black hat BRIEFINGS

AUGUST 6-7, 2025
MANDALAY BAY / LAS VEGAS

FACADE

High-Precision Insider Threat Detection Using Contrastive Learning

Alex Kantchelian
Google

Elie Bursztein
Google DeepMind

with **Casper Neo**, **Ryan Stevens**, **Sadegh Momeni**, **Birkett Huber**, **Yanis Pavlidis** and **many** other Googlers

SCAN ME

Presentation slides:

https://elie.net/facade

10 billion+

events processed annually to protect Google from insider threats

Insider attacks threat model

Intentional

attack by a rogue employee

Unwilling

attack by a deceived or coerced employee

Accidental

harm by a well intentioned employee

Example of insider threats

Intentional	access of confidential documents without business justification through access permissions abuse
Unwilling	access made using an employee account compromised by a malware
Accidental	share confidential documents with external party without NDA in good faith

Why detecting insider attacks is hard

Very low incidence

Insider threat incidence events are extremely low volume

Heavily context dependent

Risk depends on user roles and their relations to the resources accessed

Wide attack surface

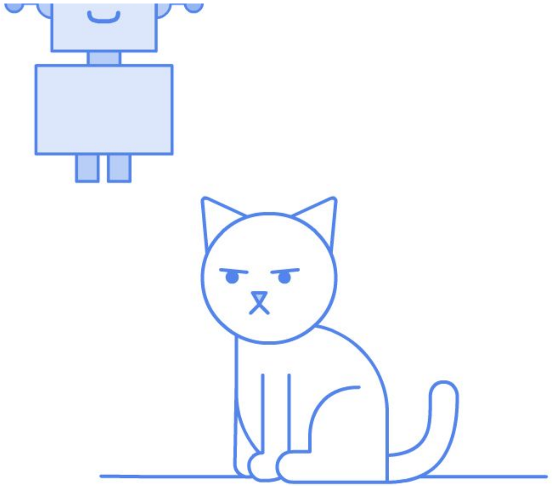
Insider attackers have broad access to the enterprise infrastructure via legitimate credentials low false alerts

FACADE: A High-Precision Insider Threat Detection Using Deep Contextual Anomaly Detection

Deep learning model

User and resource aware

How likely is the acces?



Highly accurate anomaly detection? Really?

Red Team attacks ranked in the top 0.01% of suspicious events and many red team attackers in the top-10 most suspicious users during the attack period, with 10+ millions events ranked by FACADE during that timespan.

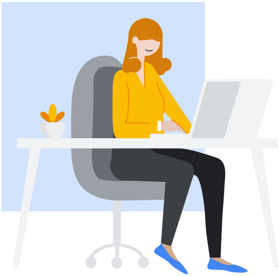
Agenda

- FACADE Overview
- Featurization of Resources and Users
- Scoring Arbitrary Time Periods
- Finding Insider Attacks with FACADE

FACADE Overview

Problem formulation

Is it normal for a given user to access a given resource?



