Unlocking CPU telemetry for software identification

Work in Progress

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Side channels: a curse of modern computing?

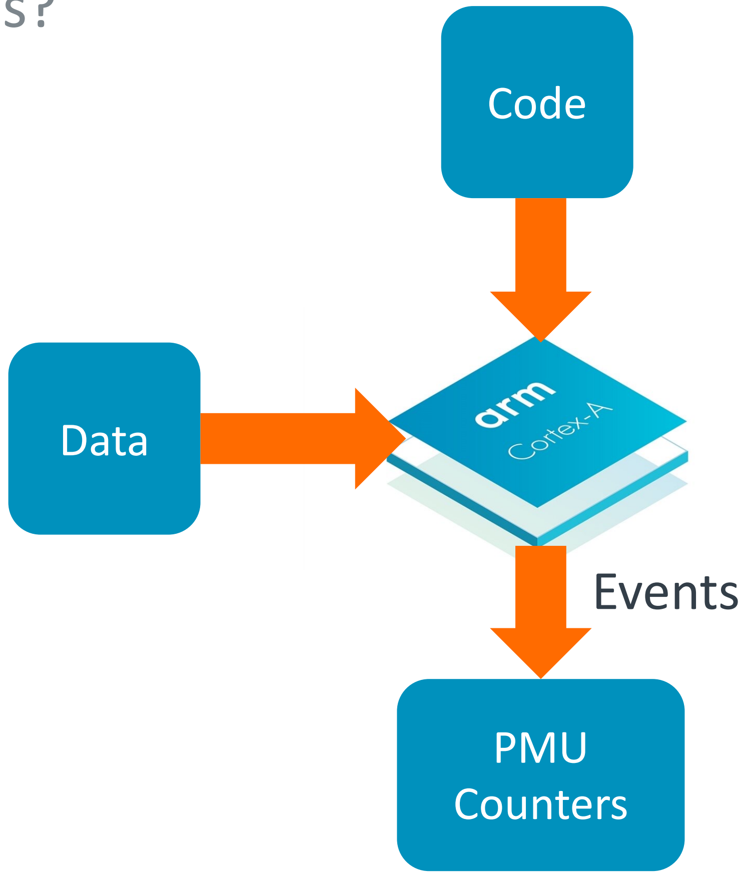
- Improving CPU performance means deviating from the programmer's model
- Deviations with state create side channels
  - Unintentional paths for information
  - Side channels are the inescapable reality of modern processors
- Attackers can use side channels to extract data
- Telemetry: outside the programmer's model
- What if we could turn the tables and use side channels to identify attacks?
  - One very promising side channel: hardware performance counters (HPC) (e.g. the Arm Performance Monitoring Unit (PMU) or the Intel Performance Counter Monitor (PCM))
  - Existing research in this area, but subject to limitations of extant hardware

What is the PMU?

Are Performance Monitoring Units side-channels?

- Collects events from the CPU core, e.g.:
  - Loads/stores
  - Branches taken
  - Instructions retired
  - Cache misses
- Aggregates events in a few counters
- Allows profiling of code

- Profiled code shows behavior
- Enables timing attacks
- Enables other profile-based attacks



Pitfalls of PMUs for software analysis

- External sources
- Non-determinism
- Overcounting
- Variations in tool implementation
- Loss of temporal ordering

- Needs very high accuracy to be deployable
  - Accuracy limits operational relevance:
    - 5% FPR means 1 in 20 samples are misclassified as malware
    - 80% TPR means 1 in 5 malware attacks are missed

SoK: The Challenges, Pitfalls, and Perils of Using Hardware Performance Counters for Security

Das et al, Oakland 2019

PMU, but for security?

Which constraints/pitfalls could we avoid?

- What if we redesigned the event processing hardware, to be used for security?

- External sources
  - Cache behavior necessarily multi-process: system-level behavior monitoring
- Non-determinism / overcounting
  - Architectural events are deterministic => use these
- Variations in tool implementation
  - Correctible, but arguably not what we're looking for.
- Loss of temporal ordering
  - Fundamental to counter architecture => do not use counters

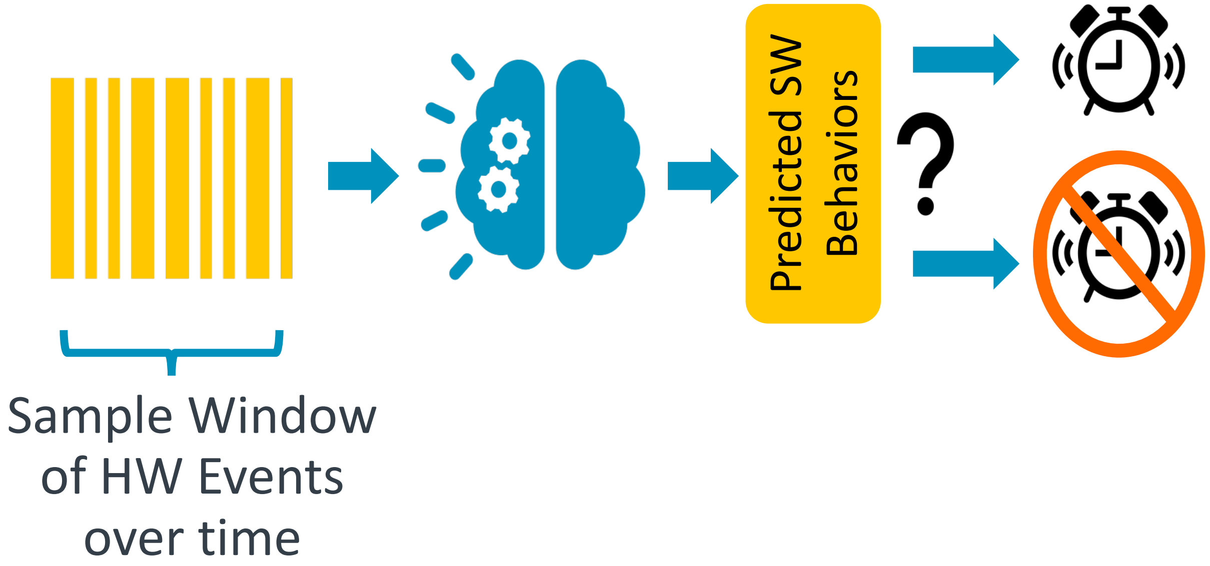
Program behavior as indicator of identity

- Programs contain substantial subdivisions in complexity
  - Basic blocks and sequences of basic blocks make up functions
  - Functions make up modules
  - Modules make up programs
  - Program execution often takes a circuitous route through all of these
- More detail presents further challenges
  - Preserving detail at context switches
  - Noise is not filtered out as effectively
  - Data, bandwidth, memory, compute load increase
- Options for extracting sufficient detail
  - Long windows might provide enough detail for direct classification
  - Short windows could be classified and used as the input to a second-tier classifier

