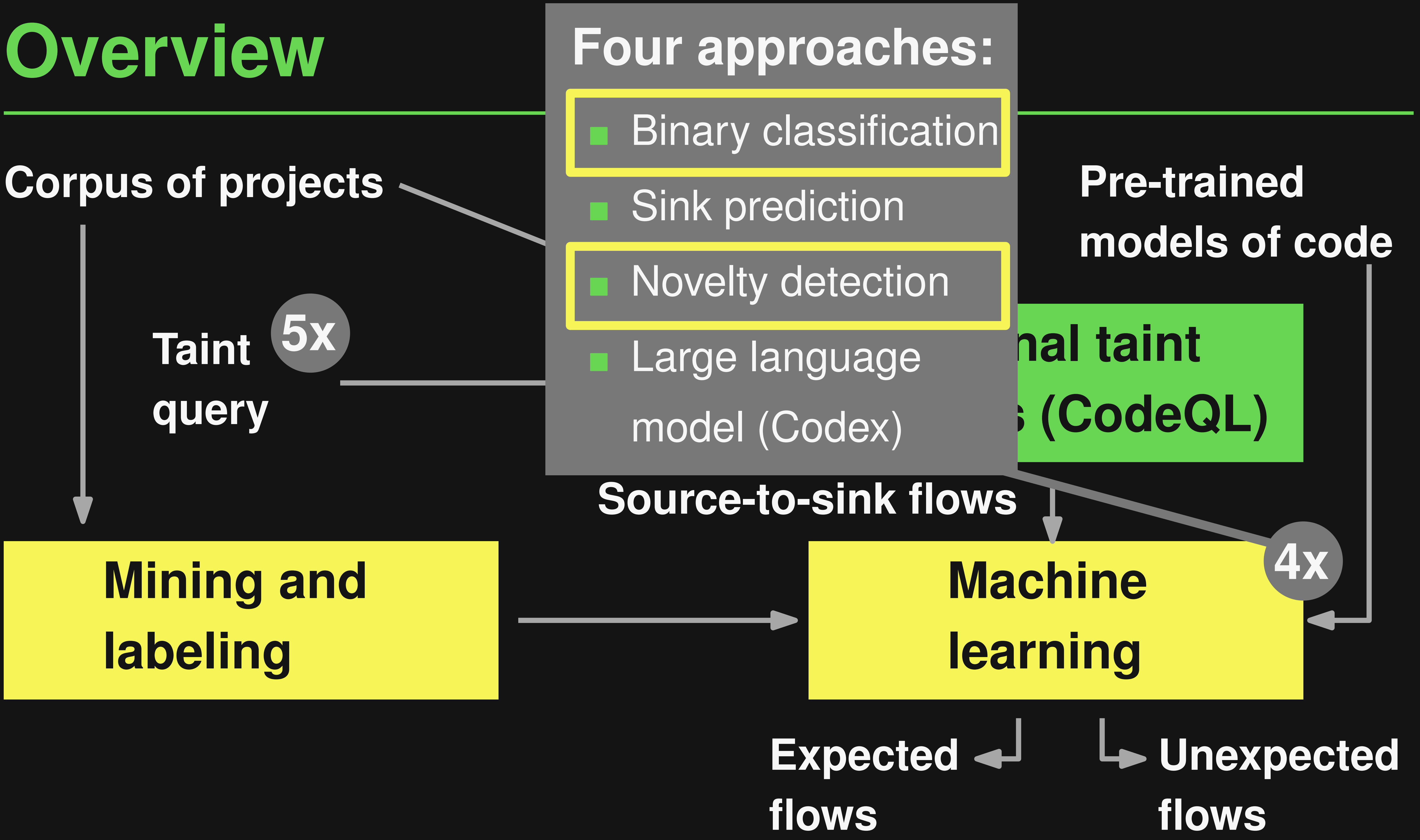

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Approach 1: Binary Classification

Goal: **Predict whether a flow is expected**

$$M : N \times N_{fct} \times D \rightarrow \{Expected, Unexpected\}$$

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Name of the source (e.g., parameter)

