Is In-network Machine Learning So Easy?

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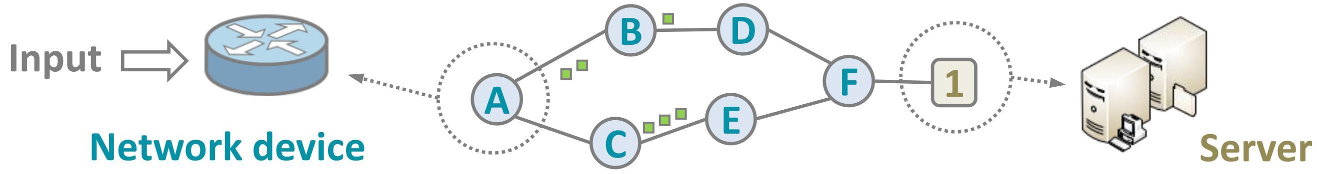
Background

Growth of network connections & data



Growth of programmable data plane architecture

Traditional Network

- Bound to specific hardware
- Limited programmability
- High barrier to modification

Programmable Network

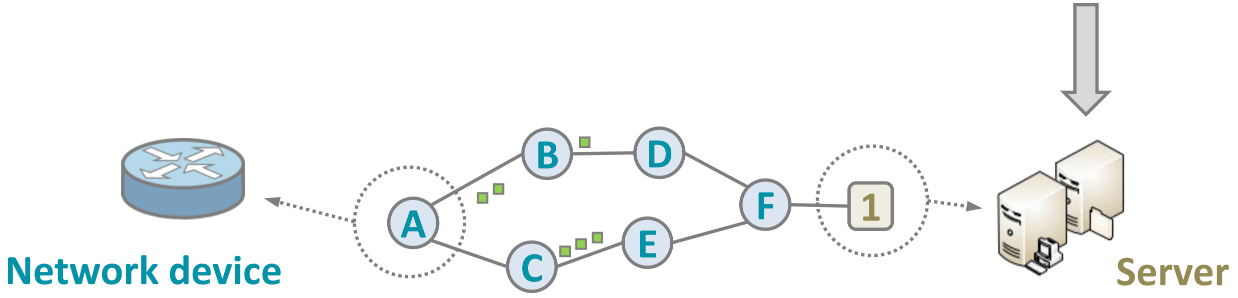
- Different hardware, same architecture
- Enable programmable control
- Easy and centralised control and modification

What Is In-Network Machine Learning?

In-network ML refers to off load inference or entire ML processes to the network.

