WATSON: Abstracting Behaviors from Audit Logs via Aggregation of Contextual Semantics

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1952

Security Incidents Are on The Rise Globally

TECH | TWITTER | CYBERSECURITY

Months later, the great Twitter hack still boggles my mind

Some of the biggest accounts in the world were made to tweet a bitcoin scam

By Jay Peters | @jaypeters | Dec 15, 2020, 11:45am EST

US & WORLD | TECH | HEALTH

1.5 million affected by hack targeting Singapore's health data

Local media say the hack is believed to be state-sponsored

By James Vincent | Jul 20, 2018, 6:48am EDT

SINGHEALTH PATIENTS' DATA STOLEN

WHAT DATA WAS TAKEN?

NAME, NRIC NUMBER, ADDRESS, GENDER, RACE AND DATE OF BIRTH OF 1.5 MILLION PATIENTS

RECORDS OF OUTPATIENT MEDICINE DISPENSED TO ABOUT 160,000 PATIENTS

WHAT DATA WAS NOT TAKEN?

DIAGNOSIS AND TEST RESULTS

DOCTORS' NOTES

RECORDS WERE NOT AMENDED OR DELETED

CHANNEL NEWSASIA

What happened? **Who** is affected? **How** to prevent?

Endpoint Monitoring Solutions

Endpoint monitoring solutions record **audit logs** for attack investigation

elastic splunk> LogRhythm

Audit logs:

- A history of events representing OS-level activities
- Provide visibility into security incidents with data provenance

type=SYSCALL msg=audit(**30/09/19 20:34:53**.383:98866813) : arch=x86_64
syscall=read exit=25 **a0=0x3** ppid=15757 **pid=30204** auid=junzeng sess=6309

⇩ Provenance Analysis

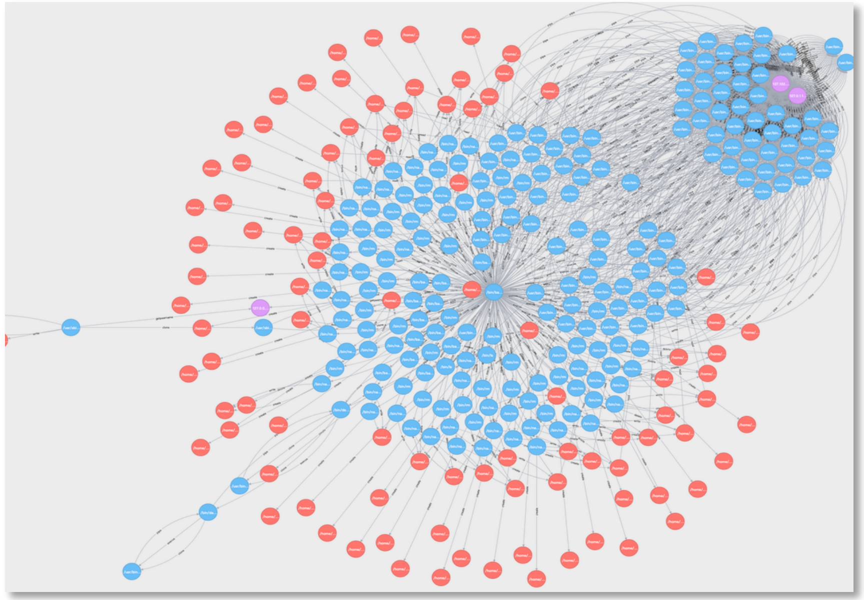
Investigation Using Audit Logs

Researchers use a **provenance graph** to navigate through audit logs:

- Nodes: system entities (e.g., process, file, and socket) & Edges: system calls
- **Backward/forward tracking** to find root cause of an attack and its ramifications

Real-world audit logs are always **large-Scale,** and provenance graphs are **Sophisticated!**

{"@timestamp":"2020-10-31T14:14:47.777Z","@metadata":{"beat":"auditbeat","type":"doc","version":"6.8.12"},"user":{"suid":"0","fsgid":"0","gid":"0","name_map":{"egid":"root","gid":"root","uid":"root","sgid":"root","suid":"root","auid":"yinfang","euid":"root","fsgid":"root","fsuid":"root"},"sgid":"0","uid":"0","euid":"0","egid":"0","fsuid":"0","auid":"1000"},"process":{"name":"sshd","exe":"/usr/sbin/sshd","pid":"18104","ppid":"1689"},"auditd":{"sequence":166719,"result":"success","session":"705","data":{"tty":"(none)","a3":"8","a0":"4","exit":"384","arch":"x86_64","syscall":"read","a2":"180","a1":"7ff97aeba120"}}}
{"@timestamp":"2020-10-31T14:14:47.777Z","@metadata":{"beat":"auditbeat","type":"doc","version":"6.8.12"},"user":{"auid":"1000","fsuid":"0","fsgid":"0","egid":"0","sgid":"0","suid":"0","uid":"0","euid":"0","name_map":{"fsgid":"root","sgid":"root","suid":"root","uid":"root","auid":"yinfang","egid":"root","euid":"root","fsuid":"root","gid":"root"},"gid":"0"},"process":{"pid":"18104","ppid":"1689","name":"sshd","exe":"/usr/sbin/sshd"},"auditd":{"data":{"a3":"8","a2":"180","arch":"x86_64","tty":"(none)","a0":"4","exit":"384","a1":"7ff97aeba120","syscall":"read"},"sequence":166720,"result":"success","session":"705"}}
{"@timestamp":"2020-10-31T14:14:47.777Z","@metadata":{"beat":"auditbeat","type":"doc","version":"6.8.12"},"user":{"egid":"0","auid":"1000","fsgid":"0","name_map":{"euid":"root","fsuid":"root","gid":"root","sgid":"root","auid":"yinfang","fsgid":"root","suid":"root","uid":"root","egid":"root"},"suid":"0","euid":"0","uid":"0","sgid":"0","fsuid":"0","gid":"0"},"process":{"name":"sshd","exe":"/usr/sbin/sshd","pid":"18104","ppid":"1689"},"auditd":{"sequence":166721,"result":"success","session":"705","data":{"a1":"7ff97aeba120","arch":"x86_64","a3":"8","exit":"384","syscall":"read","a2":"180","a0":"4","tty":"(none)"}}}



