CSC 458/2209 – Computer Networking Systems

Handout # 27: Data Center Networks & Networks for Machine Learning

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Announcements

- Programming Assignment 2: Buffer Sizing
  - Due Friday November 28th at 5pm.

- This week's tutorial:
  - Programming Assignment 2 Q&A

- Next week:
  - Sample final exam review
  - Sample final and solutions posted on class website

- Final Exam:
  - Please check A&S website for time/location

The Story So Far

- Layering
  - Link layer
  - Network layer
  - Transport layer

- Queueing Mechanisms, Middleboxes,
- Software-Defined Networking

- **Today**: Data Center Networks & Networks for Machine Learning

Machine Learning and Computer Networks

- Machine Learning (ML):
  - Significant growth in the recent years
  - Lots of attention and impact

- How does it affect computer networking?
  - **Networks for ML**: can traditional networks handle ML requirements?
    - Our focus is on data center networks here.
  - **ML for Networks**: how can ML be used to enhance computer networks?
    - Networks in general.

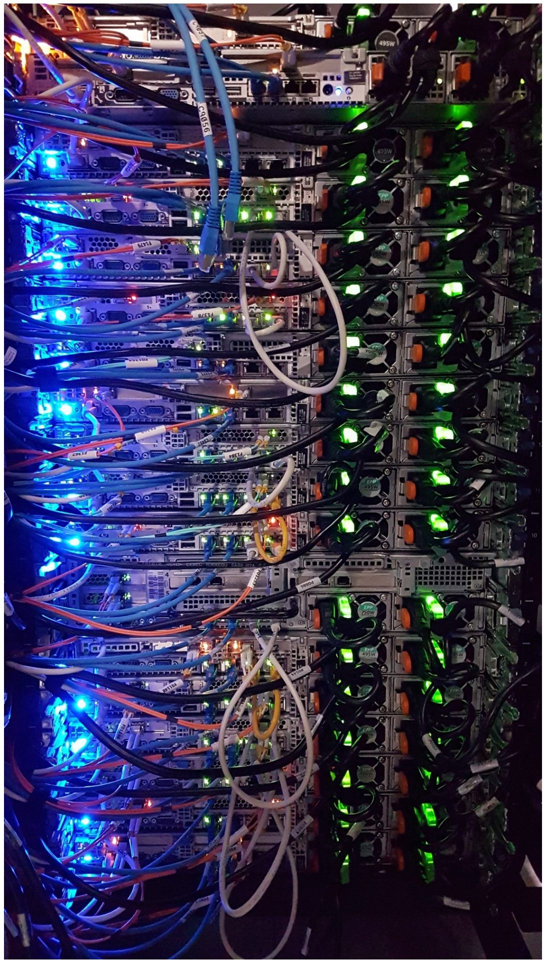
Today's Lecture

- Data Center Networking
  - Design Decisions
  - Topology
  - Transport
- Networks for ML
- ML for Networks

Data Center Network (DCN)

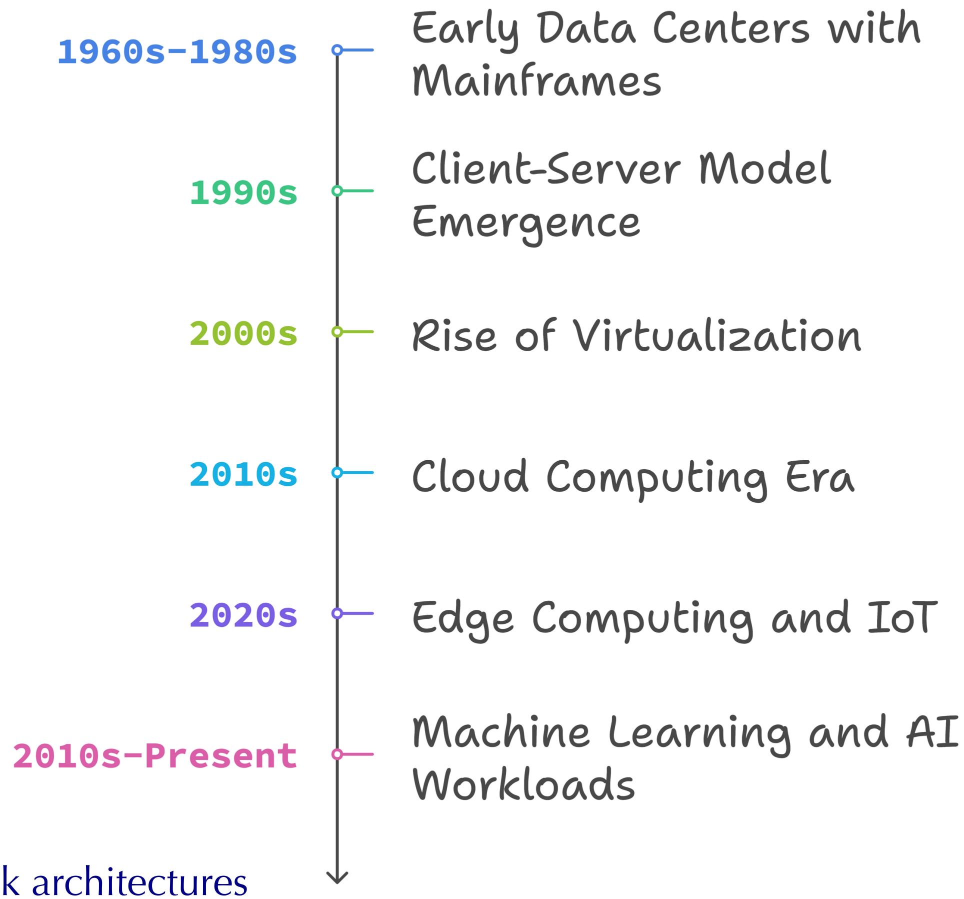
- A network of computing and storage resources
  - Proximity of components (within the data center) facilitates communication, i.e., high-performance
  - Can lead to reduced cost and overheads
    - Major cost upfront but less cost in long run.

- Functions
  - Data Storage and Management
    - Security, efficiency, reliability
  - Application Hosting
    - End-users and business applications, cloud computing and SaaS models
  - Data Processing
    - Large volumes of data for analytics and processing, big data and AI workloads
  - And more …

