Handout # 4:
Networks and Machine Learning

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Announcements

- Final project
  - Form your team (2-3 students)
  - Start drafting your project proposal
    - Due: Friday, Feb. 13
    - Please check class website for sample project topics, and more information.

- List of papers for Week 5 posted
  - Volunteers?
    - 5% bonus

- Next week:
  - Three paper presentations
  - Please read before class

Today

- Networks and Machine Learning
- Data Center Network Transport
- Network-Application Integration

In the Beginning …

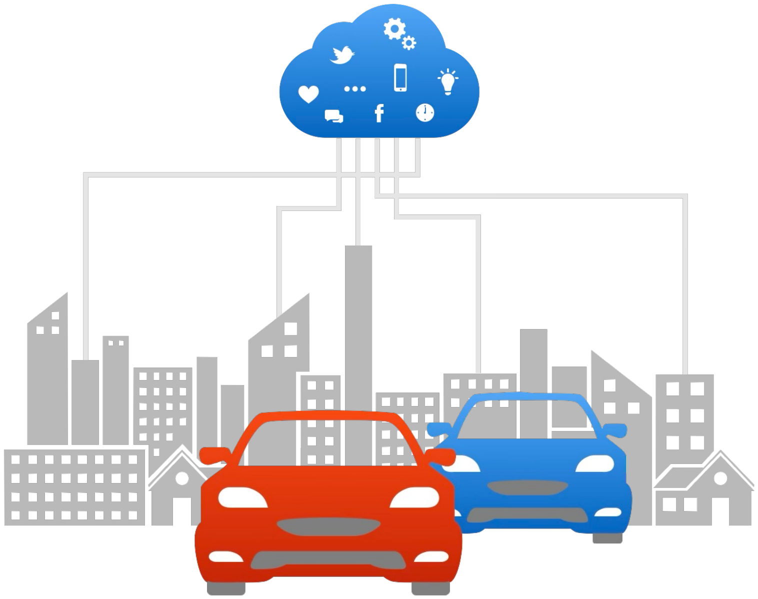
- **Main Design Objective**: today's networks were designed to grow rapidly.

- **Design Decisions**: any design choices were side-effects of this objective:
  - Best-effort service model
  - End-to-end principle
  - Simplicity (ease of growth)
  - Packet-based design
  - Distributed control model
  - …

All these design decisions are based on the "rapid growth" objective.

New Needs

- **Question**: Do principles/design of current networks match our current and future needs?
- Examples:
  - Smart cities, IoT, …
  - Self-driving cars
  - Remote surgery
  - Exascale ML training



- Can we rely on today's networks?
  - Delay, bandwidth, availability, reliability, scale, …

The Mismatch

Current and Future Needs	Past Design
Need performance guarantees • Bandwidth, latency, … • At scale	No performance guarantees • Best-effort service design • Scale → performance degradation
Need optimality • Minimize cost, and energy, …	Ad hoc optimization solutions • Not generalizable/automated
Need manageability • Network, individual components, services, …	No built-in management primitives • Simplicity, end-to-end design
Need for change • New services, protocols, …	No plan for change → ossification • Short-term focus on growth

Networks for Machine Learning

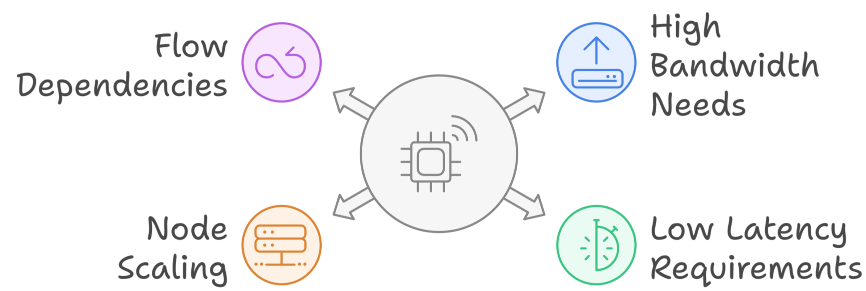
- Data Center Networks have evolved significantly
  - To accommodate demands for modern applications.
  - Example: SDN and programmable switches
  - Example: many novel congestion control algorithms in recent years:
    - Swift, timely, HPCC, DCQCN, …
    - Enablers: more accurate information from network (exact queue occupancy), assumptions about start rate (start at line rate), etc.

- Machine learning applications have grown significantly as well.
  - Used more in various domains, solving a wide range of problems.
  - At the same time, ML applications have higher demands from the underlying network

- Question: are existing DCN solutions enough?
  - I.e., can they provide the high-performance connectivity needed for ML applications?

What Makes ML Different: Challenges

- ML workloads can be extremely large:
  - E.g., Training of Large-Language Models (LLMs)
  - Need various forms of parallelism
    - Data parallelism
    - Model parallelism
    - Hybrid



- ML workloads have extremely high requirements from the underlying network:
  - High bandwidth
  - Low latency
  - Low jitter (variations in delay)

Moore's Law: the number of transistors on a microchip will double approximately every two years.
- For years, Moore's law meant we could easily grow compute power according to growth in demand.

End of Moore's Law: recently, we have hit a wall and cannot continue growing compute per node as predicted by the Moore's Law.
- However, the demand keeps growing …
- For ML even faster than what Moore's law could handle.

We need to add more nodes to scale to the demands of ML means.

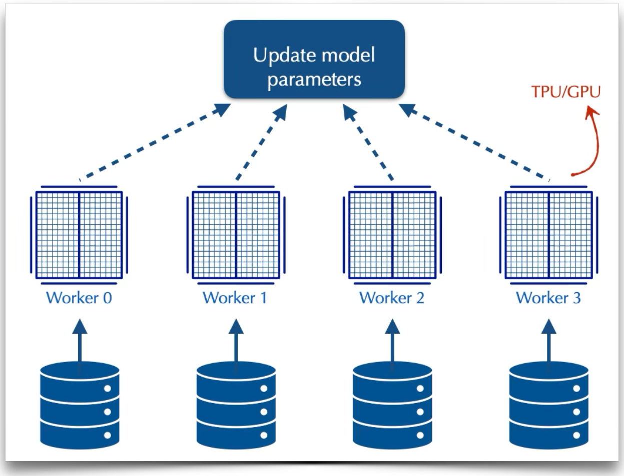
All of this leads to significant pressure on the network (throughput, latency, reliability, …)

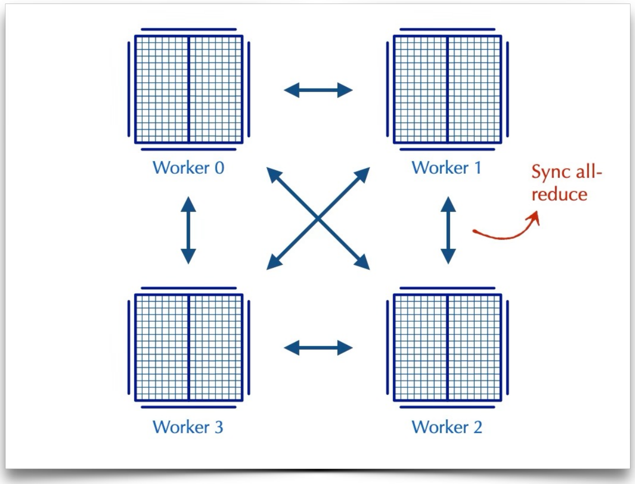
What Makes ML Different: Challenges

- Handling many independent flows in a network makes many network problems easy (easier) to solve
  - Random arrivals, each flow has a small share of bandwidth
  - Why?
- In ML, we have few flows
  - Having few flows means each flow can have a large fraction of link bandwidth
    - ⇒ Any interaction between flows can lead to significant performance degradation
- In ML flows have direct/indirect dependencies
  - Dependence between compute and communication
    - ⇒ flows directly or indirectly depend on each other
    - ⇒ Performance degradation in one flow can impact the performance of the entire job
- Providing high-performance connectivity for ML workloads is extremely challenging.
  - Due to scale, high-performance requirements (bandwidth, latency, …), larger flows, dependencies, …
- Example: load balancing in ML
  - Even two flows sharing a path can significantly reduce the overall performance.