Related Work

- Scale up provenance analysis:
  - Data reduction [NDSS'16, 18 …] & Query system [Security'18, ATC'18 …]
  - Recognizing behaviors of interest requires intensive manual efforts

A semantic gap between low-level events and high-level behaviors

- Apply expert-defined specifications to bridge the gap
  - Match audit events against domain rules that describe behaviors
  - Query graph [VLDB'15, CCS'19], Tactics Techniques Procedures (TTPs) specification [SP'19,20], and Tag policy [Security'17,18]

Behavior-specific rules heavily rely on domain knowledge (**time-consuming)**

Related Work

- Scale up provenance analysis:
  - Data reduction [NDSS'16, 18 ...] & Query system [Security'18, ATC'18 ...]

How can we

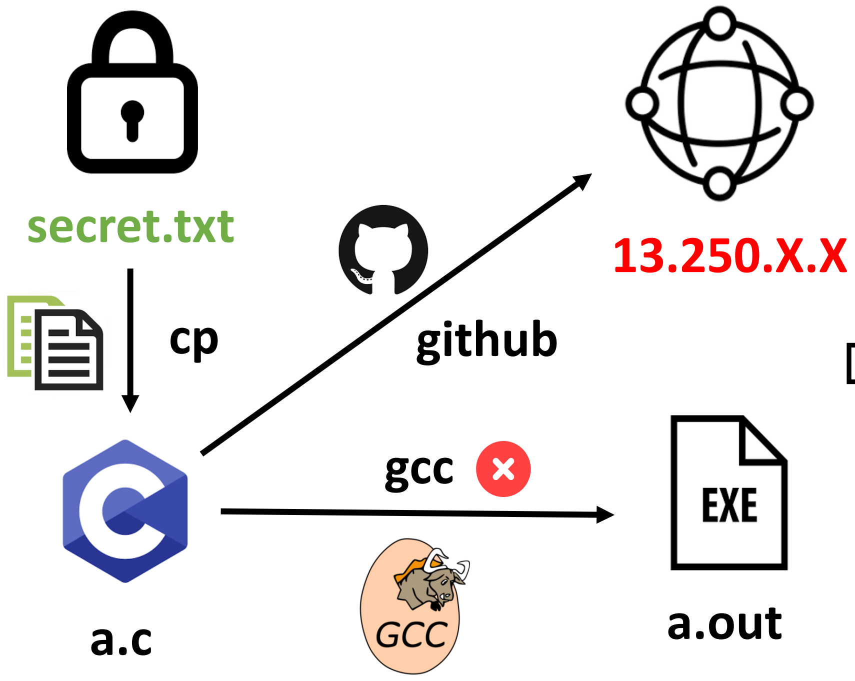
- **abstract** high-level behaviors from low-level audit logs?
- **cluster** similar behaviors to assist human investigation?

  - Query graph [VLDB'15, CCS'19], Tactics Techniques Procedures (TTPs) specification [SP'19,20], and Tag policy [Security'17,18]

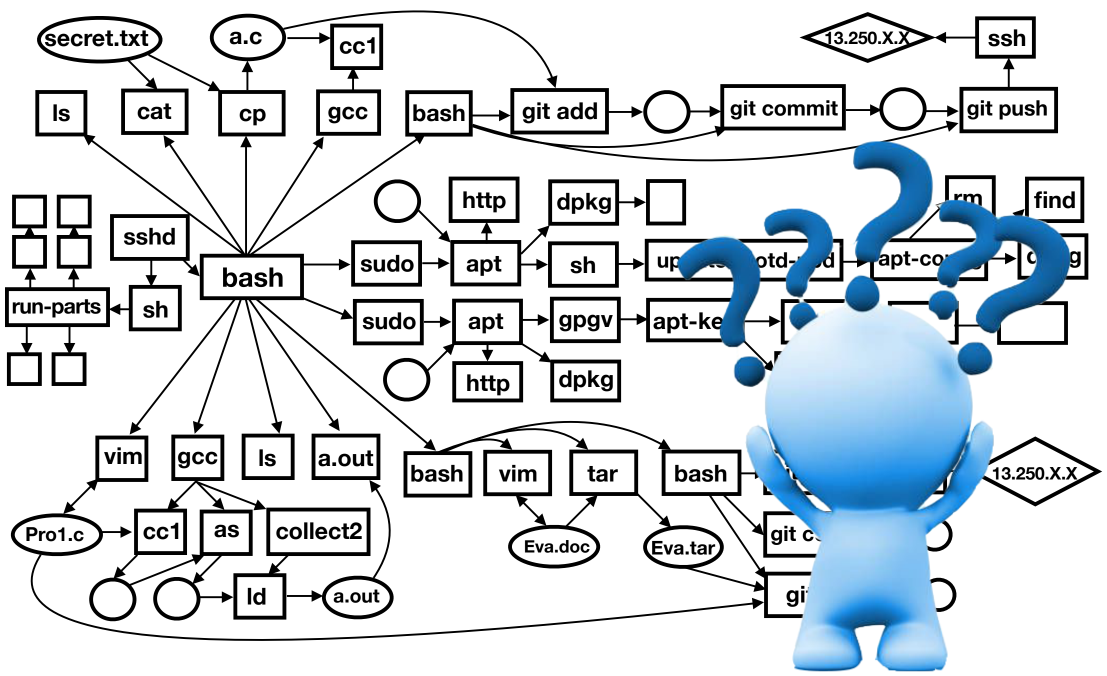
Behavior-specific rules heavily rely on domain knowledge (**time-consuming**)

