Leo: Online ML-based Traffic Classification at Multi-Terabit Line Rate

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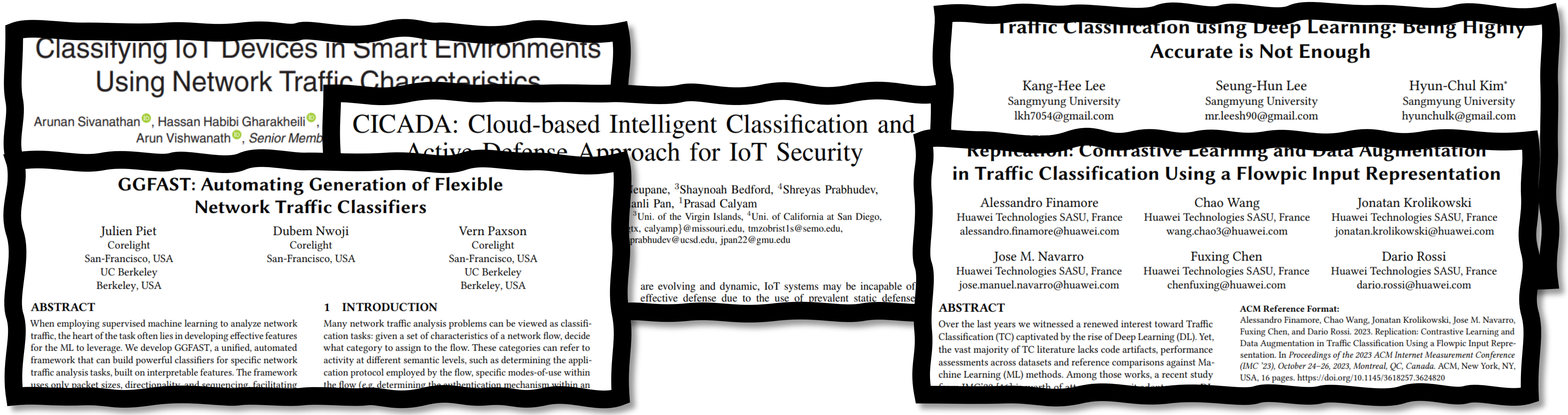
Why ML-based traffic classification?

- Detecting traffic anomalies, IoT device classification and application classification



Classifying IoT Devices in Smart Environments Using Network Traffic Characteristics

Arunan Sivanathan, Hassan Habibi Gharakheili, Arun Vishwanath, Senior Memb

CICADA: Cloud-based Intelligent Classification and Active Defense Approach for IoT Security

eupane, [3]Shaynoah Bedford, [4]Shreyas Prabhudev, anli Pan, [1]Prasad Calyam

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are evolving and dynamic, IoT systems may be incapable of effective defense due to the use of prevalent static defense

GGFAST: Automating Generation of Flexible Network Traffic Classifiers

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Dubem Nwoji, Corelight, San-Francisco, USA

Vern Paxson, Corelight, San-Francisco, USA, UC Berkeley, Berkeley, USA

ABSTRACT

When employing supervised machine learning to analyze network traffic, the heart of the task often lies in developing effective features for the ML to leverage. We develop GGFAST, a unified, automated framework that can build powerful classifiers for specific network traffic analysis tasks, built on interpretable features. The framework uses only packet sizes, directionality, and sequencing, facilitating

1 INTRODUCTION

Many network traffic analysis problems can be viewed as classification tasks: given a set of characteristics of a network flow, decide what category to assign to the flow. These categories can refer to activity at different semantic levels, such as determining the application protocol employed by the flow, specific modes-of-use within the flow (e.g. determining the authentication mechanism within an

Traffic Classification using Deep Learning: Being Highly Accurate is Not Enough

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Replication: Contrastive Learning and Data Augmentation in Traffic Classification Using a Flowpic Input Representation

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Dario Rossi, Huawei Technologies SASU, France, dario.rossi@huawei.com

ABSTRACT

Over the last years we witnessed a renewed interest toward Traffic Classification (TC) captivated by the rise of Deep Learning (DL). Yet, the vast majority of TC literature lacks code artifacts, performance assessments across datasets and reference comparisons against Machine Learning (ML) methods. Among those works, a recent study

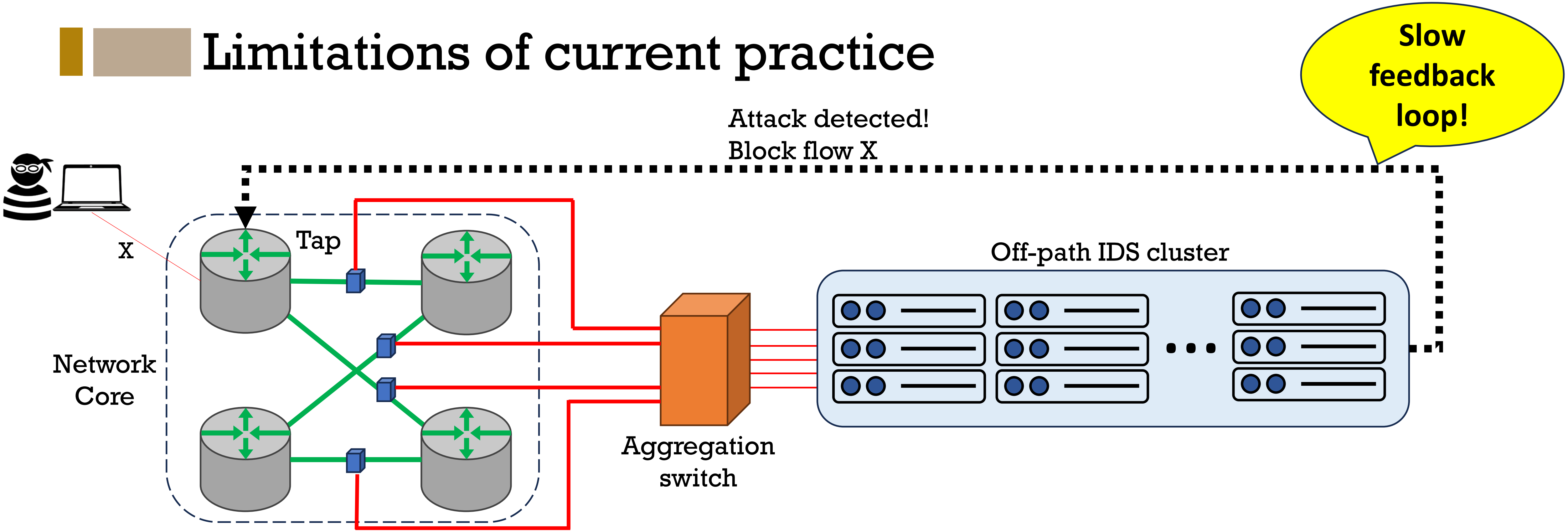
ACM Reference Format:

Alessandro Finamore, Chao Wang, Jonatan Krolikowski, Jose M. Navarro, Fuxing Chen, and Dario Rossi. 2023. Replication: Contrastive Learning and Data Augmentation in Traffic Classification Using a Flowpic Input Representation. In *Proceedings of the 2023 ACM Internet Measurement Conference (IMC '23), October 24–26, 2023, Montreal, QC, Canada.* ACM, New York, NY, USA, 16 pages. https://doi.org/10.1145/3618257.3624820