TPU schematics

Normal pattern

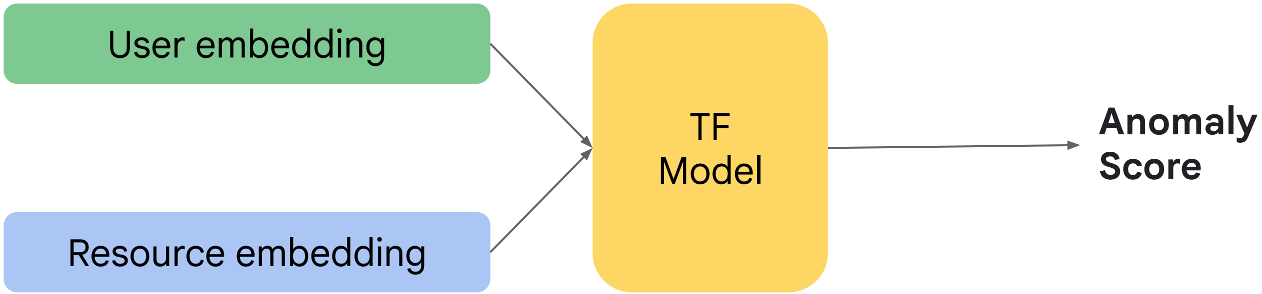
Legitimate user
Hardware division

TPU schematics

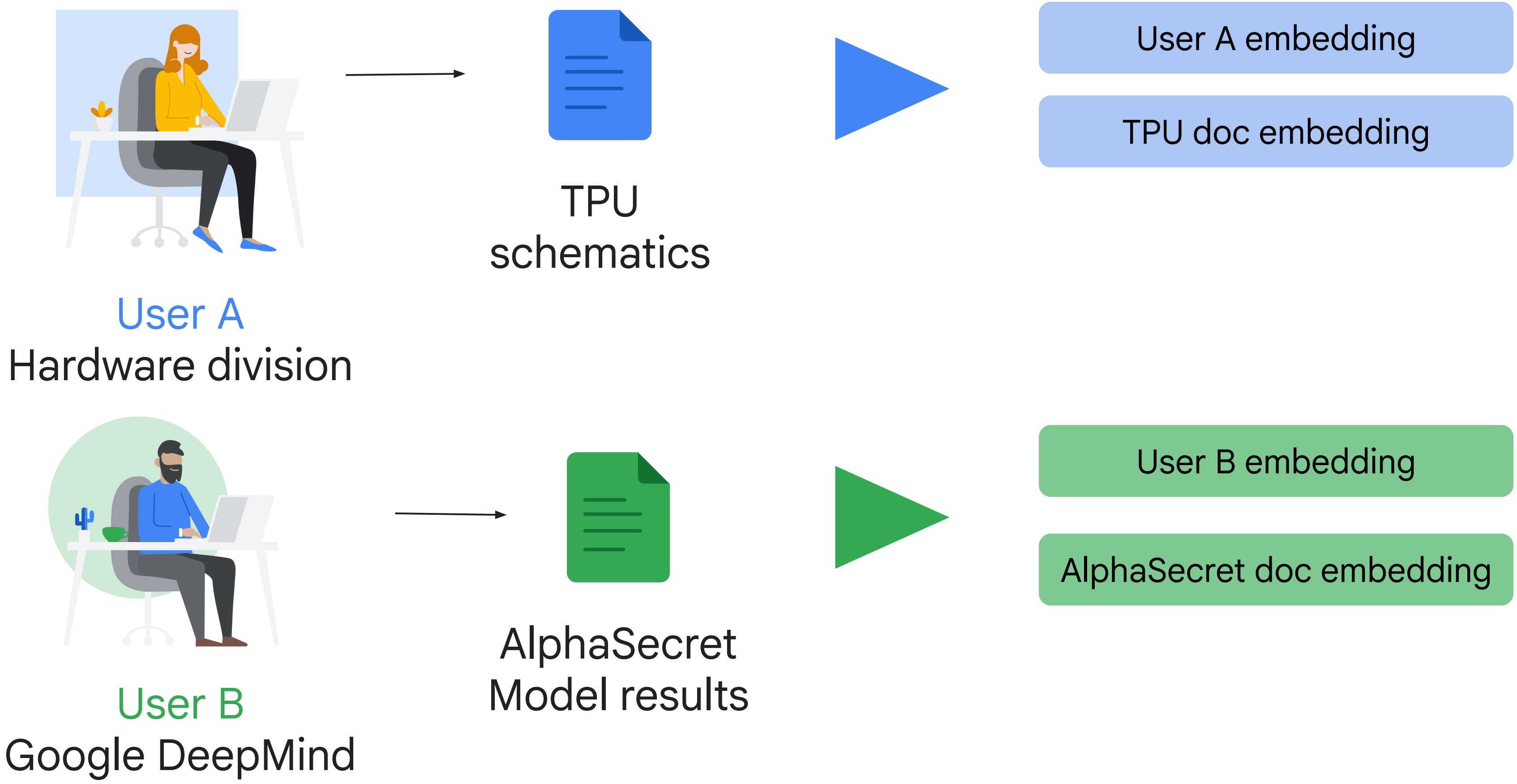
Abnormal pattern

Rogue actor
Ads Sales

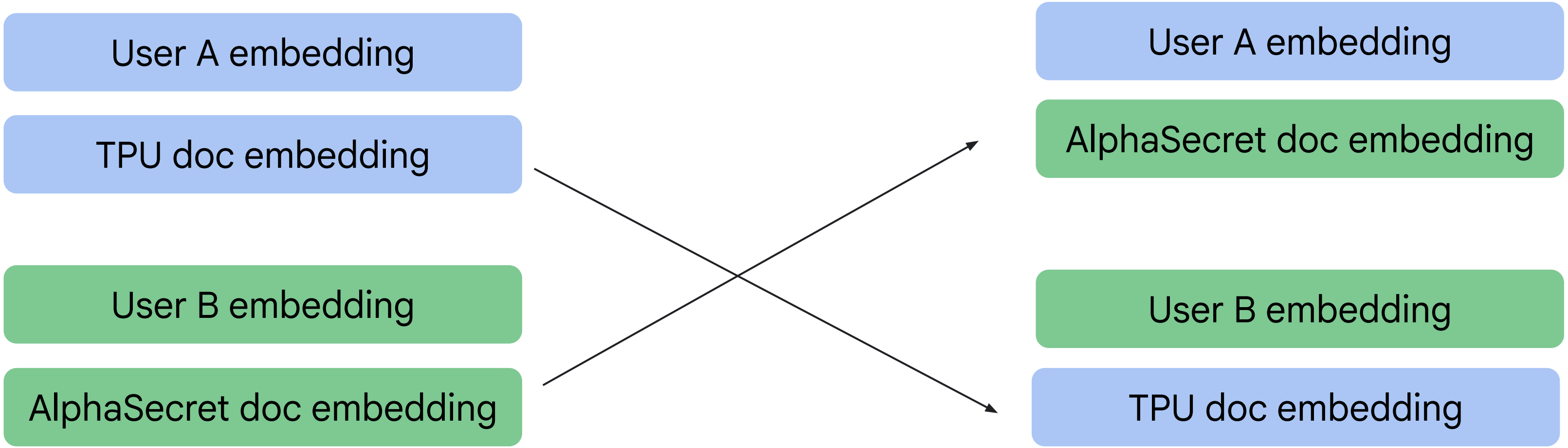
FACADE model architecture



How do we train such model with little to no insider attack examples?


User A
Hardware division
TPU
schematics
User A embedding
TPU doc embedding
User B
Google DeepMind
AlphaSecret
Model results
User B embedding
AlphaSecret doc embedding

Unsupervised Training dataset construction



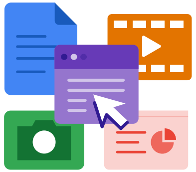
Normal behavior examples

Abnormal behavior examples

Featurization of Resources and Users

Featurization of Resources

Resource Featurization Challenges



Must handle massive, heterogeneous resources
billions of distinct items
document, spreadsheet, video, data table, RPC endpoint, URL, ...

Content-based features are impractical
case-by-case development & maintenance cost
computationally expensive at inference time

Large distribution drift
new resources at inference time *is the norm*, e.g., documents
inherent difficulty in predicting appearance of novel topics in content

How to turn the open space of resources into a dense representation suitable to deep-learning training?