Akira Architecture

Akira's approach

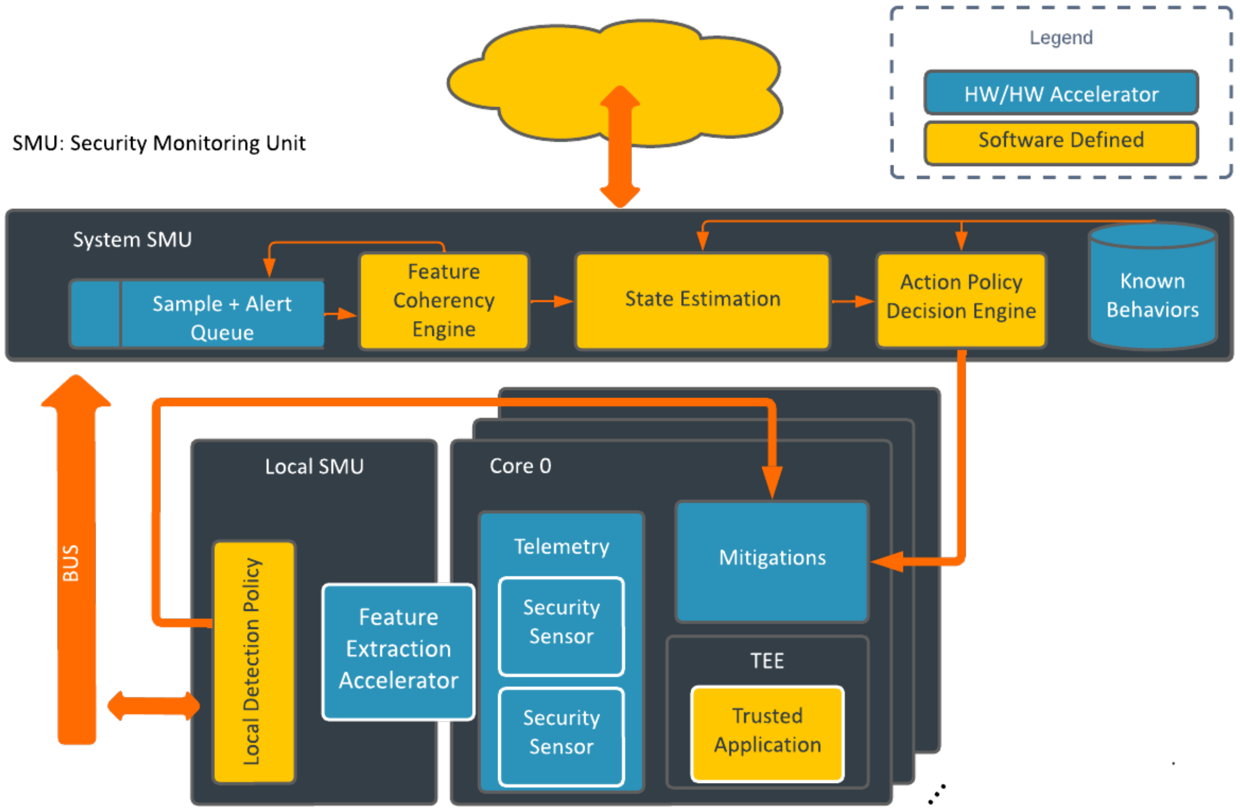
- Local low-power always-on TinyML
  - "Listen" for software behaviors
  - Enable mitigations / throw alerts when needed
  - "Respond" to emerging threats for years
- State of the Art uses standard or augmented PMU
  - **Events** are **aggregated** by PMU prior to analysis
  - E.x. 34 cache misses and 10 branch mispredicts since last time sample
- Akira processes Raw Telemetry Events
  - E.x. 1 [new] cache miss @ cycle: 5678



Akira Architecture: Tiered approach

On-SoC: The blocks

- Telemetry and Mitigations highly privileged blocks!
  - Careful to protect a high-resolution side channel
- Local Security Monitoring Unit (SMU)
  - On or near core
  - Custom feature extraction accelerator HW
  - Need access to a secure ML Accelerator
    - Updateable with lifecycle
  - Triggers basic mitigations if confidence high enough
  - Emits alerts + feature summarizations
    - Benign features sampled at random
- System SMU
  - Aggregates across local SMUs, while maintaining temporal consistency
  - Correlates samples w/ system context and known patterns to estimate
    - 1) what samples are “linked” or related
    - 2) and to what behaviors
  - Proposes course of action (or not)



Temporal Ordering

- Raw telemetry events
  - More detail for analysis
  - Departure from established practice
  - CPU designer needs to implement
- Impact on non-determinism
  - Multi-issue, superscalar reordering, speculative execution produce noise
- Impact on bandwidth
  - Counters: $m \log_2 n$ bits/window
  - Event trace: mn bits/window

- A transform may help
  - Path Signatures [Chen 1958, Chevyrev 2016]
    - Good properties. Resistant to:
      - Offsets
      - Timing variation
      - Warping
      - reparameterization
  - Bandwidth: $\left(\sum_{i=1}^{L} im^i\right) \log_2 n$ bits/window
    - More bandwidth than counters, less than trace
    - dependent on
      - event sources m
      - window size n
      - signature depth L
- $S(X)_{a,t}^{i_1,\ldots,i_k} = \int_{a<t_k<t} \cdots \int_{a<t_1<t_2} dX_{t_1}^{i_1} \cdots dX_{t_k}^{i_k}$
- $S(X)_{a,b} = \left(1, S(X)_{a,b}^1, \ldots, S(X)_{a,b}^d, S(X)_{a,b}^{1,1}, S(X)_{a,b}^{1,2}, \ldots\right)$

Akira's approach: Compress instead of aggregate

- A limited set of events routed into a feature extraction accelerator
- Accelerator for 5 event sources has negligible area cost
- 5 event sources generates a 55-element vector (log signature)

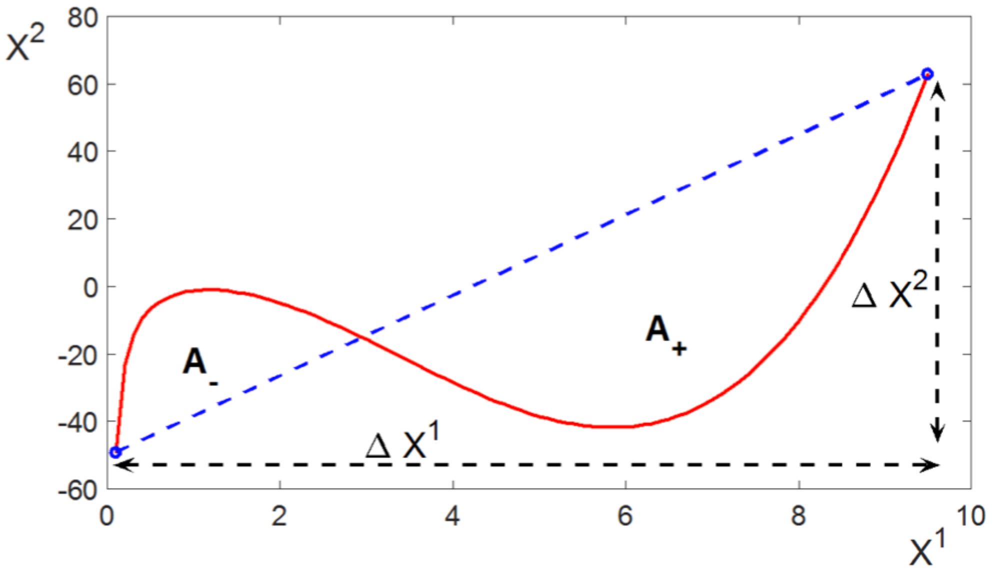
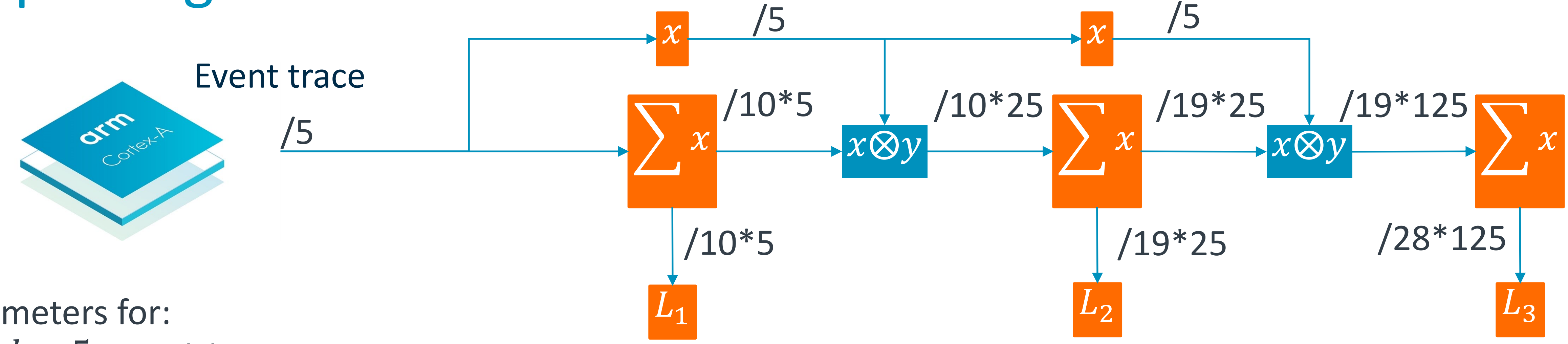


Figure 5: Example of signed Lévy area of a curve. Areas above and under the chord connecting two endpoints are negative and positive respectively.