Name of the API function

Documentation of the API function

Approach 1: Binary Classification

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$$M : N \times N_{fct} \times D \rightarrow \{Expected, Unexpected\}$$

Model:

- Bi-directional RNN with LSTMs
- Input tokens embedded with pre-trained model
- Training data: 1,398 manually labeled examples (total across five taint queries)

Approach 3: Novelty Detection

- Goal: Predict whether a source/sink is unusual
- One-class support vector machine applied to embedded names of source/sink

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Sink type	Seed names
Integrity (names expected to flow to sink):	
Command injection	`execute`, `command`
Code injection	`eval`, `execute`, `compile`, `render`, `callback`, `function`, `fn`
Reflected XSS	`sent`, `content`
Path traversal	`file`, `directory`, `path`, `cwd`, `source`, `input`
Confidentiality (names not *expected to flow to sink):*	
Clear-text logging	`authkey`, `password`, `passcode`, `passphrase`

Evaluation

- **Datasets**
  - 250k JavaScript projects → 7.5M taint flows
  - SecBench.js [ICSE'23] → 131 known vulnerabilities
- **Baselines**
  - Simple, frequency-based approach
  - Regular expressions

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- **Baselines**
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- 1,398 manually labeled flows
- Validated by four external experts ($\alpha = 0.74$)

Ground truth

Effectiveness

How effective is Fluffy at identifying unexpected flows?

- 81%–97% precision and 80%–100% recall
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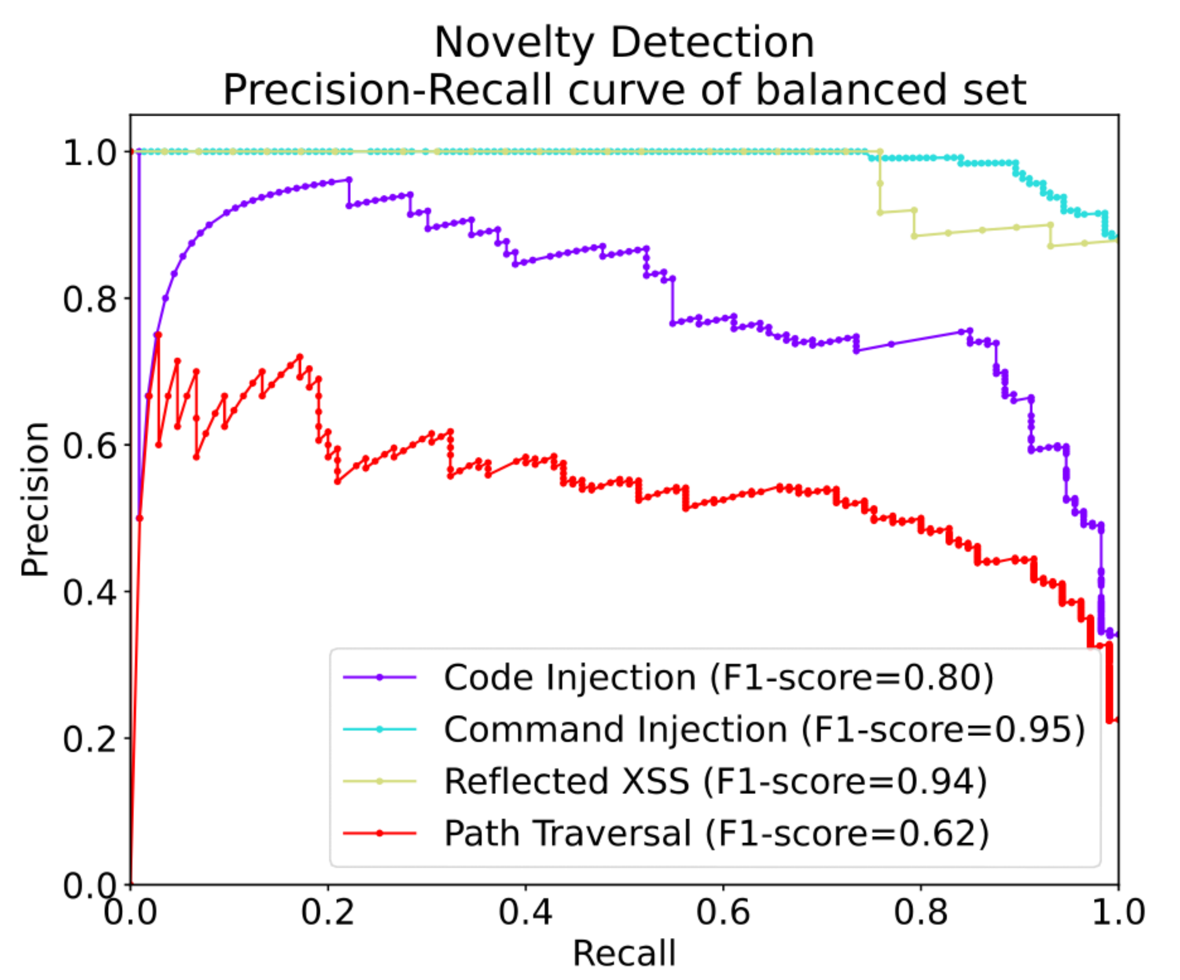