Motivating Example

Attack Scenario: A software tester exfiltrates sensitive data that he has access to



Data Exfiltration Steps



Motivating Example Logs

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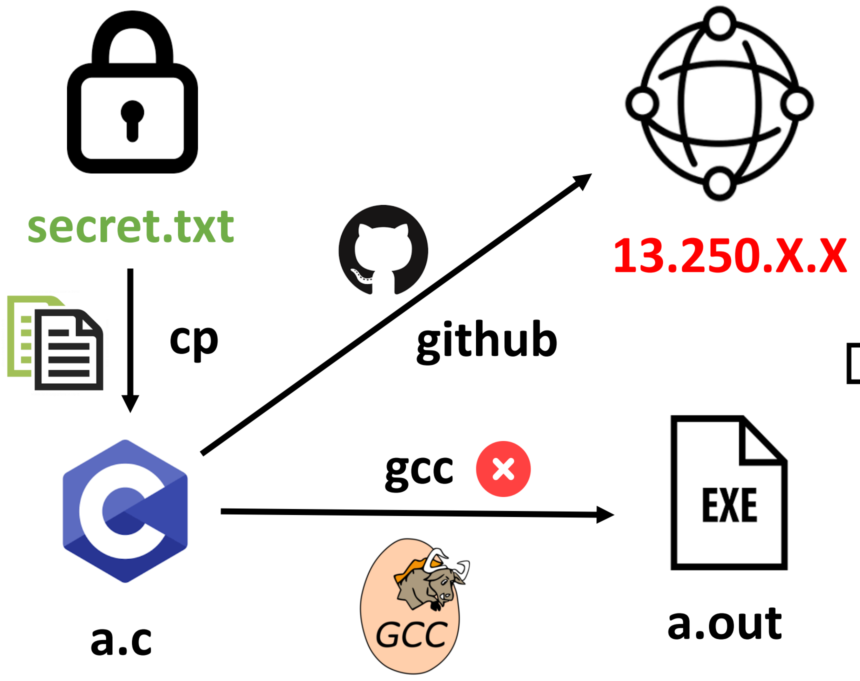
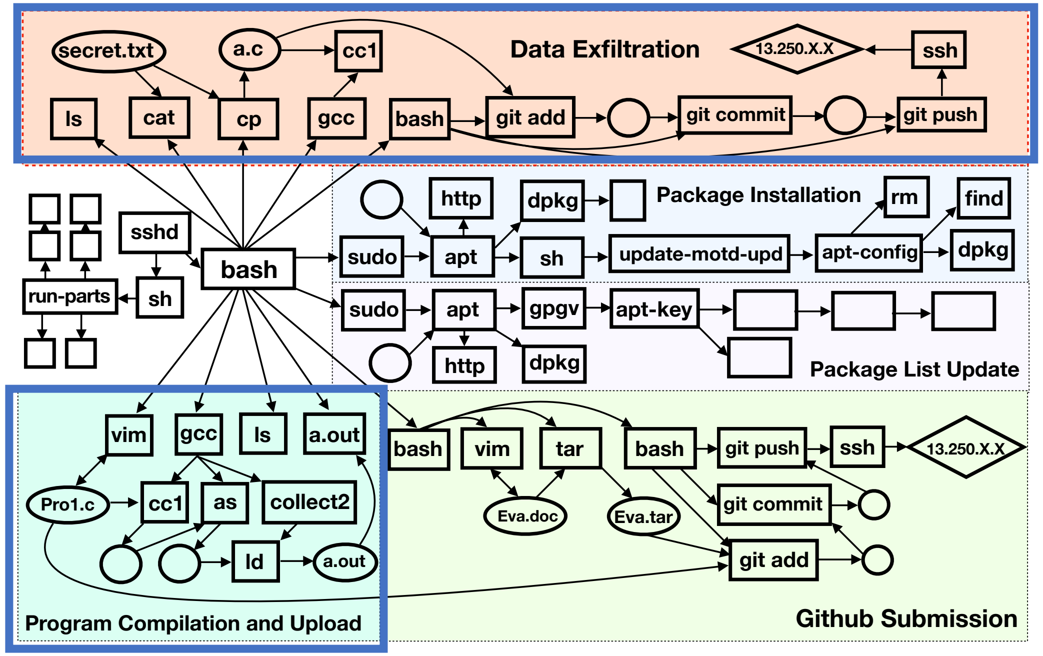


Data Exfiltration Steps

Data Exfiltration



Program Compiling and Upload (cluster)