A path signature accelerator



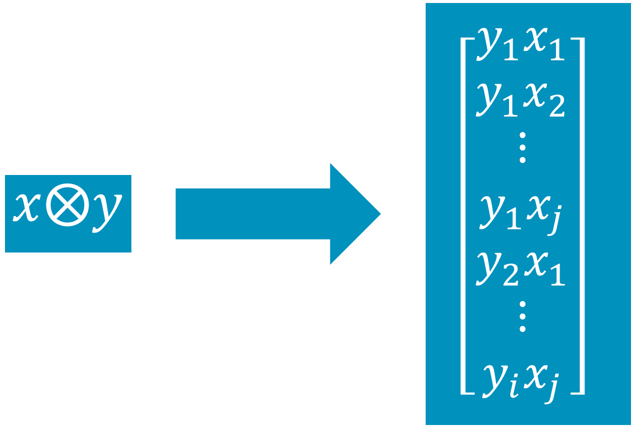
Parameters for:

$d = 5 \; event \; types$

$n = 1024 \; events/window$

Combinatorial elements

Sequential elements



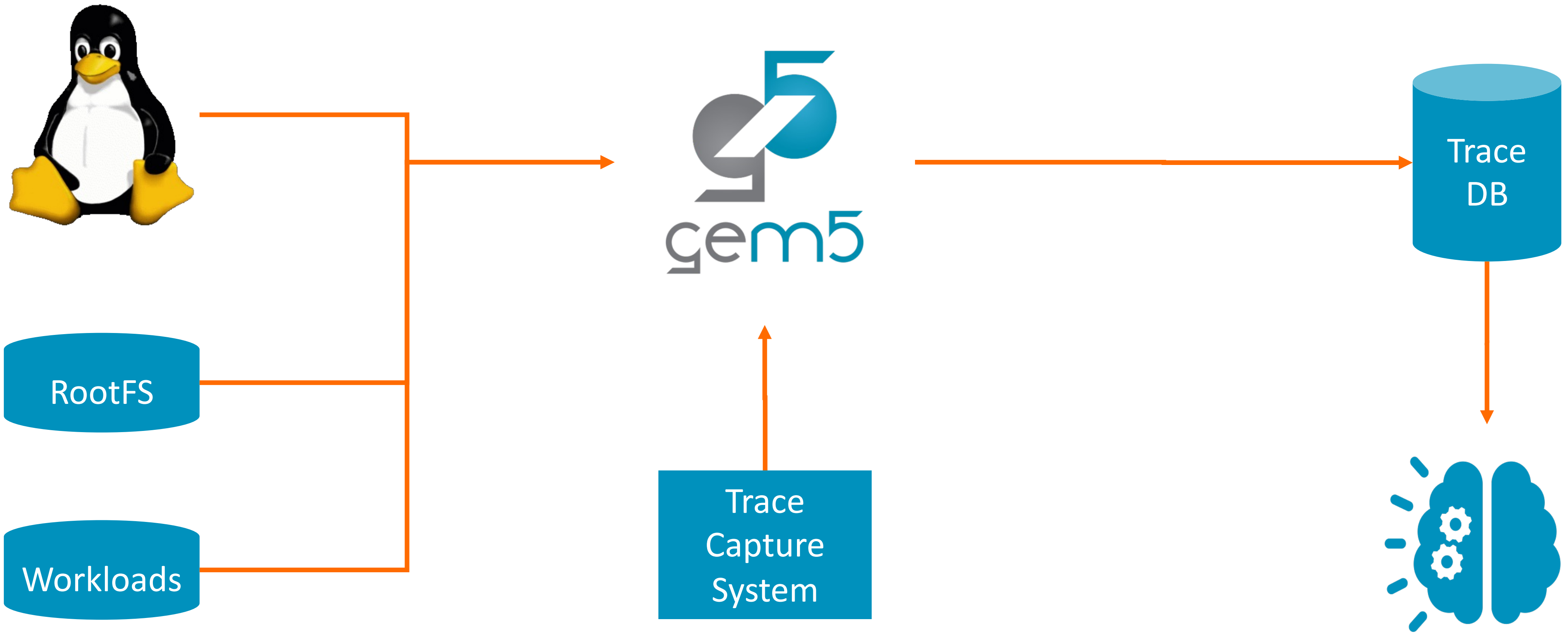
$x \otimes y$ can be implemented by gating each element of y on each element of x, forming an outer product

Experimental Methodology & Early Results

Early answers about early warnings

Data collection setup

Akira Simulation Infrastructure



Akira: The Data

Trace Capture

Goal – Know exactly when and where things run

- Modified Gem5 instances
  - Direct PMU event capture in CPU
  - OS PIDs pushed to CPU regs
  - Magic NOPs for marking windows
  - Running bare metal + booting Linux
  - Capturing PC trace for labelling

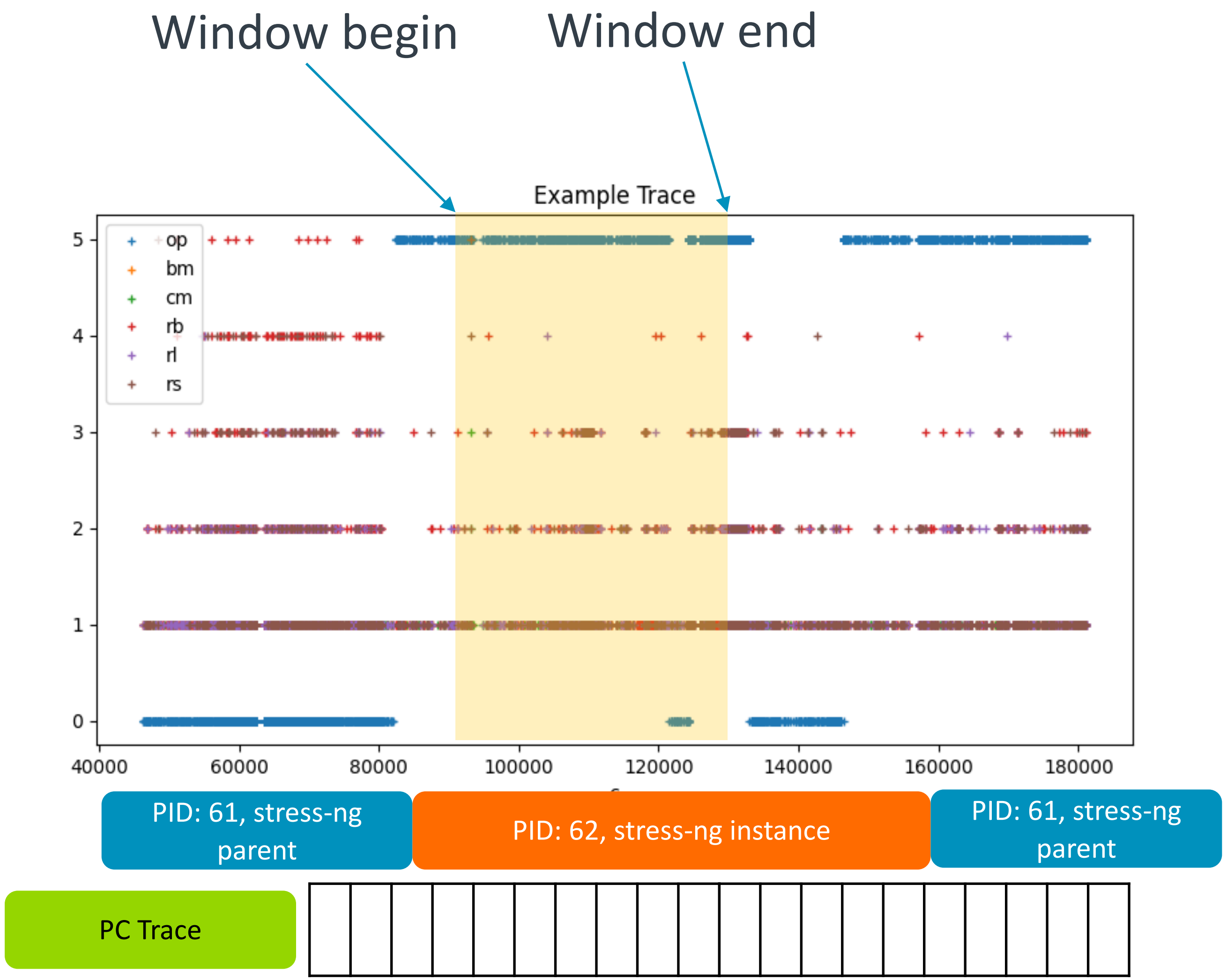
Workloads (More on this later)