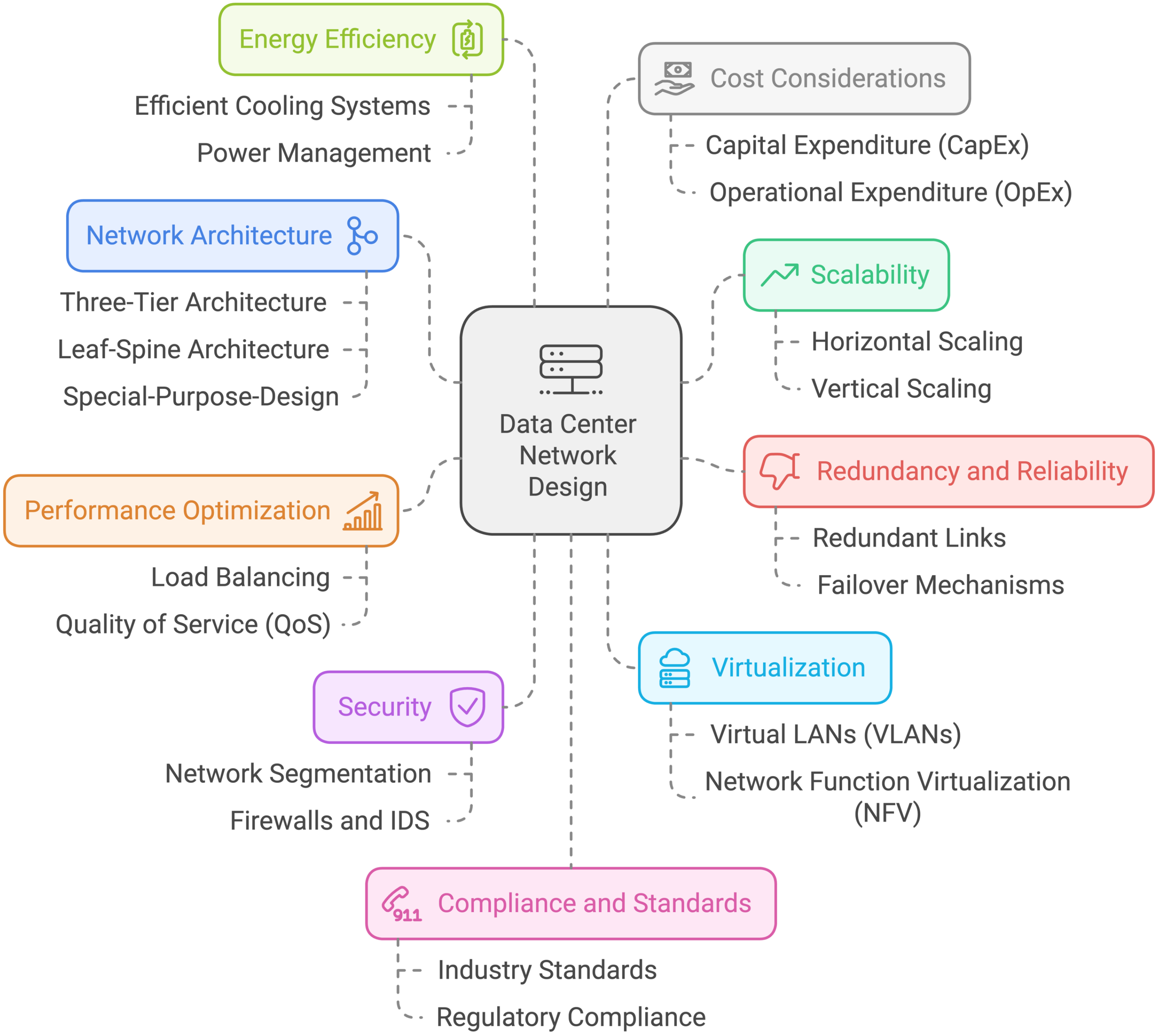


Evolution of DCN

- Early Data Centers (1960s-1980s)
  - Mainframes
  - Centralized computing: limited networking
  - Point-to-point and proprietary connections
- Client-Server Model (1990s)
  - Distributed computing
  - Ethernet, TCP/IP
- Rise of Virtualization (2000s)
  - Virtual machines
  - Efficiency and scalability
  - VLANs, network segmentation
- Cloud Computing Era (2010s)
  - Cloud services
  - SDN: Scalability and automation
- Edge Computing and IoT (2020s)
  - Demand for low-latency, distributed network architectures
  - Micro data centers closer to data sources
- Machine Learning and AI (2010s-Present)
  - Exascale high-performance computing
  - Network as the bottleneck: stringent performance requirements



DCN Design Dimensions



Data Center Network Design

Energy Efficiency
- Efficient Cooling Systems
- Power Management

Network Architecture
- Three-Tier Architecture
- Leaf-Spine Architecture
- Special-Purpose-Design

Performance Optimization
- Load Balancing
- Quality of Service (QoS)

Security
- Network Segmentation
- Firewalls and IDS

Compliance and Standards
- Industry Standards
- Regulatory Compliance

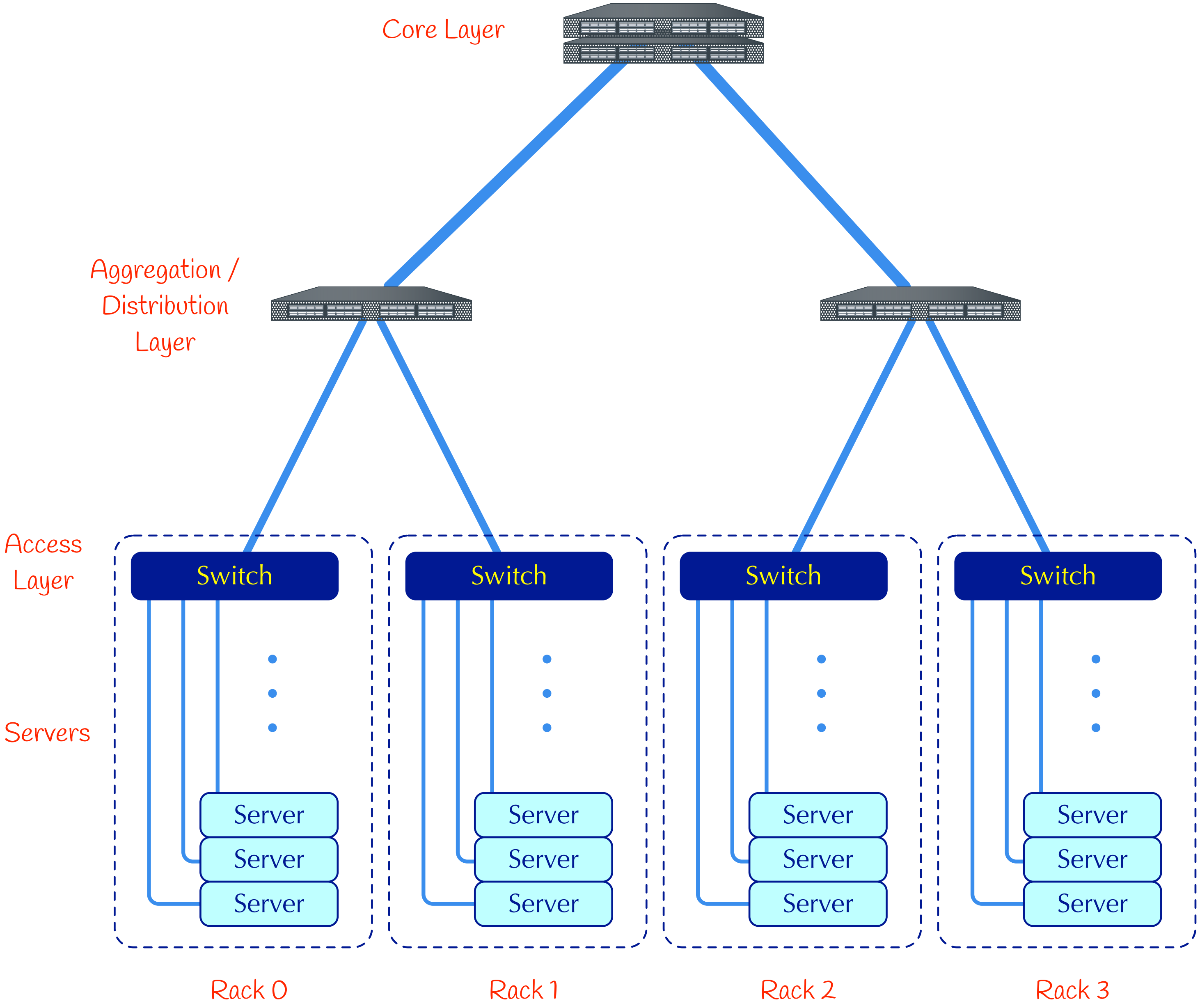
Cost Considerations
- Capital Expenditure (CapEx)
- Operational Expenditure (OpEx)