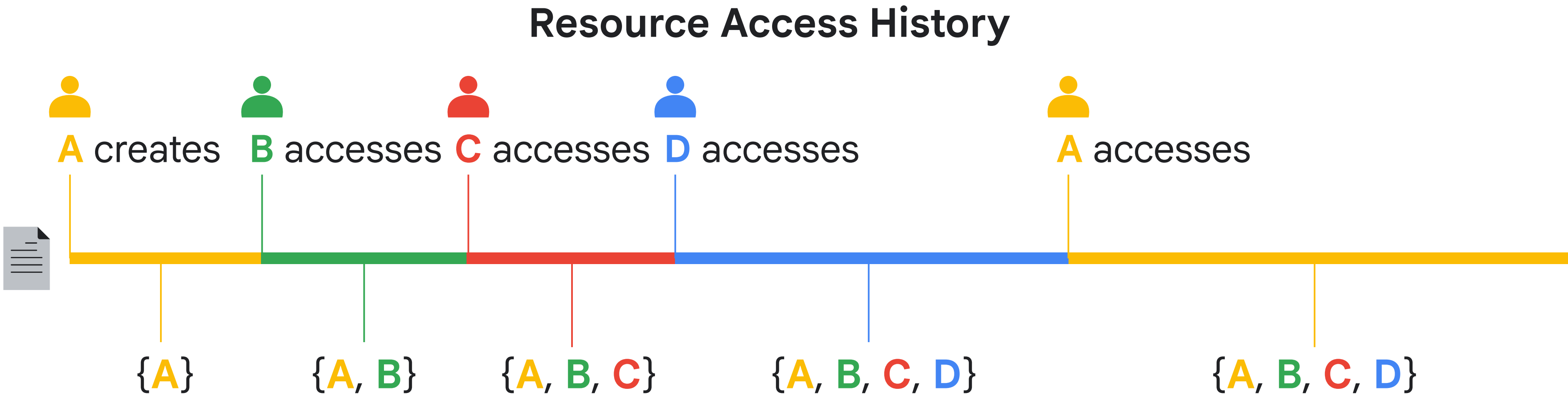
Intuition

If the following held, could treat resource as categorical feature:
the set of resources is mostly constant
the set of resources is not too large
each resource keeps a stable meaning throughout its existence

Idea: project resources into a more stable set of opaque identifiers
the set of user ids on a corporate system is a good candidate

History-based Featurization
Bag-of-words of user ids who have previously accessed it

History-based Featurization



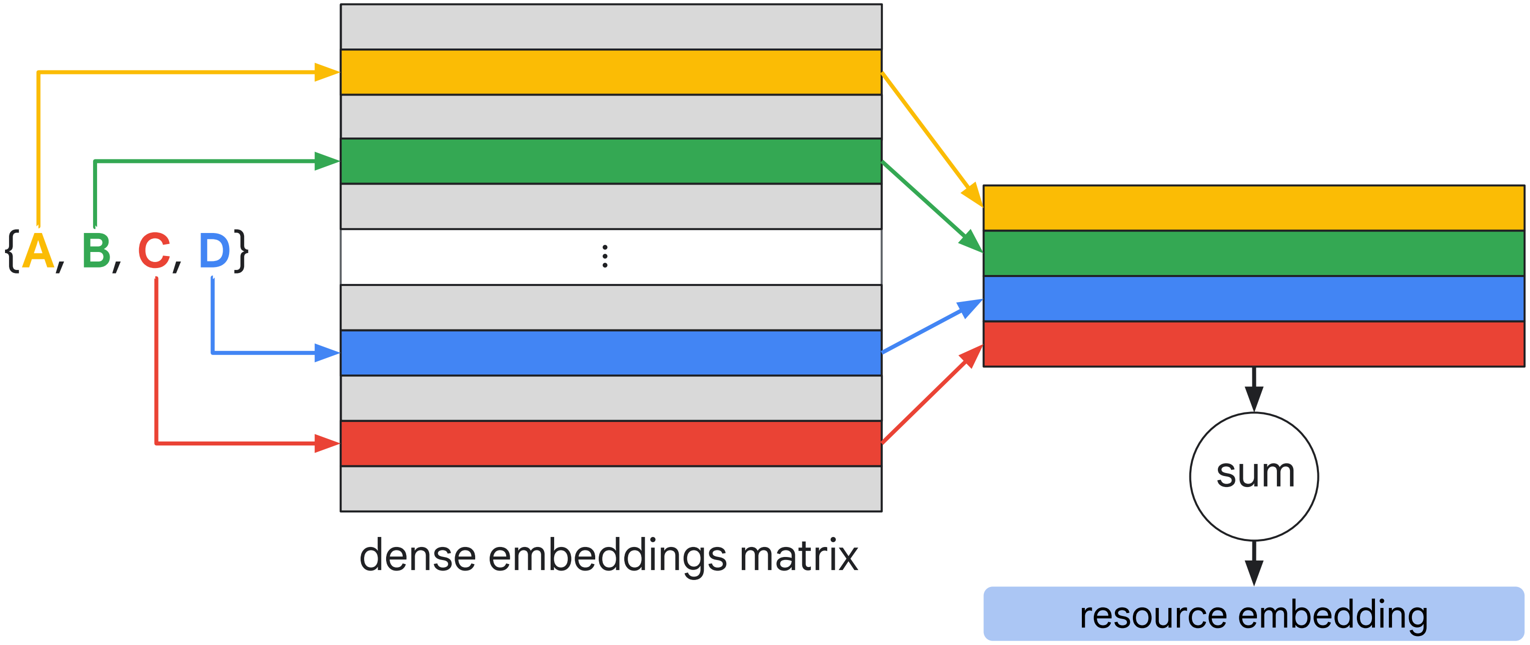
Resource featurizations for given time periods
Handles distribution drift (changing content)