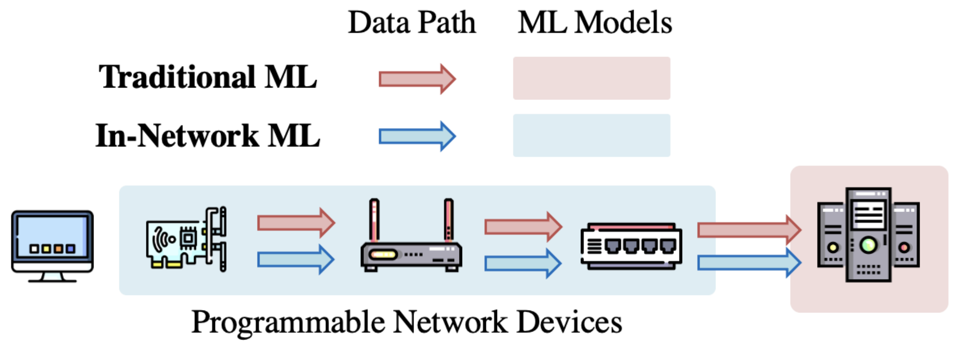
In-Network

Machine Learning Inference



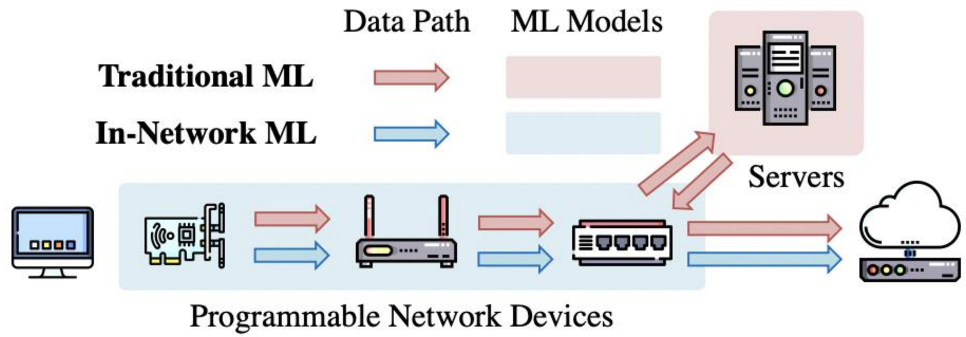
Motivation: 3Ls

Location



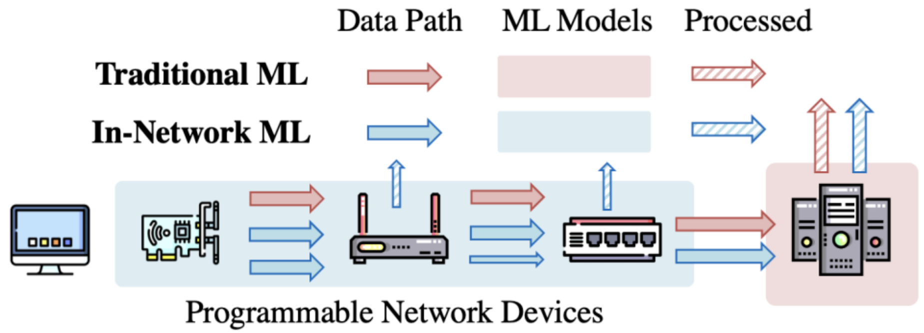
- Along the path
- Already exist

Latency



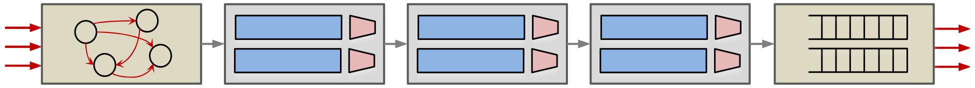
- Shorter path

Load



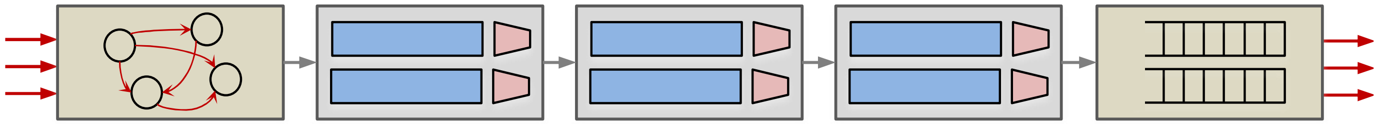
- Higher throughput
- Early termination

What Is In-Network Machine Learning?

General Machine Learning	**vs**	***In-Network Machine Learning***
Local PC, Servers, …	Location	*Network Infrastructures*
CPU, GPU, …	Device	 **PISA**
C, Python, MATLAB, …	Language	*P4*
Training & Inference	Manner	*Offline Training Online Inference*

Challenges

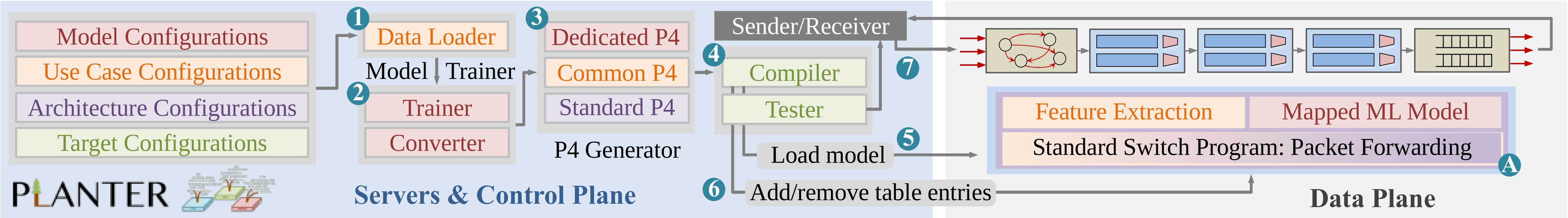
Resources on network devices are very limited compared to PC or servers.