Motivating Example Logs

Challenges for Behavior Abstraction

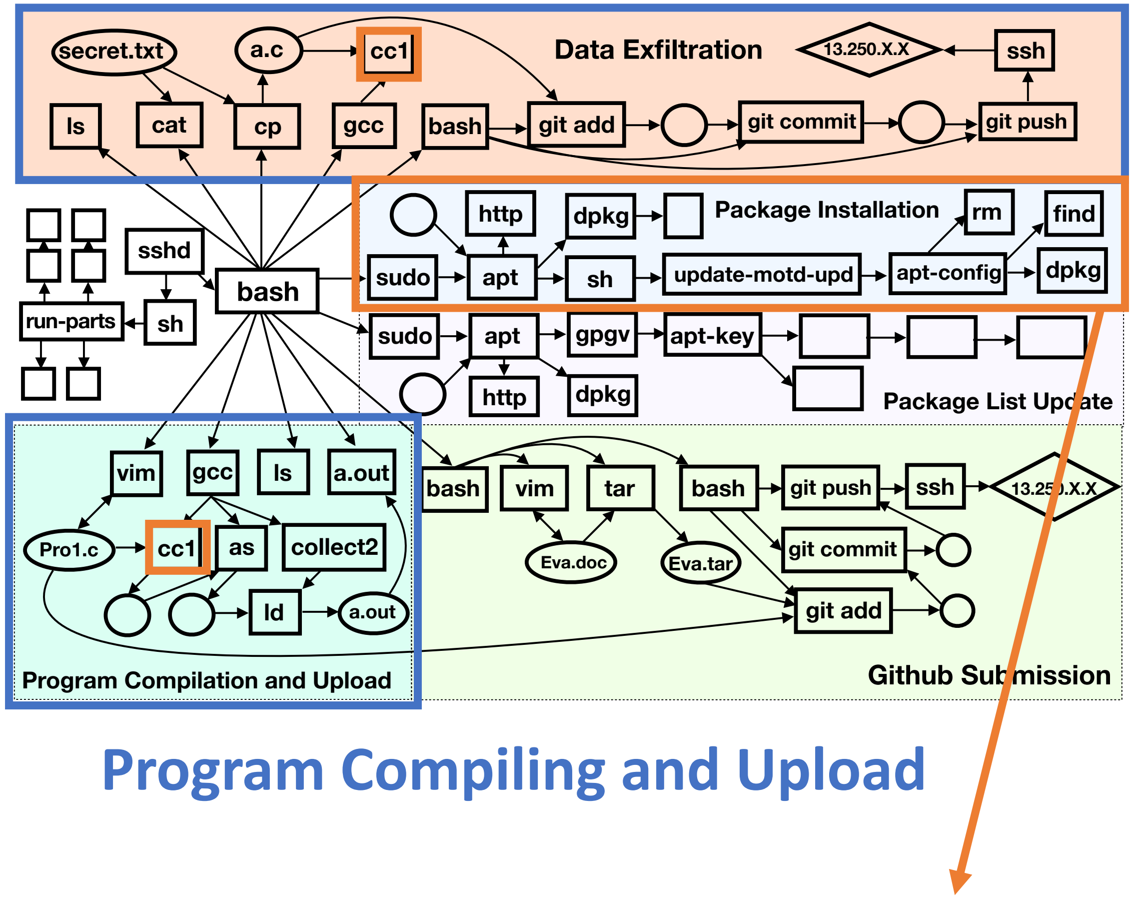
Event Semantics Inference:

- Logs record **general-purpose** system activities but lack knowledge of **high-level semantics**

Individual Behavior Identification:

- The volume of audit logs is **overwhelming**
- Audit events are **highly interleaving**

Data Exfiltration

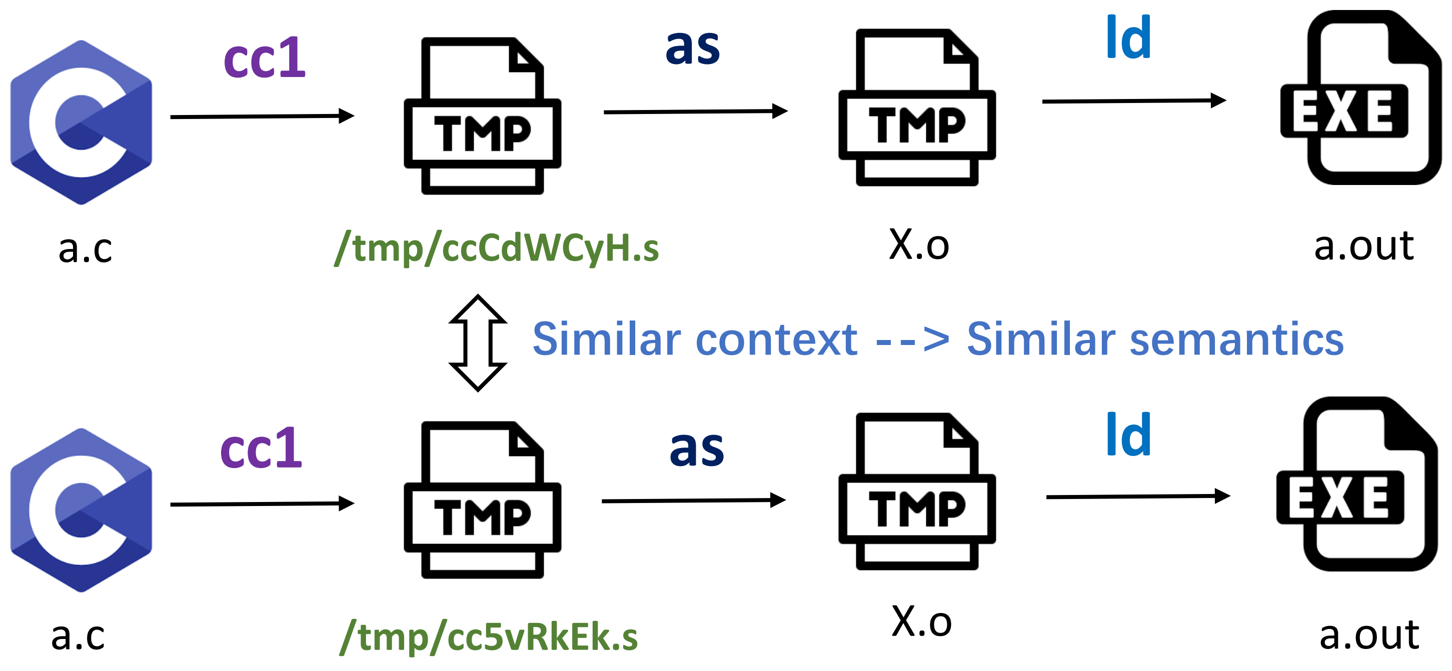


Program Compiling and Upload

Package Installation Events > 50,000

Our Insights

How do analysts manually interpret the semantics of audit events?