Access Event Input Example

```
{
  id: "e767…"              # An unique identifier for this access event
  occurred_at: 1710…       # Timestamp of the event
  principal: "A"           # The id of the user performing the access
  type: "doc_access"       # Resource type (doc, db table, hostname, …)
  resource_id: "8bca…"     # Resource identifier, e.g., document id
}
```

You only need to choose a stable-in-time resource identifier
Facade takes care of the rest (history-based featurization)

History Set to Dense Vector



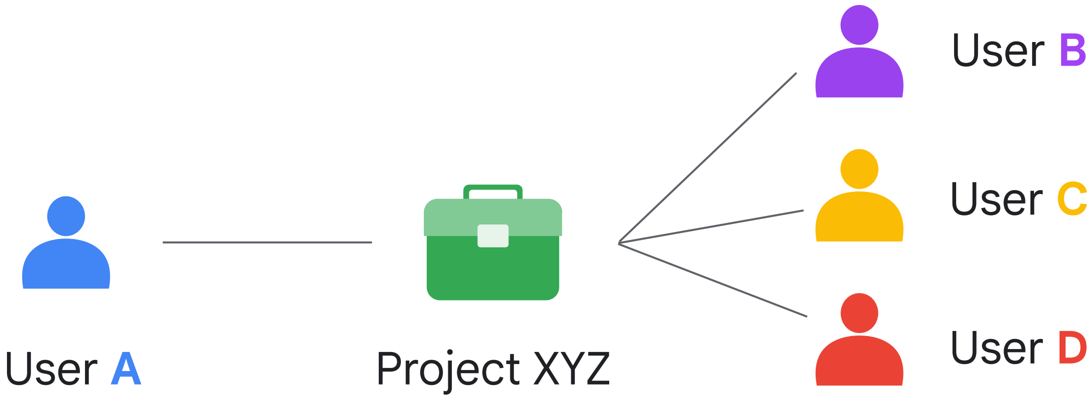
Featurization of Users

Two Types of User Attributes

Low cardinality, stable attributes
E.g. Job title (receptionist, software engineer, hardware engineer, etc)
⟶ Direct categorical featurization

High cardinality, unstable attributes
E.g. team, projects assigned, meetings attended, PRs reviewed, ...
Large distribution drift (re-orgs, new projects, employees, etc)
⟶ Implicit social network featurization

Implicit Social Network Featurization



"`project`" feature for user **A** is bag-of-words {**B**, **C**, **D**}

Any user is featurized by a set of sets of other user ids
one set per attribute type (team, project, department, etc)

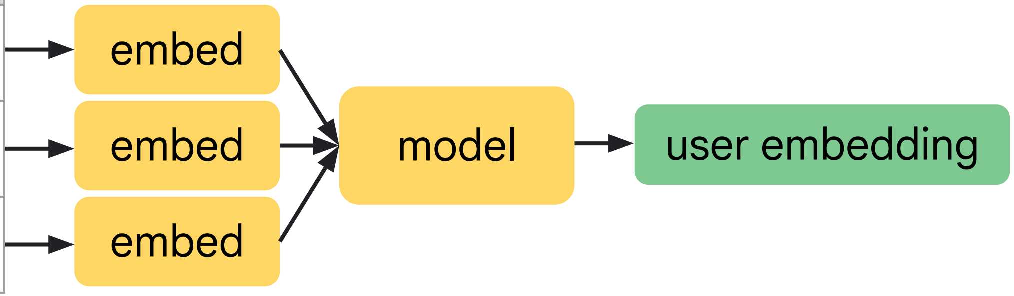
User Context Event Input Example

```
{
  valid_from: 1700...  # Start of validity for this context fragment
  principal: "A"       # The id of the user this pertains to
  name: "project"      # User attribute (team, project, meetings, ...)
  value: "XYZ"         # Opaque identifier
}
```

You only need to choose the user attributes you want to use
Facade takes care of the rest (implicit social network featurization)

User features to dense vector

Feature Name	Feature Value
job_title	software_eng
team	{A, B, C}
project	{B, C, D}