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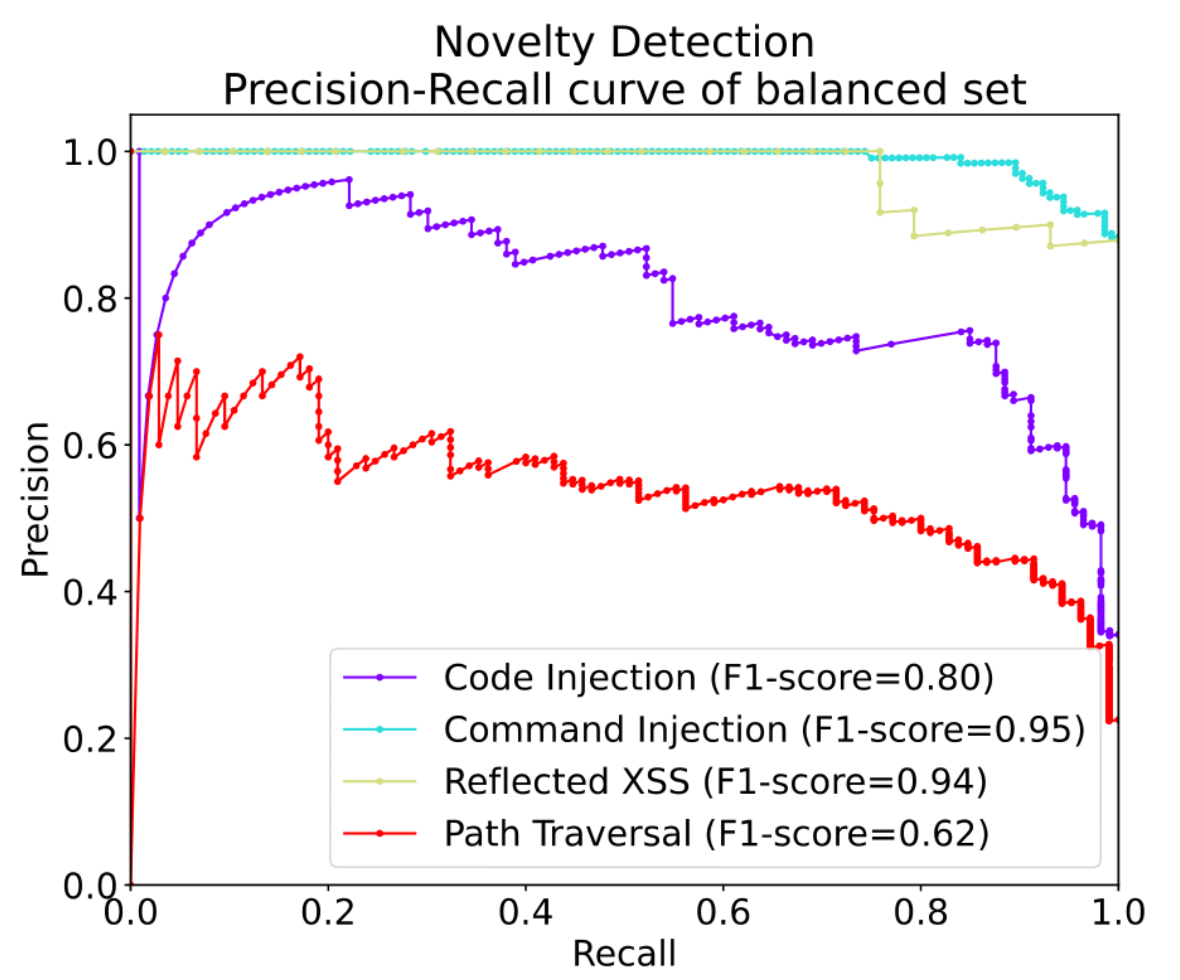