- Stress-NG
- Juliet
- SpectreV1

Linux Testing Project

IARPA StoneSoup (SSL)

SPEC 2017

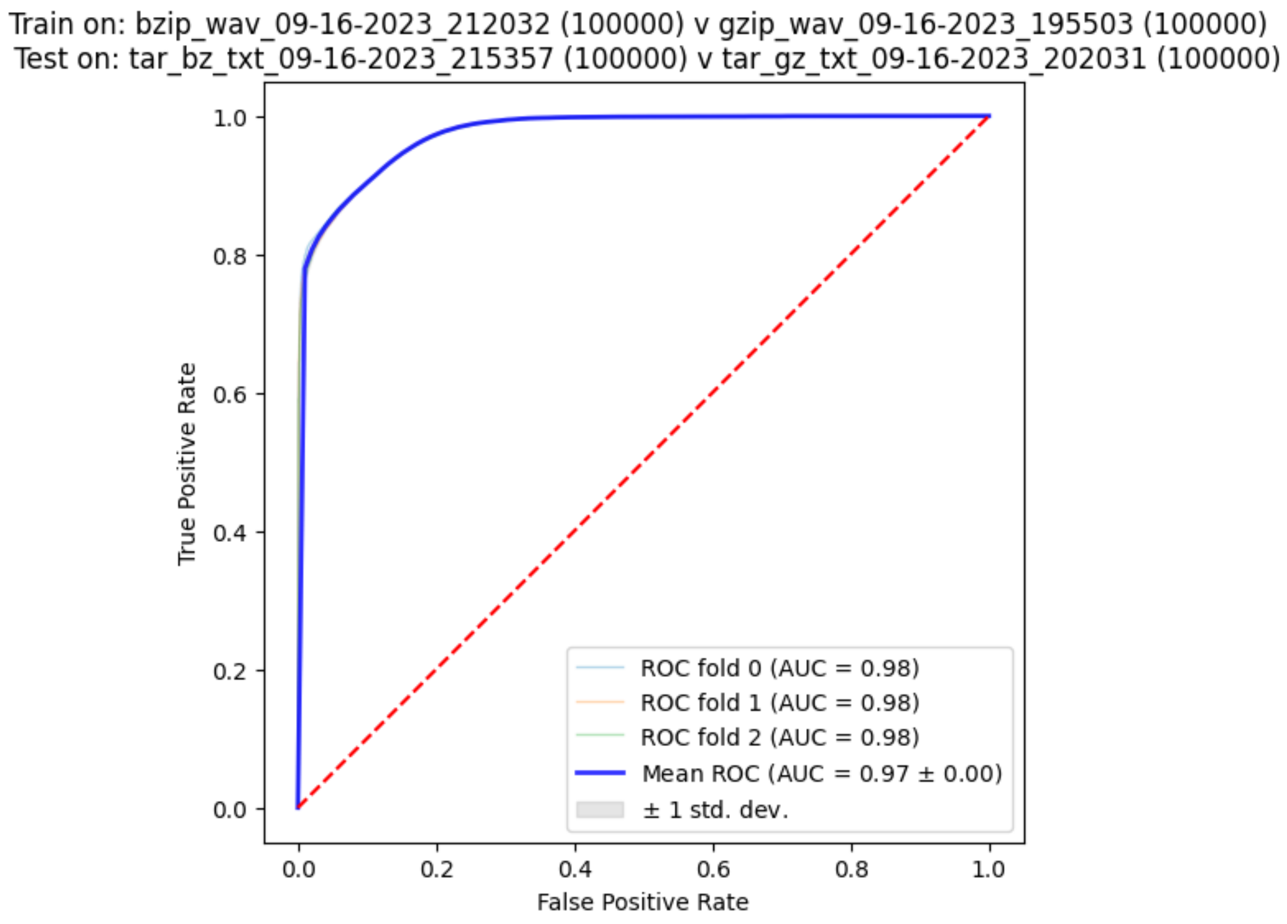


Identifying programs

Interim Results – Program Identification

gzip vs bzip2

- Trained on gzip, bzip2 of wav file
- Tested on tar -z, tar -j of text file
- Model:
  - XGBoost
  - Path Signature feature extraction
  - Long windows (512)

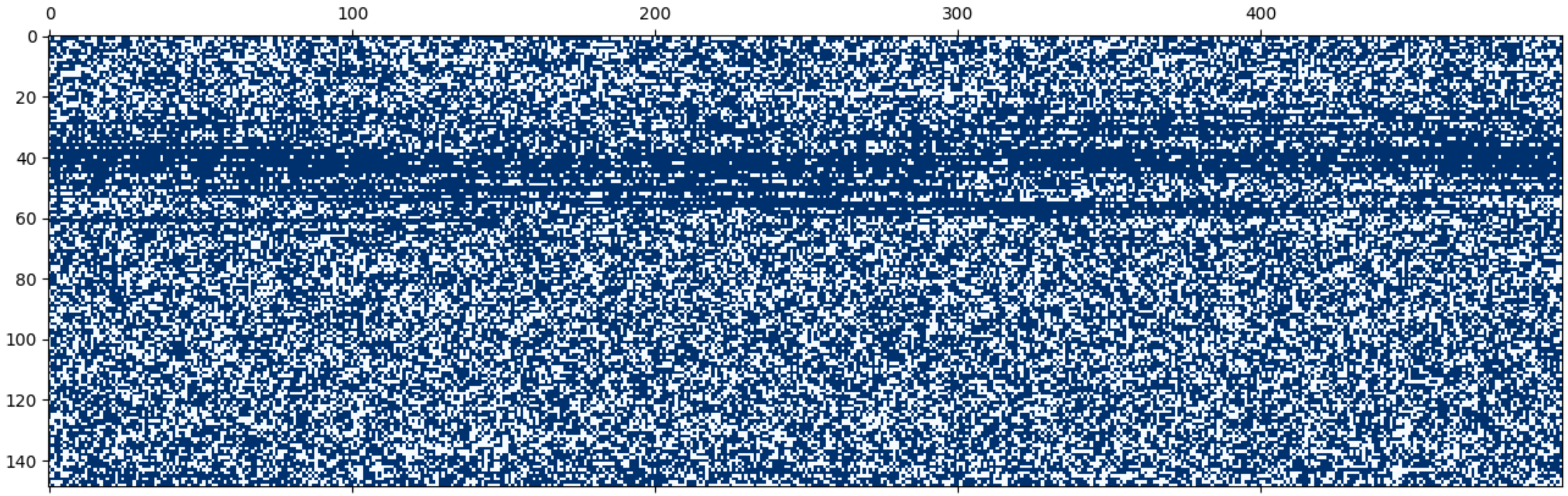


Linux kernel behavior identification

Interim Results – Kernel Function Identification

Classifying kernel behavior by PMU events

- Ran long-running Linux Testing Project test cases
- Filtered via Exception Level
- Matched PC Trace to kernel functions
  - 84 behaviors used often enough to be relevant
- Ranked possible classes of test sample (25-event windows, XGBoost, path signatures)
- Accuracy
  - 97.5% top-1
  - 99% top-4



'LTP_fcntl27_06-07-2023_204644'