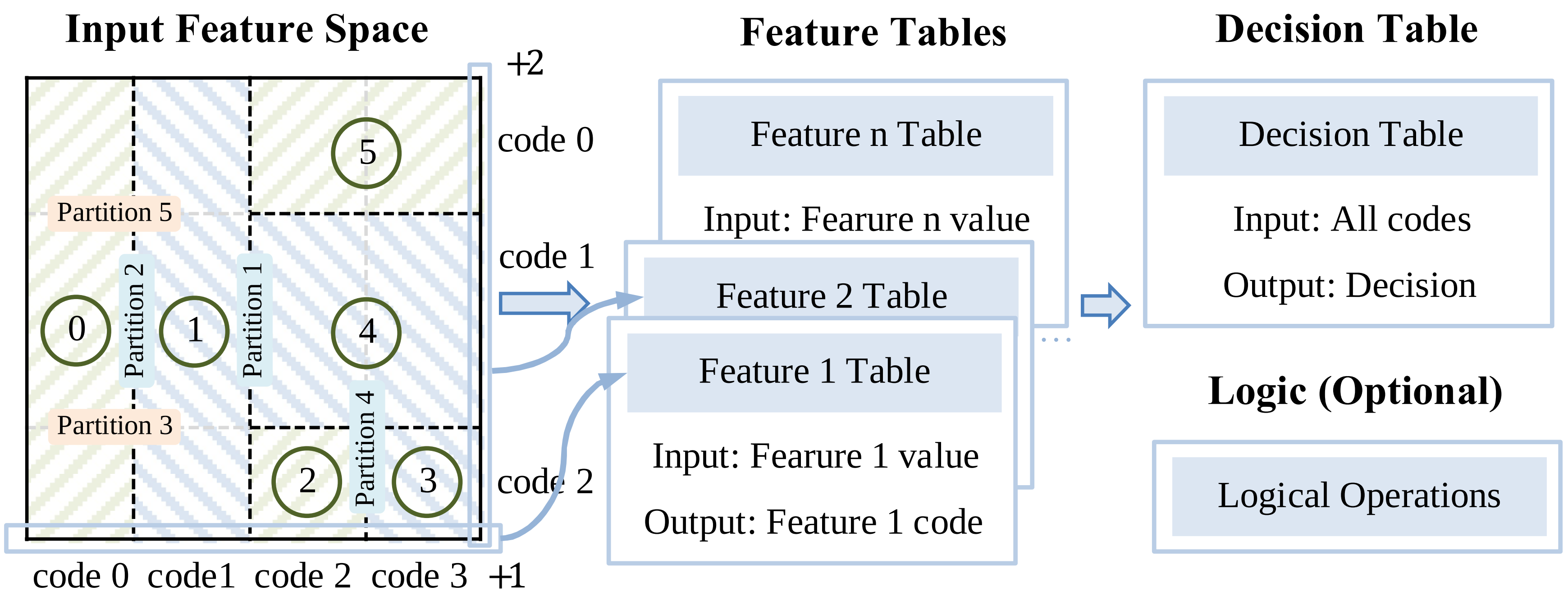
1. **Limited mathematical operations**
2. **Limited memory**
3. **Limited data types**
4. **Limited stages**

How to map?

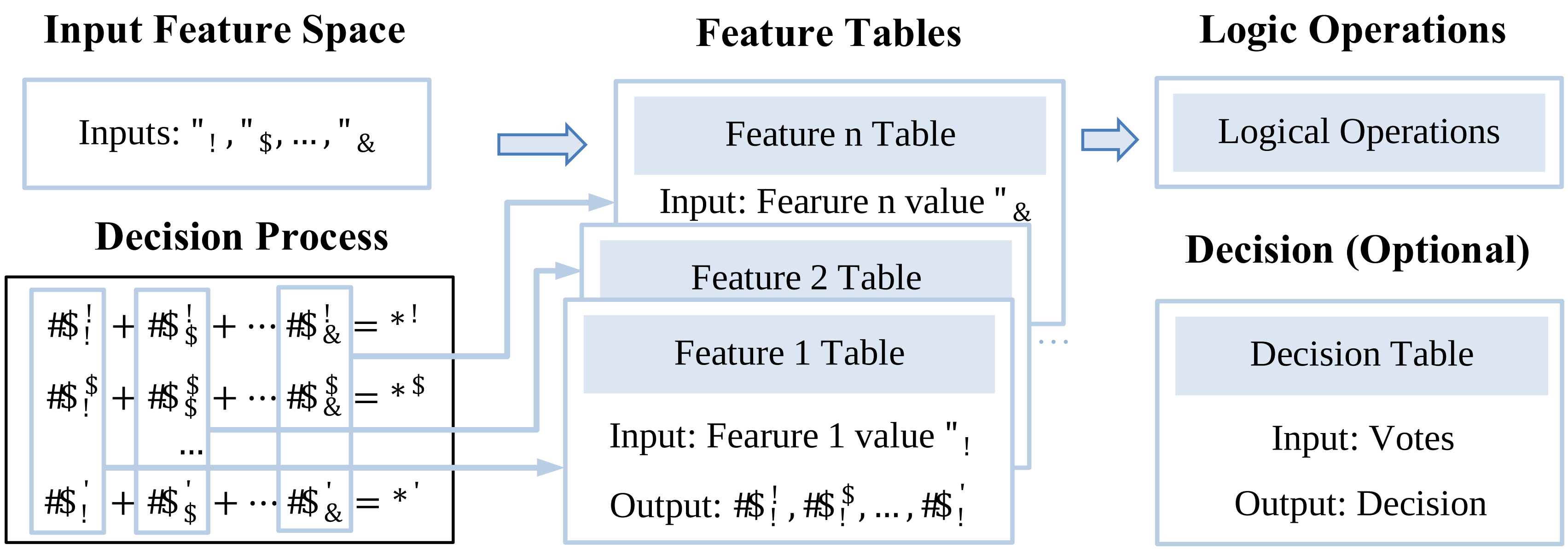
1. **Direct mapping solution**
2. **Encode based solution**
3. **Look up based solution**



