

# **Taurus:** A Data Plane Architecture for Per-Packet ML

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# Datacenter networks are becoming harder to manage...

Our current generation — Jupiter fabrics — can deliver more than 1 Petabit/sec of total bisection bandwidth >>

A Look Inside Google's Data Center Networks<sup>1</sup>

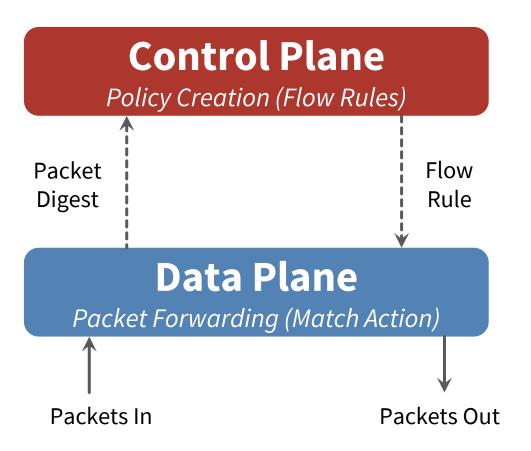
Networks require complex management with high performance

# Automate decision-making with machine learning (ML)

- Making decisions based on data 
   — machine learning
- Machine learning can:
  - Approximate network functions based on data
  - Customize network functions based on data
- Currently, we use by hand-written heuristics in the network...

# Where in the network should ML happen?

#### Software Defined Network



# A Taurus network introduces ML for management

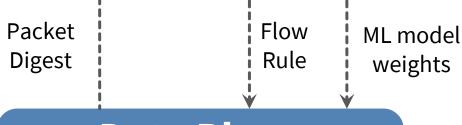
#### **Software Defined Network**

# **Control Plane** Policy Creation (Flow Rules) Packet Flow Rule Digest **Data Plane** Packet Forwarding (Match Action) Packets In Packets Out

# Software Defined Network with Taurus

## **Control Plane**

Policy Creation (Flow Rules + ML Training)



#### **Data Plane**

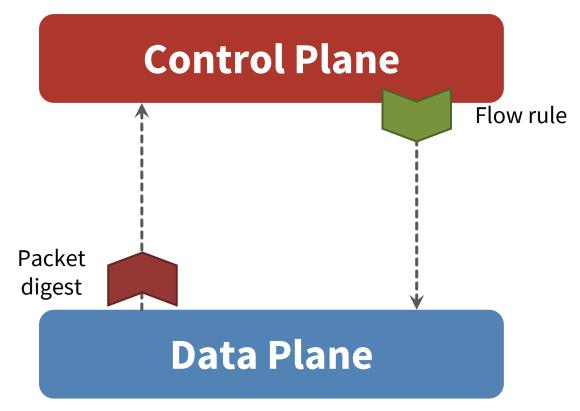
+ Decision Making (ML Inference)

Packets In Packets Out

# ML inference should happen per-packet in the data plane

# **Example: Anomaly Detection**

Processing time: **1. bms** 



# 1.5 M Packets missed during flow rule installation time

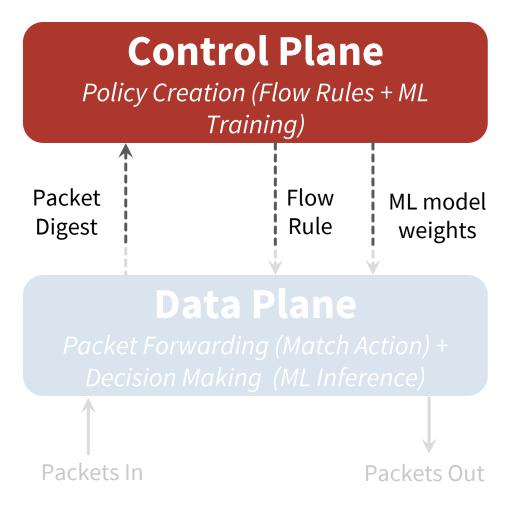
# Robustness and performance of the network are determined by:



# ML training happens in the control plane

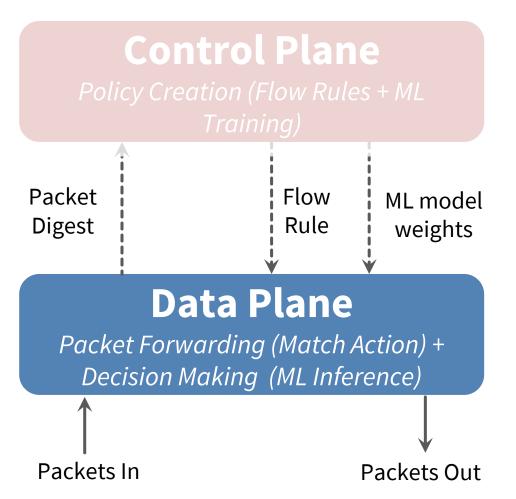
# Software Defined Network with Taurus

# ML Training is off critical path



# ML Inference happens in the data plane

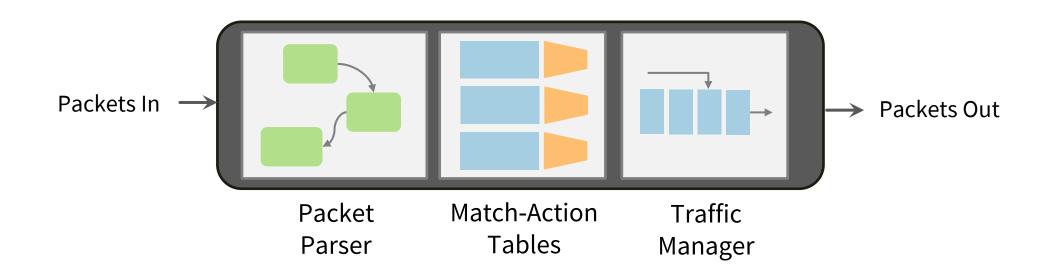
# Software Defined Network with Taurus



ML Inference is on critical path

# Taurus is an architecture for per-packet ML inference in the data plane

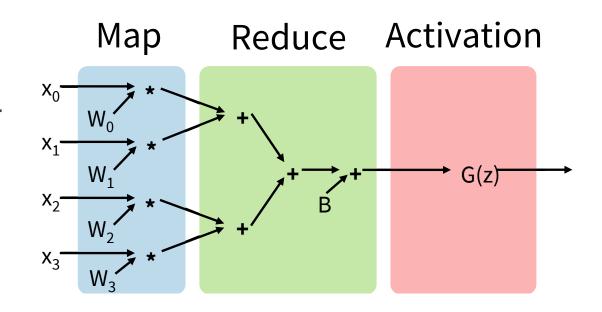
# What do programmable switches look like?



A Protocol Independent Switch Architecture (PISA)

## What abstraction should we use?

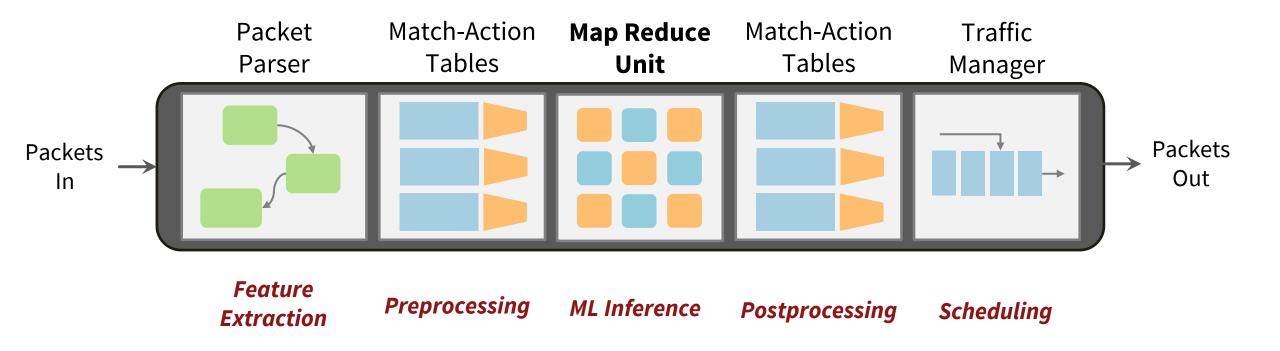
- Map-reduce can support linear algebra operations common in ML
  - Neural networks, SVMs, etc.
- SIMD Parallelism enables performance with minimal logic



- Unrolling patterns allows for flexibility
  - More unrolling 

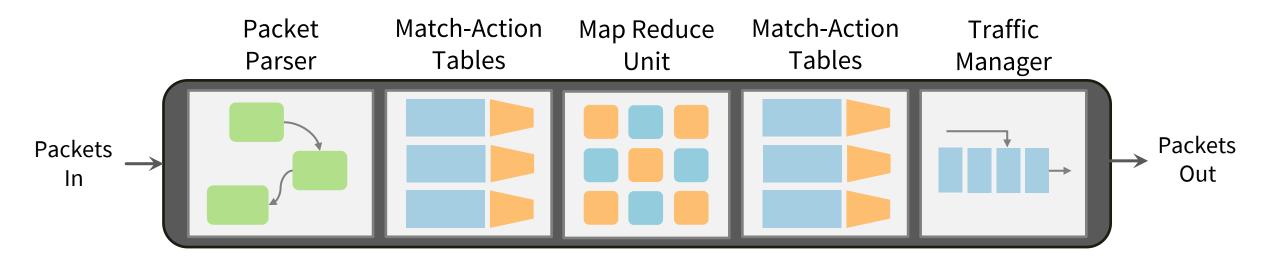
    better performance
  - Less unrolling → less resource usage