Compiling program using GCC

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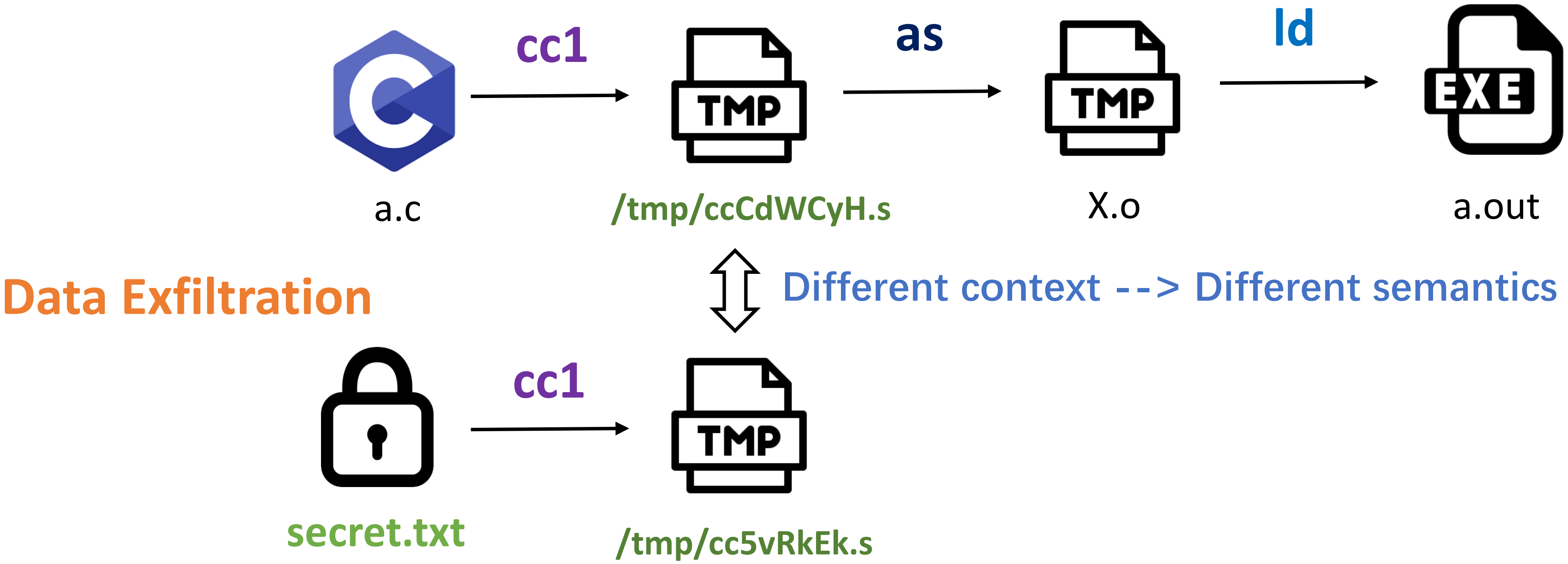
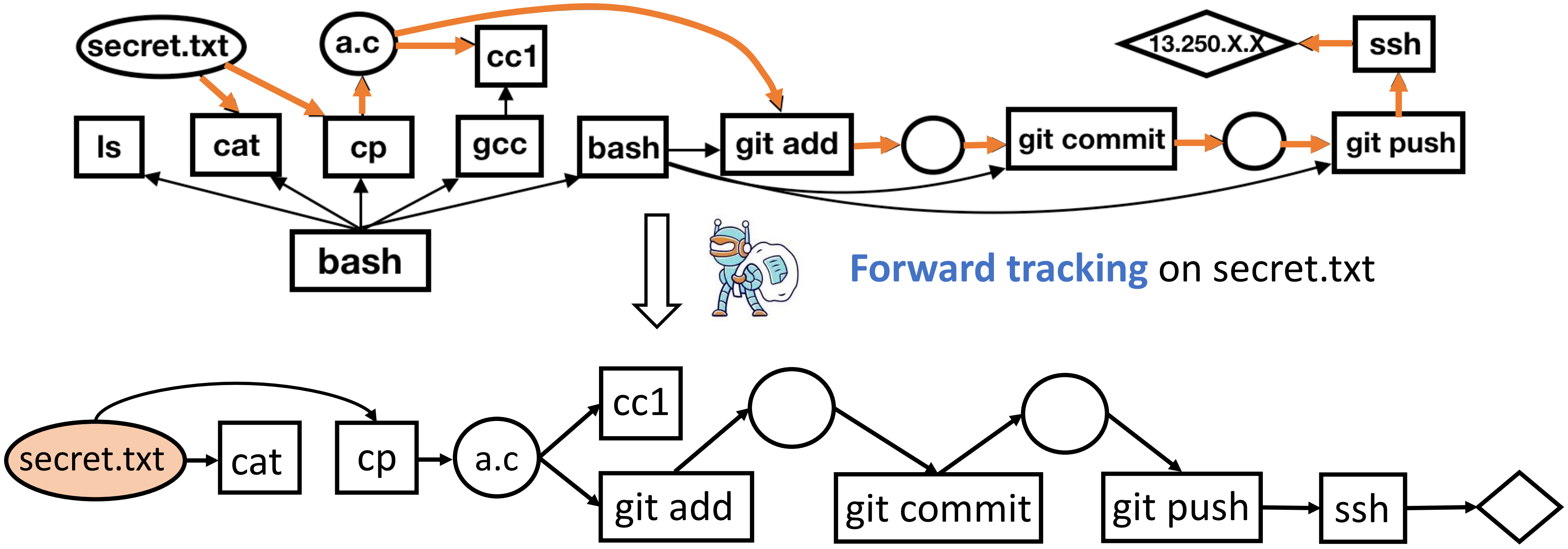


Compiling program using GCC

Reveal the semantics of audit events from their usage **contexts** in logs

Our Insights

How do analysts manually identify behaviors from audit events?