Scalability
- Horizontal Scaling
- Vertical Scaling

Redundancy and Reliability
- Redundant Links
- Failover Mechanisms

Virtualization
- Virtual LANs (VLANs)
- Network Function Virtualization (NFV)

Three-Tier Architecture



Hierarchical tree network topology

- Commonly used in traditional DCNs

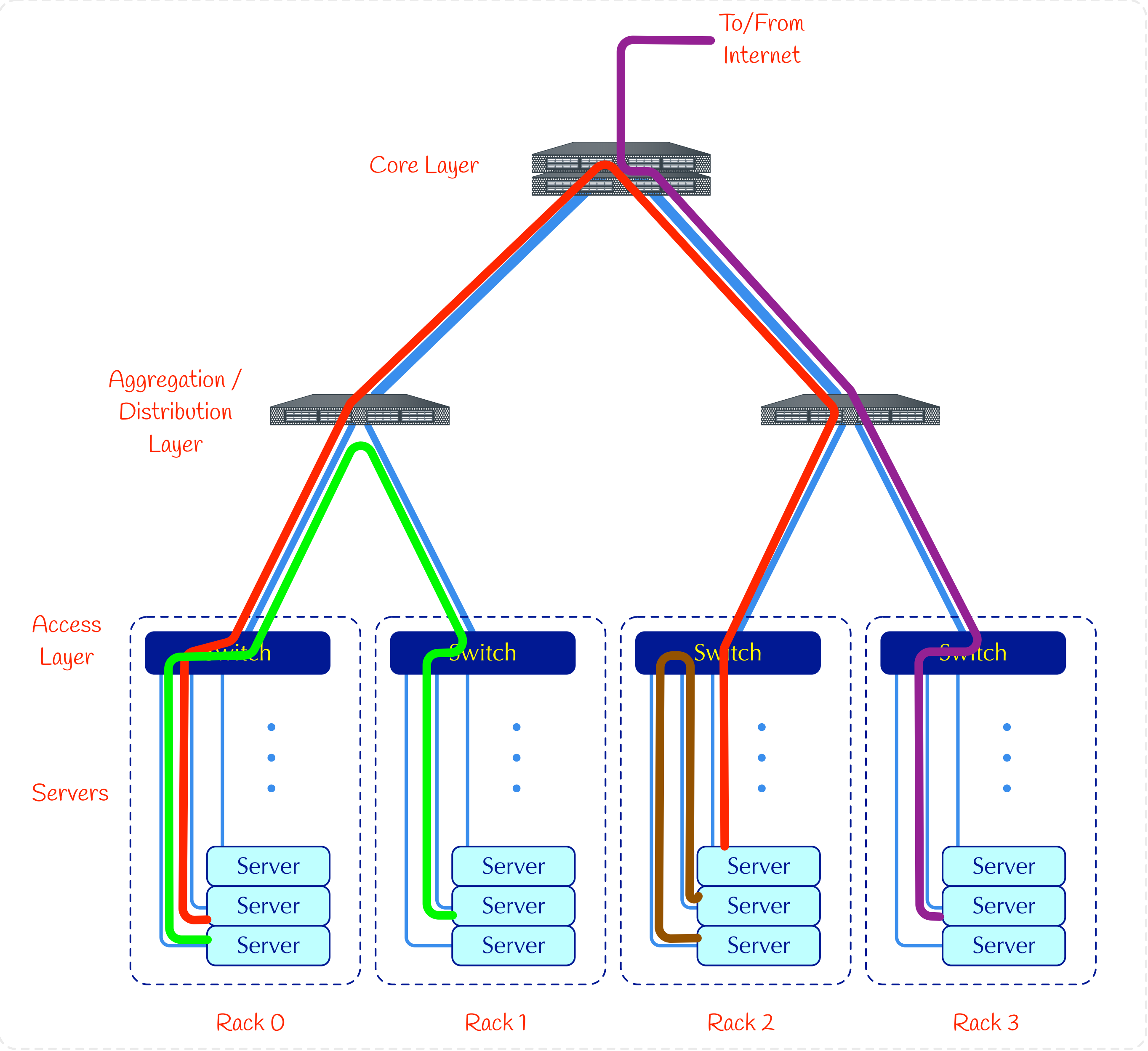
Three layers:

- Core:
  - Layer 3 (network layer)
  - Fully connected high-speed mesh of multiple routers
  - Connect to the external networks
- Aggregation:
  - Layer 3 and 2 (network and link layers)
  - Connect to core with few high-speed links (e.g., 100 Gb/s links), to access with many low-speed links (e.g., 10Gb/s) → simplify cabling
  - Middleboxes sit here (firewall, load balancer, …)
- Access: layer 2 (link)
  - Connect to each server in the rack (e.g., through one or two 10Gb/s links)
  - VLANs used to limit broadcast