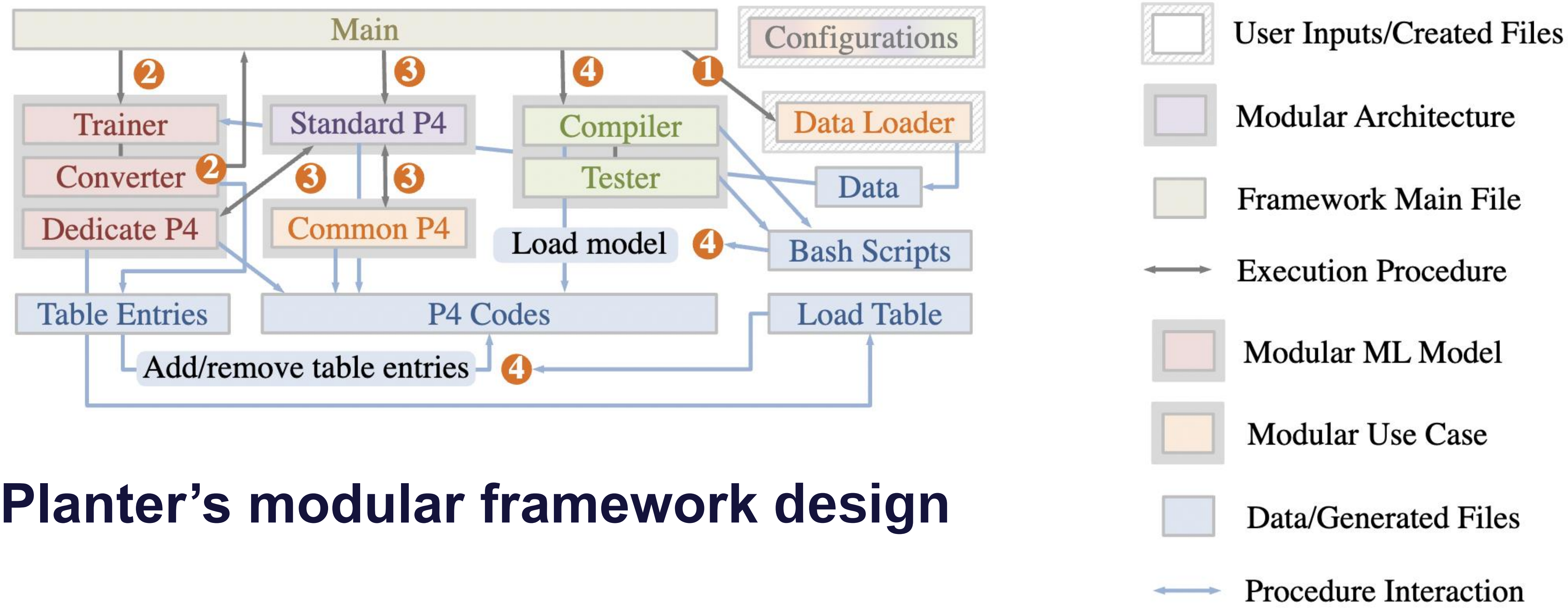
Encode based solution



Look-up based solution

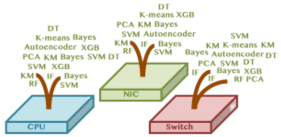


Planter Framework



Planter's modular framework design

Planter Framework



Models: SVM, DT, RF, XGB, IF, NB, KM, KNN, PCA, AE, NN

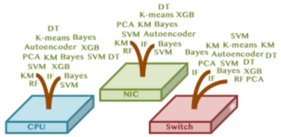
Architectures: PSA, v1model, TNA

Targets: Tofino, BMv2, P4Pi, Alveo FPGA

Datasets: Iris, UNSW, CICIDS, AWID3, KDD …

Use Cases: Anomaly Detection, Financial Transaction …

Planter Use Cases



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Anomaly Detection

