

Advanced Computer Networks

Machine Learning for Networking

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Period 2, Fall 2021

Course outline

Warm-up

- Introduction (history, principles)
- Networking basics
- Networking data structures and algorithms
- Network transport

Data centers

- Data center networking
- Data center transport

Programmability

- Software defined networking
- Network automation
- Network function virtualization
- Programmable data plane

Application

- Network monitoring
- In-network computing
- **Machine learning for networking**

Learning objectives

How to leverage machine learning for **video streaming**?

How to leverage machine learning for **network packet classification**?

Machine learning paradigms

Supervised learning
(regression, classification)

Unsupervised learning
(clustering)

Reinforcement learning
(decision making)

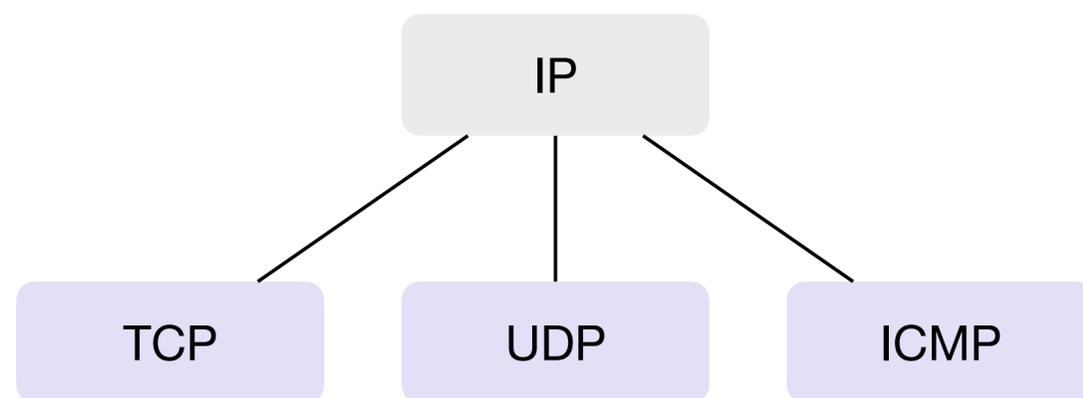
Where does **deep learning** sit? Well, deep learning is part of a broader family of machine learning methods that are based artificial neural networks and can fit in any of the above categories.

Deep learning: in the spotlight

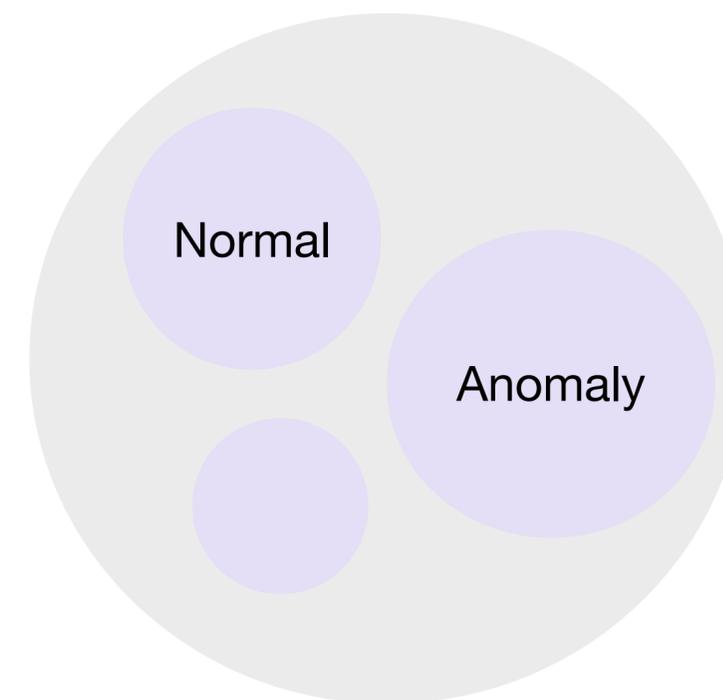


RL-based agent beat human experts on Go and more

ML in networking: examples



Decision tree for packet classification

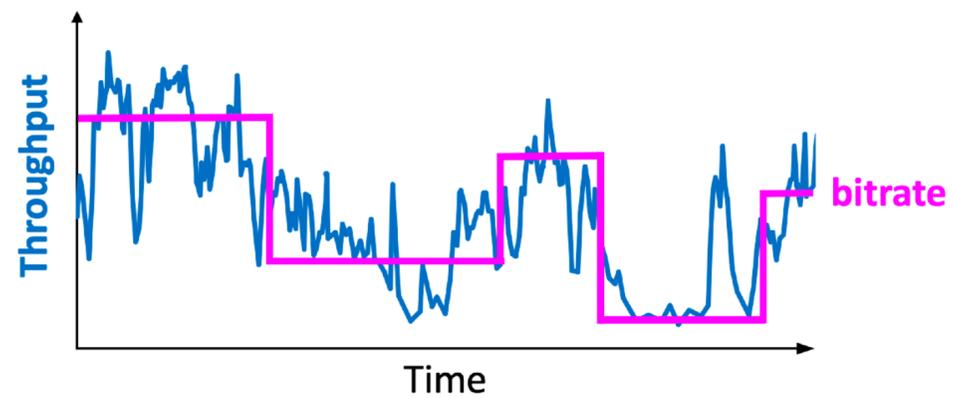
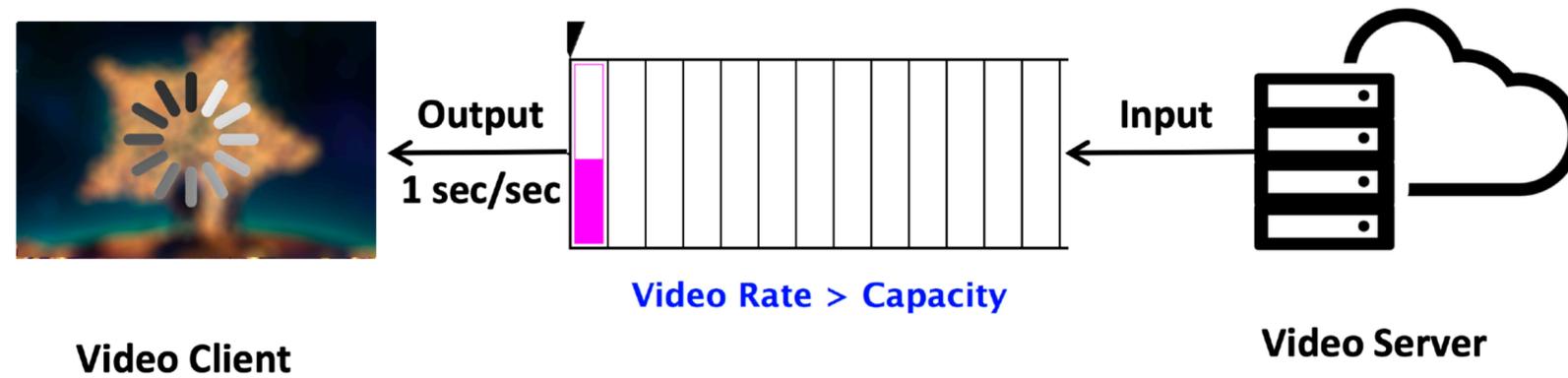


Clustering for anomaly detection

Machine learning for video streaming

Video streaming

Dynamic Streaming over HTTP (DASH)