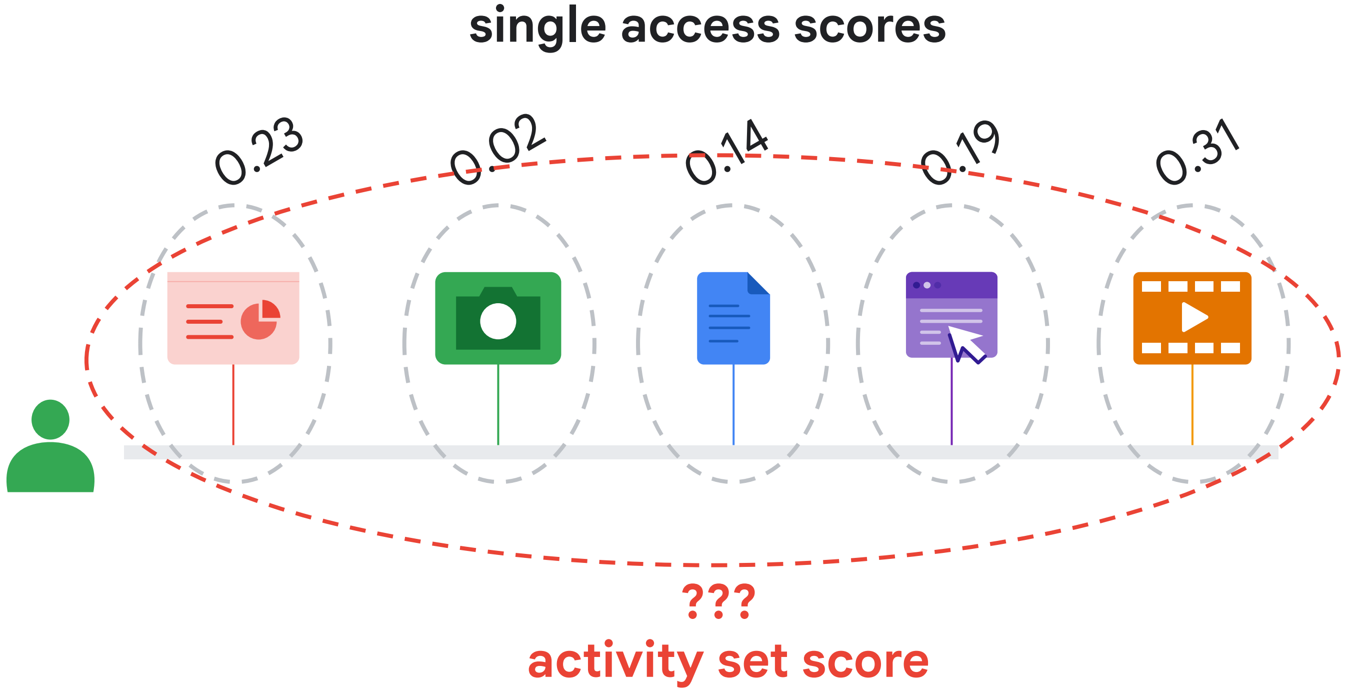


Featurization Takeaways

1. Universal featurization method
2. Robust to distribution drift
3. New resources and users w/o retraining
4. Fast and efficient

Scoring Arbitrary Time Periods

Pointwise VS Activity Set Scoring



A Simple Problem?