Modular design

- Easy to expand

Traffic Direction in 3-Tier Architecture



🟫 **Within a rack**

🟥 **Between racks**

🟩 **Between racks**

🟪 **To/from Internet**

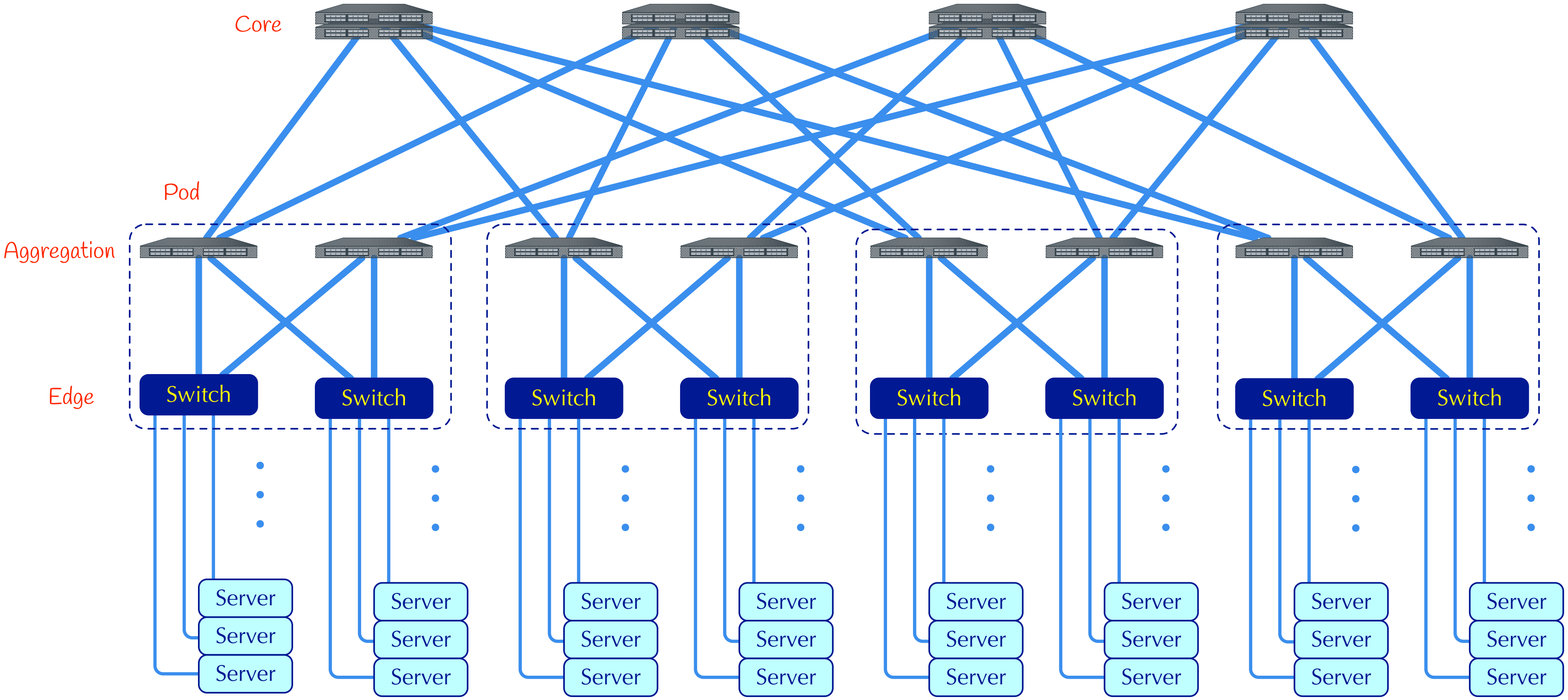
Switching and Routing:

- Communication within a rack or within the same aggregation switch happens at link layer (switching).
- Traffic going through core (between aggregation switches and to/from external networks/Internet) happens at network layer (routing).
- Different flows might have different RTTs (even within DCN)

Total Link Capacities at Each Layer Might Be:

- Equal to lower layers, or
- Less (over-subscription)
- Reason:
  - Cost-saving: less bandwidth → lower cost
  - Locality: most communication within the same rack, or within the same cluster.

Fat-Tree Architecture



Properties of Fat-Tree Architecture:

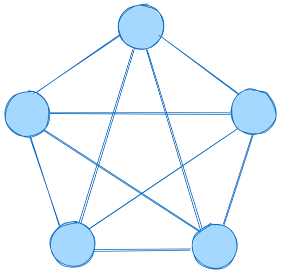
- Scalable: easily expandable
- Low latency, high throughput
- Cost-effective
    - Commodity hardware
    - Lower operational costs

Reliability and Improved Performance:

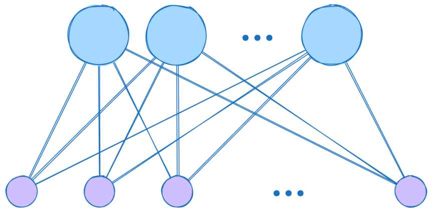
- Edge and aggregation switches are grouped into “pods”.
    - Multiple-paths (choice of aggregation and core)
    - Automatic failover
- Leads to better load balance, redundancy, and thus
    - Reliability and high availability, and
    - Improved performance

Other DCN Architectures/Topologies

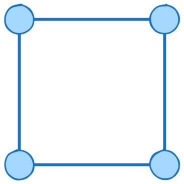
- Mesh: every node is connected to every other node
  - Direct communication, costly, but high performance
- Leaf-Spine topology: two-tier structure, servers and storage node connect directly to leaf switches
  - Switched environment, VLANs to limit broadcasts
- Hyper-cube: multi-dimensional cube structure
  - Used in high-performance computing and ML solutions
- Hybrid: combine two or more topologies
  - Tailored to specific requirements of DCNs
- And many more …
- Question: what are the properties of each of these topologies?
  - End-to-end latency?
  - Simplicity?
  - Scalability?
  - …



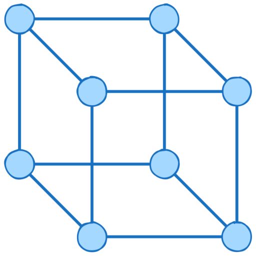
Mesh Topolog



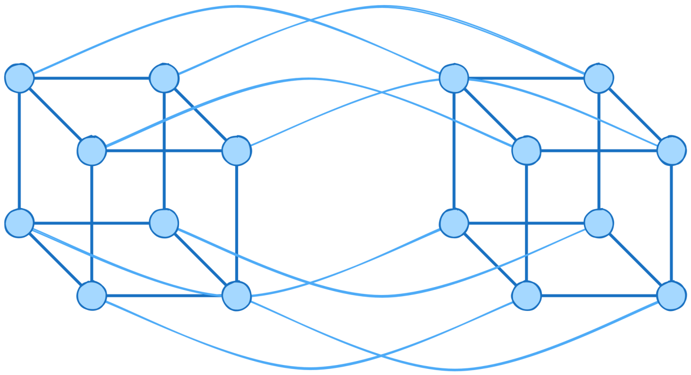
Leaf-Spine Topology



Two Dimensional Hypercube



Three Dimensional Hypercube



Four Dimensional Hypercube

Transport in Data Center Networks

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

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

ECN + DCTCP

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

- DCTCP
  - A variant of TCP
  - Uses ECN as congestion signal Use → reduced packet loss

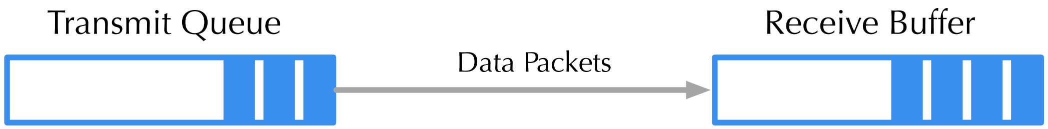
- How does DCTCP work?
  - Congestion measured based on fraction of packets marked with ECN (called α).
    - α is the moving average of the observed fractions (like estimatedRTT)
  - Adjust congestion window based on the extent of congestion: $cwnd \leftarrow cwnd \times (1-\alpha/2)$
    - Instead of halving the window in case of congestion.