Effectiveness varies depending on taint query and ML model

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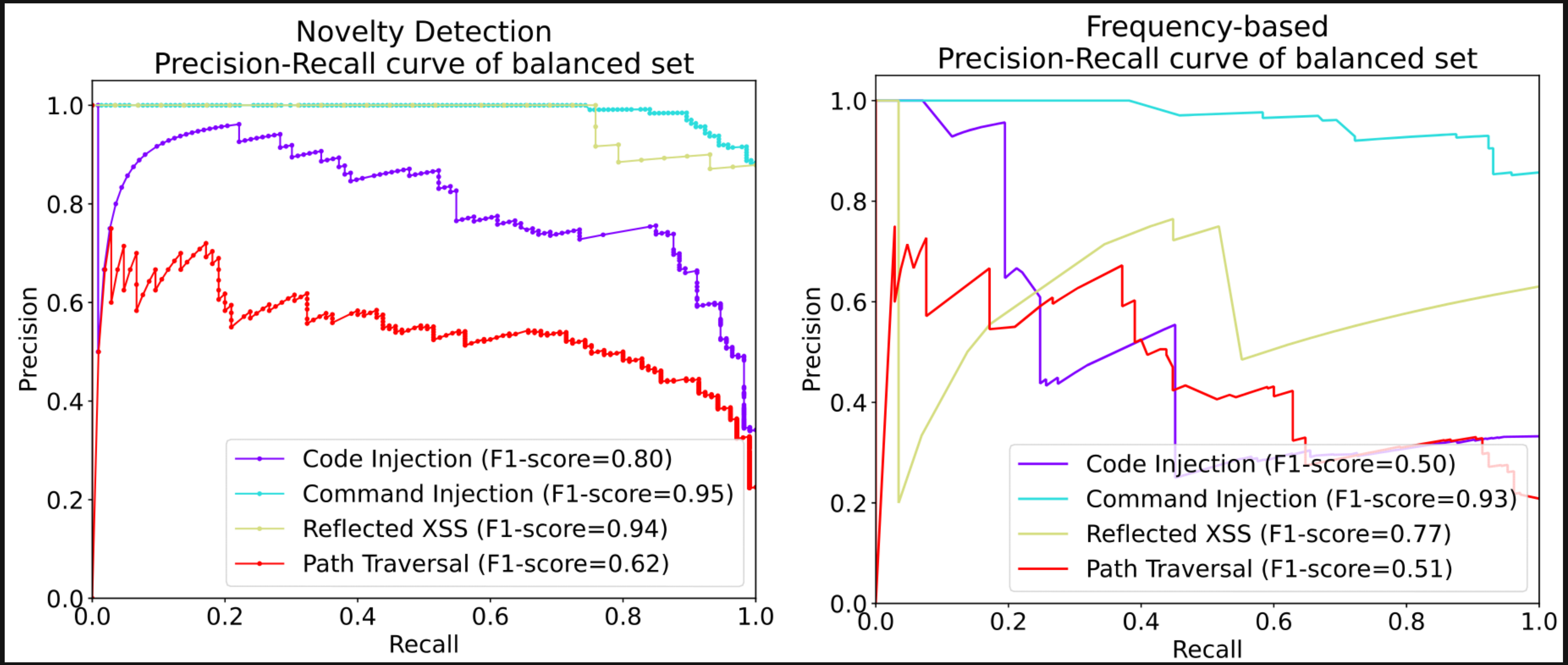