LRAP: Label Ranking Average Precision

Evaluating Akira’s multi-label ranking behavior

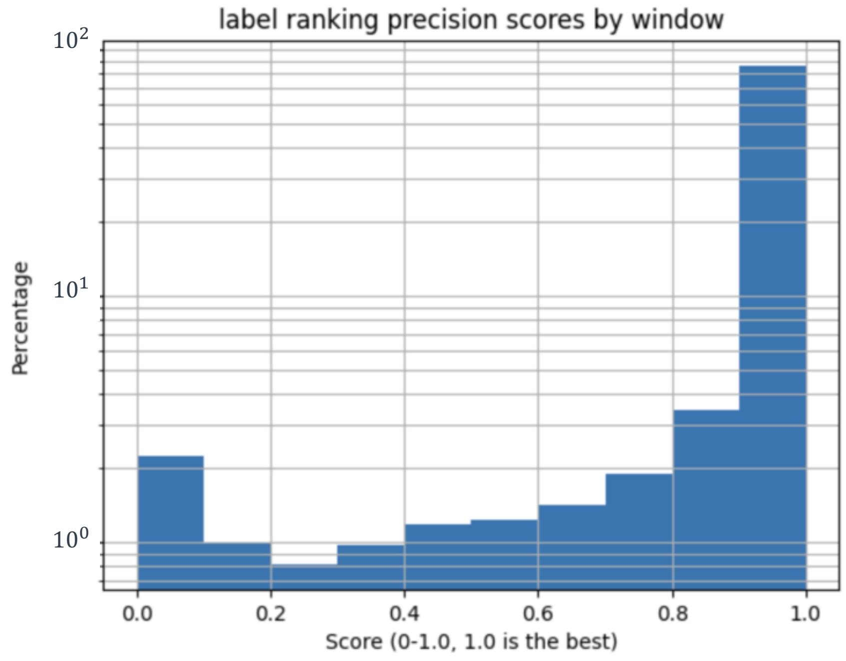
- Rank samples by most likely behavior “class”
- Identify how many false classes are ranked below ground truth for each sample
- Average these results across all samples for a given test
- May be multiple ground truths for some samples
  - i.e. One sample window == mix of software "behaviors"
  - For better score all the ground truths in a sample should be nearer the top rank

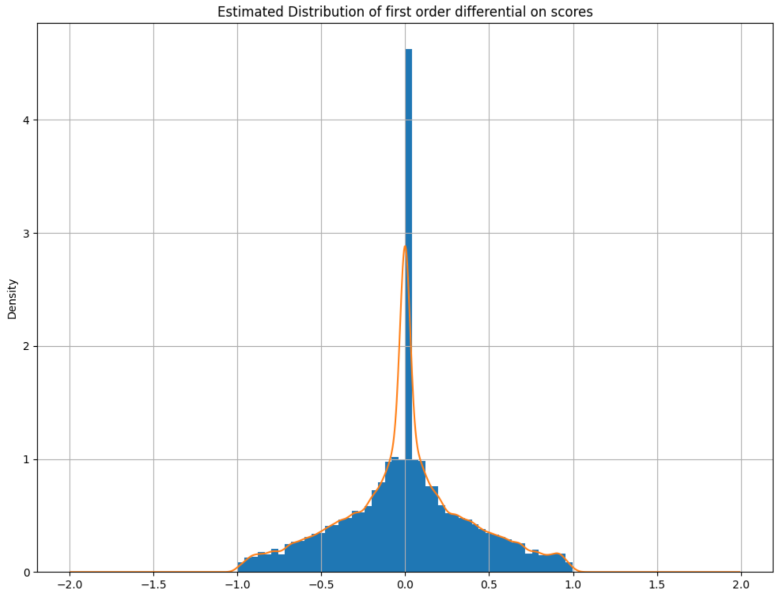
- Practical implications:
  - Real-world classifier will consume top-N ranked classes for each sample and perform disambiguation.

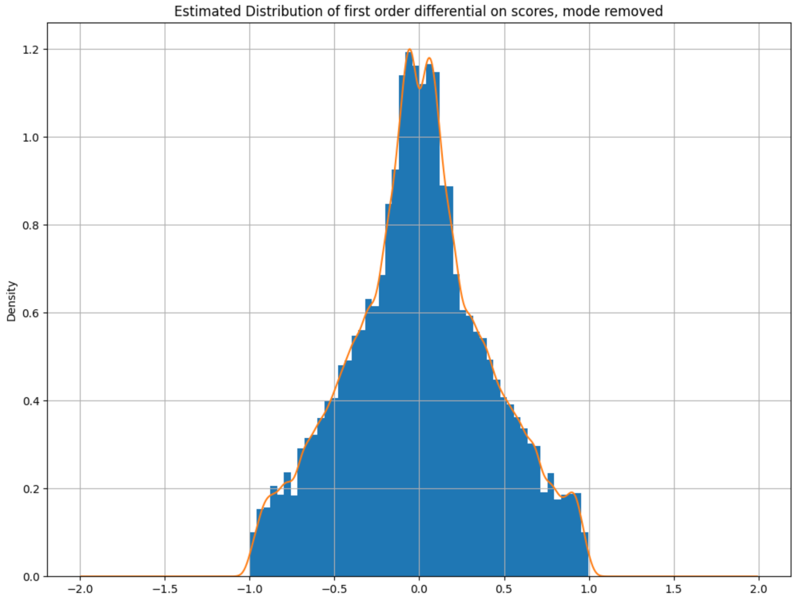
Interim Results – Kernel Function ID

Can we go deeper?

- Q: Can we identify specific code paths in software using telemetry?
  - We can distinguish between 1372 kernel functions with >85% "accuracy" using samples **only 25 events long**



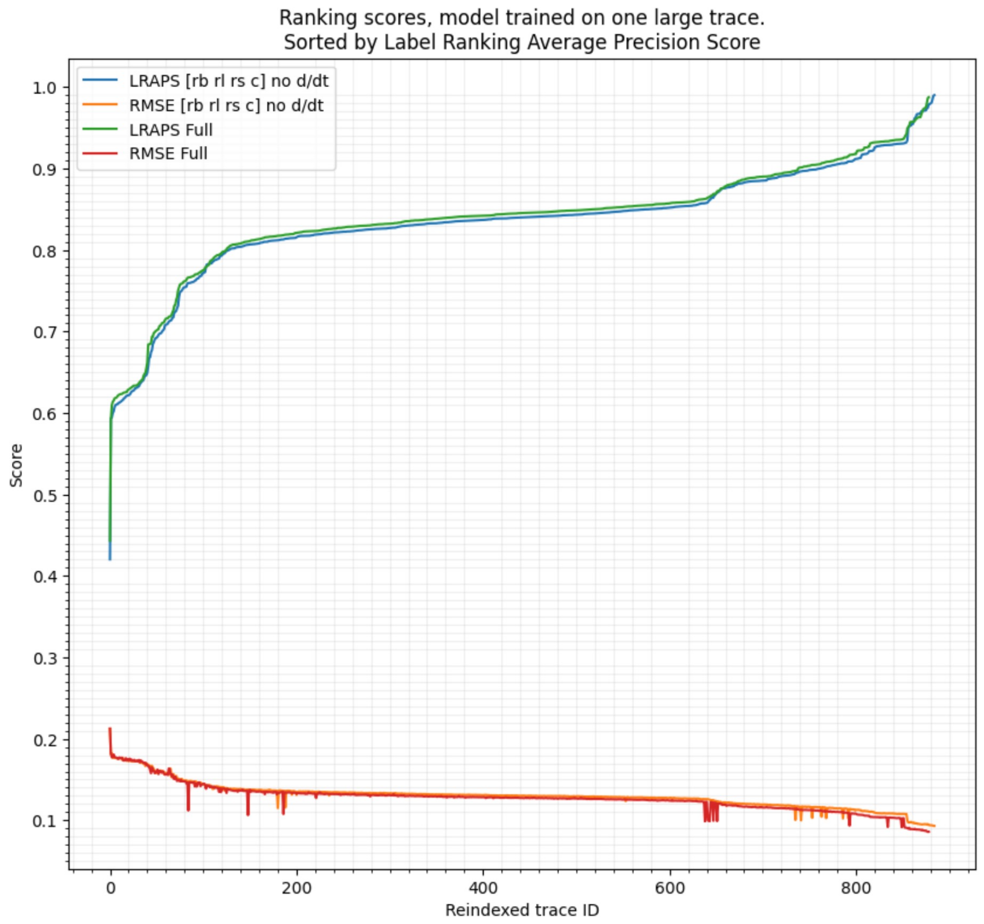




Interim Results – Generalizing Kernel Function ID

How well does training on one trace generalize to other traces?