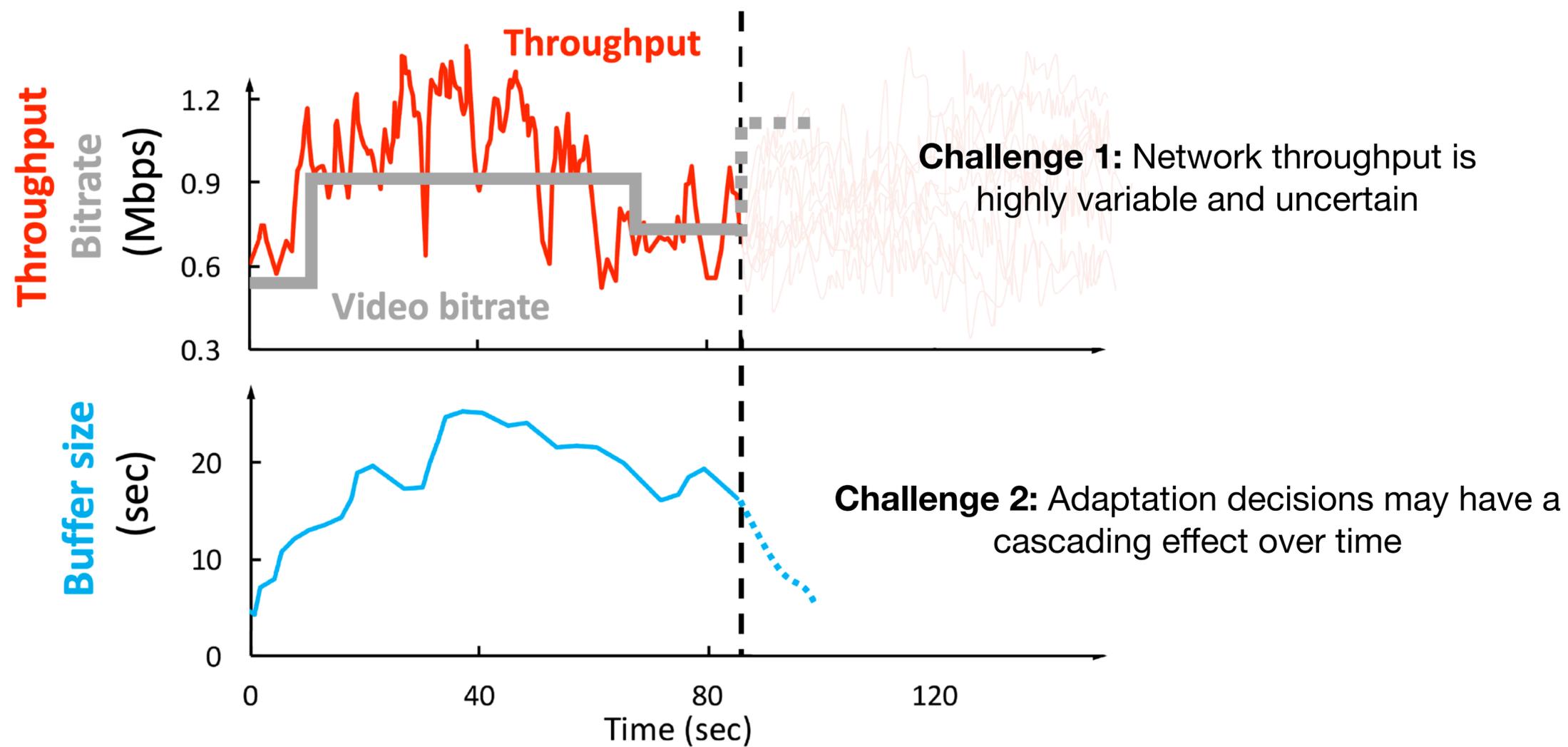


Adaptive bitrate (ABR) algorithms:

- Rate-based
- Buffer-based

For video streaming basics, please refer to: <https://linwang.info/docs/acn20/09-streaming.pdf>

Why is video streaming a challenging problem?



Existing solutions

Rate-based: pick bitrate based on **predicted throughput**

- FESTIVE (CoNEXT'12), PANDA (JSAC'14), CS2P (SIGCOMM'16)

Buffer-based: pick bitrate based on **buffer occupancy**

- BBA (SIGCOMM'14), BOLA (INFOCOM'16)

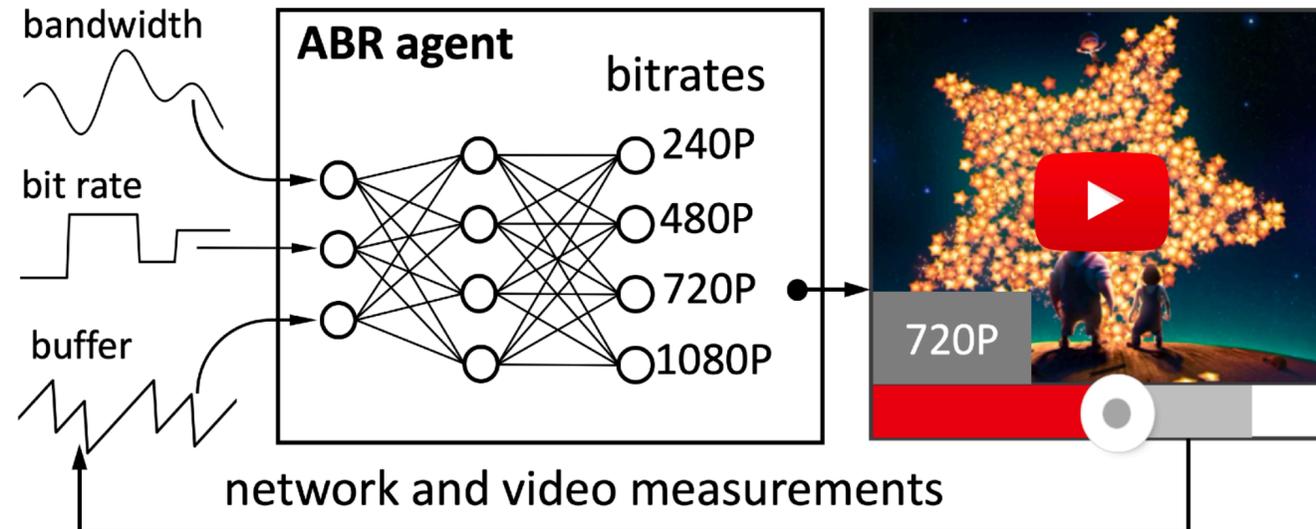
Hybrid: use both throughput prediction and buffer occupancy

- PBA (HotMobile'15), MPC (SIGCOMM'15)

All these solutions are fixed heuristics and are based on the designer's insight. All of them rely on **simplified inaccurate model** which leads to suboptimal performance.

Can we automatically learn how to choose bitrates?

Pensieve: learning-based ABR algorithm



Pensieve **learns** ABR algorithm **automatically** through experience

Neural Adaptive Video Streaming with Pensieve

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ABSTRACT

Client-side video players employ adaptive bitrate (ABR) algorithms to optimize user quality of experience (QoE). Despite the abundance of recently proposed schemes, state-of-the-art ABR algorithms suffer from a key limitation: they use fixed control rules based on simplified or inaccurate models of the deployment environment. As a result, existing schemes inevitably fail to achieve optimal performance across a broad set of network conditions and QoE objectives.

We propose Pensieve, a system that generates ABR algorithms using reinforcement learning (RL). Pensieve trains a neural network model that selects bitrates for future video chunks based on observations collected by client video players. Pensieve does not rely on pre-programmed models or assumptions about the environment. Instead, it learns to make ABR decisions solely through observations of the resulting performance of past decisions. As a result, Pensieve automatically learns ABR algorithms that adapt to a wide range of environments and QoE metrics. We compare Pensieve to state-of-the-art ABR algorithms using trace-driven and real world experiments spanning a wide variety of network conditions, QoE metrics, and video properties. In all considered scenarios, Pensieve outperforms the best state-of-the-art scheme, with improvements in average QoE of 12%–25%. Pensieve also generalizes well, outperforming existing schemes even on networks for which it was not explicitly trained.

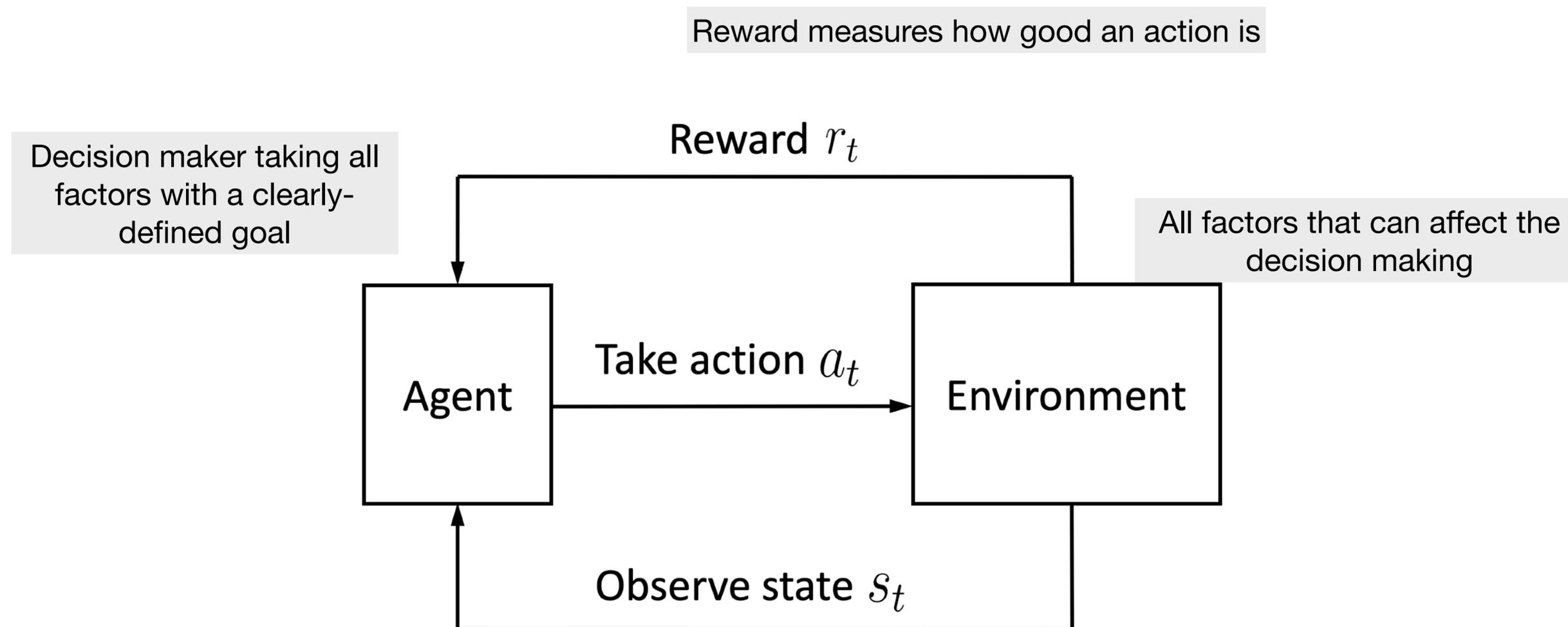
content providers [12, 25]. Nevertheless, content providers continue to struggle with delivering high-quality video to their viewers.