- Capture complex patterns w/o peeking into payload
- Learn behavioral patterns from network flow statistics

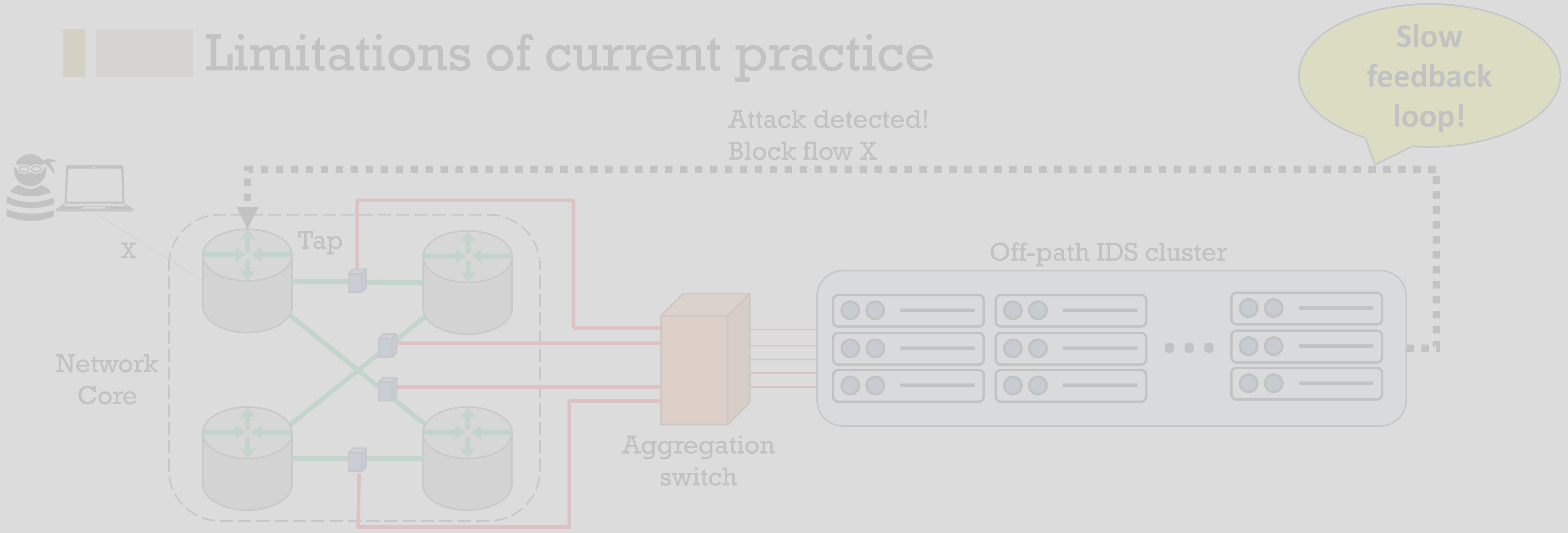
➔ Applicable to encrypted traffic

Limitations of current practice



- Traffic sent off-path for analysis
- Asynchronous → slow reaction time
- Challenging to analyze traffic at line rate

Limitations of current practice



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- Asynchronous → slow reaction time
- Challenging to analyze traffic at line rate

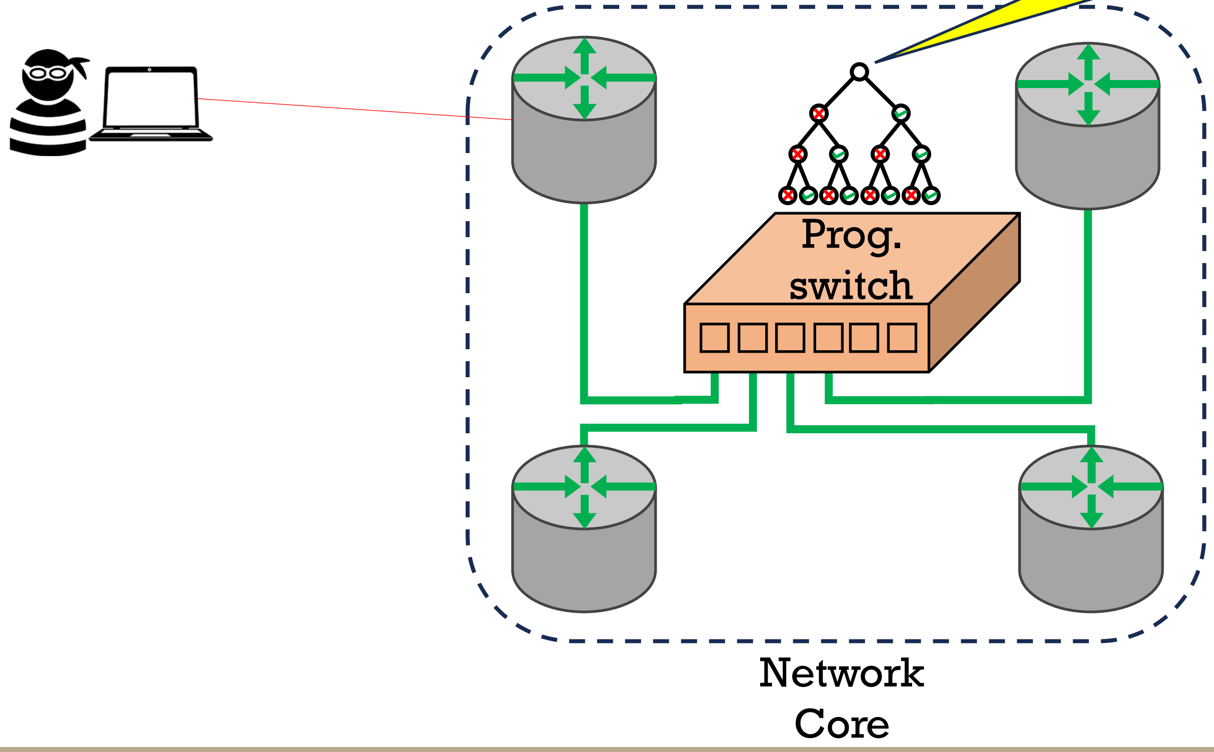
Can we do classification synchronously at line rate?

Opportunity: In-network compute

Programmable switches offer new opportunities

- Ability to define custom packet processing logic
- Multi-terabit execution of user programs

Goal: Classify packets in real-time!