- **Training:**
  - Ingest sampled form of one large trace (v4.7.1)
    - Treat as a lower bound on model performance
  - Target extremely small models and learn 2 rank
    - 25-event windows, path signatures, XGBoost
  - See if we can correctly identify top ~60 kernel functions
- **Testing:**
  - How well does this model work on all other traces (v5.12.2)?
    - Hint: it's very good

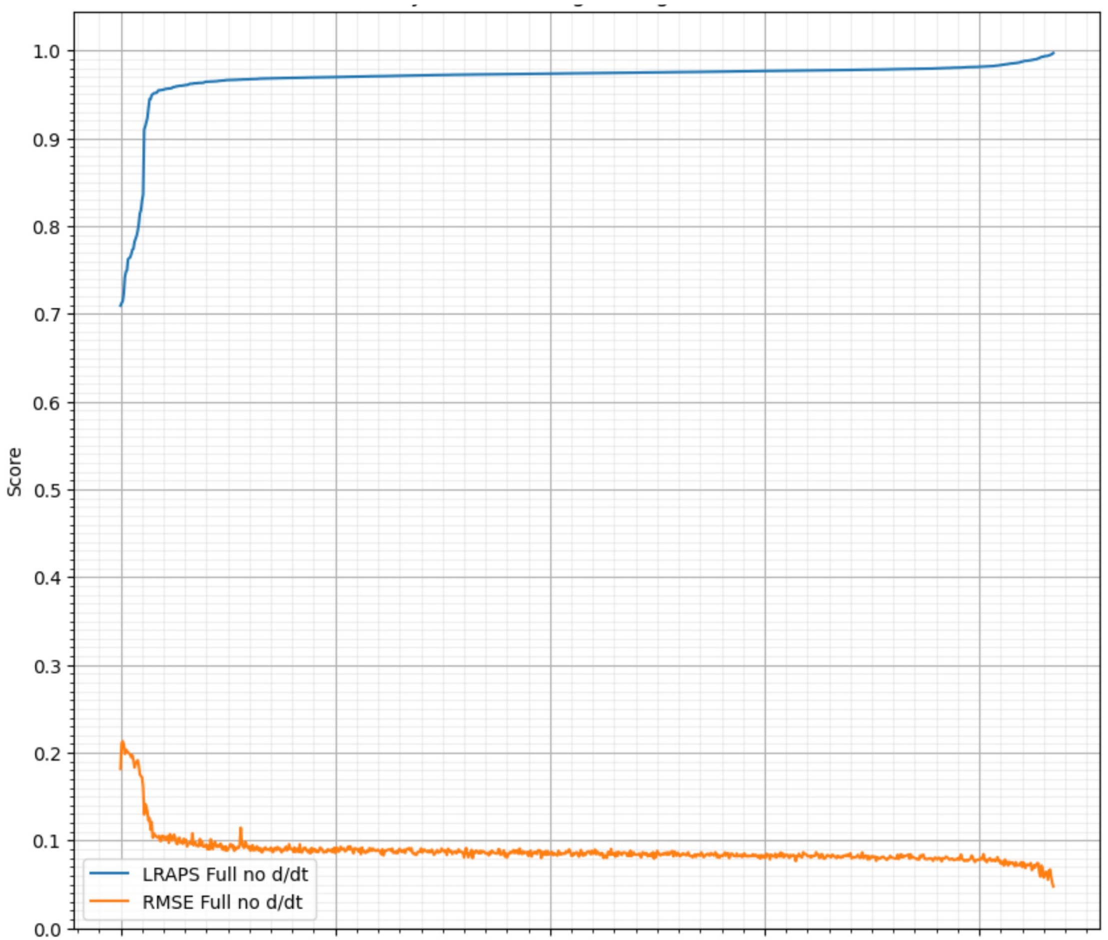


Userspace code identification

Results – User space code classification

Does the kernel-space classification system work on user-space code?

- Top 20 user-space labels in the 969 LTP traces
- Training:
  - Windows containing target set labels for at least 25% of duration
  - No “unknown” labels
  - 25-event windows, path signatures, XGBoost
- Testing:
  - holdout set
  - LRAPS is 97.2%, per window
  - RMSE is 8.7%, per window