What Makes ML Different: Opportunities

- ML workloads are more more predictable
  - Repeating patterns of communication
  - Collective Communications: scatter, gather, all-reduce, …
- Knowing communication patterns ⇒ opportunities for …
  - Building specialized hardware
    - E.g., topology that matches the flow requirements
      - Today's most successful ML networking solutions
  - Build network solutions that adapt based on application requirements
    - Application-aware scheduling
    - Reconfigurable topology
    - Adaptive routing, …
- Access to "Collective Communication Libraries" can provide significant opportunities





Network Topology

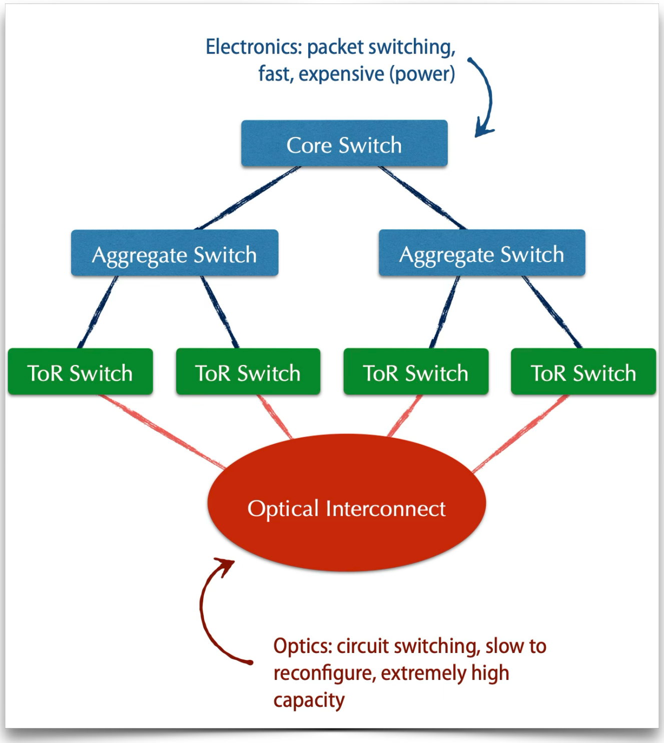
- DCN topology: fat-tree, leaf-spine, …
  - Static and uniform
  - Needs to work with a wide range of workloads
    - Tuned for average workload

- Distributed ML application have high demand which is not necessarily uniform
  - More demand for certain paths

- Two options to deal with extra traffic
  - Add extra capacity and over-provision; or
  - Use existing capacity better:
    - Measurement studies show there is extra capacity available, it just needs to be used effectively

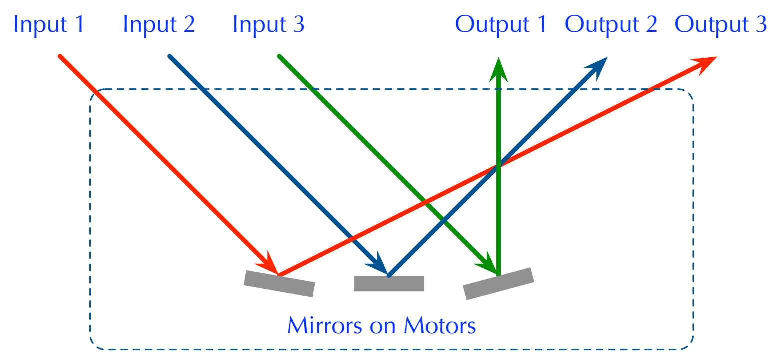
Adapt Network Topology to Demand

- Needs to adapt topology to workload
  - Even more important when you share the infrastructure
    - Cloud-based ML training, or various ML jobs sharing the network
- How can we adapt the topology to match demand? Two paradigms:
  - Customize the topology for specific classes of traffic
    - Special-purpose design
    - Can be optimal, but very expensive
    - What happens if new communication patterns emerge?
  - Dynamically rearrange the topology
    - How?

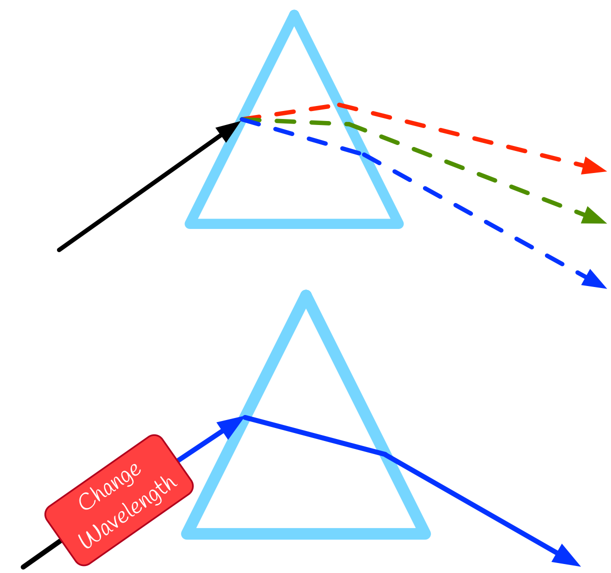


Reconfigurable DCN Topology

- Optical Circuit Switching:
  - Reconfigure input/output connectivity of switch ports
  - Avoids electronic-optic-electronic conversion
  - Various technologies:
    - MEMS-based Switching: mechanically rearrange mirrors to change connectivity of ports
    - Arrayed Wave Guide (AWG) Switching: change wavelength to connect to different output ports
- Benefit: shifting capacity to where it is needed on demand
- Challenge: reconfiguration might take some time
  - Not ideal for typical packet switching scenarios
- What if we know the demand and it is fairly stable?
  - Google's Jupiter: estimate demand matrix, adapt topology using a fast control plane
- ML Workloads are predictable ⇒ opportunity to change the switch connectivity to meet demand in real time
- RDCN performance improvements:
  - High bandwidth (1.6-4x increased in available bandwidth), 70-80% lower power, micro to nano-second scale delay