Opportunity: In-network compute

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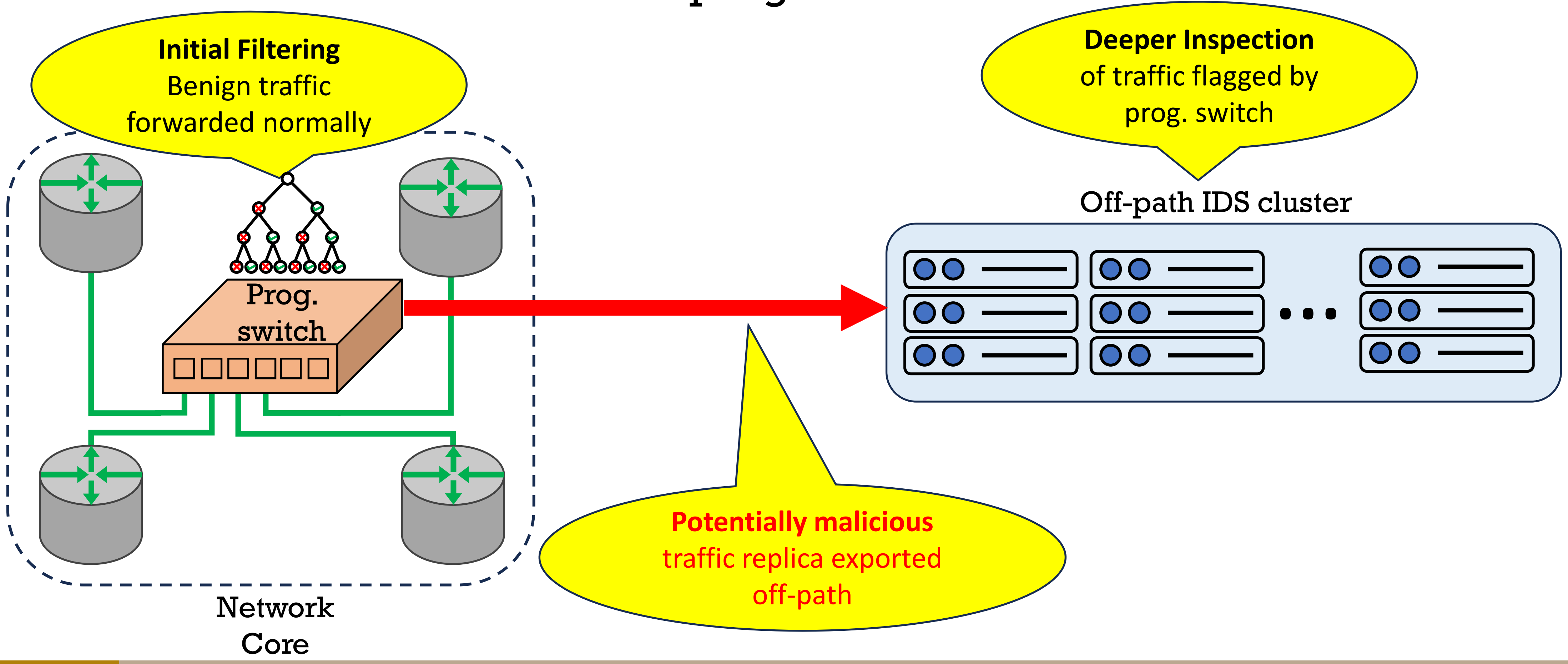


Challenges

Run-time programmable

- Allow model updates with no switch downtime!

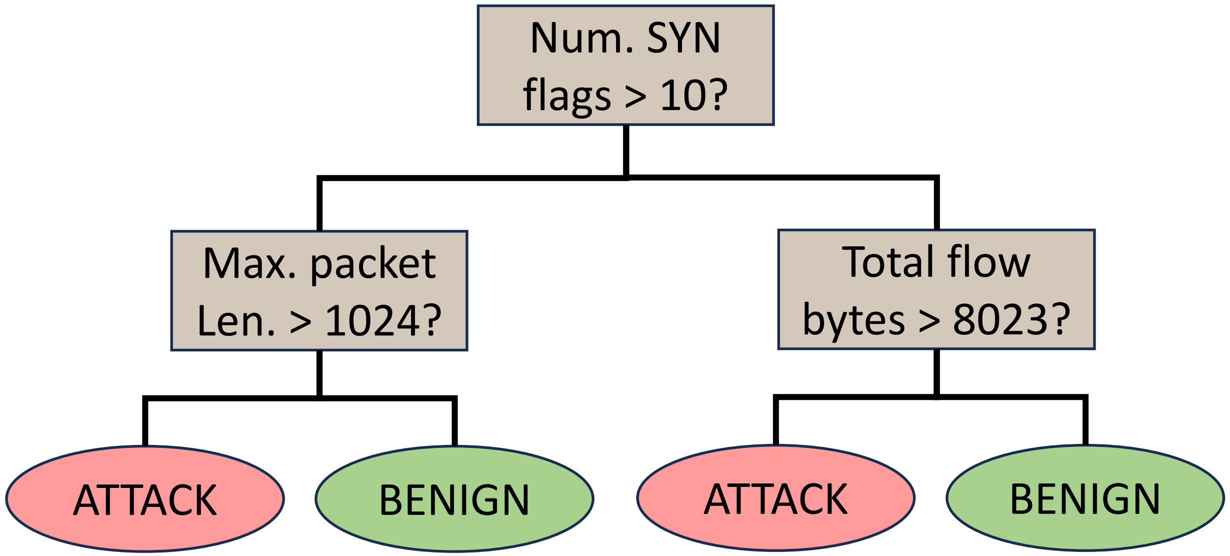
Resource-efficient

- Switch HW resources are reserved at compile time
- Worst-case bounds on resources are important!

Programmable switches have limited expressivity

Our focus: Decision Trees

- Programmable switches sufficiently expressive for decision tree operations
- Easily interpretable compared to "black box" models
- Competitive accuracy [1, 2]



[1] Nigel Williams, Sebastian Zander, and Grenville Armitage, "A preliminary performance comparison of five machine learning algorithms for practical IP traffic flow classification," 2006 SIGCOMM Computer Communication Review 36, 5. (SIGCOMM CCR)

[2] M. Shafiq, X. Yu, A. A. Laghari, L. Yao, N. K. Karn and F. Abdessamia, "Network Traffic Classification techniques and comparative analysis using Machine Learning algorithms," *2016 2nd IEEE International Conference on Computer and Communications (ICCC)*

Leo contributions

Support a class of decision trees in a runtime programmable fashion

- Can support any tree within a (depth, leaves, features) class
  - Emphasis on supporting a class of trees, not a specific tree
- Update the model with no switch downtime

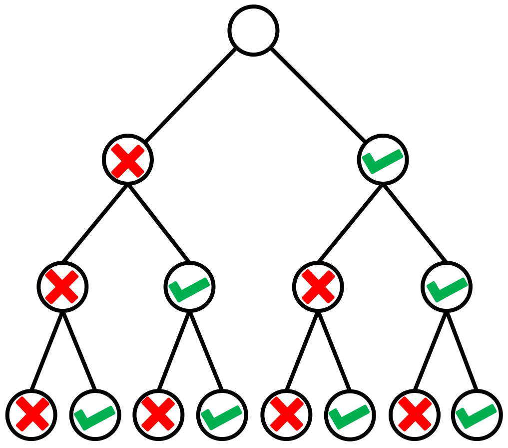
Scalable

- Resource-efficient (memory, ALUs and pipeline stages)
- Scales to large depths (2x of prior work)
- 1 million flows (using 56 stateful feature bits per flow)

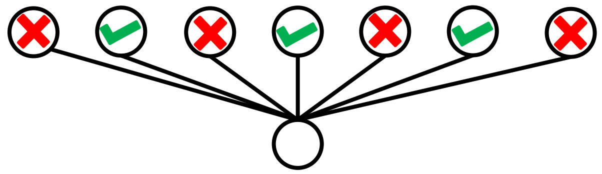
High accuracy

- Comparable F1 score to control plane (SRAM : 93%, TCAM : 98%)

Prior attempts to support decision trees in data plane



Follow natural tree dependency



Break tree dependency

Memory ↓
Stages ↑

Memory ↑
Stages ↓

pForest [1]
SwitchTree [2]
Infocom [3]

IIsy [4]

Bottleneck: switch stages

Question:
How well does it perform?