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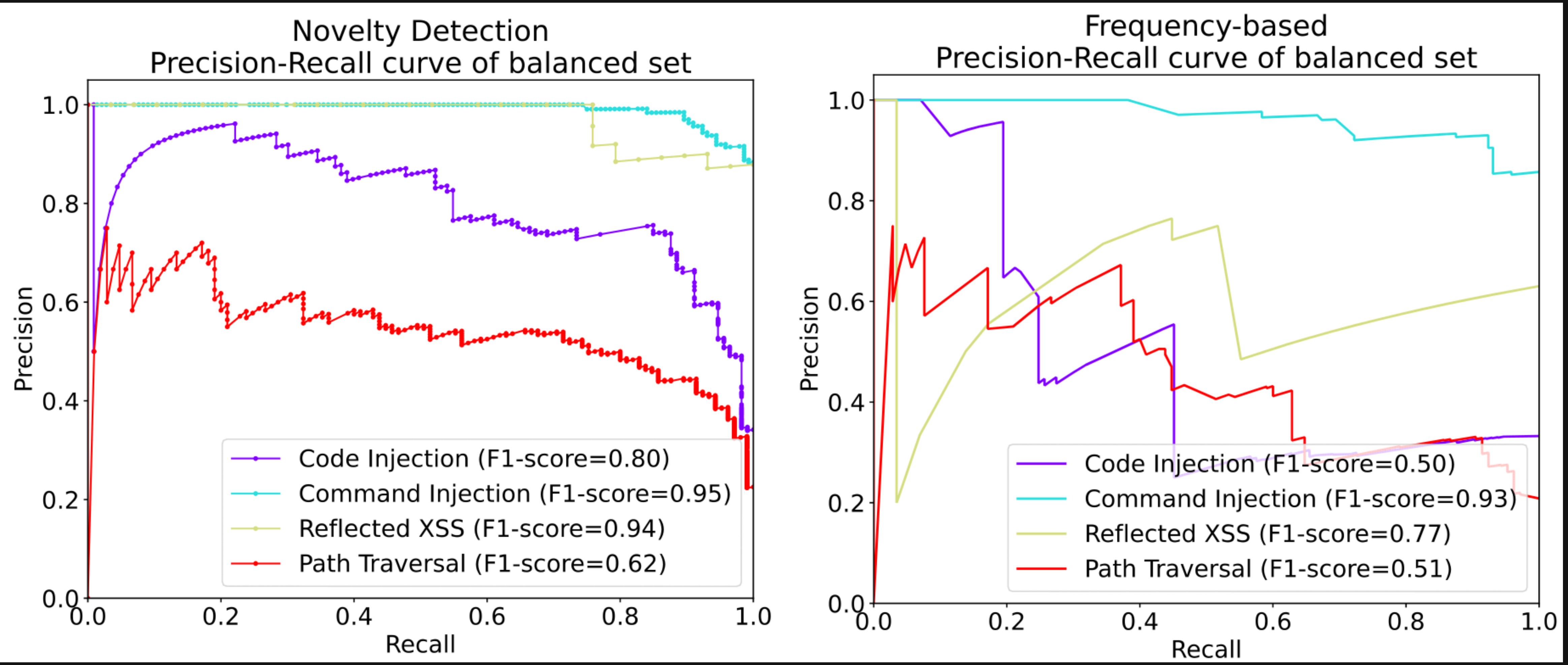
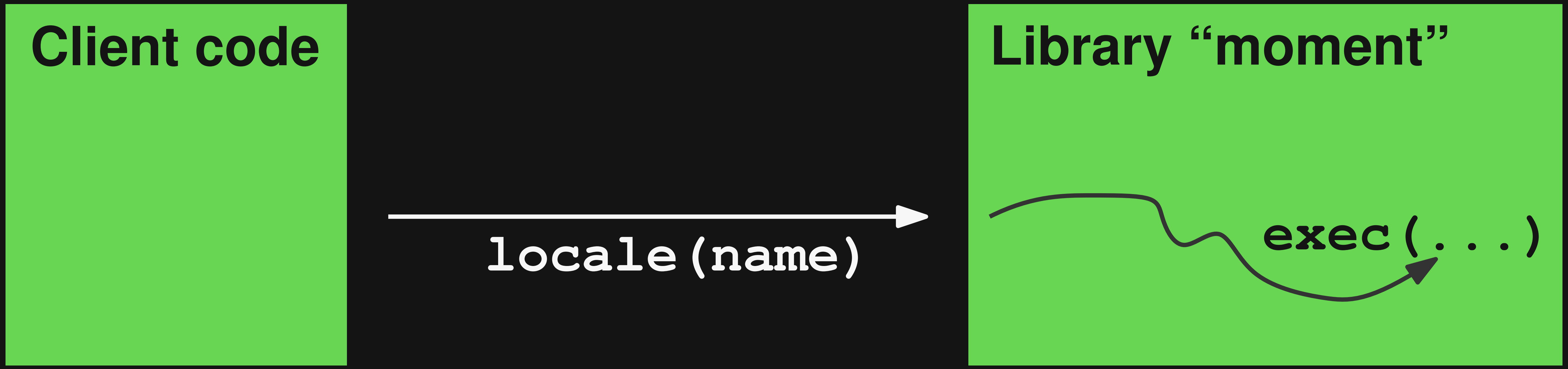