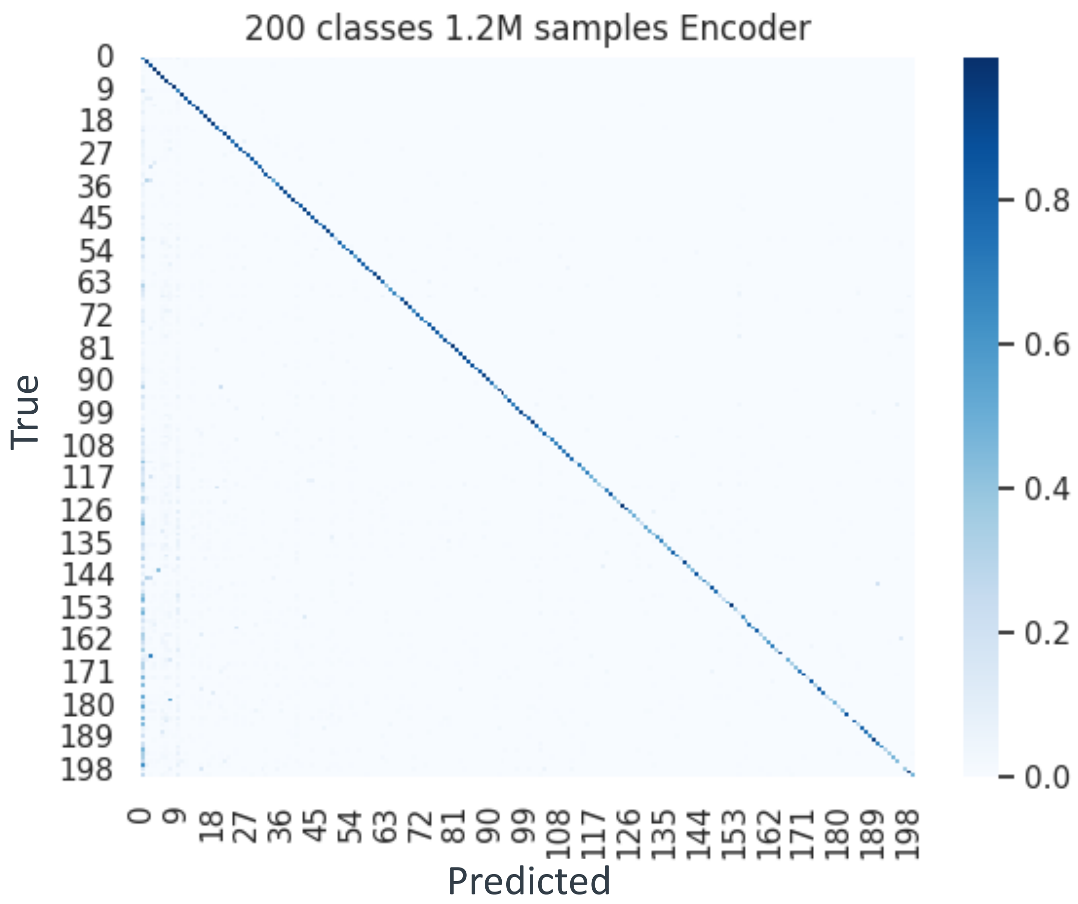


General behavior identification

Distinguishing between code segments

Using a transformer to identify code based on behavior

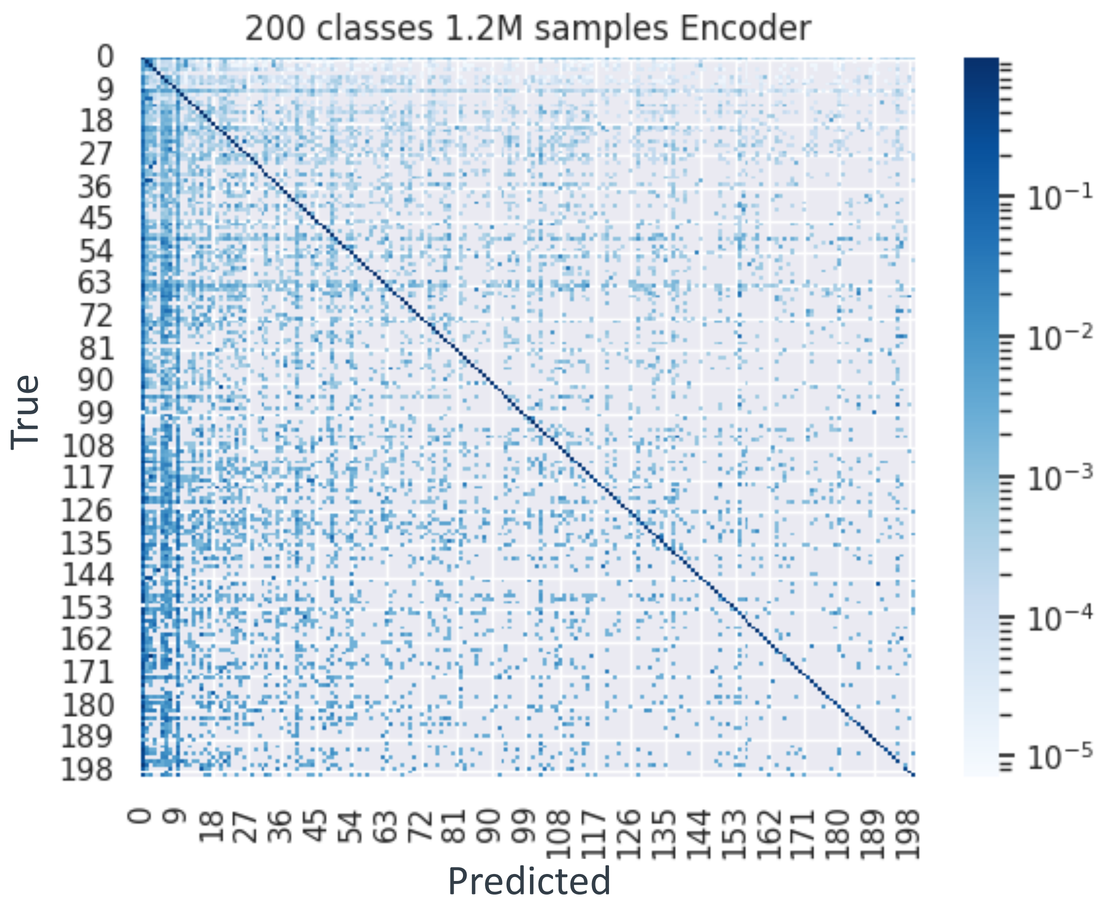
- Transformer is trained on 1.2M samples with the top 200 classes highlighted
  - 969 traces are sampled, with a training set and a holdout set
- Sources of misclassification:
  - Each sample labelled with top-1
  - All classes not in the top 200 are binned into class 0
  - Most confusion occurs when the model predicts class 0 (the catchall class)
- Avenues for improvement:
  - Top-n labelling
  - More classes (fewer in catchall)



Distinguishing between code segments

Confusion matrix in log-scale

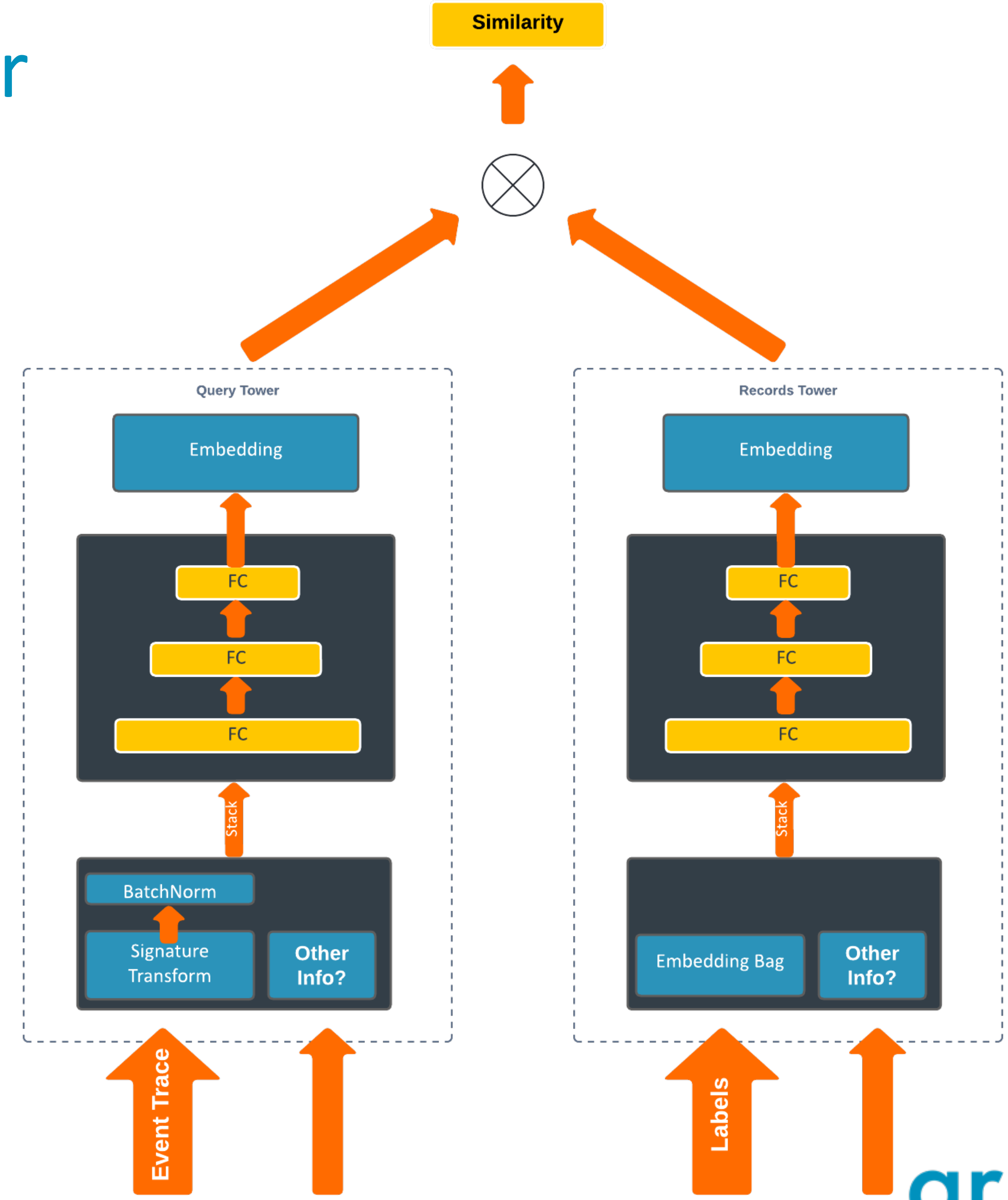
- Most incorrect predictions < 1:10
- Clear bias towards more common classes
- Misprediction rate improves substantially below class 10
- Avenues for improvement:
  - Improve sampling balance



Handling imbalance

Two Tower Candidate Generator

- One Tower encodes the measurements
- Other Tower encodes our knowledge of this record
- Model pairwise trained
  - "Sample related to Record"
- True validation is maximum inner product search
  - Expensive, but for science!
- In practice, inference leverages vector DBs
- Can add info to input vectors for cheap