Our analysis of IIsy

- To support all trees with depth $\leq$ D, a subset of N features taking values [0..K] in a run-time programmable manner:
  - **Proposition 1:** The total SRAM to provision with IIsy is exponential in number of features
  - **Proposition 2:** There exist a family of trees with polynomial # of leaves w.r.t K but requires at least an exponential # of TCAM rules
- See paper for full analysis!

Leo – Overview

Workflow

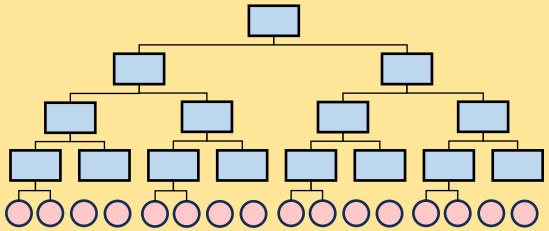
I want to support all trees in the class: (D=4, L=16, F=5)

User

1. User specifies a tree class: (Depth, Leaves, Feature set)

Leo Compiler

2. Chooses a representative tree structure



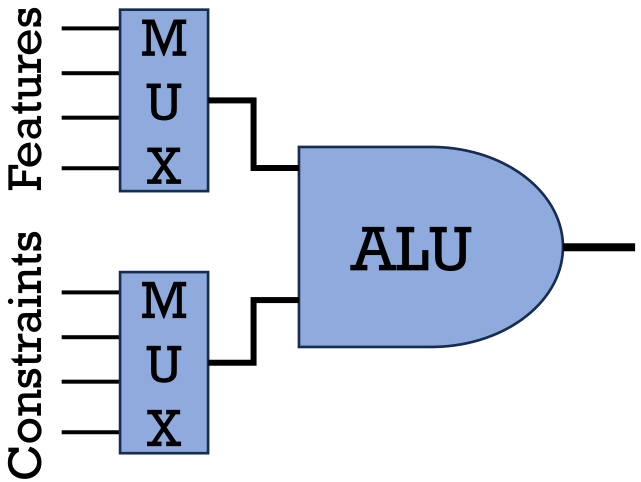
3. Provisions resources for the representative tree in the switch data plane

4. At runtime, switch control plane can configure any tree in the (D, L, F) class into the data plane

Leo – Programmable Tree Node

Challenge: To implement different trees in the (D, L, F) class:
Node **features** and **constraints** need to be runtime programmable

Leo provides a Multiplexed ALU abstraction:



Now to build a runtime programmable tree:

- Reserve a Mux ALU for every node in tree
- Prohibitively expensive ALU requirement!

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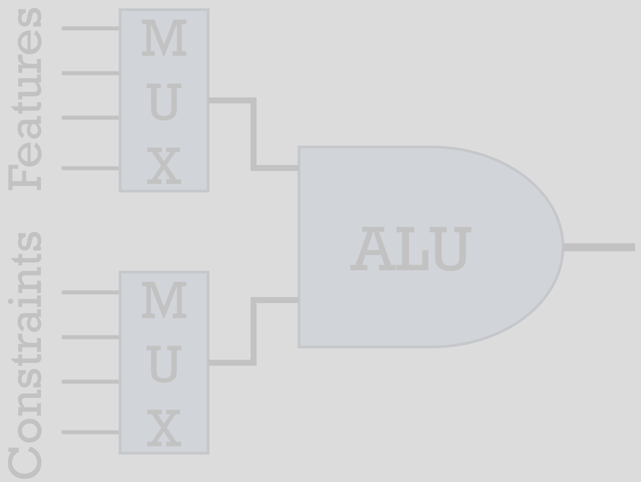
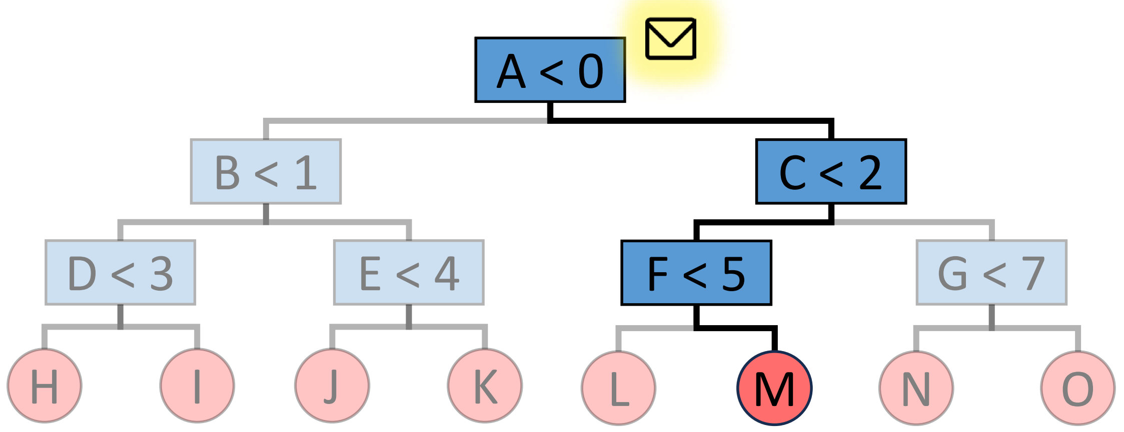


Now to build a runtime programmable tree:
- Reserve a Mux ALU for every node in tree
- Prohibitively expensive ALU requirement!

Question: How to make resource requirements tractable?

Leo – Node Multiplexing

Key Observation: At runtime, only 1 node per level is accessed



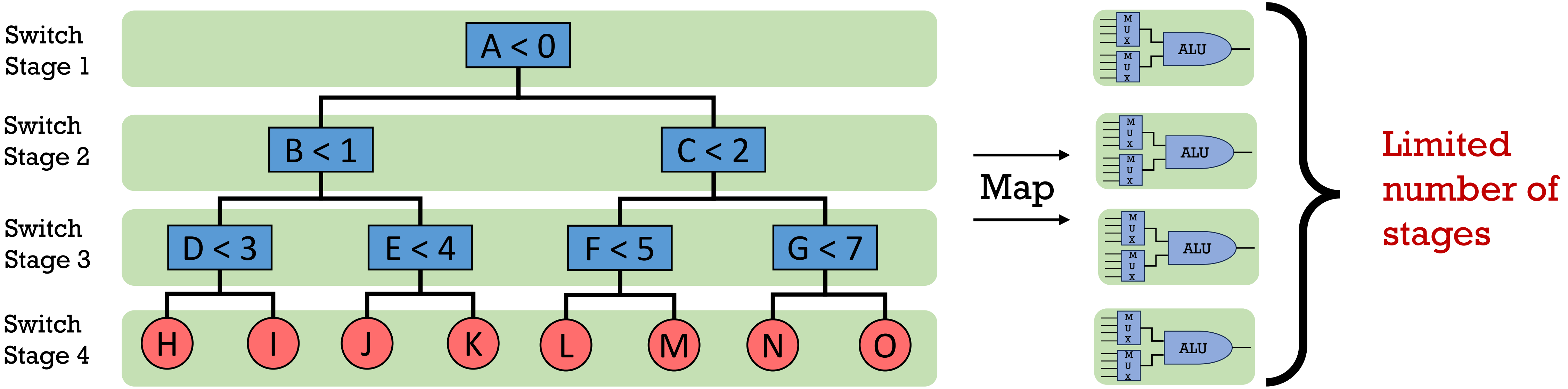
- Allocate resources for only one node per level
- At runtime, multiplex the feature comparisons at each node

Results in resource (ALU) efficiency!