Average of scores
attacker can decrease score by adding benign accesses

Sum of scores
users with more activity will be more anomalous

Max score
ignores all but one access

Scoring Diversity of Anomalous Activity

Eliminate redundant and repetitive anomalies

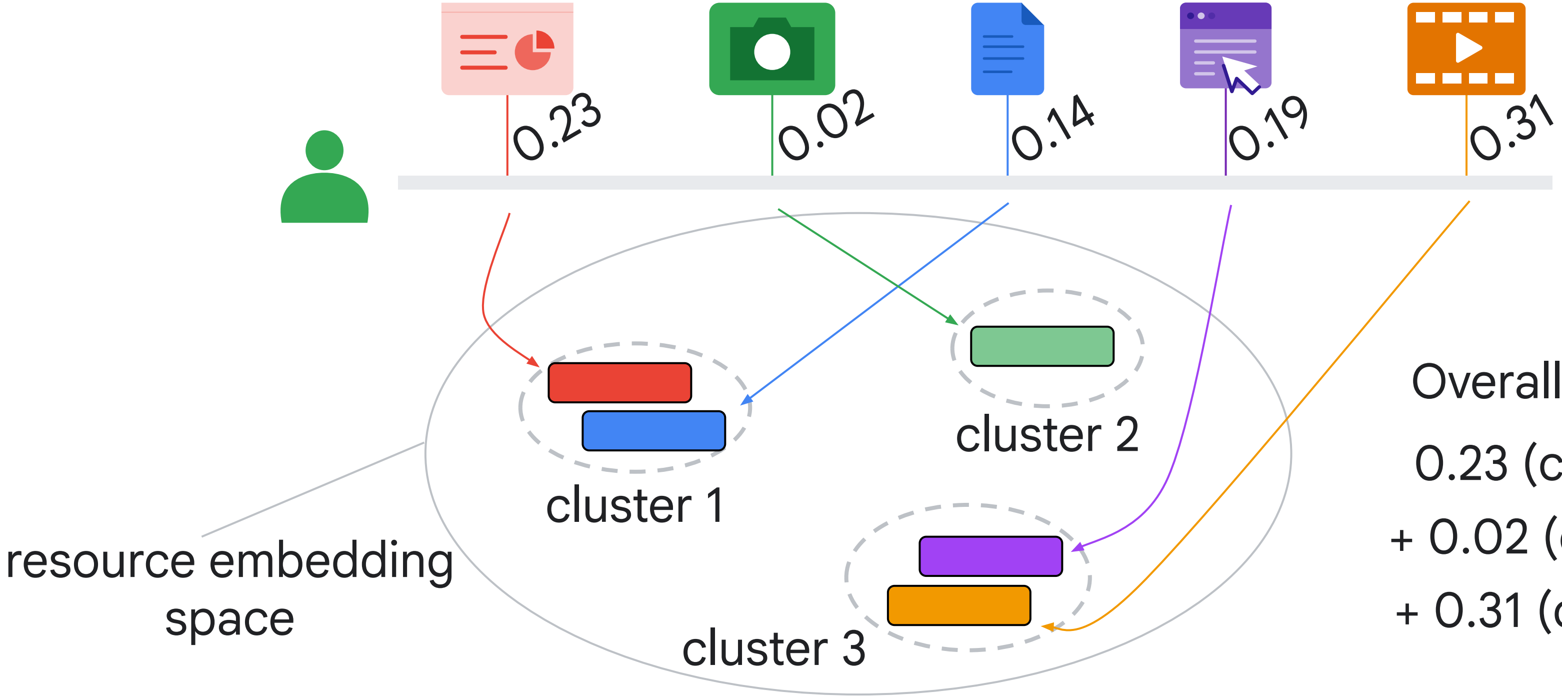
Use the resource embeddings for similarity

1. **Cluster** **similarly-anomalous** accesses together
2. **Sum** together **max** score of each cluster

Prevent attacker from hiding malicious activity

More diversely-anomalous sets score higher

Example



Overall score is:

0.23 (cluster 1)

+ 0.02 (cluster 2)

+ 0.31 (cluster 3)

Finding Insider Attacks with FACADE

Red Team Insider Threat Scenarios

Media Sharing Platform
Attackers seek corporate financial data, individual creators' earnings, …

Hardware Product
Attackers seek next gen device design, timelines, pictures, schematics, …

AI Research
Attackers seek next gen AI: unpublished papers, code, model weights, …

Operational Setup

15 participants
Full-time employees with interest in cyber security

High-level playbooks provided
attackers seek to discover and access sensitive information
attackers not provided detailed attack plans or target resources

Various levels of attack success per participant

Evaluation results

~180,000+ user accounts

Triaging budget: top 10 users/day

Detects 4 out of 15 attackers

More details in
https://arxiv.org/abs/2412.06700

Try it yourself

Reference implementation

https://github.com/google/facade

Note: as mentioned Facade is meant to work on large scale data and requires you bring your own modeling. Using it on small datasets won't work well.

Takeaways

Insider threats: low incidence high impact attacks
Detection requires contextual analysis

FACADE: high-precision contextual anomaly detection
Works for single-access *and* activity set

Adaptable to many systems and use-cases
Open-source model and featurizer code available

Slides:

https://elie.net/facade

Code:

https://github.com/google/facade

Google

SCAN ME