# The Taurus pipeline with a Map Reduce Unit



- Map Reduce Unit must:
  - be reconfigurable
  - meet line rate (with a fixed clock)
  - incur minimal area and power overhead

# Example Application: Anomaly Detection



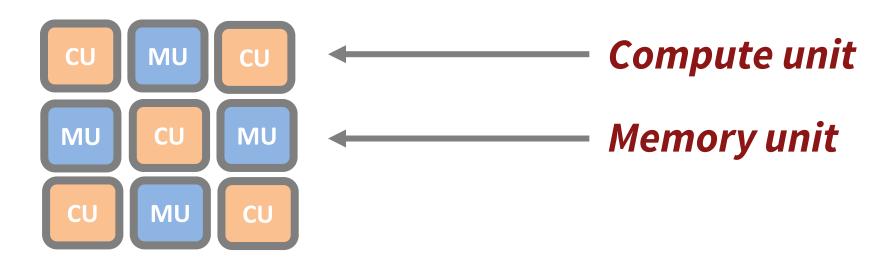
Packet

**Read local features** (e.g., IP address) Retrieve out of network events (e.g., failed logins per IP) Apply learned anomaly detection

**Select a port or action** (e.g., drop if score == 1) Send packet to destination

## **Evaluation of a Taurus ASIC**

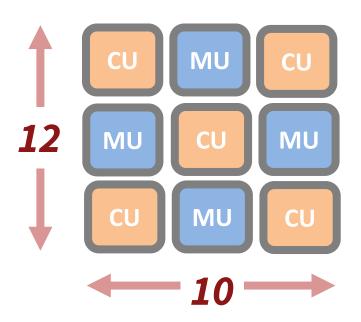
- Our evaluation platform is based on *Plasticine*
- We program our map-reduce applications in the Spatial HDL



More architectural details in full paper!

## **Evaluation of a Taurus ASIC**

- Our evaluation platform is based on Plasticine
- We program our map-reduce applications in the Spatial HDL



	Area		
Hardware	mm <sup>2</sup>	+%	
12x10 MR Grid	4.8 x 4	3.8	
Prog. Switch	500		

\*Overheads are calculated relative to state of the art programmable switches

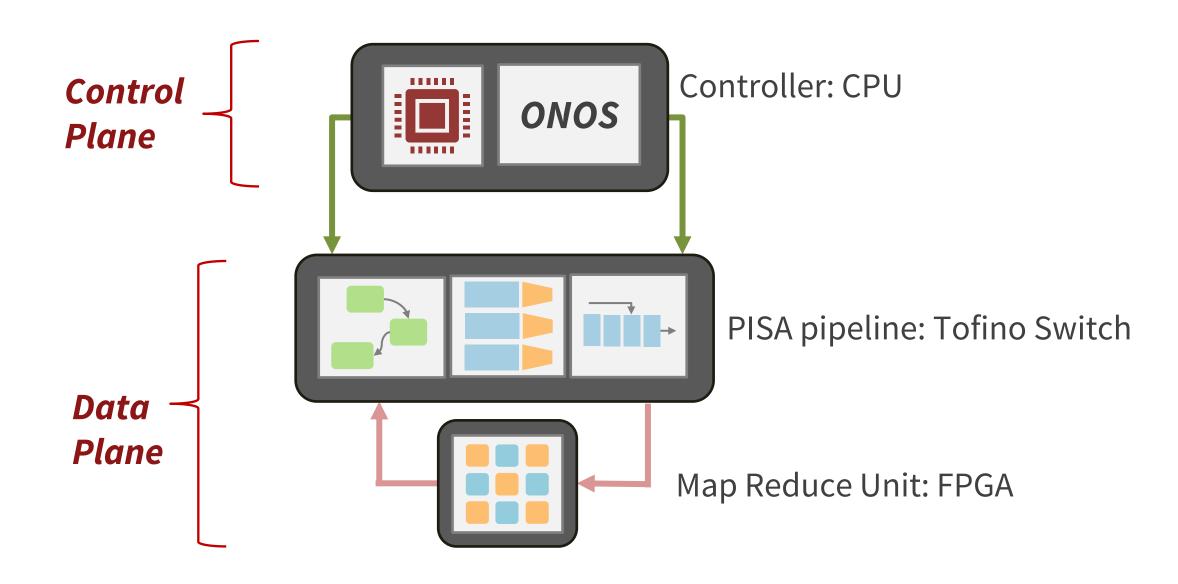
# Evaluation of an Anomaly Detection (AD) benchmark

- AD SVM: 8 support vectors
- AD DNN: 4 layers 12x6x3x2 neurons

Overhead of Map Reduce Unit		Area	Power	
Model	TP (GPkt/s)	Lat (ns)	+%	+%
SVM	1	83	0.5	0.6
DNN	1	221	0.8	1.0

<sup>\*</sup>Overheads are calculated relative to state of the art programmable switches

# We provide an open-source, FPGA-based testbed



# Questions?

Try it out!

https://gitlab.com/dataplane-ai/taurus