- DCTCP Properties:
  - 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

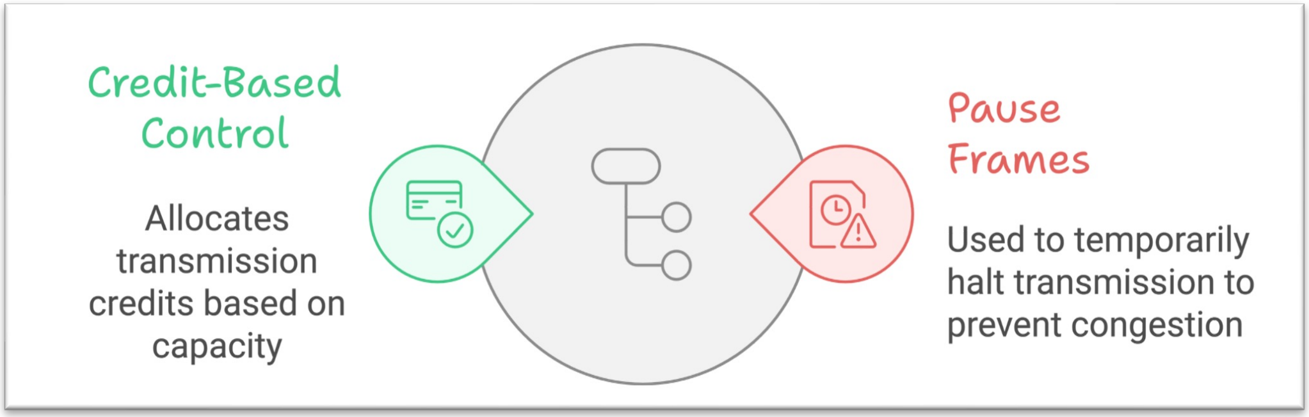
Flow control mechanism used to create lossless networks.

- 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



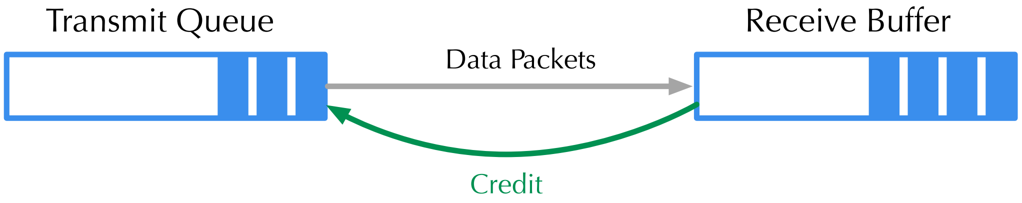
Credit-Based Control

Allocates transmission credits based on capacity

Pause Frames

Used to temporarily halt transmission to prevent congestion

Credit-Based Link-Level Flow Control

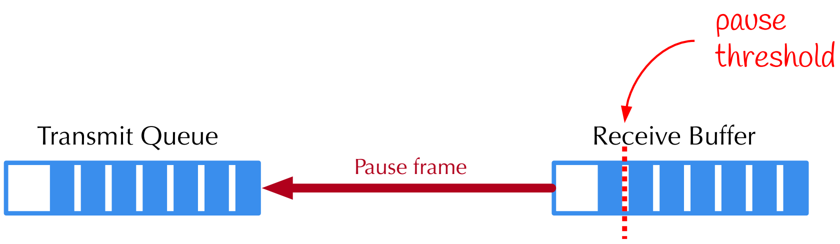


- Receiver provides credits to the sender when it has room
  - Credit unit: bytes or packets

- 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



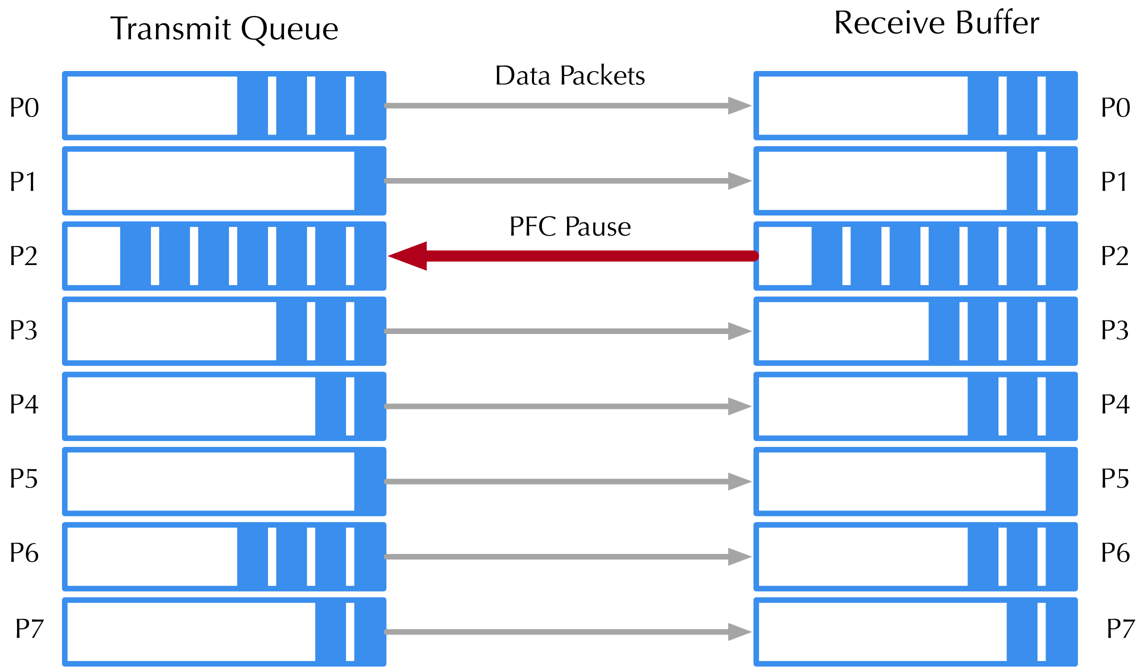
- Transmitter does not need permission to start.

- 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.

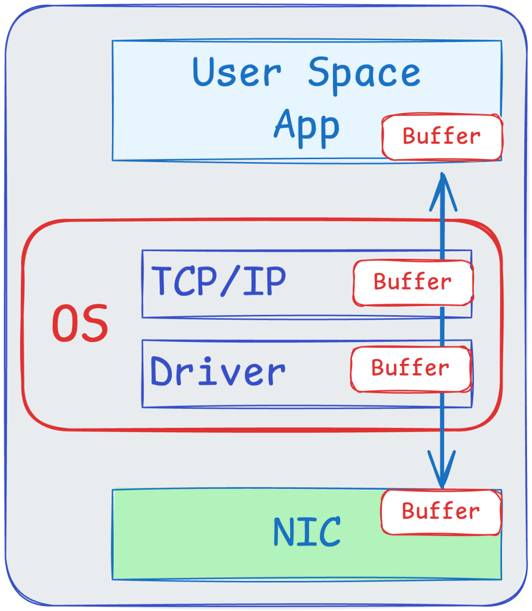
Priority-based Flow Control (PFC)