MEMS-based Optical Circuit Switch

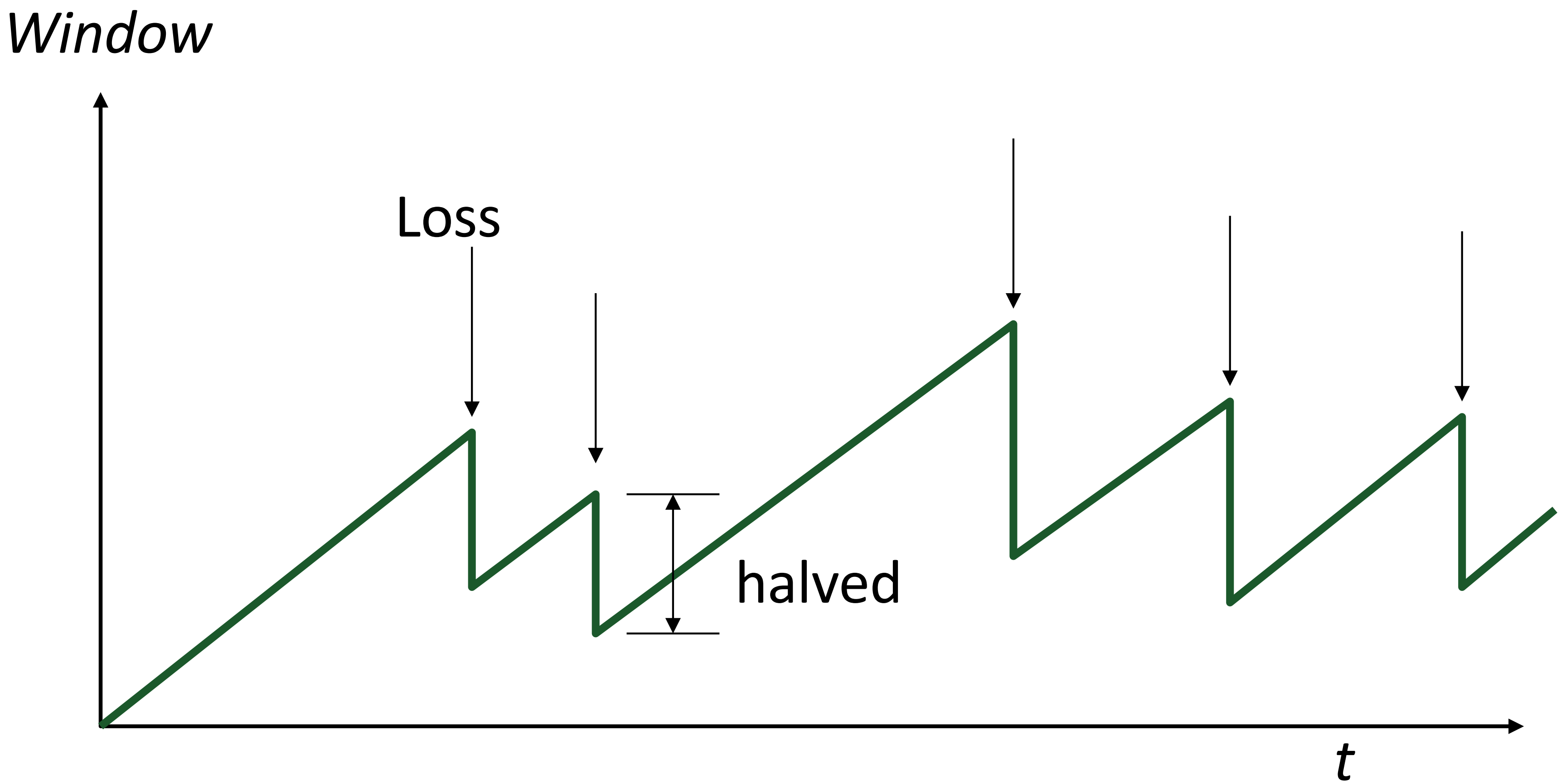


Some Examples

- Optical interconnect for ML
  - Nvidia GPU Clusters: DGX-H100 → DGX SuperPOD
  - SiP-ML: Hybrid data and model parallelism
  - TPUv4: OCS for interconnection
  - Communication pattern supported efficiently on the network
  - Task partitioning/placement based on degree and network latency

Transport in Data Center Networks

TCP "Sawtooth"

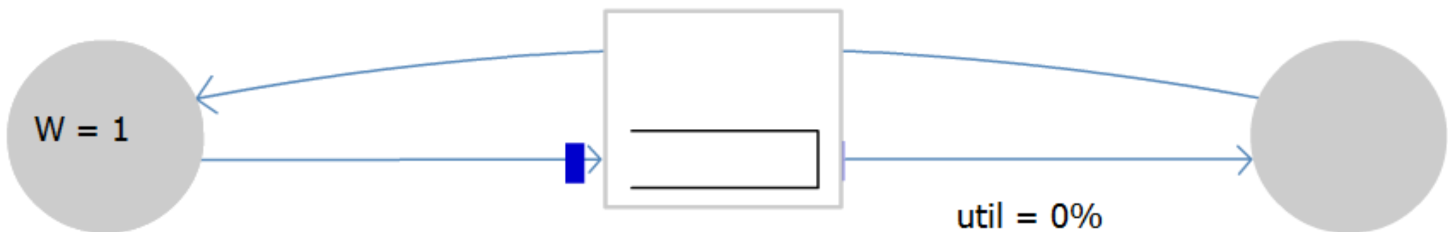


Congestion Window Evolution

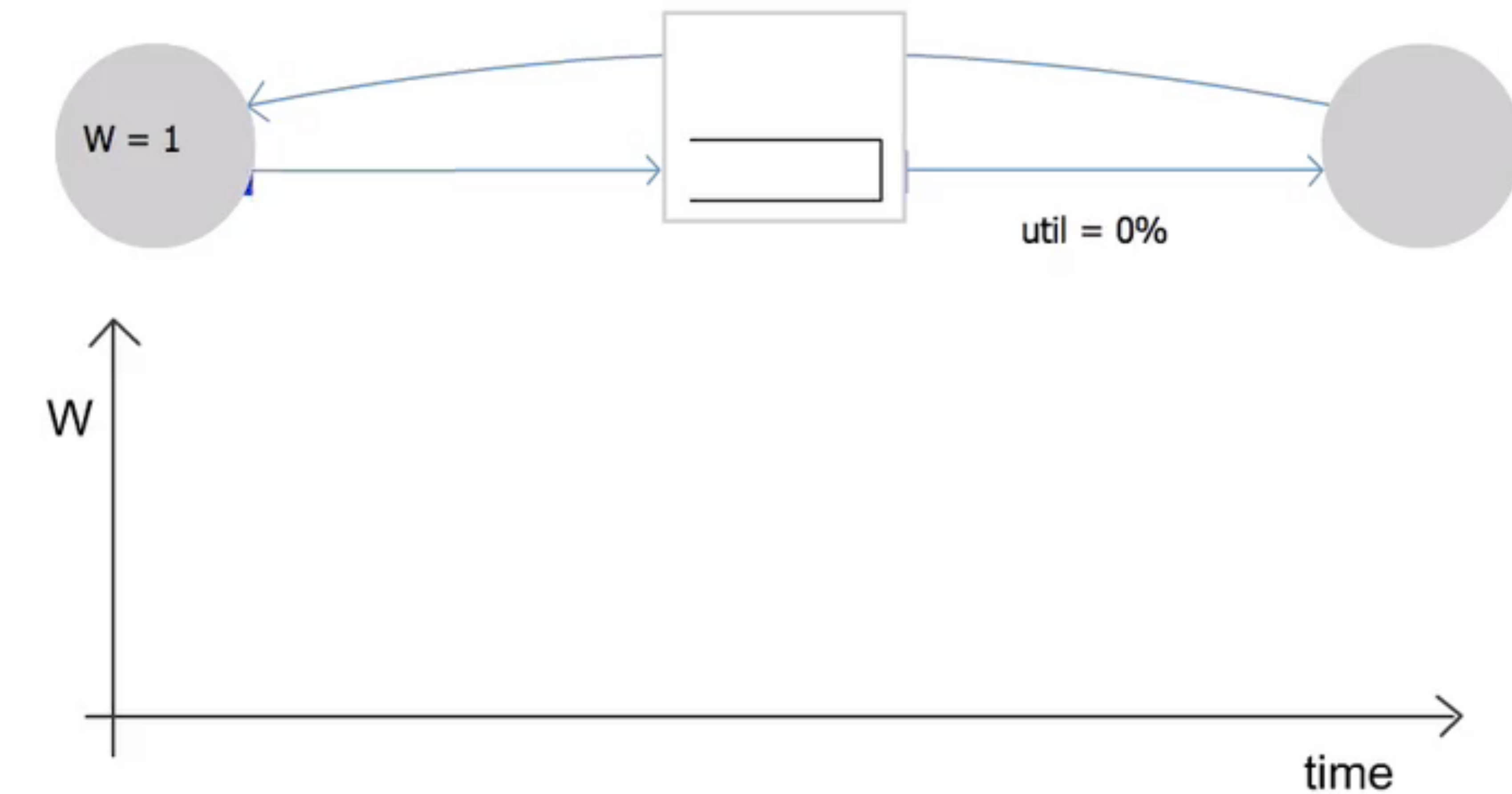
Only W packets may be outstanding

Rule for adjusting W

- If an ACK is received: $W \leftarrow W + 1/W$
- If a packet is lost: $W \leftarrow W/2$



Congestion Window Evolution

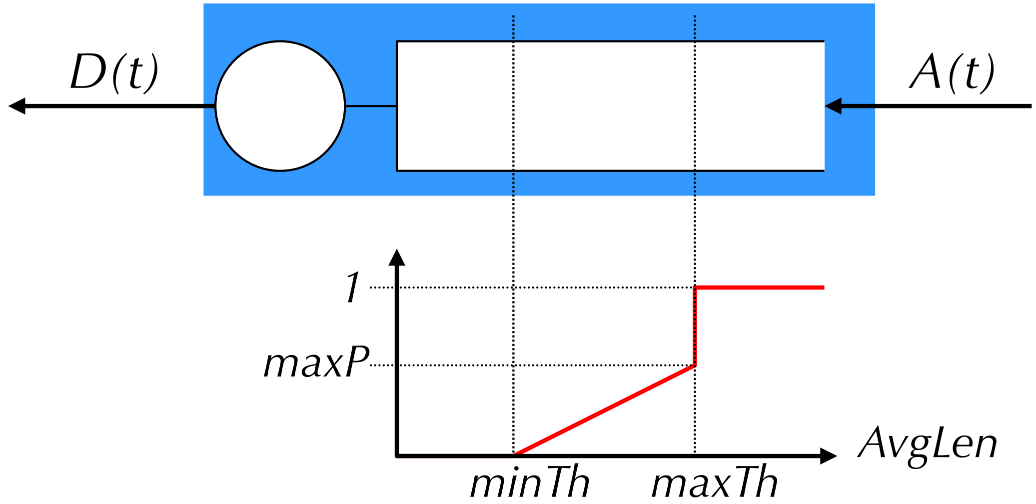


Transport in Data Center Networks

- Data center network properties:
  - Extremely short RTTs
  - Extremely high bandwidth links
  - Extremely large transfer
  - Single authority (typically)

- Leads to new challenges and opportunities
  - Can you think of any challenges for providing good transport solutions?
  - How about opportunities?