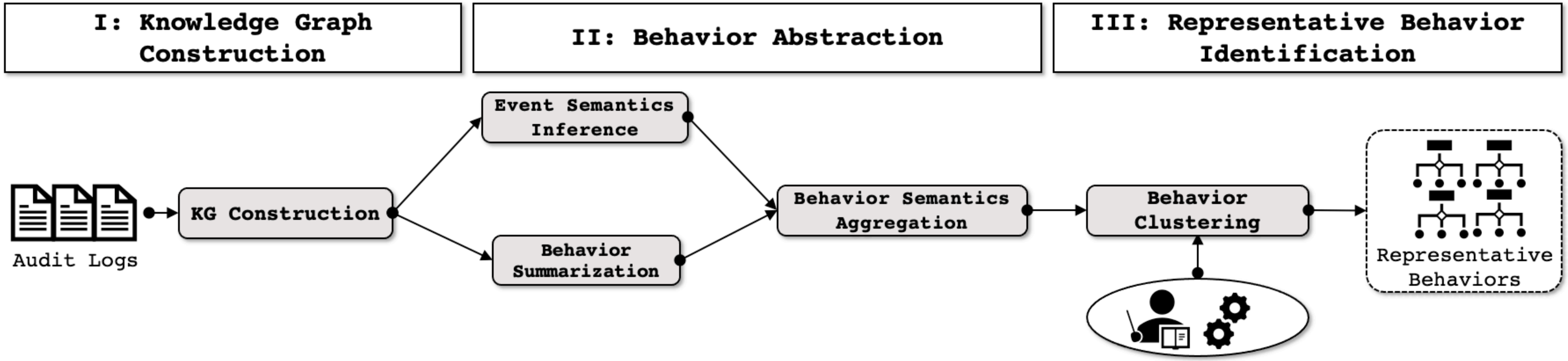
Data Exfiltration Behavior

Summarize behaviors by tracking **information flows** rooted at **data objects**

WATSON

An automated behavior abstraction approach that **aggregates the semantics of audit logs to model behavioral patterns**

- Input: audit logs (e.g., Linux Audit[1])
- Output: representative behaviors



[1] Linux Kernel Audit Subsystem. https://github.com/linux-audit/ audit-kernel.

Knowledge Graph Construction

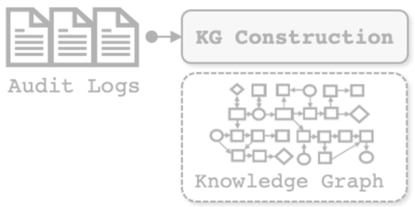
We propose to use a **knowledge graph** (KG) to represent audit logs:

- KG is a directed acyclic graph built upon triples
- Each triple, corresponding to an audit event, consists of three elements (head, relation, and tail):

$$\mathcal{KG} = \{(h, r, t) | h, t \in \{Process, File, Socket\}, r \in \{Syscall\}\}$$

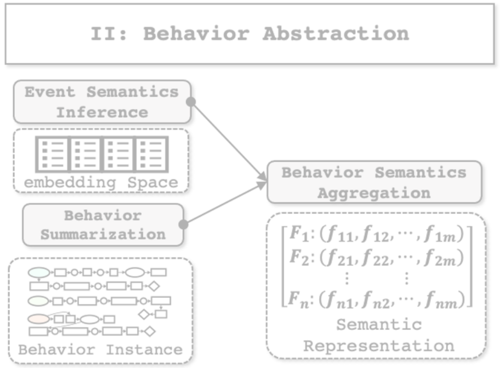
- KG unifies **heterogeneous** events in a **homogeneous** manner

I: Knowledge Graph Construction



Event Semantics Inference

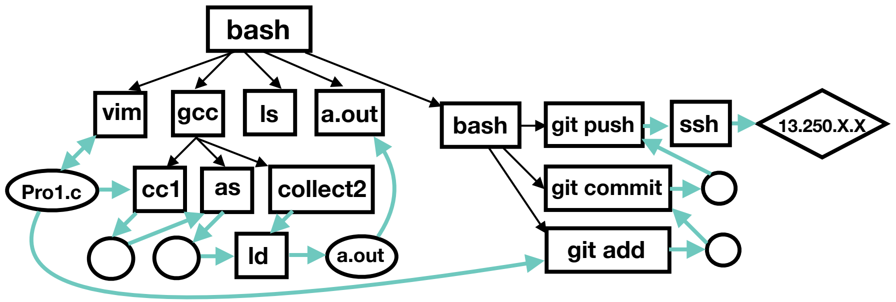
- Suitable **granularity** to capture contextual semantics
  - Prior work [CCS'17] studies log semantics using events as basic units.
  - Lose contextual information within events
  - Working on **Elements** (head, relation, and tail) preserves more contexts
- Employ an embedding model to extract contexts
  - Map elements into a vector space
  - Spatial distance represents semantic similarities
  - **TransE:** a translation-based embedding model
  - **Head + Relation ≈ Tail → Context decides semantics**



Behavior Summarization

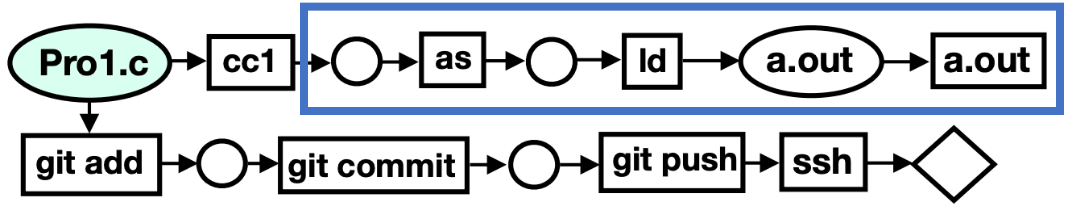
Individual behavior identification: Apply an adapted depth-first search (DFS) to track information flows rooted at a data object:

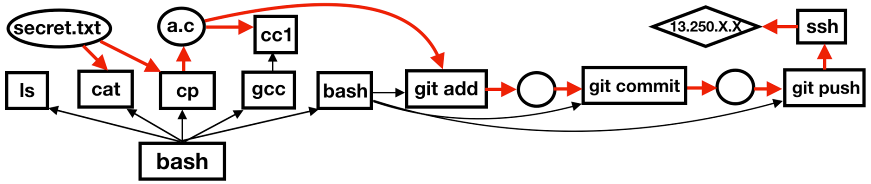
- Perform the DFS on every data object except libraries
- Two behaviors are merged if one is the subset of another



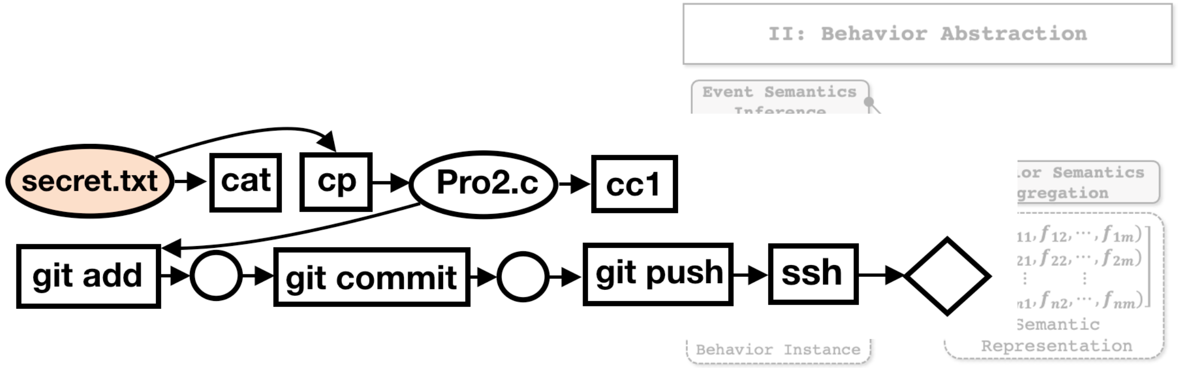
Program Compiling and Upload

Different!





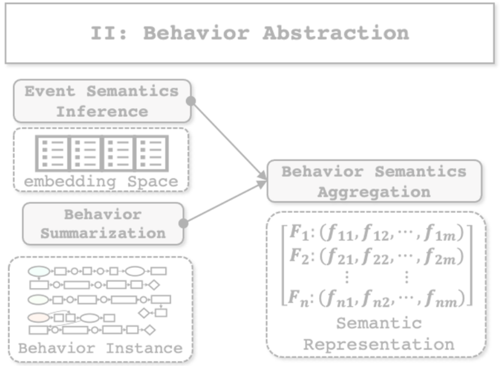
Data Exfiltration



Behavior Semantics Aggregation

- How to aggregate event semantics to represent behavior semantics?
  - Naïve approach: Add up the semantics of a behavior’s constituent events
  - Assumption: audit events equally contribute to behavior semantics

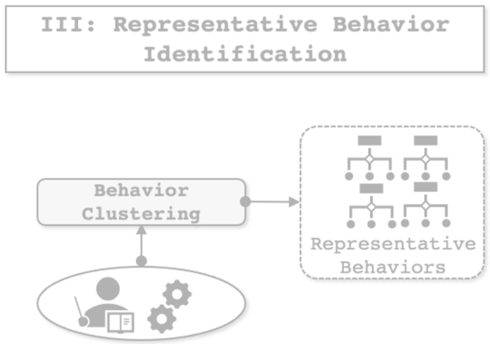
- **Relative event importance**
  - Observation: behavior-related events are common across behaviors, while behavior-unrelated events the opposite
  - Apply frequency as a metric to define event importance
  - Quantify the frequency: **Inverse Document Frequency (IDF)**
- The presence of **noisy events**
  - Redundant events [CCS’16] & Mundane events



Representative Behavior Identification

- Cluster semantically similar behaviors: **Agglomerative Hierarchical Clustering analysis (HCA)**

- Extract the most representative behaviors
  - Representativeness: Behavior's average similarity with other behaviors in a cluster
  - **Analysis workload reduction**: Do not go through the whole behavior space



Evaluation

- **Experimental Setup:**
  - Simulated dataset: **275,863,292** events in 4,280 SSH sessions
  - DARPA Trace Dataset[2]: **726,072,596** events in 211 graphs

- **Behavior Abstraction Accuracy:**
  - Can WATSON cluster similar behaviors?
- **Event Semantics Explicability:**
  - Does inferred event semantics match our domain knowledge?
- **Efficacy in Attack Investigation:**
  - How many manual efforts can WATSON save?

[2] Transparent Computing Engagement 3 Data Release. https://github.com/ darpa-i2o/Transparent-Computing/blob/master/README-E3.md

Behavior Abstraction Accuracy

Use vector-representation semantics of behaviors to predict SSH sessions with similar behaviors:

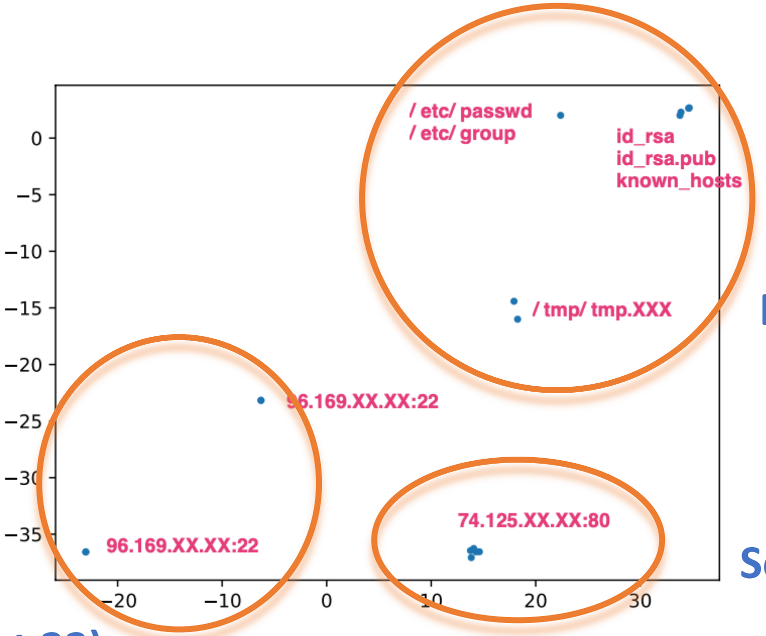
- 17 daily routines and 8 real-life attacks
- Extensive noisy behaviors