1. Models Mapping
2. Planter Framework
3. **Packet/Flow/File Level**

IIsy **Planter**

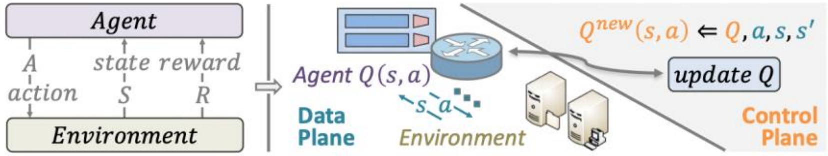
IoT Traffic Classification

1. **Continuous learning**
2. **Runtime model update**
3. **Federated learning**

P4Pir **FLIP4**

Load Balancing

1. **In-network Q-Learning**
2. **QCMP Load Balancing**

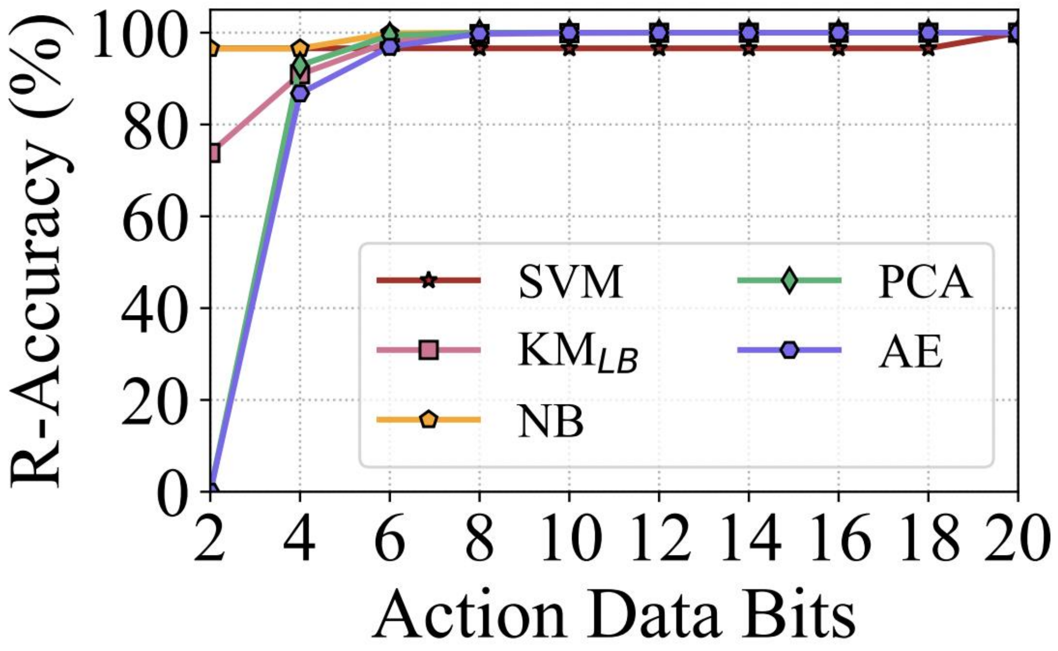


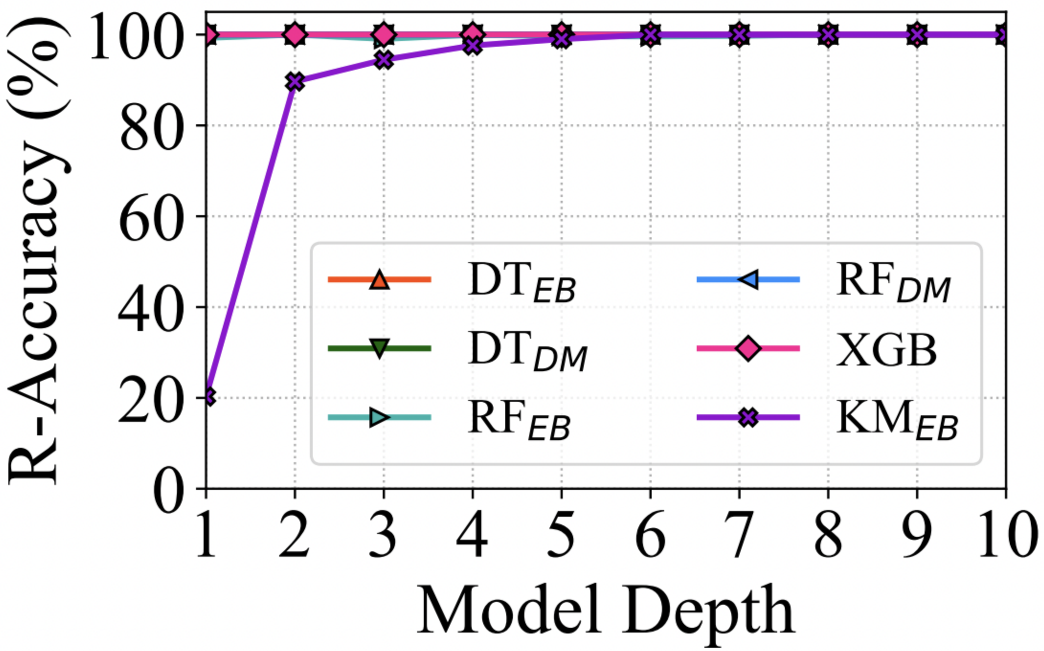
QCMP: SIGCOMM23 FIRA Workshop

Edge Computing, Financial Market Prediction…

Planter Results: Same Accuracy?