Explicit Congestion Notification



- Explicit Congestion Notification
  - Router marks the packet with an ECN bit
  - Receiver reflects the ECN bit in the ACK
  - … and sending host interprets as a sign of congestion

- Sender can use this as congestion signal
  - Instead of packet loss

DCTCP

- Easier to ensure ECN is enabled on all devices in DCN
  - Single authority

- Use ECN marks as congestion signal → reduced packet loss
  - Congestion measured based on fraction of packets marked with ECN (called α).
  - α is the moving average of the observed fractions (like estimatedRTT)

- Adjust congestion window based on the extent of congestion: $cwnd \leftarrow cwnd \times (1 - \alpha/2)$
  - Instead of halving the window in case of congestion.

- More responsive and less aggressive to network conditions compared to traditional TCP

- Keeps queue lengths shorter (as reacts faster) → low latency

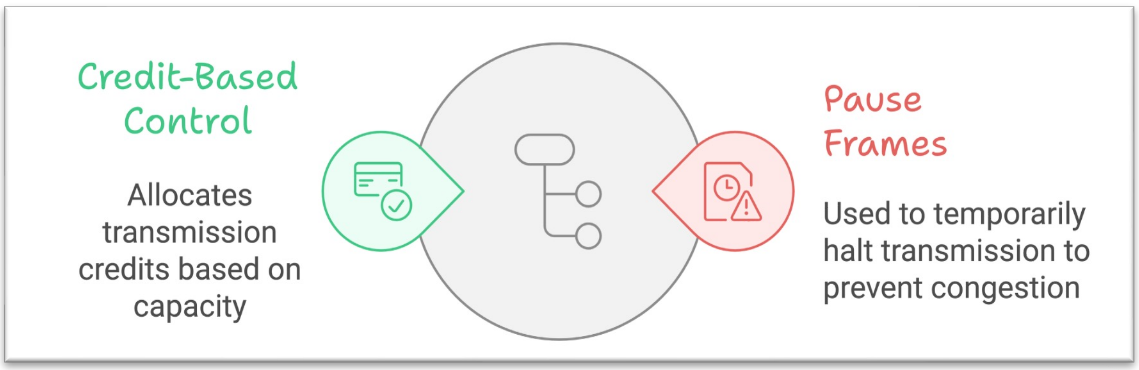
Link Layer Flow Control

Flow control mechanism used to create lossless networks.

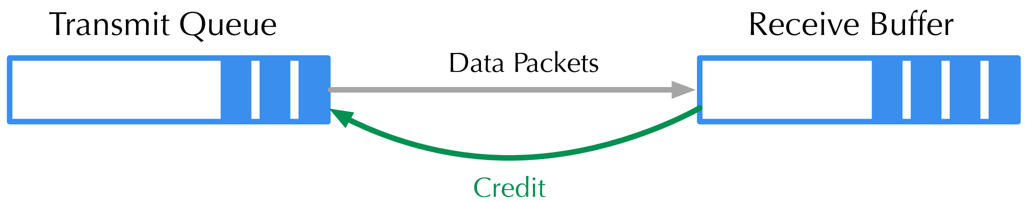
- Not to be confused with flow control in transport layer which is end-to-end.
- Setup: two nodes (end-hosts or switches) connected via a link.
  - Both have buffer (transmitter queue and receive buffer).
- Goal: ensure the receiver can handle the traffic injected on the link → no packet loss

Two prominent techniques:

- Credit-based
- Pause-based



Credit-Based Link-Level Flow Control

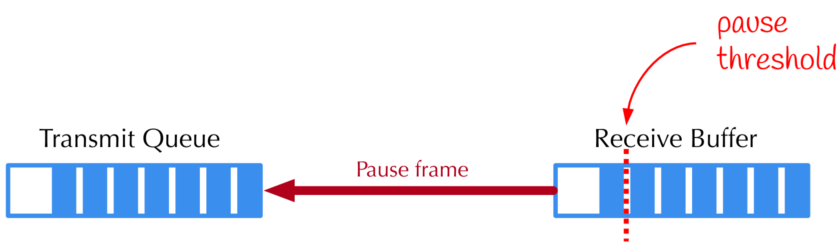


- Receiver provides credits to the sender when it has room
  - Credit unit: bytes or packets

- Credit allocation:
  - At the beginning certain (fixed) credit is allocated.
    - Question: how much credit should be allocated initially?
  - Transmitter uses credit when transmitting.
    - Pauses if there is no more credit available.
  - Receiver replenishes transmitter credits as receiver buffer becomes available.

- Note: we also can have credit-based congestion control. This is not what we are covering here. The concepts are similar, but at different layers.

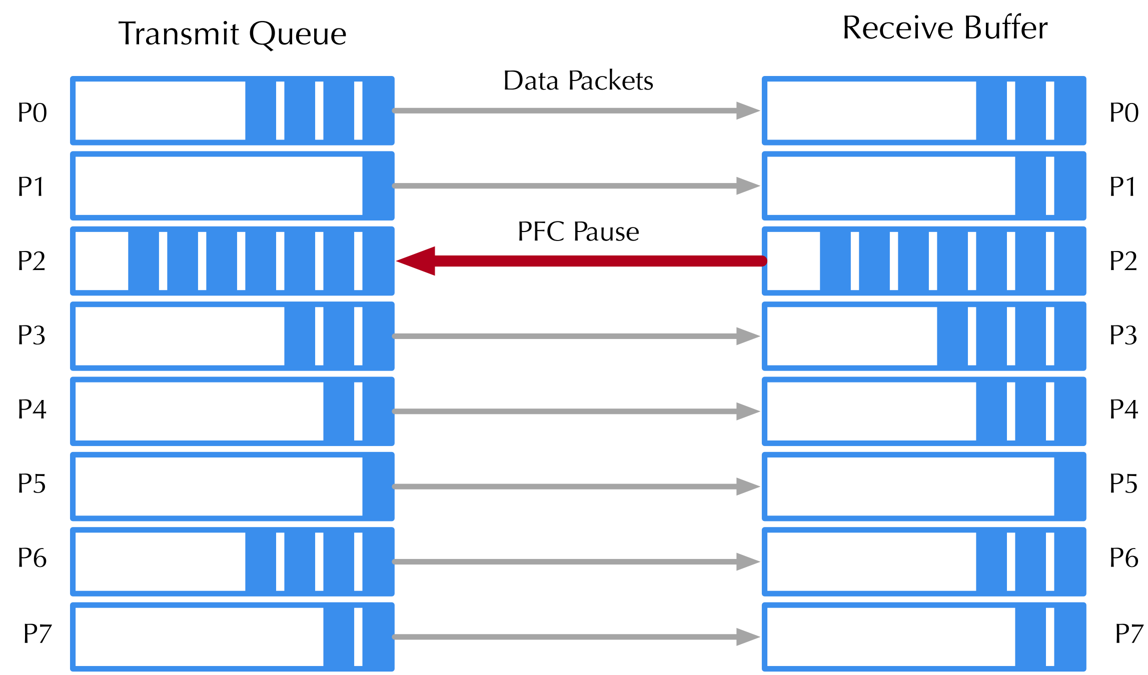
Pause-based Link-Level Flow Control



- Transmitter does not need permission to start.
- Receiver signals the transmitter when it is running out of buffer space.
  - When buffer occupancy goes above a fixed pause-threshold.
  - Pause-frame sent to transmitter
  - Transmitter halts transmission
- Once the receiver buffer has sufficient space …
  - Receiver sends a resume frame to the transmitter
  - The transmitter can resume sending.