Node Multiplexing – Limitation

→ Depth of decision tree limited by # of switch stages

- A switch with D match-action stages can support a decision tree of depth at most D!



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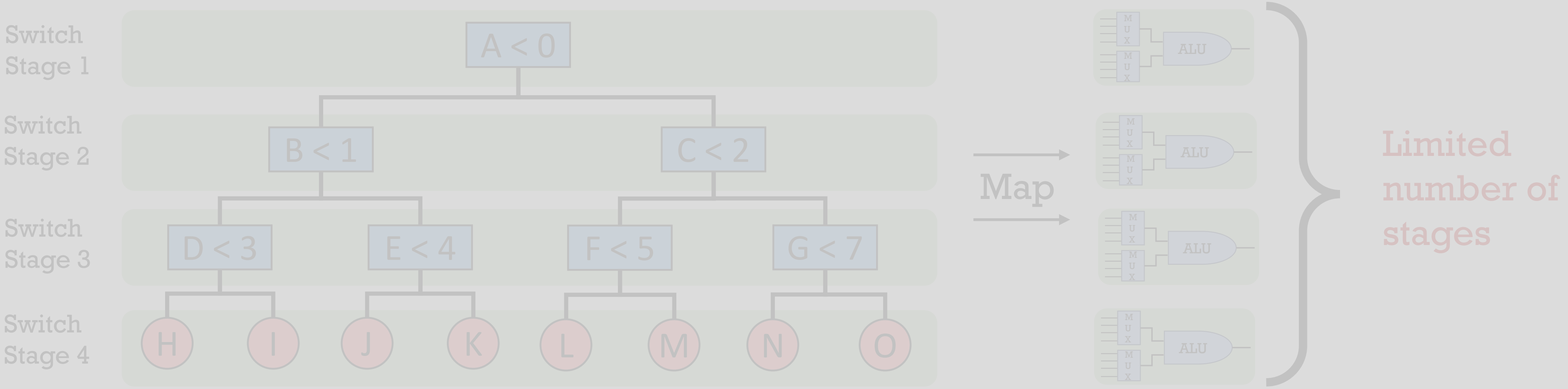
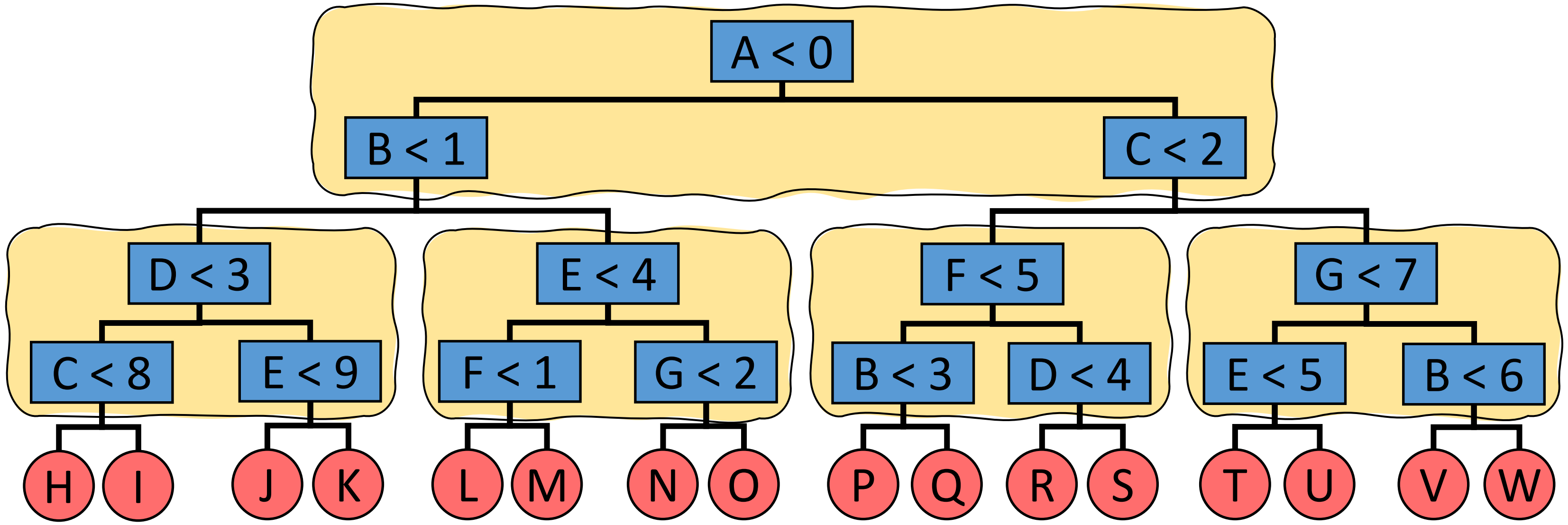


Question: How to scale tree depth?

Leo – Subtree Flattening & Multiplexing

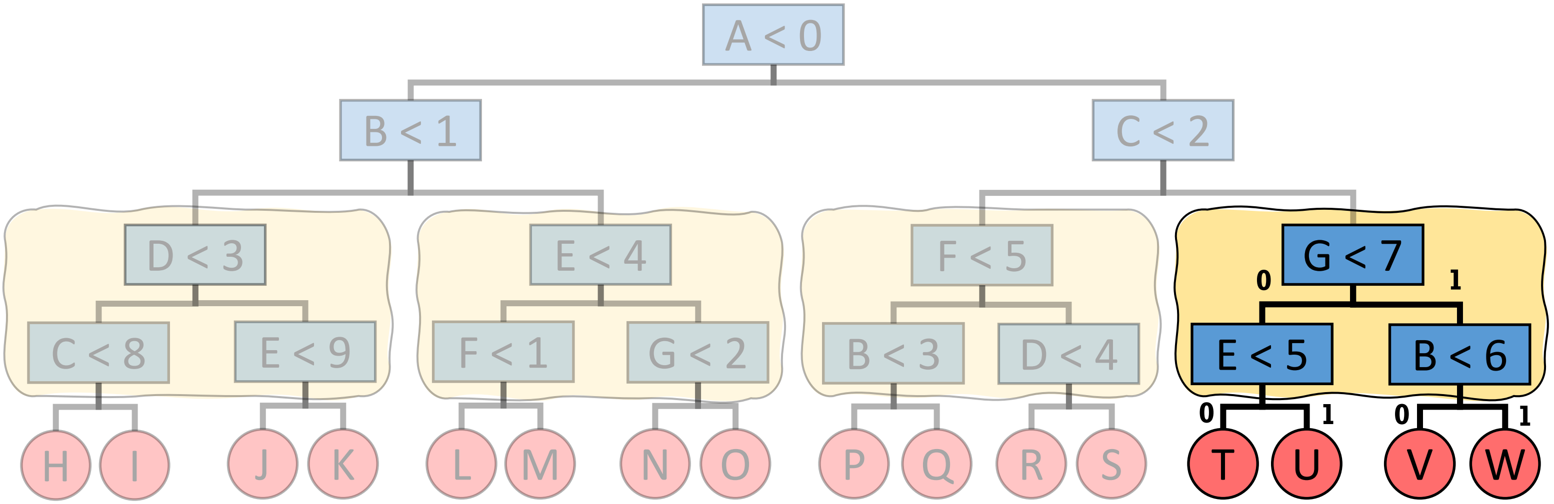
→ Key insight: trees have a common substructure → Subtrees
- Flatten the subtree
- Multiplex between subtrees