- 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

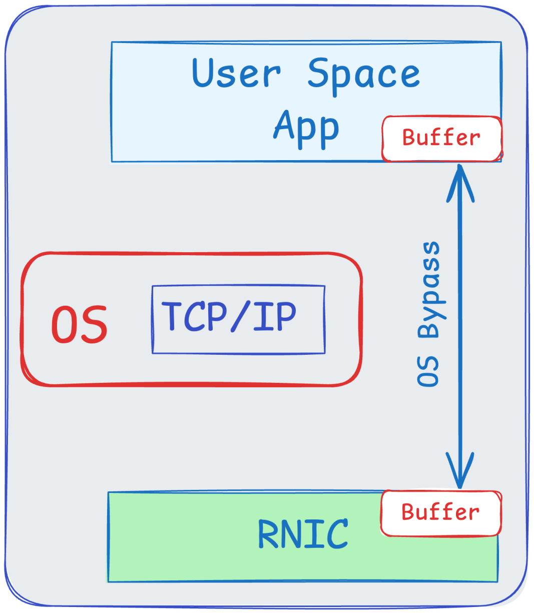


Remote Direct Memory Access

- 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)

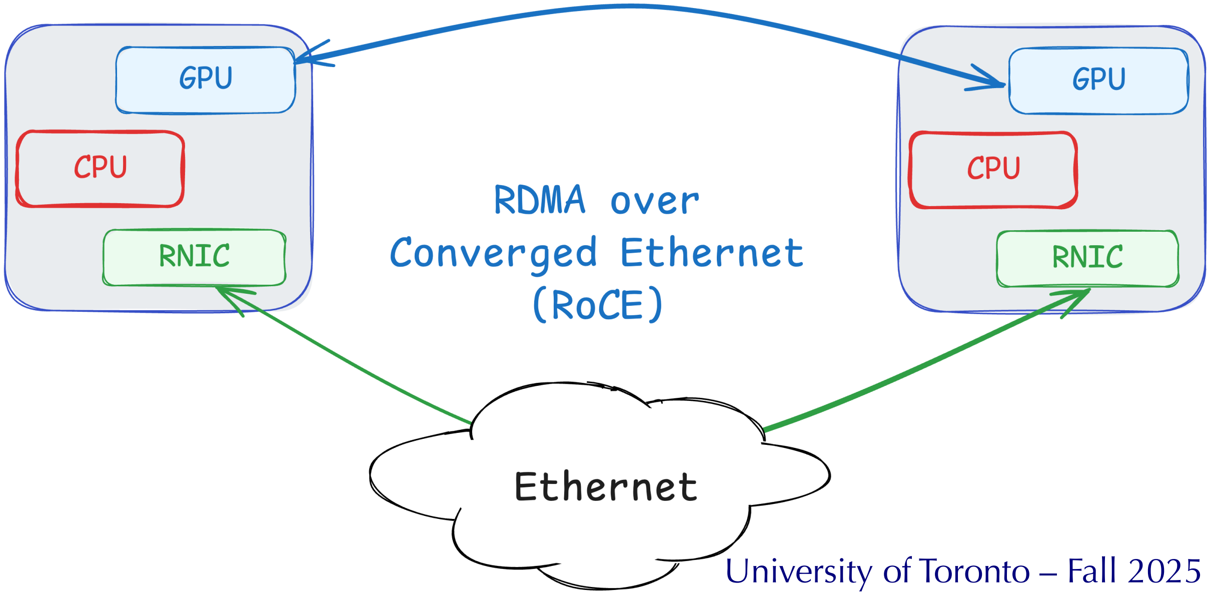
- Applications: High-Performance Computing (HPC), Storage, …

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



Networks for Machine Learning

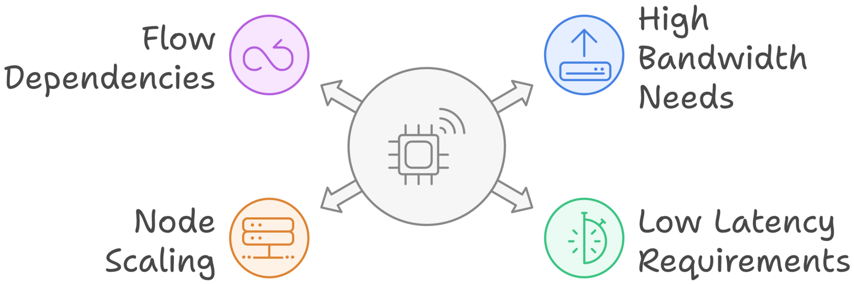
- Data Center Networks have evolved significantly
  - To accommodate demands for modern applications.
  - Example: many novel congestion control algorithms in recent years:
    - Swift, timely, HPCC, DCQCN, …
    - Enablers: more accurate information from network (exact queue occupancy), assumptions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

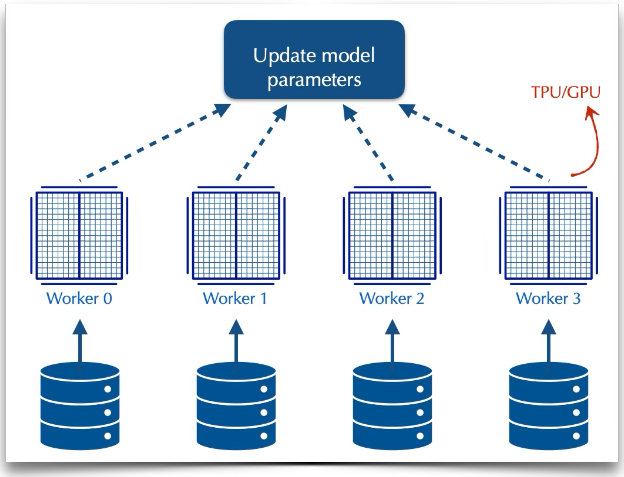
All of this leads to significant pressure on the network (throughput, latency, reliability, …)

What Makes ML Different: Challenges

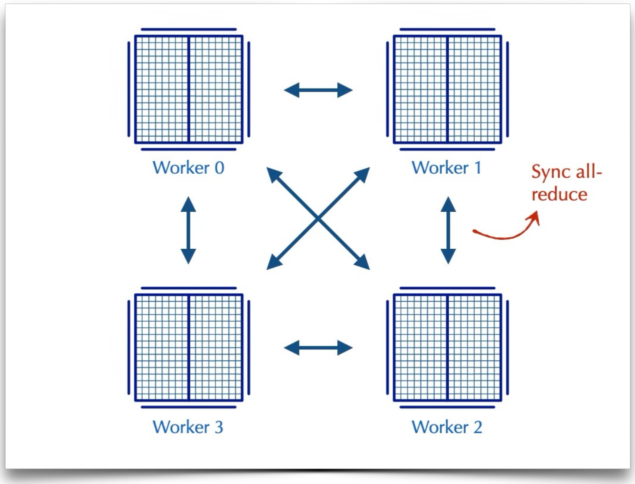
- Handling many independent flows in a network makes many network problems easy (easier) to solve
  - Random arrivals, each flow has a small share of bandwidth
  - Why?
- In ML, we have few flows
  - Having few flows means each flow can have a large fraction of link bandwidth
    - ⇒ Any interaction 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