Adaptive bitrate (ABR) algorithms are the primary tool that content providers use to optimize video quality. These algorithms run on client-side video players and dynamically choose a bitrate for each video *chunk* (e.g., 4-second block). ABR algorithms make bitrate decisions based on various observations such as the estimated network throughput and playback buffer occupancy. Their goal is to maximize the user's QoE by adapting the video bitrate to the underlying network conditions. However, selecting the right bitrate can be very challenging due to (1) the variability of network throughput [18, 42, 49, 52, 53]; (2) the conflicting video QoE requirements (high bitrate, minimal rebuffering, smoothness, etc.); (3) the cascading effects of bitrate decisions (e.g., selecting a high bitrate may drain the playback buffer to a dangerous level and cause rebuffering in the future); and (4) the coarse-grained nature of ABR decisions. We elaborate on these challenges in §2.

The majority of existing ABR algorithms (§7) develop fixed control rules for making bitrate decisions based on estimated network throughput ("rate-based" algorithms [21, 42]), playback buffer size ("buffer-based" schemes [19, 41]), or a combination of the two signals [26]. These schemes require significant tuning and do not generalize to different network conditions and QoE objectives. The

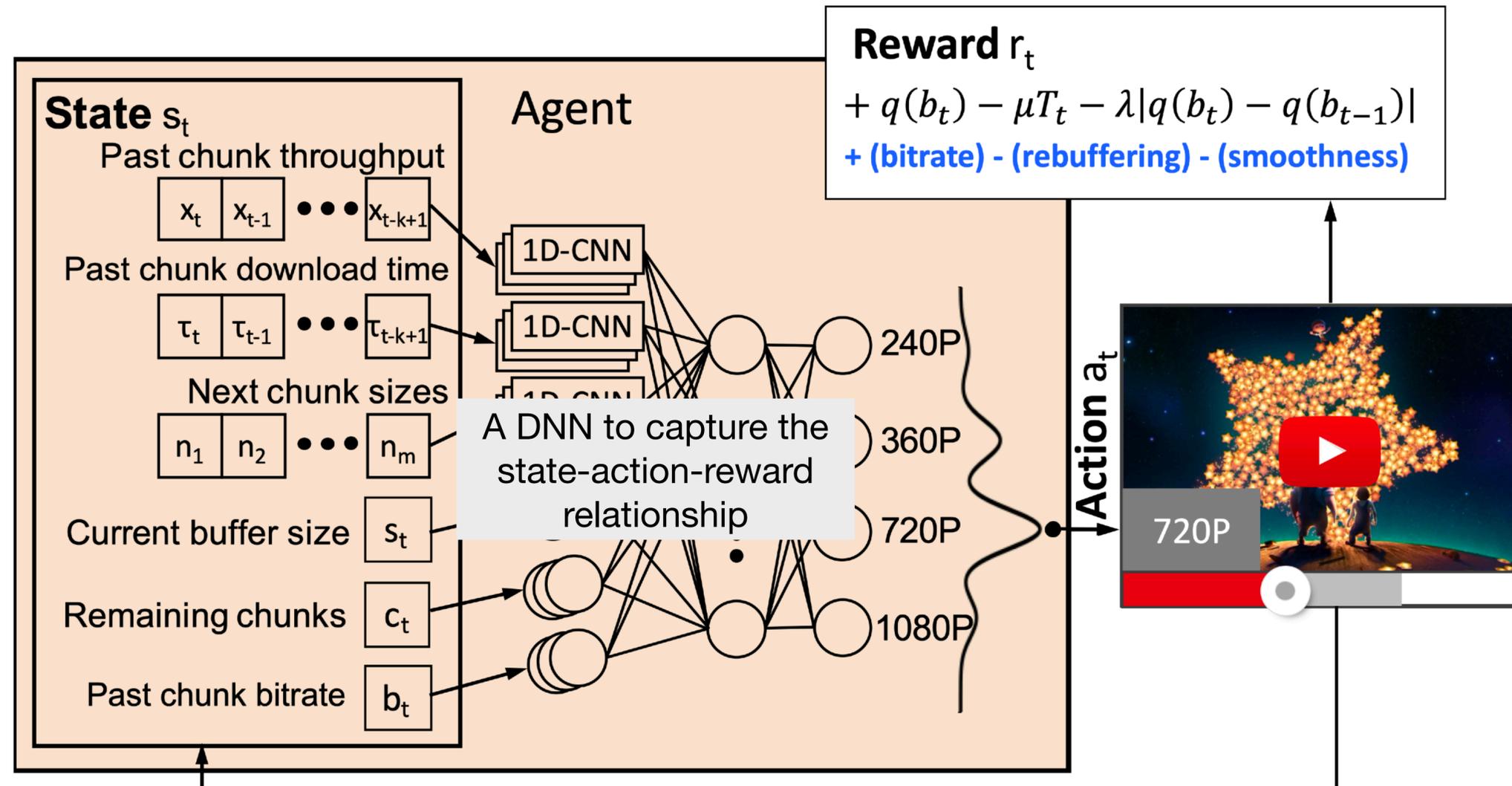
ACM SIGCOMM 2017

Reinforcement learning

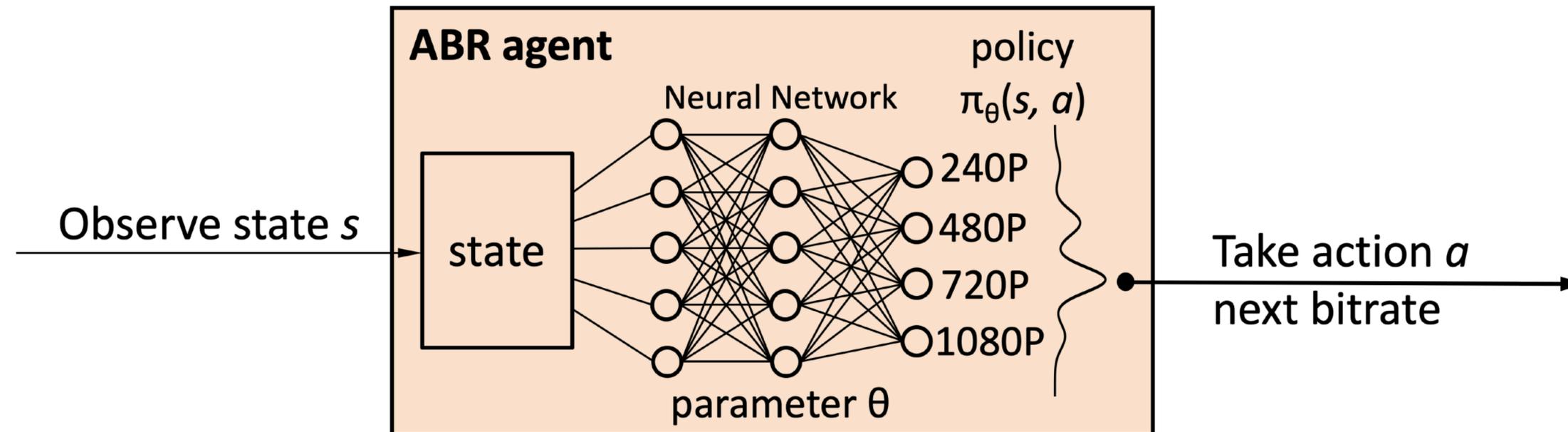


Goal: maximize the cumulative reward $\sum_t r_t$

Pensieve design



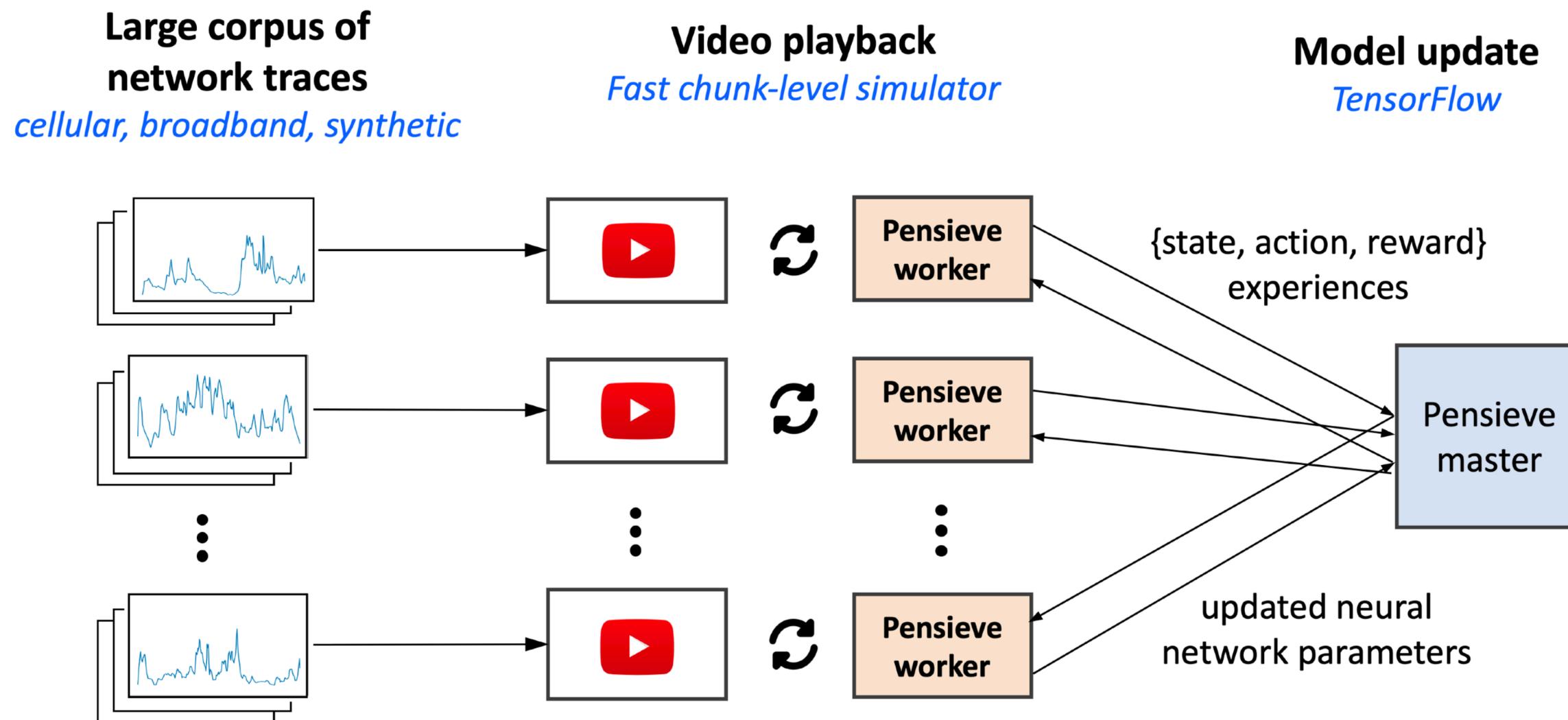
Training of the system



We train the system by **letting the system experience collected history data**: trajectories of [state, action, reward]

Gradient descent:
$$\theta \leftarrow \theta + \alpha \nabla_{\theta} \mathbb{E}_{\pi_{\theta}} \left[\sum_t r_t \right]$$

Training of the system



Advantages of Pensieve

Learn the dynamics **directly from experience**

Optimize the high level QoE objective **end-to-end**

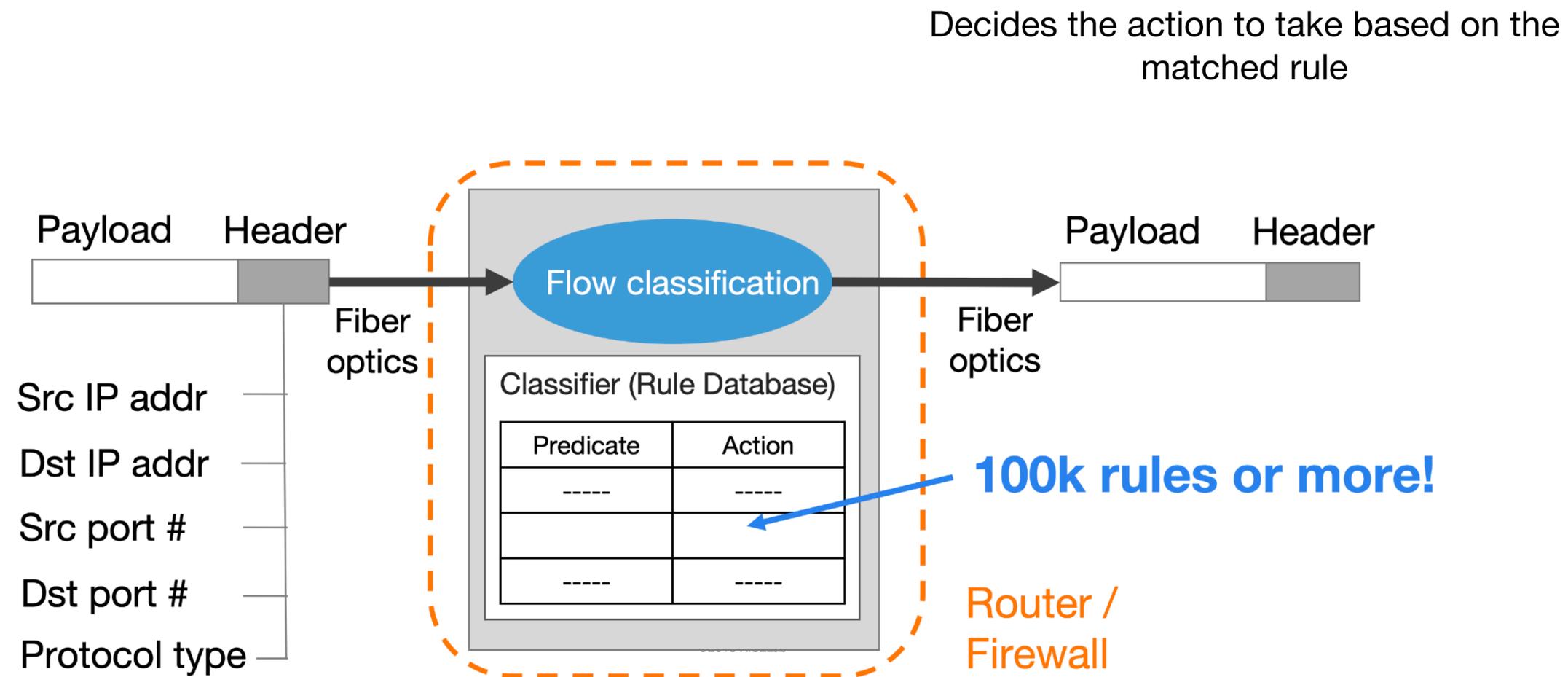
Extract control rules from **raw high-dimensional** signals

Machine learning for network packet classification

Packet classification

Fundamental problem in computer networking

- Building blocks for routing, access control, QoS, defense against attacks



Packet classification example

Priority	Src IP	Dst IP	Src Port	Dst Port	Protocol
2	10.0.0.0	10.0.0.0/16	*	*	*
1	*	*	[0, 1023]	[0, 1023]	TCP
0	*	*	*	*	*