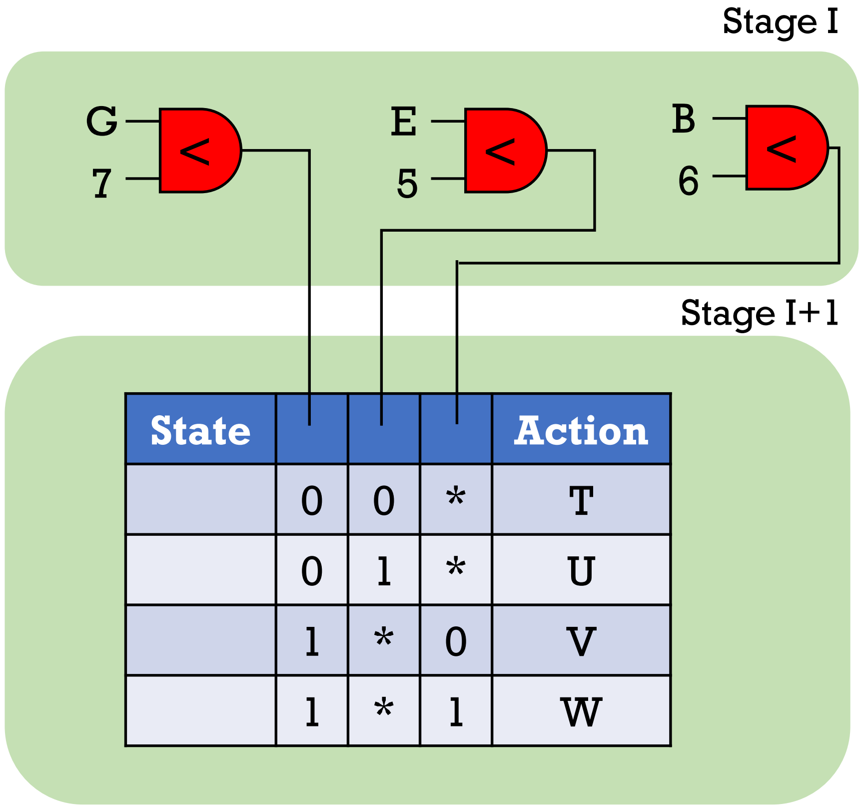
1. Identify subtrees



Subtree Flattening & Multiplexing

2. Flatten subtrees



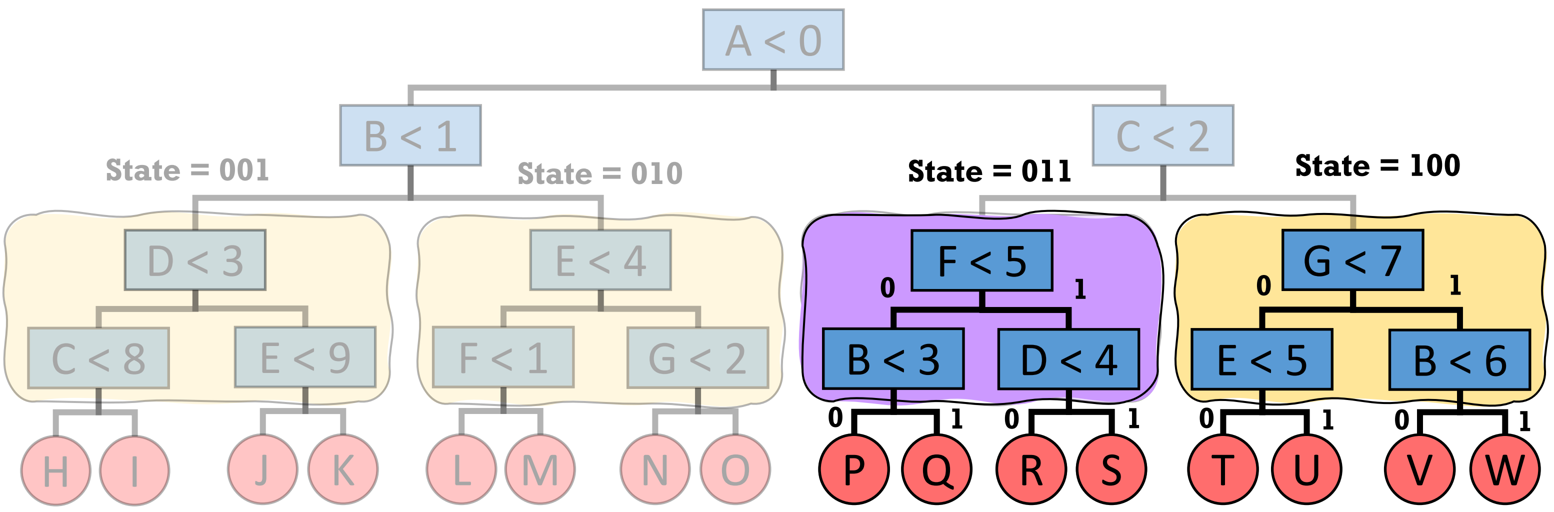


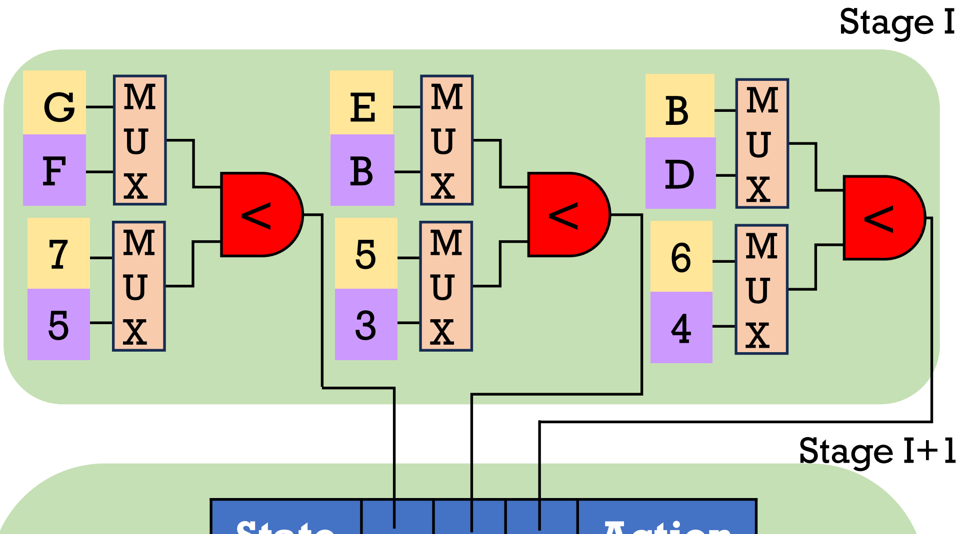
State				Action
	0	0	*	T
	0	1	*	U
	1	*	0	V
	1	*	1	W