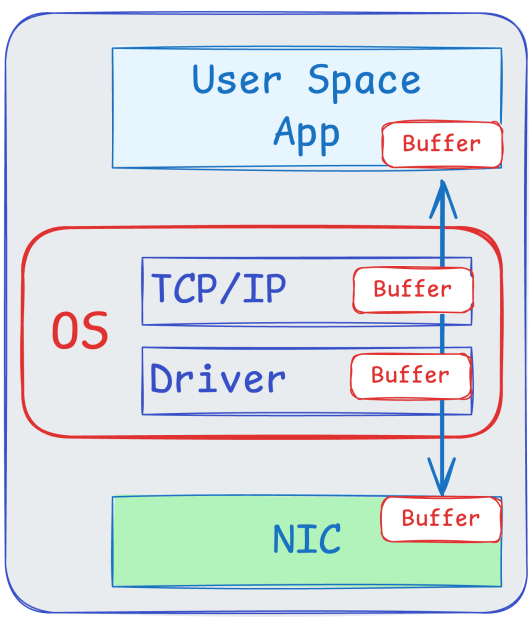
Priority-based Flow Control (PFC)

- Allows multiple priority-queues.
- Pause individual queues not all traffic
  - Allows other priority queues to continue transmitting even if a single queue is paused.
- Improves impact of pause on non-congested traffic to some extent
- Still, we might pause non-congested flows
  - Why?
  - Is there an easy way to solve this problem?
- Known issues: head-of-line blocking (deadlock), PFC storm

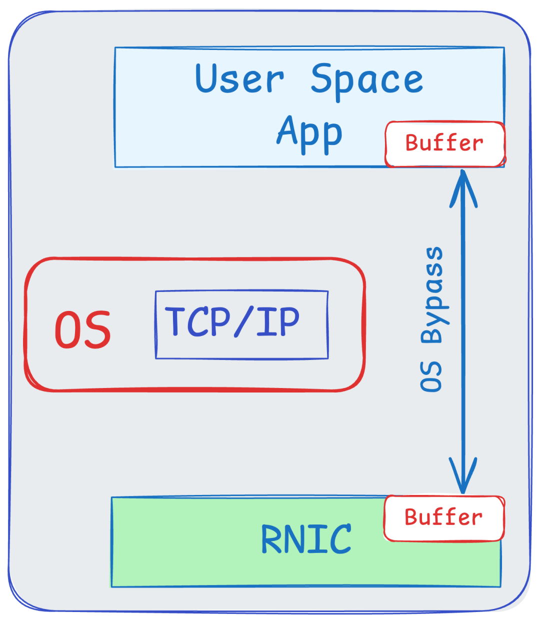


Remote Direct Memory Access

- Directly write to remote server's memory
  - Both sides register *memory regions* to give RDMA direct access permission and mapping
  - Need trust/cooperation between two ends
- RDMA-capable NIC (RNIC) handles data transfer entirely in hardware
  - No need to involve CPU for transfer
- Queue Pairs (QPs): a send queue and a receive queue.
  - Supports various operations like send, receive, read, and write.



Traditional Mode



RDMA Mode

Benefits of RDMA

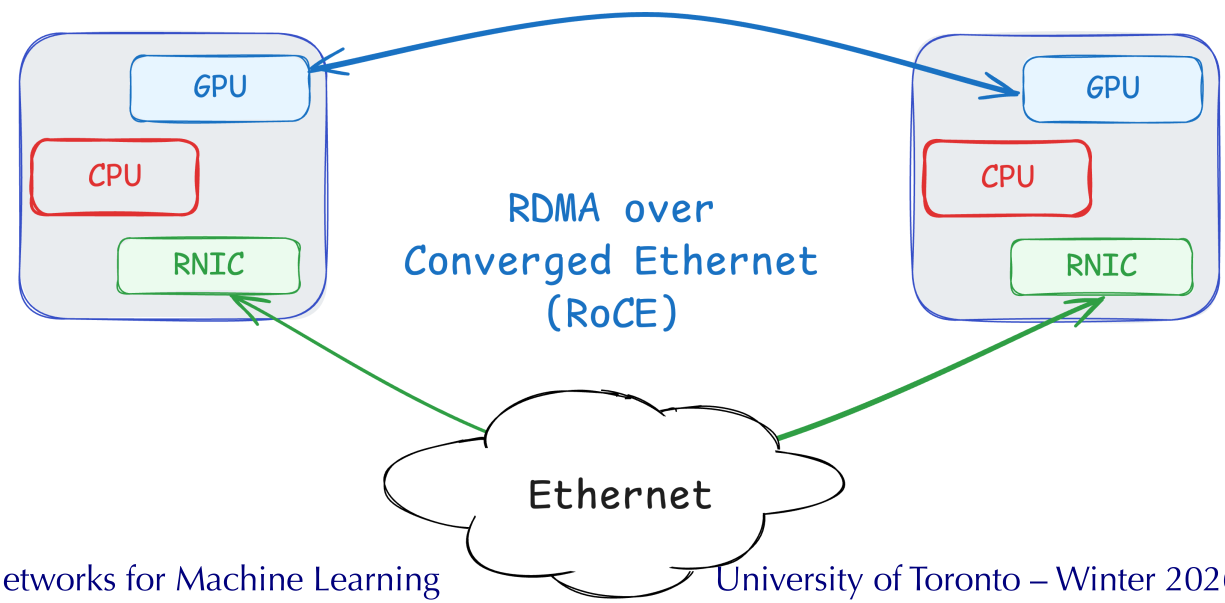
- Low Latency
  - Minimizes delays by avoiding CPU intervention.
  - Ideal for applications requiring real-time data processing.
- High Throughput
  - Enables faster data transfer rates.
  - Suitable for high-performance computing and large data sets.
- Reduced CPU Load
  - Frees up CPU resources for other tasks.
  - Improves overall system efficiency.
- Zero-copy data transfer.
  - Eliminate (or minimize data copies)
- Applications: High-Performance Computing (HPC), Storage, …

From Proprietary to Commodity

- Original technology InfiniBand
  - Touching physical layer, link layer, and transport layer in the stack.
  - Small number of vendors

- Later RDMA enabled over Ethernet
  - RoCE: RDMA over Converged Ethernet
  - With and without PFC support (RoCE v1 vs. v2)

- And even in WAN
  - iWARP (Internet Wide-Area RDMA Protocol)
  - Implemented over TCP/IP, no need for lossless network
  - Significant challenges here, especially over long distances