Exact matching

Prefix matching

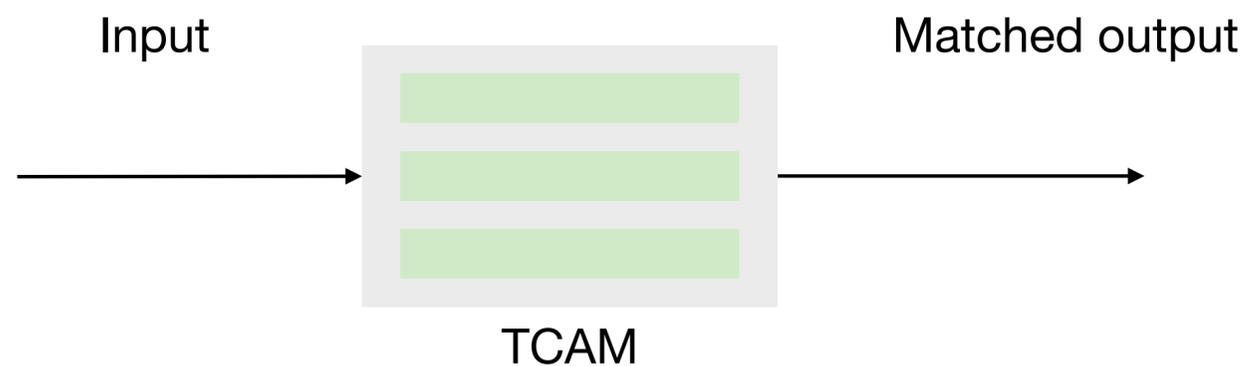
Range matching

Any matching

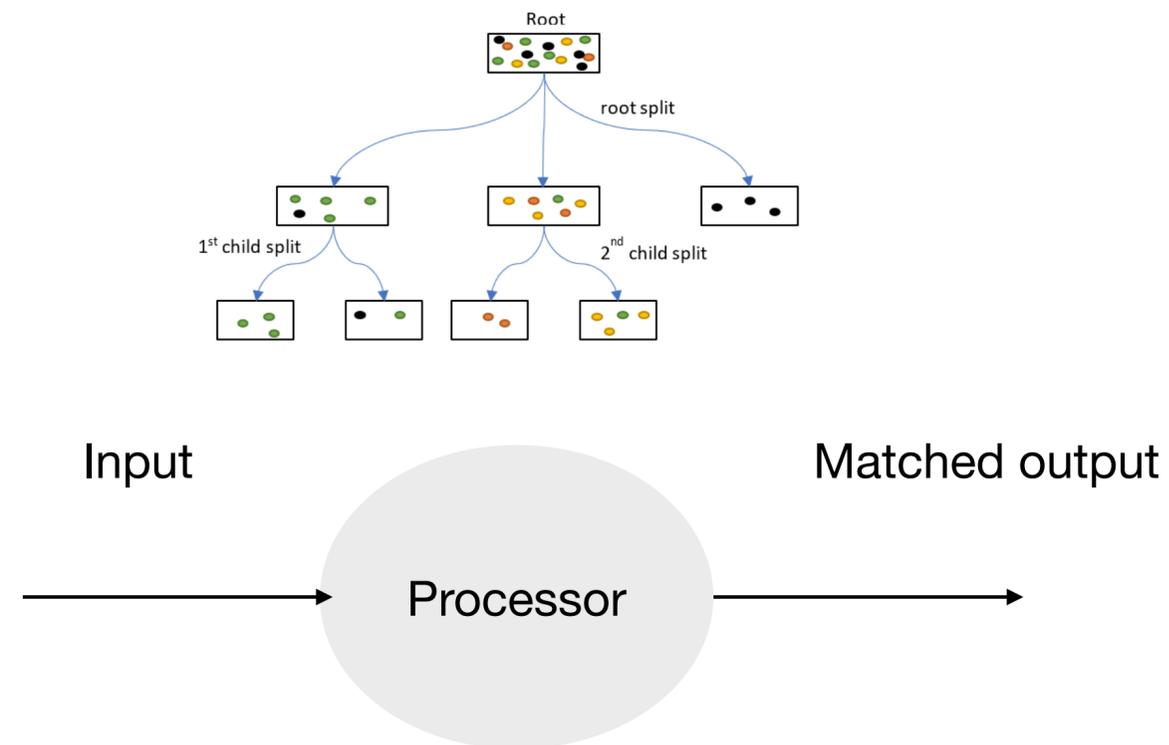
Example: (10.0.0.0, 10.0.0.1, 0, 0, 6)

Matches on all the 3 rules in the above table, but only the one with the highest priority will be taken.

Two solution directions



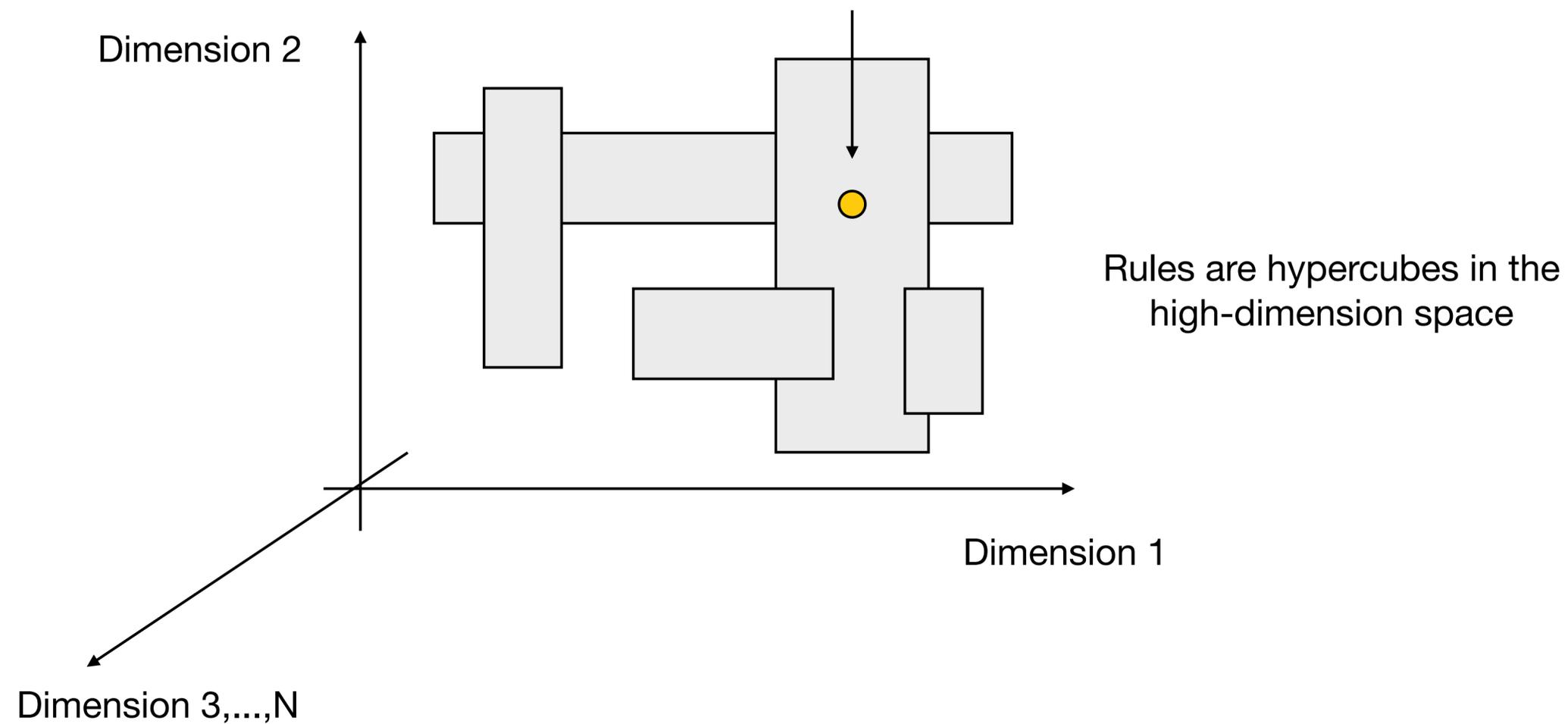
Hardware-based (e.g., TCAM): fast, expensive, energy-consuming, hard to scale



Software-based (e.g., decision-tree): scalable, slow and require large memory

Packet classification: a point-location problem

Problem: find out which hypercube contains the given point?



Theoretical analysis on packet classification complexity

Hard time-space tradeoff for point-location problem

- $O(\log N)$ time and $O(N^d)$ space
- $O(\log^d N)$ time and $O(N)$ space
- N : number of rules, d : number of attributes to match on, $N \approx 100K$, $d = 5$

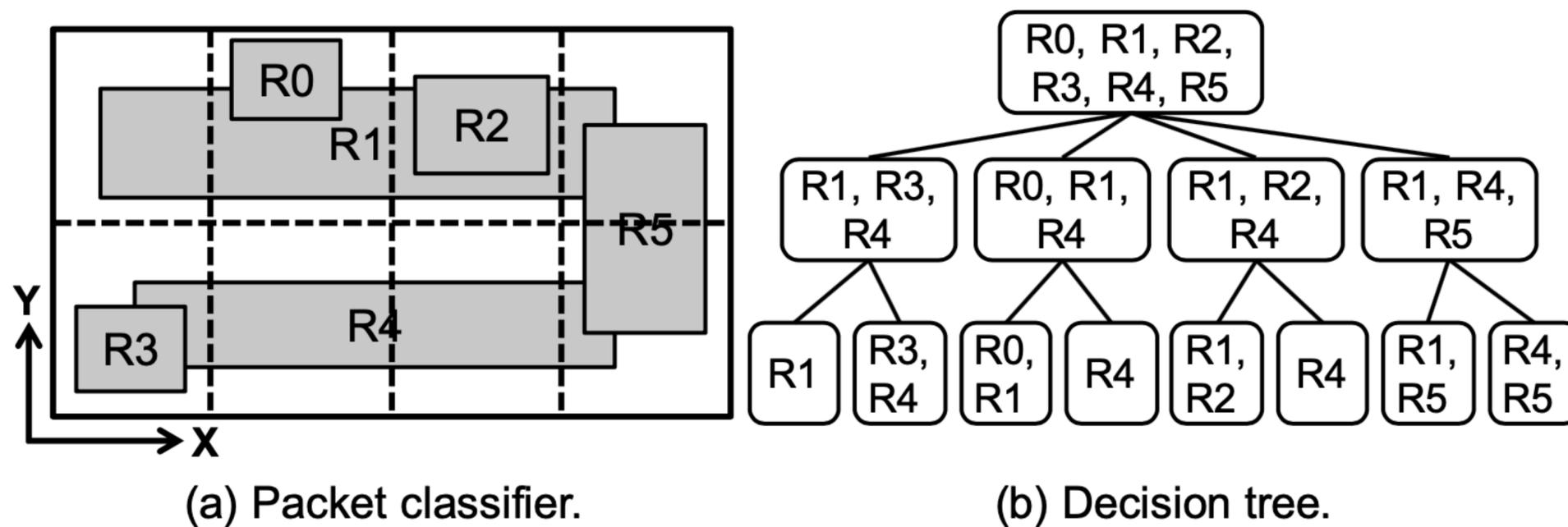
TL;DR: logarithmic time, exponential space; linear space, exponential time → none of them is attractive

Even harder than the point-location problem

- Rules have priorities and can overlap with each other

Existing techniques: node cutting

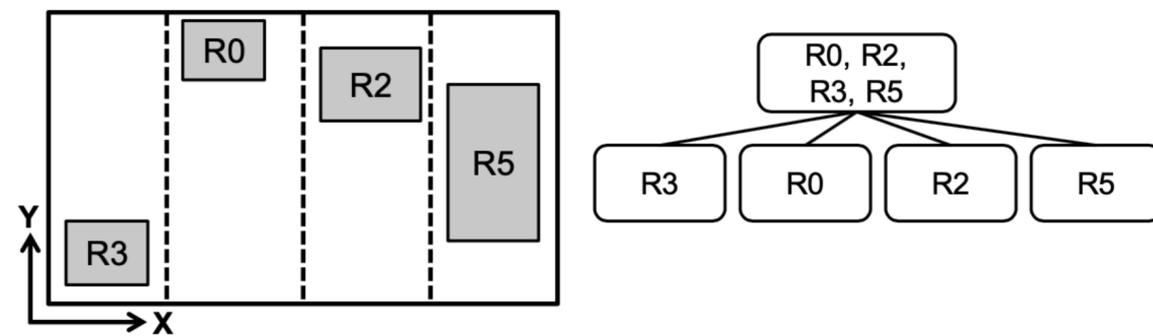
Cut the space into smaller areas and each area corresponds to a leaf in the decision tree