A decision tree may be represented as binary table

Subtree Flattening & Multiplexing

3. Multiplex subtrees





State				Action
100	0	0	*	T
100	0	1	*	U
100	1	*	0	V
100	1	*	1	W
011	0	0	*	P
011	0	1	*	Q
011	1	*	0	R
011	1	*	1	S

Need half as many stages! (For subtree size = 3)

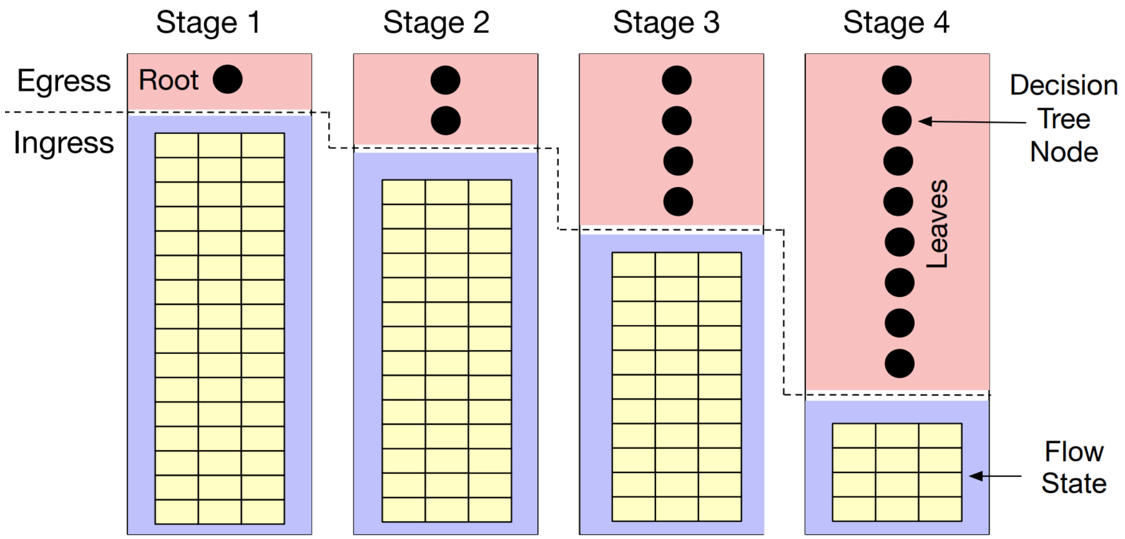
In general:

Reduce # of stages by factor of $\lceil \log K \rceil$

K = subtree size

Leo – Implementation Optimizations

- **Handling stateful features while making efficient use of pipeline stages**



- **Handling transient states correctly during tree updates**
- **Optimization: TCAM stage reduction**
- **See paper for details**

Leo – Worst-case bounds

Leo has acceptable upper bound on the resource requirement:

- For subtrees with $k = 3$ and I internal nodes

  SRAM entries = $8I + 3$

- IIsy number of entries is exponential in number of features N:

  SRAM entries = $(\frac{I}{N} + 1)^N$

See paper for more analysis (TCAM entries, general subtrees, …)

Evaluation: setup

Compare Leo with:
- IIsy, pForest and SwitchTree

Methodology:
- Deploy Leo and related work on Intel Tofino switch to find supported tree classes
- Train decision trees to find highest accuracy tree in supported class

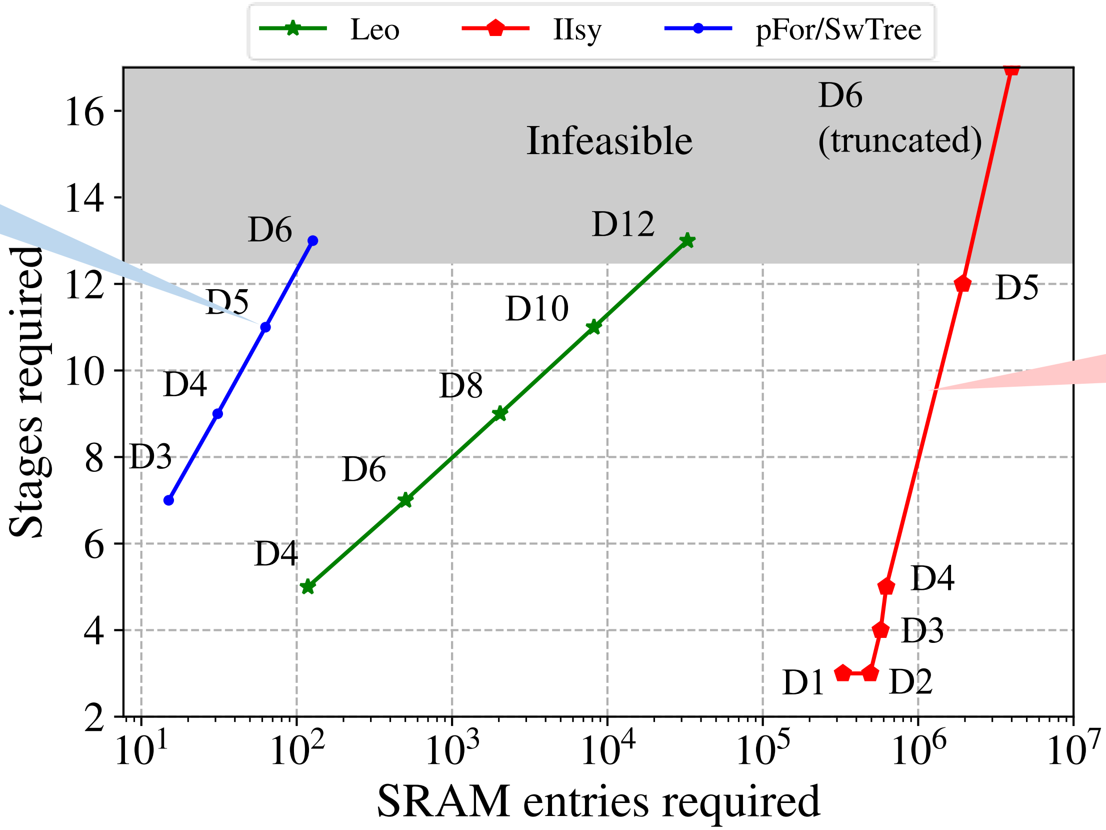
Two intrusion detection datasets:
- UNSW-NB15 – as a binary classification problem
- CICIDS-2017 – as a multi-class classification