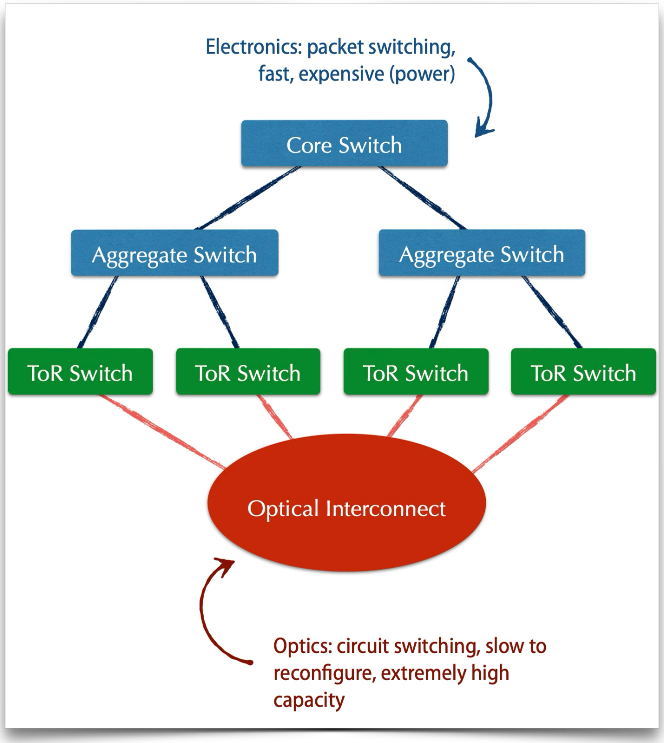
- DCN topology: fat-tree, leaf-spine, …
  - Static and uniform
  - Needs to work with a wide range of workloads
    - Tuned for average workload

- 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

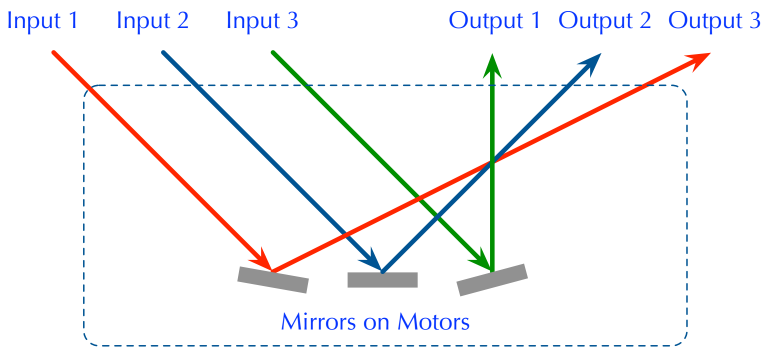
Adapt Network Topology to Demand

- 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:
  - Customized 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?


Electronics: packet switching, fast, expensive (power)
Core Switch
Aggregate Switch
Aggregate Switch
ToR Switch
ToR Switch
ToR Switch
ToR Switch
Optical Interconnect
Optics: circuit switching, slow to reconfigure, extremely high capacity

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

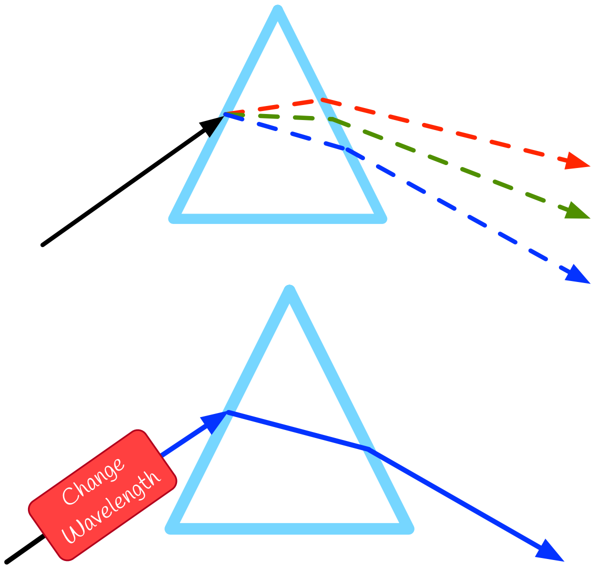


MEMS-based Optical Circuit Switch

- 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

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.

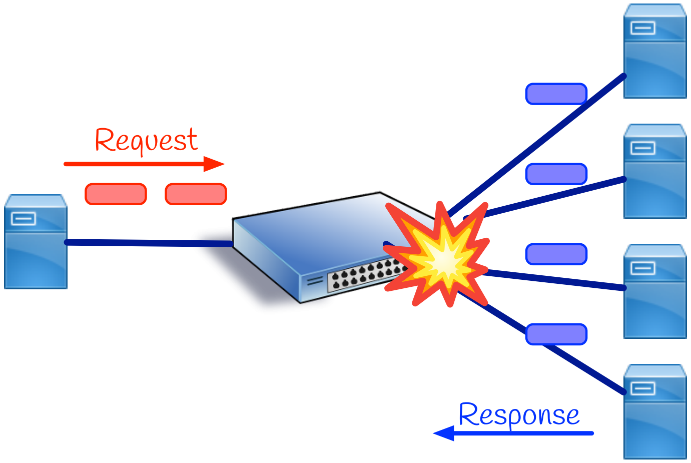
Example: Incast Problem

- 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

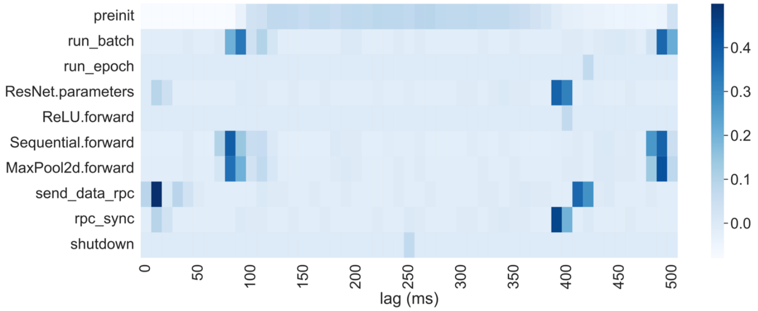
- Network does not know when incast will happen
  - Cannot react in a timely manner.
  - Over-provisioning seams to be the only viable solution.