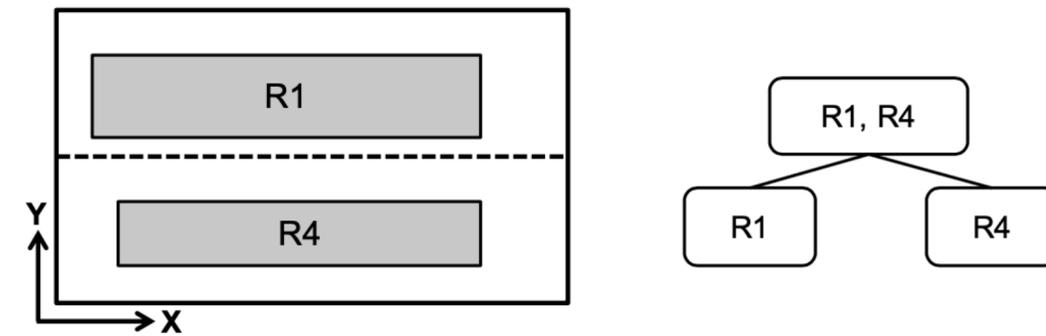
Match by traveling through the decision tree and select the rule in the matched leaf with the highest priority.

Existing techniques: rule partitioning

Partition the space into two parts and build a separate decision tree (or a subtree) for each part



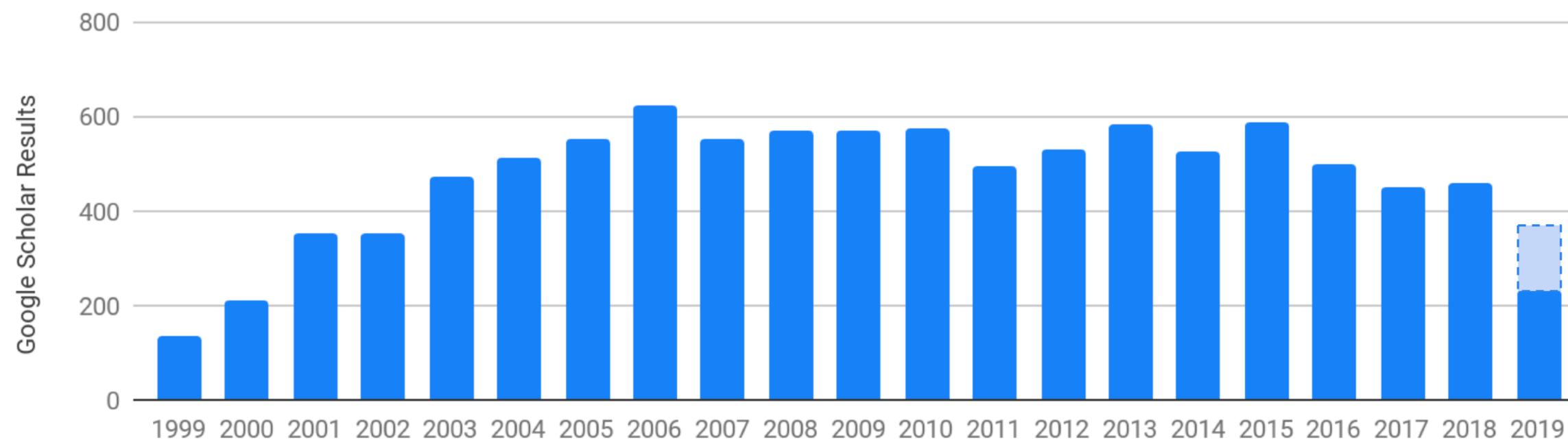
(a) Partition 1.



(b) Partition 2.

Match by traveling through all the decision tree and select the rule in the matched leaf in every tree with the highest priority.

20 years of active research



HiCuts ('99), HyperCuts ('03), EffiCuts ('10), CutSplit ('15)

Almost all of these solutions are engineered with hand-tuned heuristics targeting different objectives

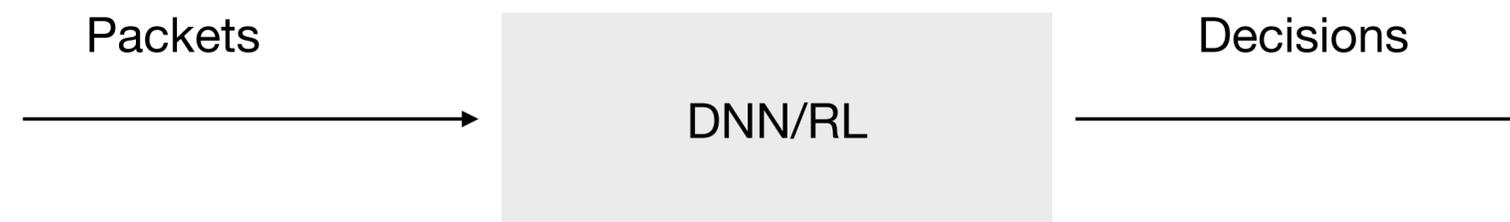
Can we apply learning?

Reinforcement learning **models long-term outcomes of actions** unlike heuristics

Reinforcement learning can **optimize for the end objectives** directly unlike heuristics

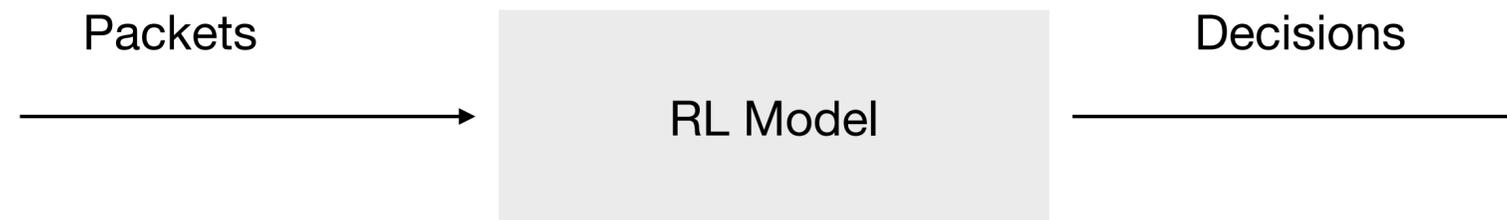
Historically, efficient RL formulation means super-human performance (e.g., AlphaZero, AlphaStar, AlphaFold).

End-to-end learning



Replace the decision tree with a DNN or an RL agent, does this work?

End-to-end learning



Pros

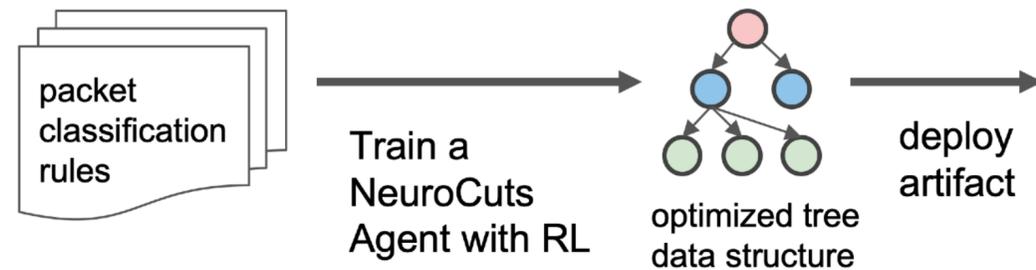
- May not need to build a data structure at all

Cons

- **Cannot guarantee classification correctness** (critical for applications like access control)
- Very large space of inputs → **hard to check model correctness**
- Packet inference **takes too long** (required time within 100s of ns)
- Need **specialized inference hardware** (e.g., GPU, TPU)

NeuroCuts

Use **deep reinforcement learning** to tackle the problem of **building decision trees**, instead of applying per-packet inference directly



Neural Packet Classification

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ABSTRACT

Packet classification is a fundamental problem in computer networking. This problem exposes a hard tradeoff between the computation and state complexity, which makes it particularly challenging. To navigate this tradeoff, existing solutions rely on complex hand-tuned heuristics, which are brittle and hard to optimize.

In this paper, we propose a deep reinforcement learning (RL) approach to solve the packet classification problem. There are several characteristics that make this problem a good fit for Deep RL. First, many existing solutions iteratively build a decision tree by splitting nodes in the tree. Second, the effects of these actions (e.g., splitting nodes) can only be evaluated once the entire tree is built. These two characteristics are naturally captured by the ability of RL to take actions that have sparse and delayed rewards. Third, it is computationally efficient to generate data traces and evaluate decision trees, which alleviate the notoriously high sample complexity problem of Deep RL algorithms. Our solution, NeuroCuts, uses succinct representations to encode state and action space, and efficiently explore candidate decision trees to optimize for a global objective. It produces compact decision trees optimized for a specific set of rules and a given performance metric, such as classification time, memory footprint, or a combination of the two. Evaluation on Class-Bench shows that NeuroCuts outperforms existing hand-crafted

given packet to a rule from a set of rules, and to do so while optimizing the classification time and/or memory footprint. Packet classification is a key building block for many network functionalities, including firewalls, access control, traffic engineering, and network measurements [13, 29, 55]. As such, packet classifiers are widely deployed by enterprises, cloud providers, ISPs, and IXPs [1, 29, 48].