Metrics:
- Evaluate on both SRAM and TCAM memory
- **(i)** Number of table entries, **(ii)** Number of switch stages, **(iii)** Mean F1 score
- **(iv)** Num. flows supported and **(iv)** Scaling depth by introducing leaf limits

Evaluation: resource utilization

SRAM utilization of **complete** tree classes (D, D^2, |F|=10)

pForest/SwitchTree: Limited tree depth

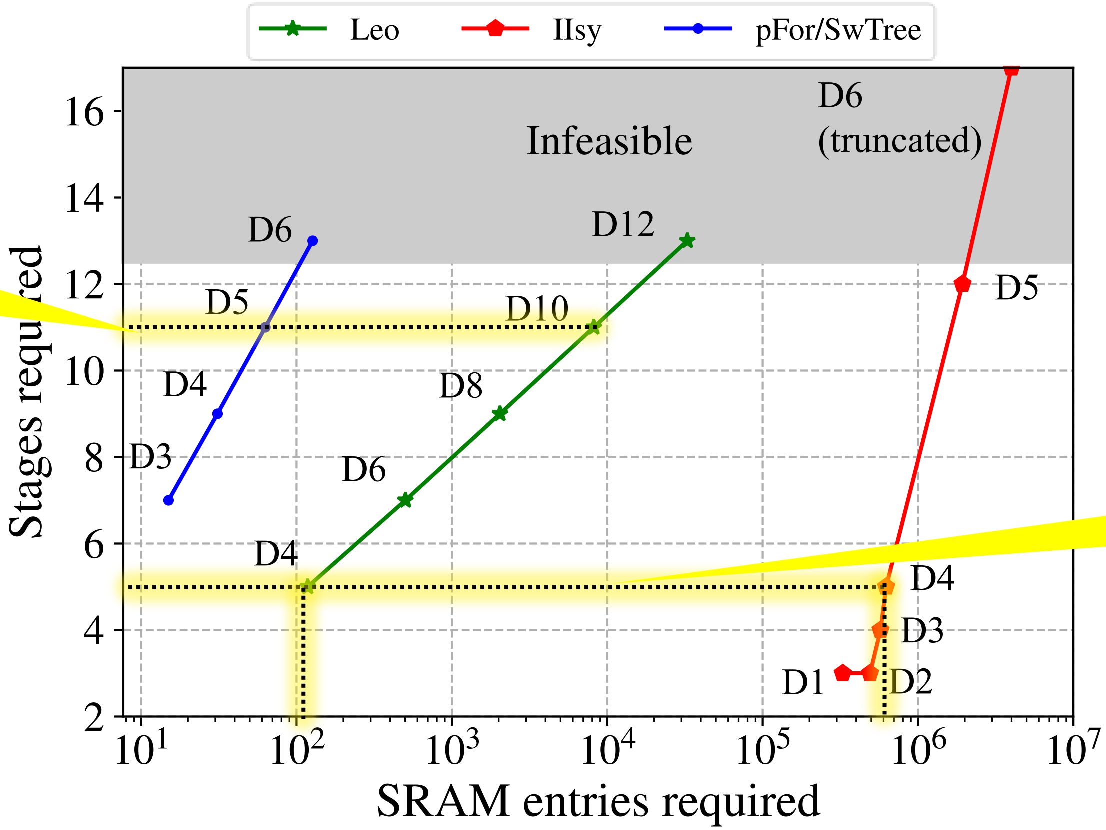


Exponential increase in resource

Evaluation: resource utilization

SRAM utilization of **complete** tree classes (D, D^2, |F|=10)

Leo supports trees with 2x larger depth (using same # stages)

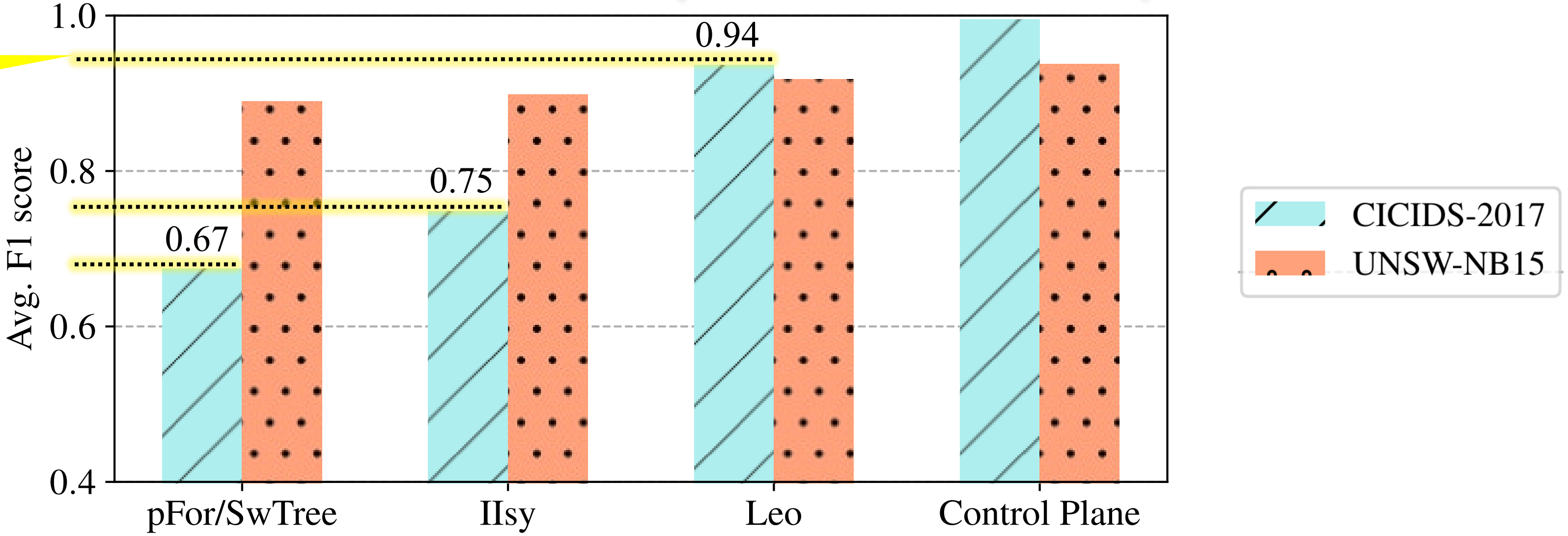


Leo: order of magnitude **fewer** entries

Evaluation: accuracy

Leo achieves accuracies close to the control plane

Leo: accuracy much higher than prior work



Baseline (Server-based)
Large Tree + All Features

More evaluation in the paper:

- With TCAM, Leo can support:
  - → Complete trees of depth 13
  - → Depth 22 with 1024 leaves
- Impact of per-flow state on number of flows
- TCAM classification accuracy results

Conclusion

Support a class of decision trees in a runtime programmable fashion

- Can support any tree within a (depth, leaves, features) class

Scalable

- To large depths (2x of prior work)
- 1 million flows (using 56 stateful feature bits per flow)

High accuracy

- Comparable F1 score to control plane (SRAM : 93%, TCAM : 98%)

We released Leo source code
https://github.com/Purdue-ISL/Leo