Fluffy outperforms the baseline

Real-World Vulnerabilities

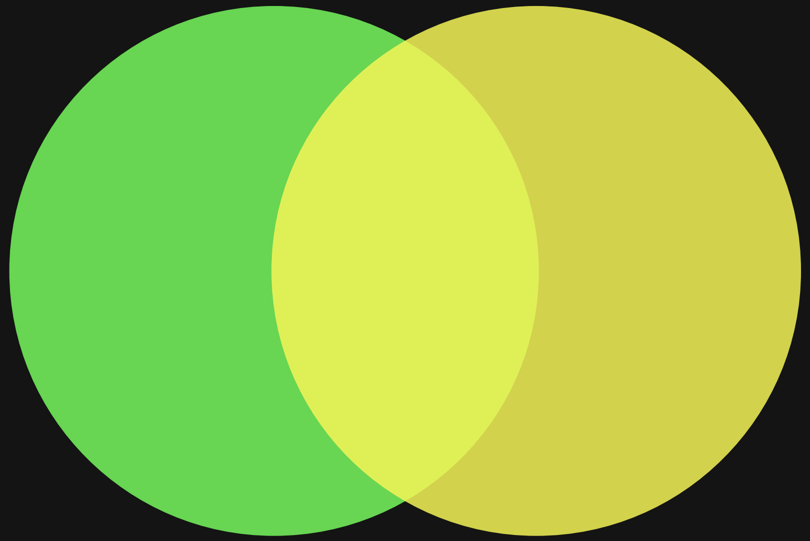
- **Found and reported 17 previously unknown vulnerabilities**
  - 10/17 confirmed and fixed so far
- **Example: CVE-2022-24785 in Moment.js**



Key Take-Aways

- **Bimodal program analysis**

Program analysis: Reason about PL semantics



Machine learning: Reason about NL embedded in code

- **Concrete application: Detecting unexpected taint flows**
  - Five kinds of vulnerabilities, four machine learning models
  - 81%–97% precision, 80%–100% recall
  - https://github.com/sola-st/fluffy