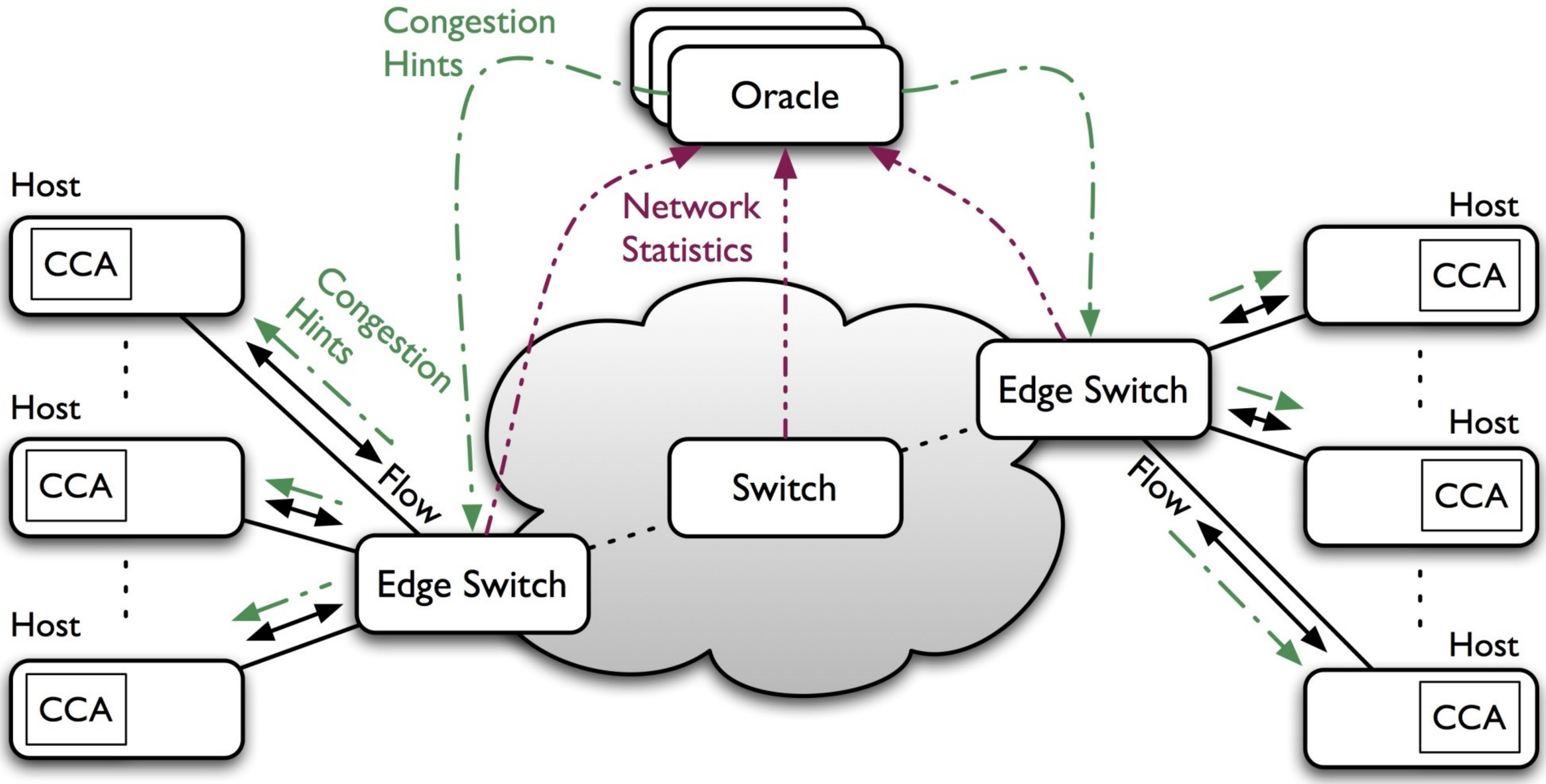


Detour: OpenTCP

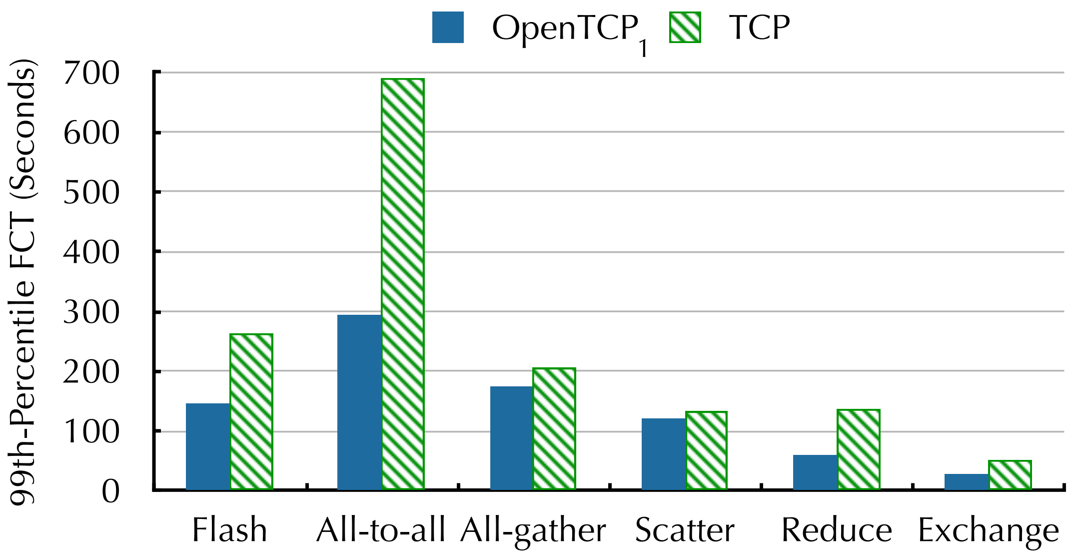
- Network can impact congestion control by using AQM schemes.
- Finding the optimal value by probing
  - Costly, and not very efficient
- What if the network could help?
  - Two extremes: end-to-end vs. centralized
- How about a solution in the middle?
  - Network guides the flows without creating dependency.

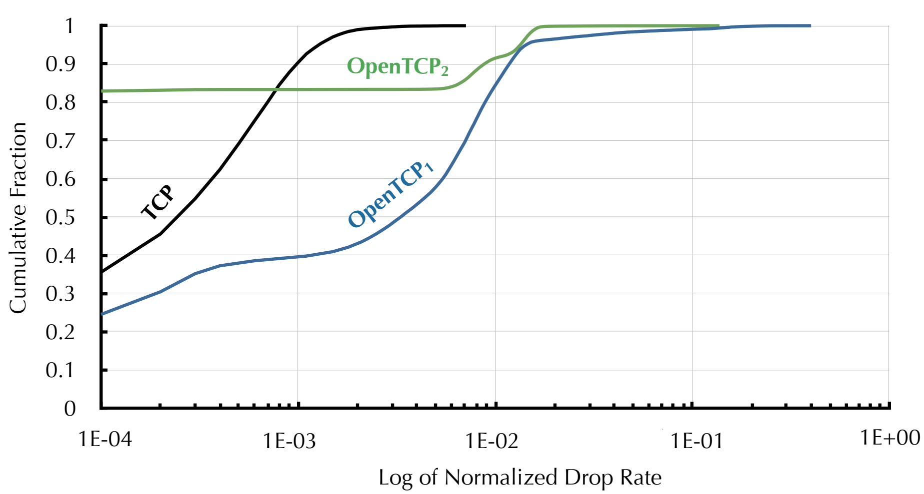
Detour:

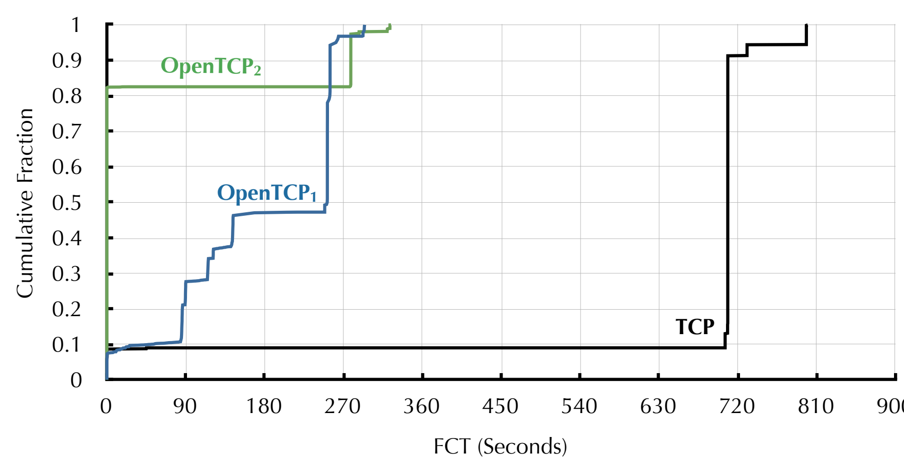
OpenTCP in Software-Defined Networks



OpenTCP: Performance Improvements







Adapting Other Network Functions

- Topology is only one dimension
- What about: routing, prioritization, scheduling, …?
- How can we optimize network behavior based on application requirements?

Application-Aware Networking

- To optimize network behavior, we need to provide information about application requirements.
  - Application-Aware Networking
  - Today's networks lack this information

- Main Question: how can we provide information from applications to the network?

- Naïve approach:
  - Create new interfaces between network and applications.
  - Allow application developers provide more information about the requirements
    - E.g., I need 10Gb/s bandwidth for 2 seconds.

- This is not very practical
  - Putting the burden on application developer
  - She/he might not even know the requirements

- Alternative: create tools/mechanisms to automatically generate signals that can help network adjust itself based on application requirements, or state.