Existing solutions for packet classification can be divided into two broad categories. Solutions in the first category are hardware-based. They leverage Ternary Content-Addressable Memories (TCAMs) to store all rules in an associative memory, and then match a packet to all these rules in parallel [23]. As a result, TCAMs provide constant classification time, but come with significant limitations. TCAMs are inherently complex, and this complexity leads to high cost and power consumption. This makes TCAM-based solutions prohibitive for implementing large classifiers [55].

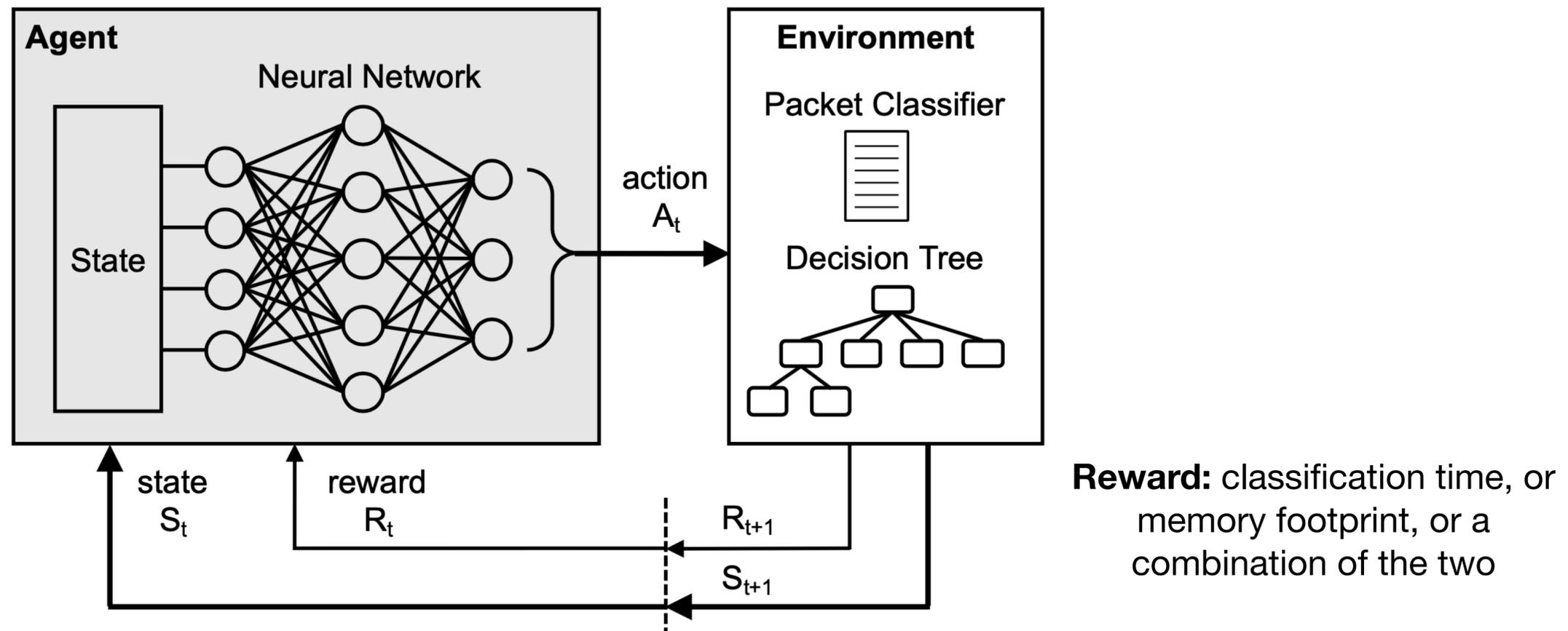
The solutions in the second category are software based. These solutions build sophisticated in-memory data structures—typically decision trees—to efficiently perform packet classification [29]. While these solutions are far more scalable than TCAM-based solutions, they are slower, as the classification operation needs to traverse the decision tree from the root to the matching leaf.

Building efficient decision trees is difficult. Over the past two decades, researchers have proposed a large number of decision tree

ACM SIGCOMM 2019

NeuroCuts design

Action: either cutting a node or partitioning a set of rules

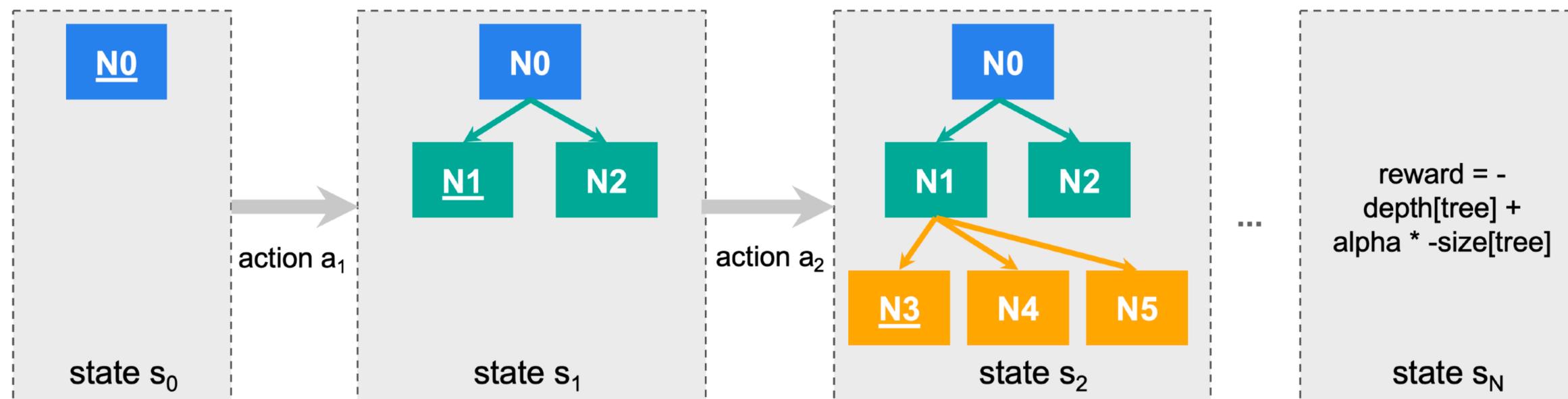


The reward is delayed and is only given when the whole tree is built.

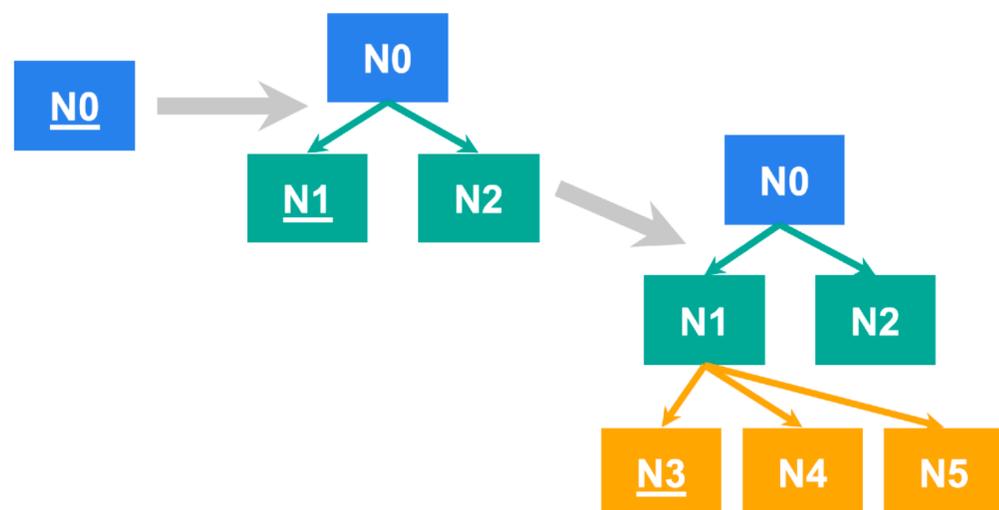
Naive MDP formulation

Sequential Markov Decision Process (MDP)

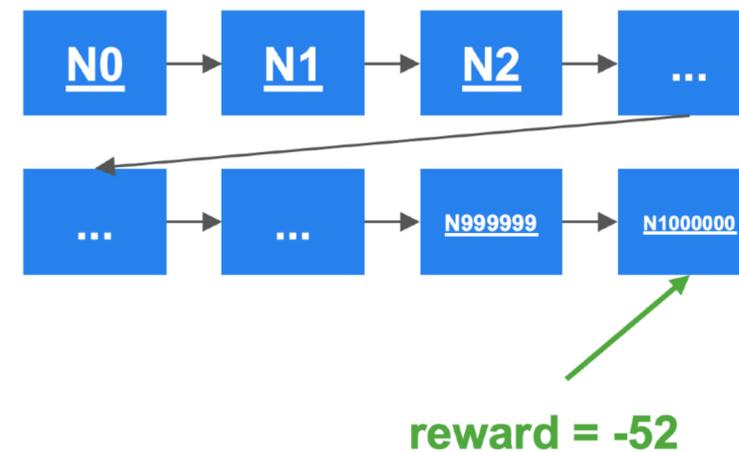
- Assumes DFS order of building the tree node by node
- Action is to cut or partition current node