Behavior	Recall	Precision	F1
Package Installation	95.3%	97.9%	96.6%
Data Theft	100%	100%	100%
…	…	…	…
Average	94.2%	92.8%	**92.8%**

High F1 score on both benign and malicious behavior abstraction

Event Semantics Explicability

Use t-SNE to project the embedding space (64 dimensional in our case) into a 2D-plane, giving us an intuition of embedding distribution

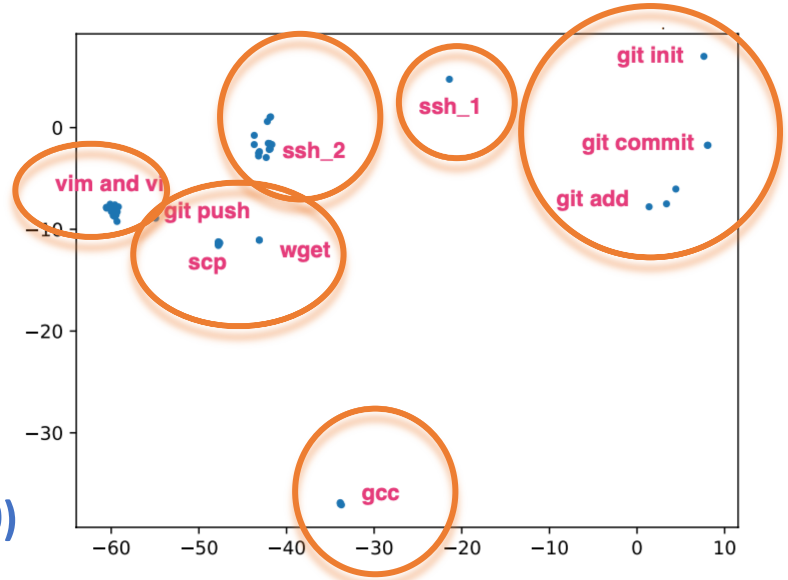


Files

Socket (port 80)

Socket (port 22)

(a) 25 data object embeddings



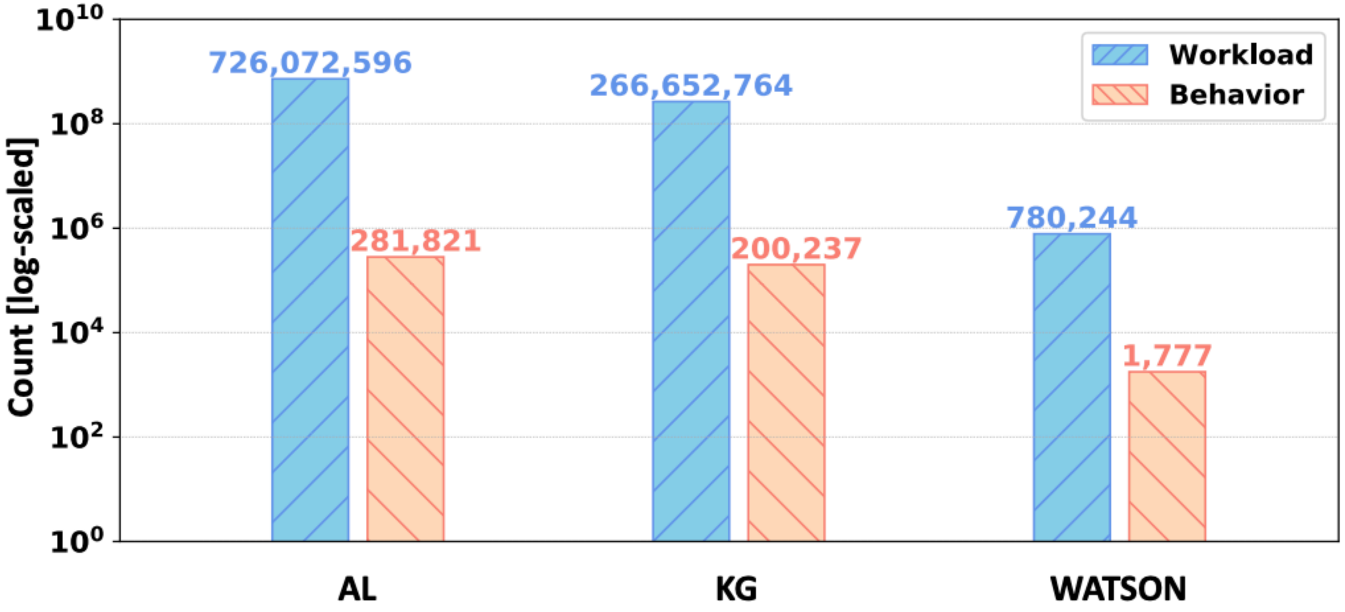
(b) 53 Program embeddings

Semantically similar system entities are clustered in the embedding space

Efficacy in Attack Investigation

Measure the **analysis workload reduction** of APT attack investigation in the DARPA TRACE dataset:

- Analysis workload: the number of events to recognize all behaviors



Two orders of magnitude reduction in analysis workload and behaviors

Summary

- We propose WATSON to
  - Abstract behaviors from audit events
  - Cluster semantically similar behaviors
- Insights
  - Infer audit event semantics by usage contexts
  - Identify behaviors with information flows rooted at data objects
- Evaluation
  - Substantially reduce analysis workload
  - High F1 score on behavior abstraction

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Thanks!

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