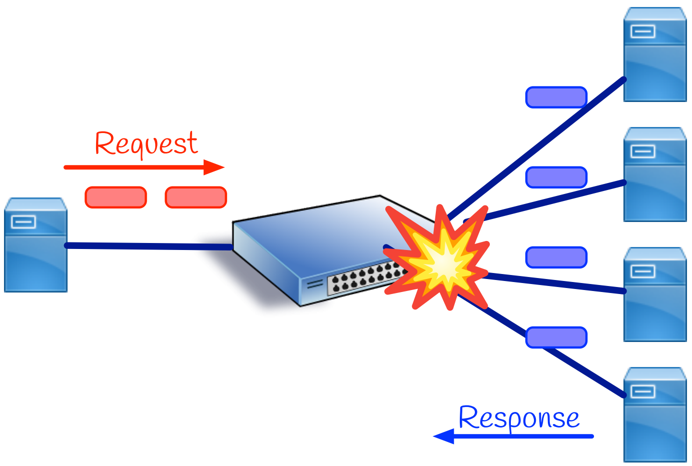
Example: Incast Problem

- Consider a simple multi-get request from a distributed storage.
  - Get some content from several servers

- The request can trigger large number of flows.
  - Quickly fill up the buffer at switch → lots of packet drops
  - This is called the incast problem
  - Very challenging problem in DCNs

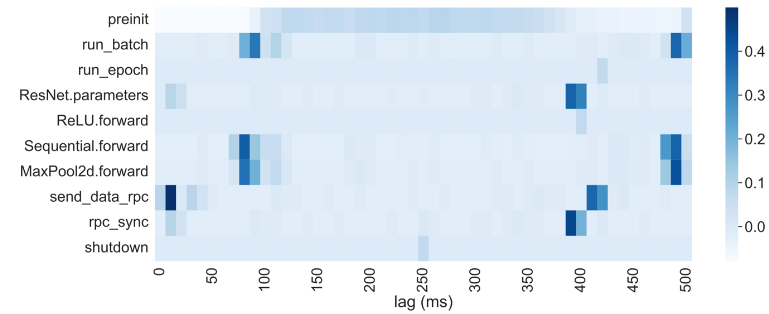
- Network does not know when incast will happen
  - Cannot react in a timely manner.
  - Over-provisioning seams to be the only viable solution.

- Applications, however, have information that can be used to predict incast.
  - E.g., multi-get request can be seen as a hint.

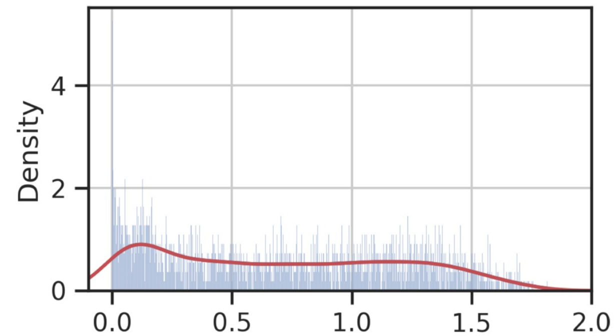


Networks and Applications*

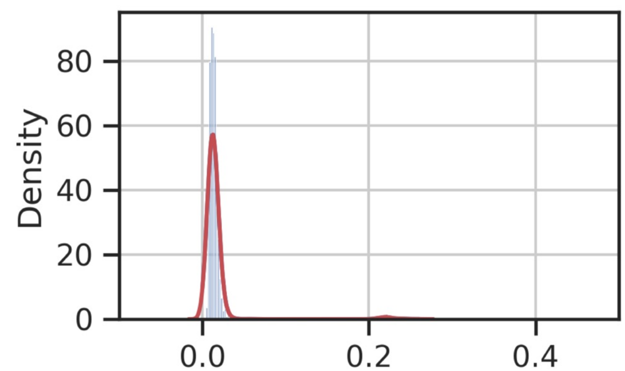
- Imagine, we have a system that observes *network events*, and
  - E.g., incast in switches
- Also, it can observe certain events in applications
  - E.g., when each function is called
- We correlate these events find out triggers on the end-host side for network events
  - I.e., which application events lead to network problems
  - E.g., each incast event in the network is preceded by a multi-get request 1 RTT before



Correlation between selected function calls and micro-bursts for a distributed ML application.



Probability of Incast in Future

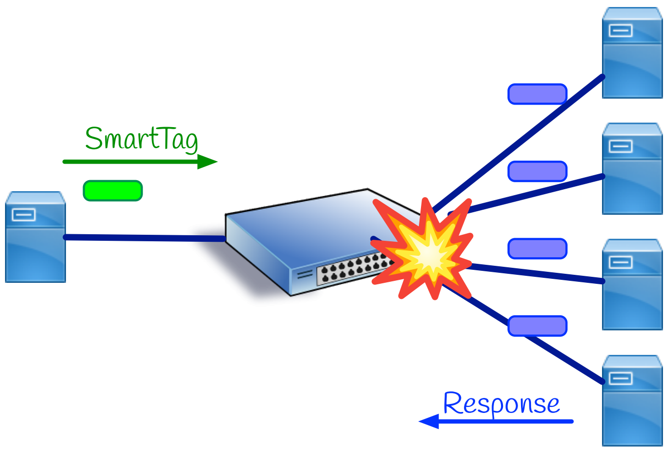


Incast Probability with SmartTag

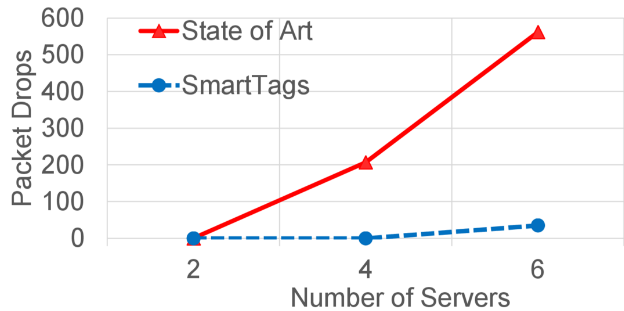
* Mortazavi, S.H., Munir, A., Bahnasy, M.M., Dong, H., Wang, S. and Ganjali, Y. 2022. EarlyBird: automating application signalling for network application integration in datacenters. Proceedings of the ACM SIGCOMM Workshop on Network-Application Integration (New York, NY, USA, Aug. 2022), 40–45.

SmartTags*

- We can use this information to generate messages on the end-host to notify the network of future network events.
  - We call these SmartTags.
- We can use SmartTags to change the behavior of the network
  - Example. To alleviate incase we can reroute traffic, delay certain flows, …
- Can lead to significant improvements in network behavior.
  - Improvements that are not possible in today's networks.
- Can be very effective for ML applications.
  - Automatically predict flow arrivals to change topology, reroute traffic, adjust flow priorities, etc.
  - Many more opportunities …



SmartTags are indicators of future events: opportunity to prepare network.



Packet Drops with and without SmartTags

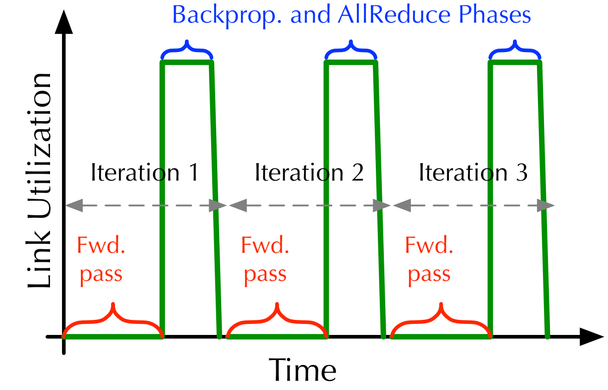
* Munir, A., Mortazavi, S.H., Bahnasy, M.M., Baniamerian, A., Wang, S., Guan, S. and Ganjali, Y. 2022. SmartTags: bridging applications and network for proactive performance management. Proceedings of the ACM SIGCOMM Workshop on Network-Application Integration (New York, NY, USA, Aug. 2022), 46–52.

Network Aware Applications

- Application-Aware Networking:
  - Adapt network based on application requirements, signals, …
- Given tighter integration of applications and network why not use network information to help applications?
  - Adapt application to network state.
- Example: scheduling ML jobs based on network state
  - Each application is aware of its own requirements at best.
    - But not network state (e.g., available bandwidth): application must estimate network state by probing
  - Network can provide information about its state
    - Help application-level scheduling
    - As well as state of other applications

Cassini: Network-Aware Job Scheduling*

- CASSINI is a network-aware job scheduler for ML clusters
  - Goal: schedule ML jobs based on network state and other jobs in the system to ensure smooth operation
- Step 1. Profile individual jobs
  - Identify communication patterns
  - Why can we do this here?
- Step 2. Convert to a geometric abstraction that represents the network demand
  - Perimeter of the circle: job's iteration time
  - Arcs of the circle: job's up and down phases.
- Question. How can we use this geometric abstraction to find good job schedules?
  - Rotating the circle is equivalent to shifting the job in time.