Challenges



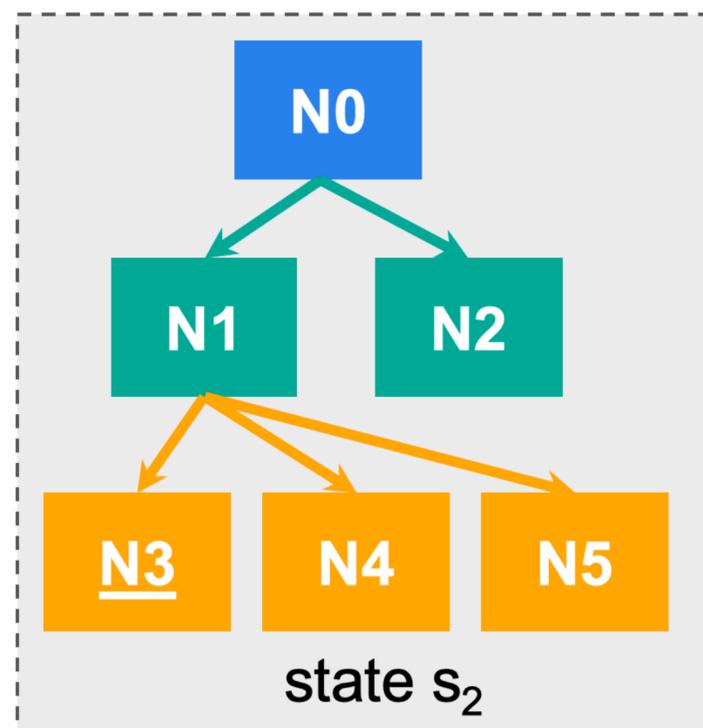
Size of the state grows in each step: hard to define the state



Reward delayed until the end: sparse reward problem

Challenge 1: state definition

Observation: node state is independent from the parent and sibling nodes



s₂ can be represented as a fixed-length vector describing N3's bounding hypercube

```
{SrcIPMin, SrcIPMax,  
DstIPMin, DstIPMax,  
SrcPortMin, SrcPortMax,  
DstPortMin, DstPortMax,  
ProtocolMin, ProtocolMax}
```

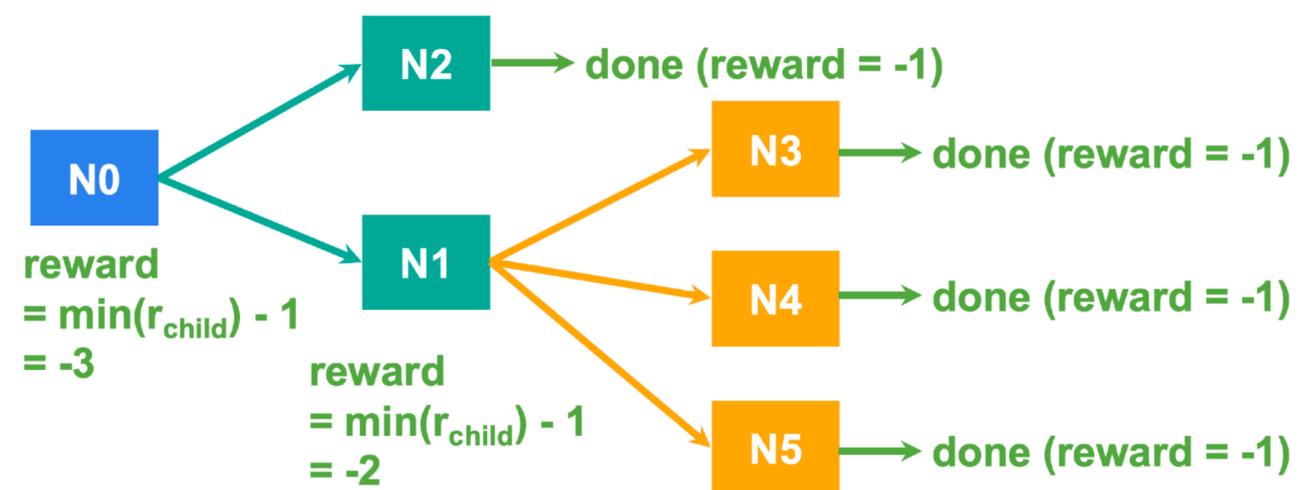
Challenge 2: reward

Observation: building a tree is a branching decision process, not sequential MDP

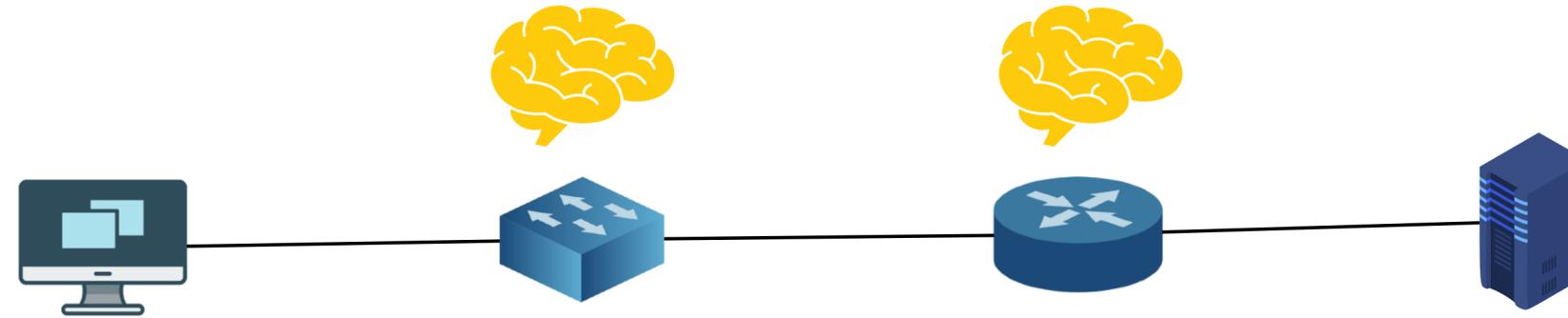
Sequential MDP: $O(n)$ steps delay between action time and reward time



Branching decision process: $O(\log n)$ steps delay between action time and reward time



Summary



Machine learning can be leverage to solve the decision-making problems in networking, e.g., adaptive bitrate selection and packet classification.

Course structure

Introduction (course logistics, Internet history)

Data structures and algorithms (hash, Bloom filter, sketch)

Data center networking (topologies and addressing)

Software defined networking (network control/management, SDN architecture, applications)

Networking basics (main concepts and terminologies)

Network transport (congestion control, multi-path, QUIC)

Data center transport (congestion control, flow scheduling)

Network automation (network configuration synthesis and verification)

Course structure

Network function virtualization (Click, ClickOS)

Network monitoring (INT, sketch-based solutions)

Machine learning for networking (Pensieve, NeuroCut)

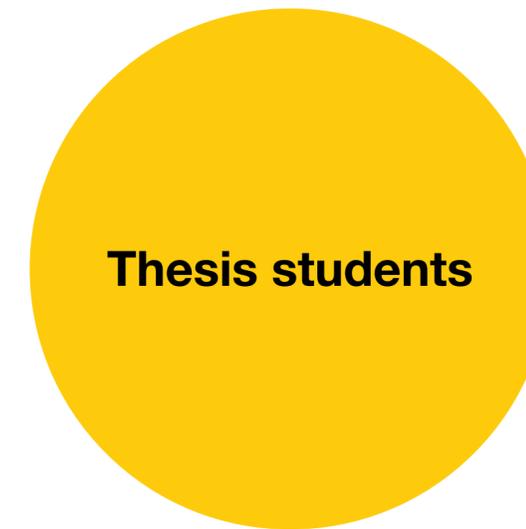
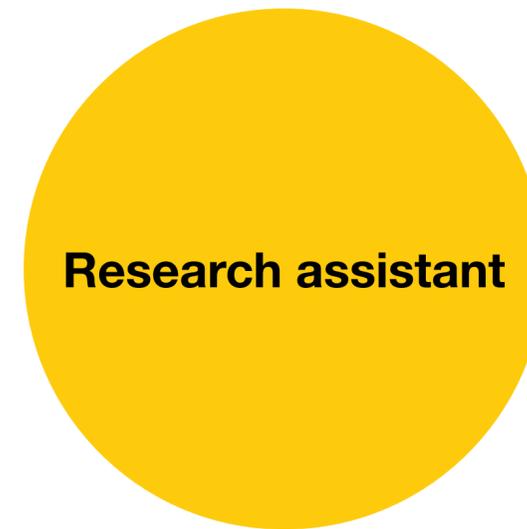
Exam

Programmable data plane (P4/PISA, hardware architecture)

In-network computing (NetCache, NetChain)

Final Q&A

Call for contributions



Check my research work at: <https://linwang.info>, contact me at: lin.wang@vu.nl

Good luck with the exam!