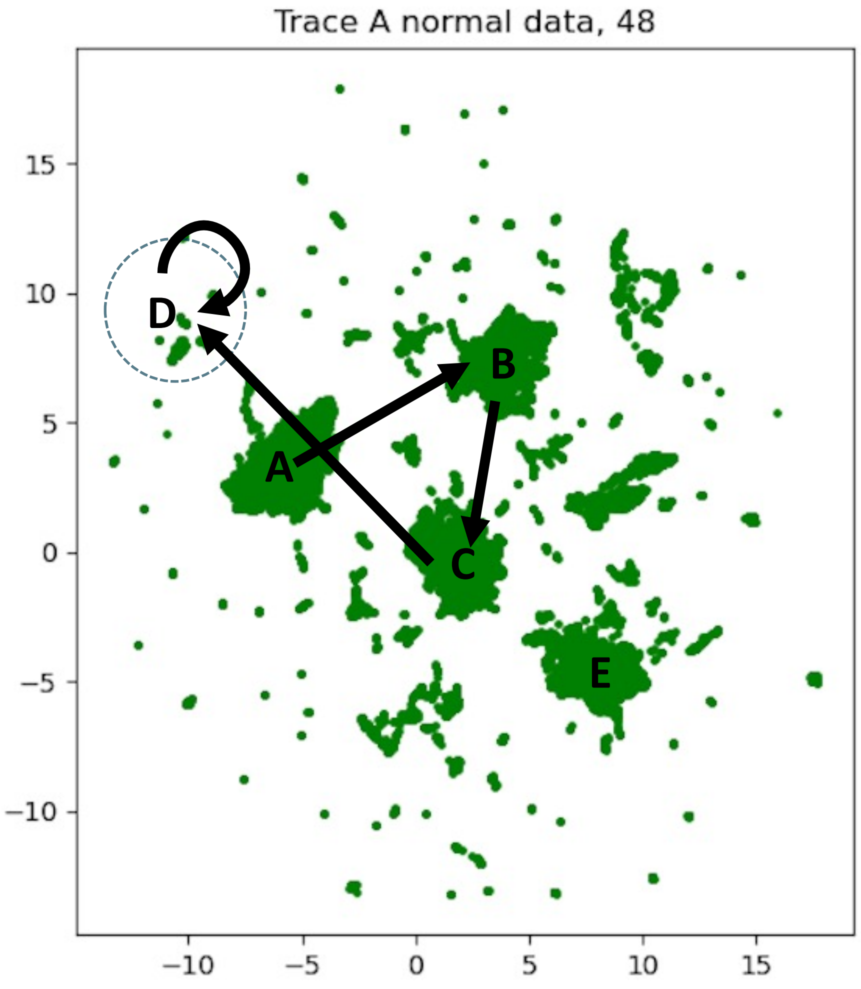
Two Towers (cont.)

- Training scales well to massive datasets
- Models are extremely flexible
  - Depending on data concatenated to input vectors we can handle different tasks
  - Missing sections can just be zeroed out
  - e.x. embedding encoded basic blocks -> identify/group data dependent behaviors
  - e.x. embedding local graph of basic blocks -> guide model towards ontologies
    - Similar to playlist learning
  - e.x. embedding doc strings for known benign code bases
  - e.x. embedding description metadata for known malicious samples (think VirusTotal)
  - e.x. embedding syscall trace
- Well suited for both cloud and system-level applications
- Currently in-progress
  - Sorting out details in the training

Second tier classification

Goal: use cluster transitions to identify software

1. Mini-batch k-means: Unsupervised labeling of all important clusters across LTP (and beyond)
2. A Trace is then a path (a 'string') between these clusters
3. We have efficiently applied this to the entire LTP data set (takes ~1 minute)
4. The resulting output has allowed us to classify program types in the LTP data set with good accuracy (75% top-1 accuracy on 12 classes, using fully unsupervised features)



String representation

Trace *i*: "ABCDD"

Freq representation

A	B	C	D	E
1	1	1	2	0

Creates a Term-Frequency structure:
Can analyze with Topic Models

Transition freq representation

	A	B	C	D	E
A	0	1	0	0	0
B	0	0	1	0	0
C	0	0	0	1	0
D	0	0	0	2	0
E	0	0	0	0	0

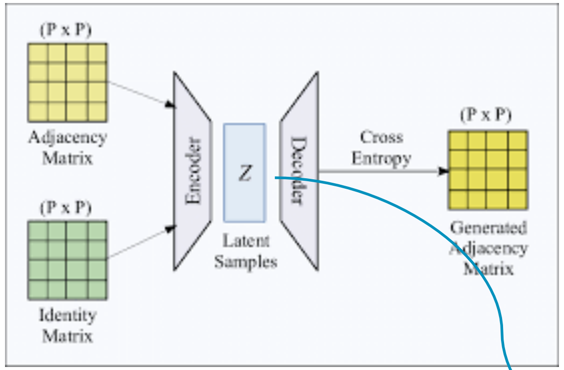
Creates a graph structure:
Can analyze with GNN, TDA

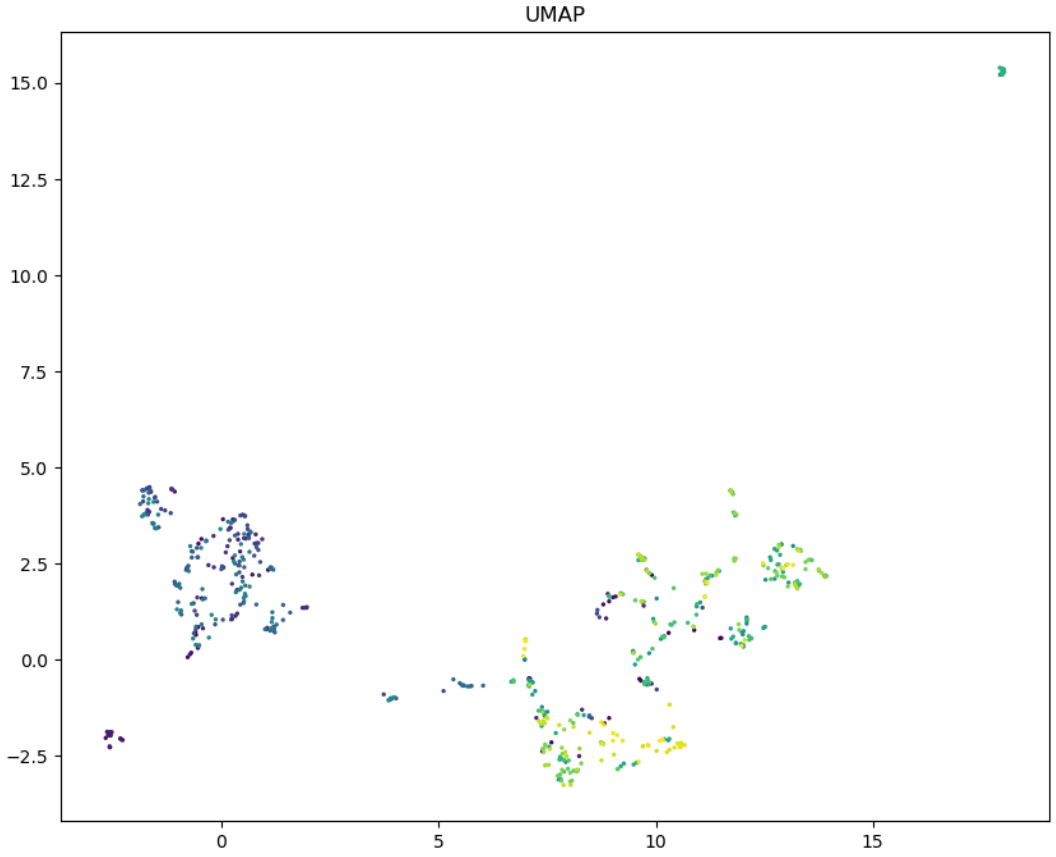
Graph Autoencoder on Soft-Label Adjacency Matrix

Transition freq representation

	A	B	C	D	E
A	0	1	0	0	0
B	0	0	1	0	0
C	0	0	0	1	0
D	0	0	0	2	0
E	0	0	0	0	0

Variational Graph Autoencoder





Points are colored temporally (window ID)

We can identify coarser phases within a trace

Conclusions & Future work

Challenges

- Deployment of a high resolution performance monitor requires action by CPU designers
  - CPU designers need strong evidence for adding a feature like this
  - Providing evidence for this feature requires extensive data collection
- Data collection without dedicated hardware can only be done in simulation
  - Collecting data in simulation is very slow
  - Running malicious software in simulation presents unique challenges

Conclusions

- The PMU provides high resolution data about software
  - As long as we keep ordering information
- Event information can be used to identify software
- Path signatures retain ordering information, but reduce data size
- Path signatures are low overhead in hardware
- Event traces can identify short behaviors with high confidence
- Sequences of short behaviors can provide identification “strings”

References

References

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Kiitos
شكرًا
ধন্যবাদ
תודה
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