Data Parallelism Communication Patterns

Similar, but more complex, patterns for other type of parallelism

* Rajasekaran, S., Ghobadi, M. and Akella, A. 2024. CASSINI: Network-Aware Job Scheduling in Machine Learning Clusters. (2024), 1403–1420.

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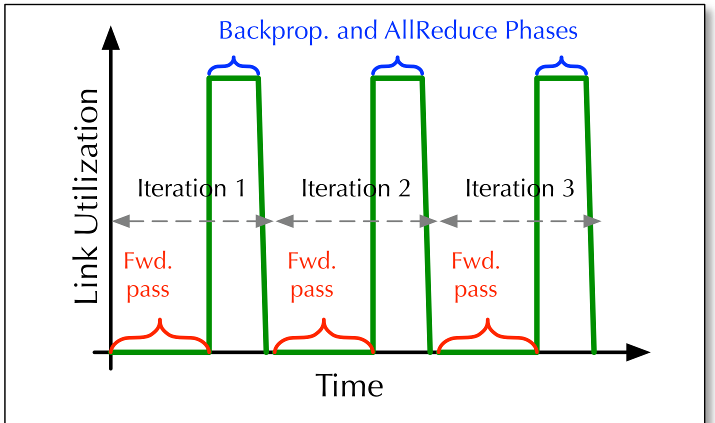
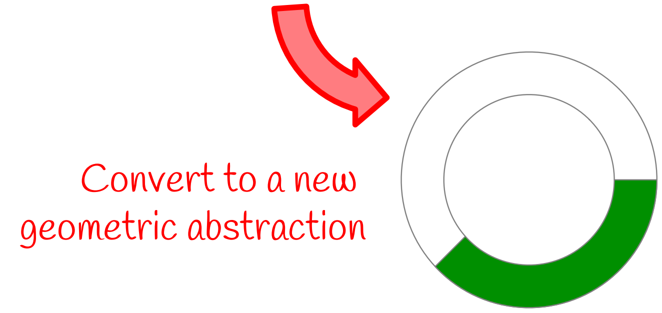
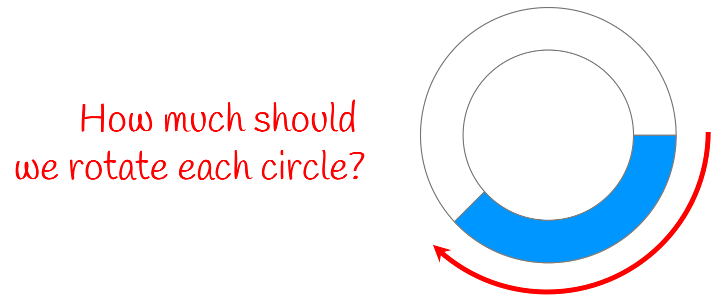
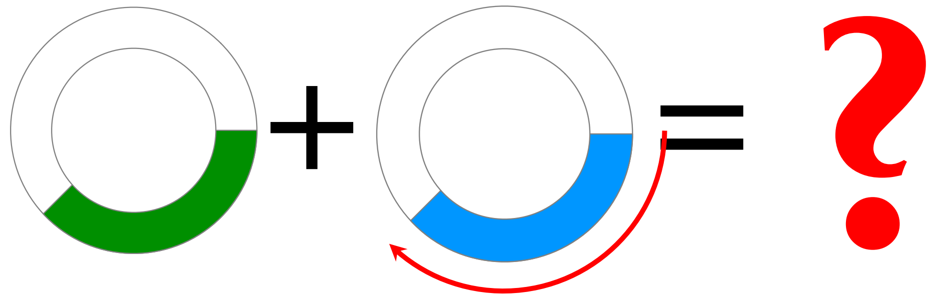


Data Parallelism Communication Patterns

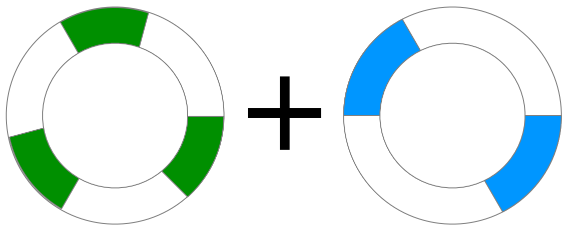




Cassini: Network-Aware Job Scheduling



- Step 3. For each link in the network:
  - Overlays the circles of jobs going through the link and rotates them
  - Find a configuration that minimizes the total bandwidth demand
  - This gives us a set of relative shifts in time
- Step 4. Extend link-level compatibility to cluster level
  - Start with job 1, set time to 0.
  - For each job that shares a bottleneck, use the method above to find the required shift in time.
- If there is no loop the output would be a job schedule
  - I.e., when each job should start
- Question 1: what if jobs have different iteration periods?
- Question 2: can we have a loop in the graph above?



ML for Networks

- So far, we have focus on how to enhance networks to meet the stringent requirements of ML applications.

- Given the advances in ML, a natural question is: *how can we use ML to enhance computer networks?*

- Any suggestions?

ML for Networks

- Traffic Prediction and Forecasting
- Congestion Control
- Network Routing and Load Balancing
- Network Configuration Automation
- Network Management and Troubleshooting:

ML for Networks Examples - Part 1

Traffic Prediction and Forecasting:

- We saw how knowing the pattern of traffic in ML workloads can help us make the network better.
- How about using ML to predict network traffic patterns
  - To optimize resource allocation, …
- We can use time-series models (e.g., ARIMA, LSTMs, etc.).
  - Analyze historical traffic data to anticipate congestion.

Congestion Control:

- We have seen some examples of how congestion control can be enhanced for certain environments (DCN, wireless, …) and workloads
- We can use ML to dynamically adjust flow rates
  - Minimize packet loss, delay, …
  - Also, use ML-based prediction of queue lengths or latency
- Train reinforcement learning (RL) models for real-time congestion-mitigation
- Examples: Orca, PCC-Vivace, …

* Abbasloo, S., Yen, C.-Y. and Chao, H.J. 2020. Classic Meets Modern: a Pragmatic Learning-Based Congestion Control for the Internet. *Proceedings of the Annual conference of the ACM Special Interest Group on Data Communication on the applications, technologies, architectures, and protocols for computer communication* (Virtual Event USA, Jul. 2020), 632–647.

** Mo Dong, Tong Meng, Doron Zarchy, Engin Arslan, Yossi Gilad, Brighten Godfrey, and Michael Schapira. 2018. PCC -Vivace: Online-Learning Congestion Control. In 15th USENIX Symposium on Networked Systems Design and Implementation (NSDI'18). 343–356.

ML for Networks Examples – Part 2

Network Routing and Load Balancing:

- Typically, rely on static routes
  - Shortest path based on fixed costs and randomized load balancing
- If information about link loads are available, we can use reinforcement learning for adaptive path selection.
  - Distribute load evenly across servers in data centers.
- E.g., apply graph neural networks (GNNs) to analyze network topologies, and find optimal routers.

Network Configuration Automation:

- Configuring switch/routers a tedious task, typically done manually
- We can use ML to automate switch/router configurations.
  - Use natural language processing (NLP) to translate operator requirements to device configuration.
  - Train models on historical configuration logs to predict optimal settings.
- Avoid misconfigurations (that can lead to outages) and optimize network performance.

ML for Networks Examples – Part 3

Network Management and Troubleshooting:

- Automatic configuration is done when the network is setup.
  - We can also think of more dynamic scenarios.
- How can we manage the network?
  - Ensure optimized behavior
- We have talked about SDN control applications.
  - Routing, access control, load balancing, …
- A management layer above can help make high-level decisions on resource allocations, adapting control applications, etc.
  - Ideally, use natural language to describe the intent of network operators, called intent-based networking
- ML can provide the tools needed to convert operator intent to rules, and policies
  - Push to the network through SDN control and management plane.
  - Also, optimize behavior based on operator intent.
- ML can also provide mechanisms for automated interaction with customers
  - E.g., troubleshooting customer systems in real-time.

Final Comments

- Largescale machine learning (training and inference) has led to significant pressure on computer networks.

- Major challenges for computer networks
  - Latency, throughput, loss, … requirements

- Opportunities to enhance networks
  - Take advantage of ML workload properties
  - Ability to integrate with existing solutions