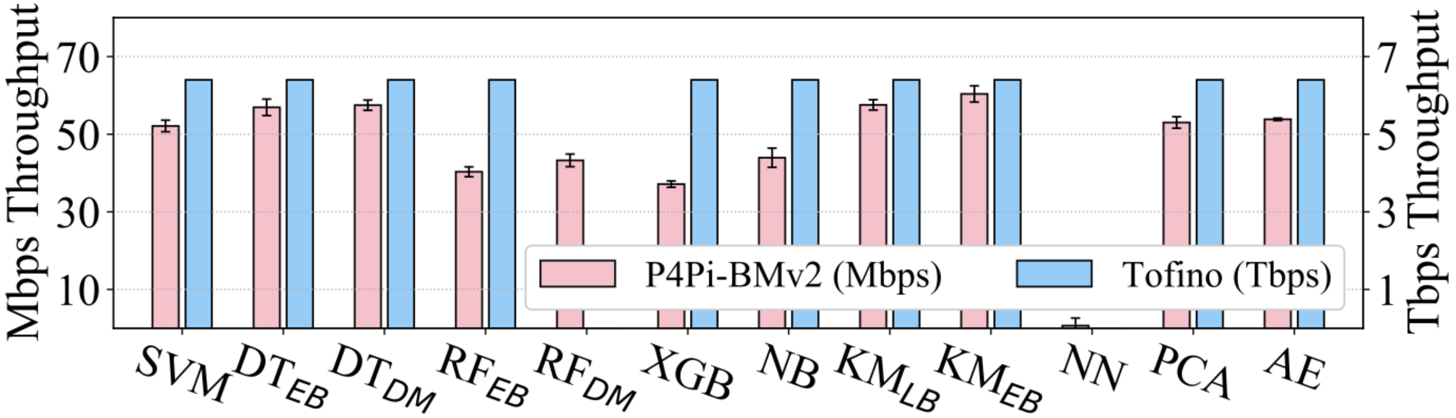
Anomaly Detection Use Case



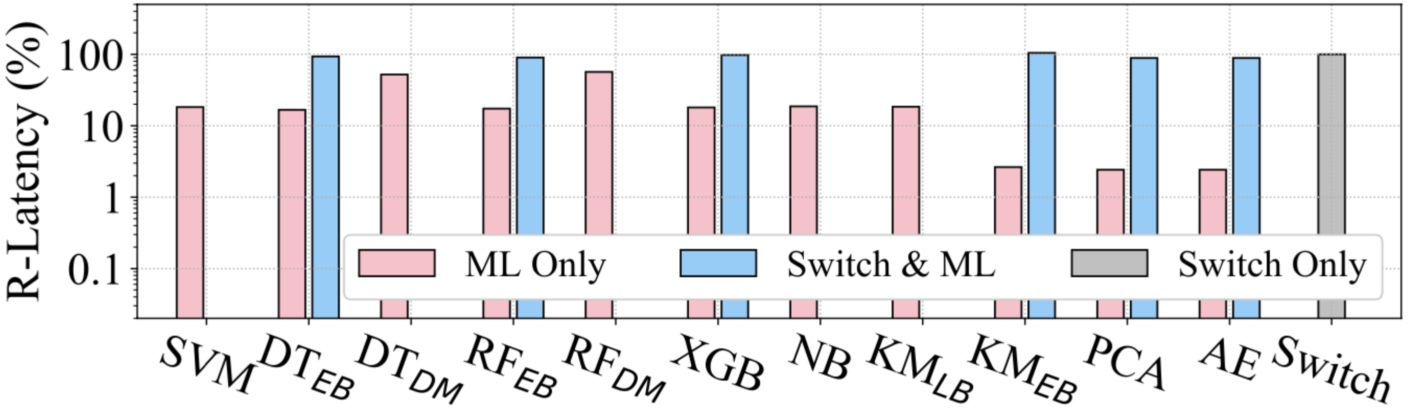


Planter Results: System Performance

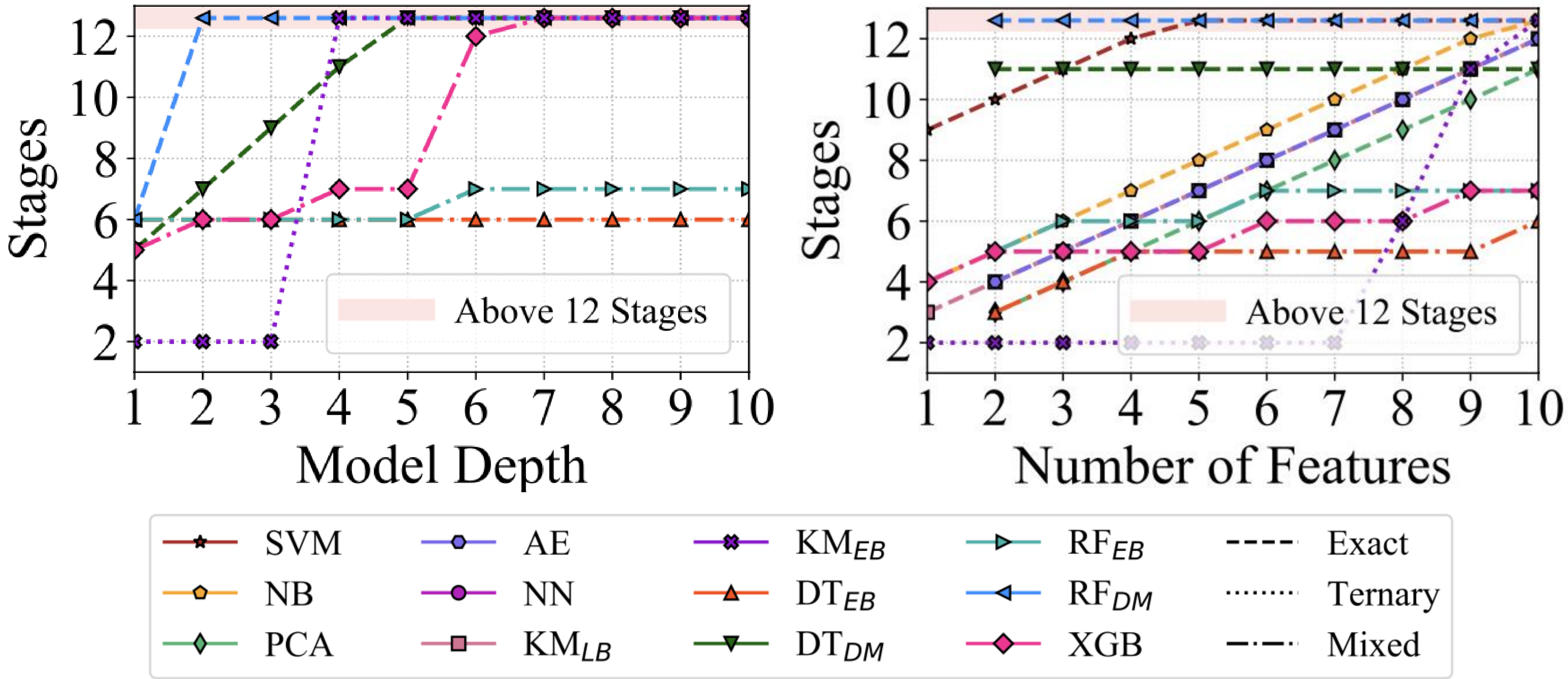
Anomaly Detection Use Case



Financial Market Prediction Use Case

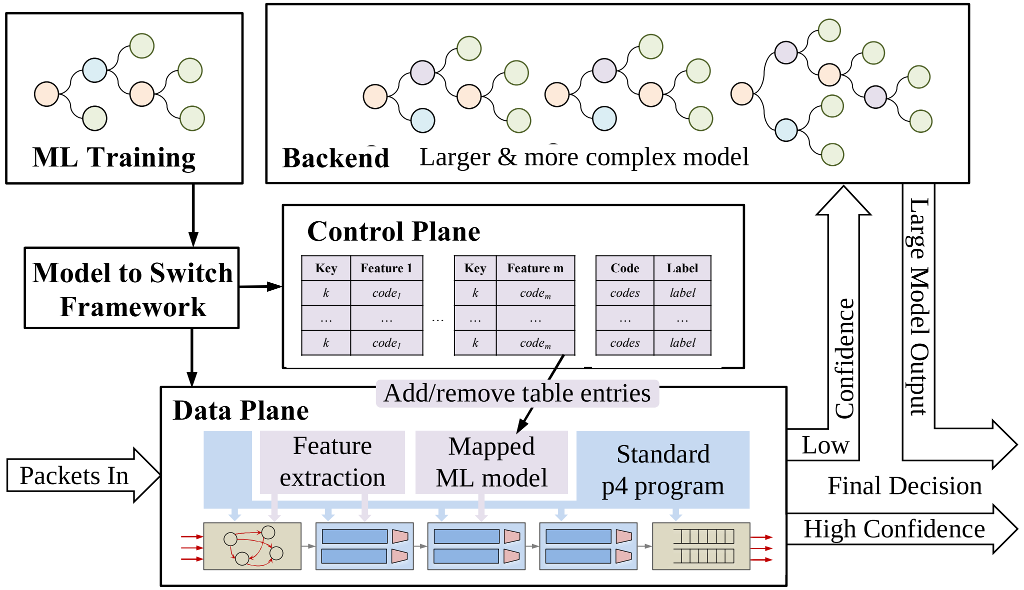


Planter Results: Scalability

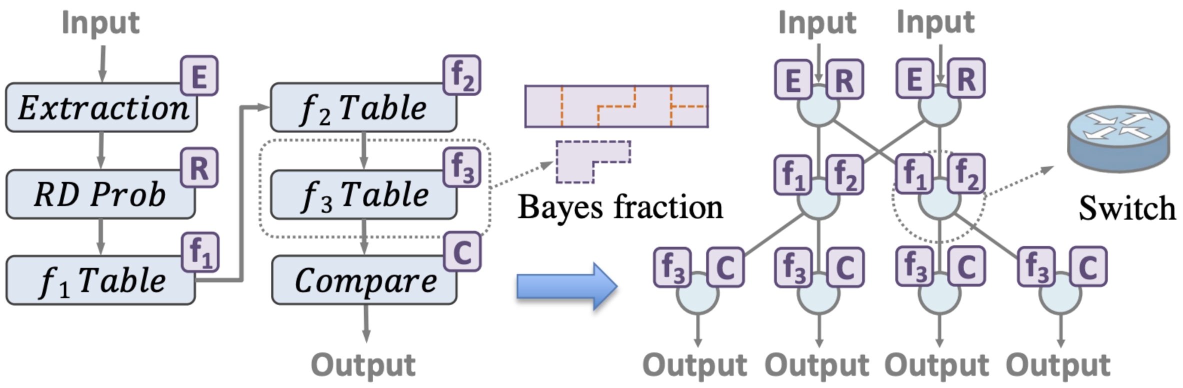


Further Scale In-Network ML?

Hybrid Deployment



Distributed Deployment



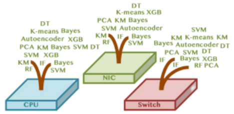
Summary

Q: How to realize in-network ML mapping?

A: Three mapping solution: DM, EB, LB.

Q: How to easily map ML to the data plane?

A: Planter framework.



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Q: How to realize personalized use cases?

A: By adding new modules.

Q: How to further scale ML model size?

A: Hybrid deployment & distributed deployment.

Use Case Ideas? New Challenges?

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List of Papers:

Xiong & Zilberman, Do Switches Dream of Machine Learning?, 2019
Zheng et al, Planter: Seeding Trees Within Switches, 2021
Zheng et al, IIsy: Practical In-Network Classification, 2022
Zheng et al, Automating In-Network Machine Learning, 2022
Hong et al, Linnet: Limit Order Books Within Switches, 2022
Zang et al, P4Pir: In-Network Analysis for Smart IoT Gateways, 2022
Hong et al, LOBIN: In-Network Machine Learning for Limit Order Books, 2023
Zang et al, Federated Learning-Based In-Network Traffic Analysis on IoT Edge, 2023
Zheng et al, QCMP: Load Balancing via In-network Reinforcement Learning, 2023

EB solution and example
LB solution and example
DM solution and example
Scalability evaluation