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

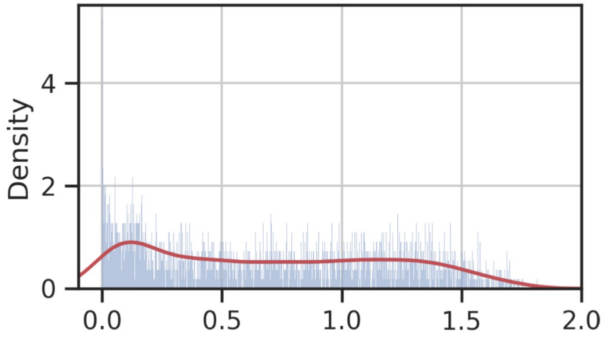


Networks and Applications*

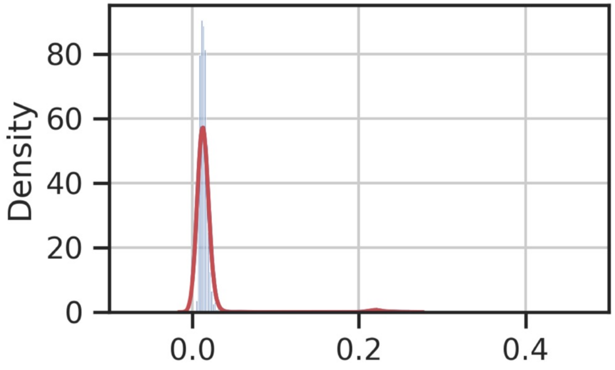
- Imagine, we have a system that observes *network events*
    - E.g., incast in switches
- Also, it can observe certain events in applications
    - E.g., when each function is called
- We correlate these events find out triggers on the end-host side for network events
    - I.e., which application 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

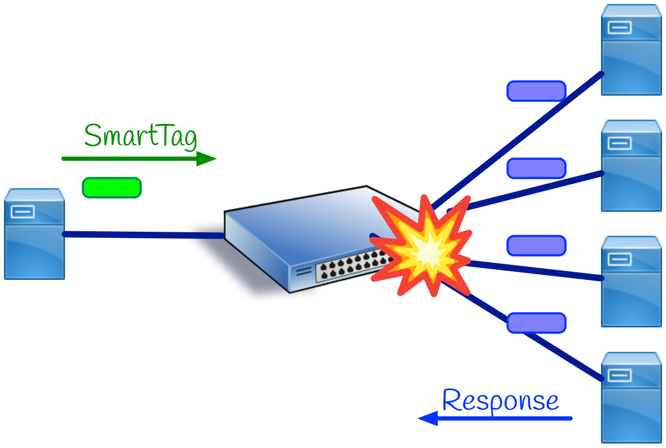


Incast Probability with SmartTag

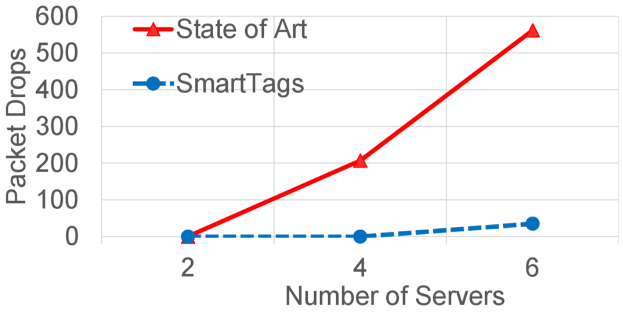
* Mortazavi, S.H., Munir, A., Bahnasy, M.M., Dong, H., Wang, S. and Ganjali, Y. 2022. EarlyBird: automating application signalling for network application integration in datacenters. Proceedings of the ACM SIGCOMM Workshop on Network-Application Integration (New York, NY, USA, Aug. 2022), 40–45.

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

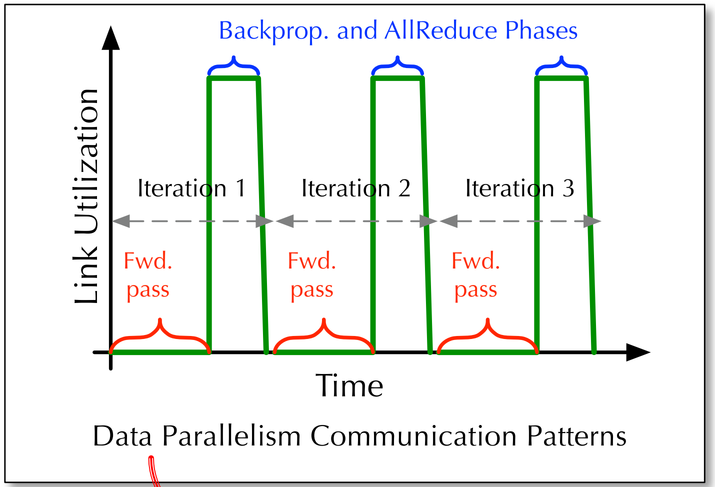
* Munir, A., Mortazavi, S.H., Bahnasy, M.M., Baniamerian, A., Wang, S., Guan, S. and Ganjali, Y. 2022. SmartTags: bridging applications and network for proactive performance management. Proceedings of the ACM SIGCOMM Workshop on Network-Application Integration (New York, NY, USA, Aug. 2022), 46–52.

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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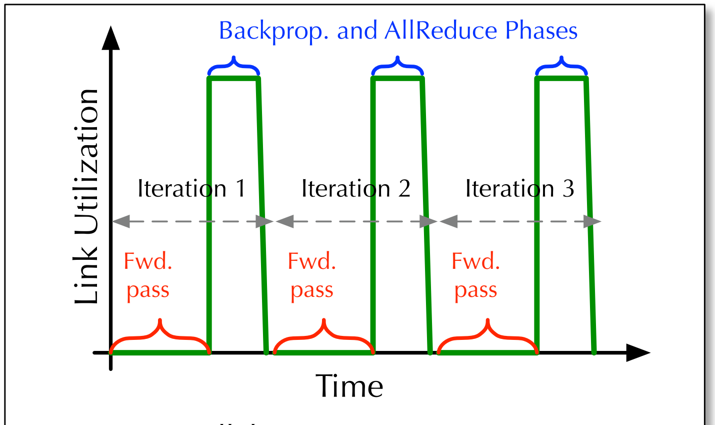
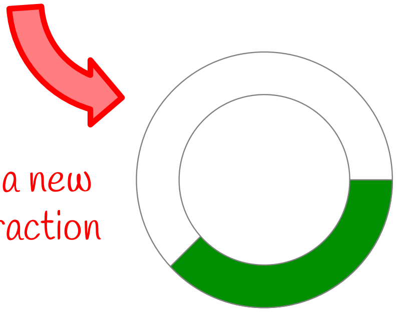
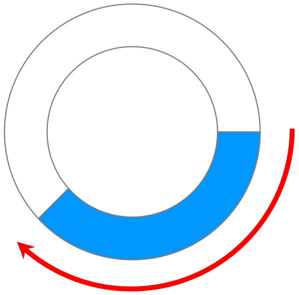


Data Parallelism Communication Patterns

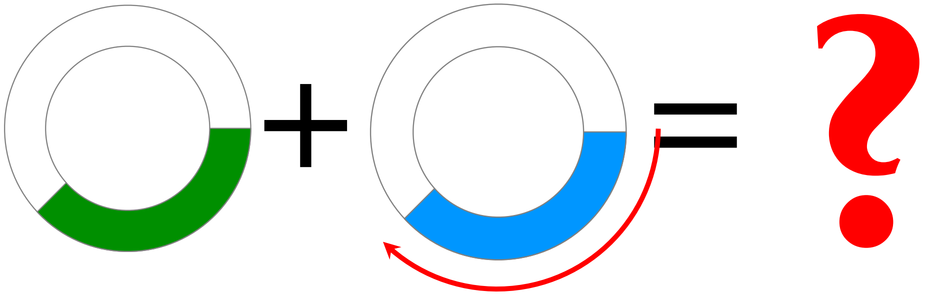


Convert to a new geometric abstraction



How much should we rotate each circle?

Cassini: Network-Aware Job Scheduling

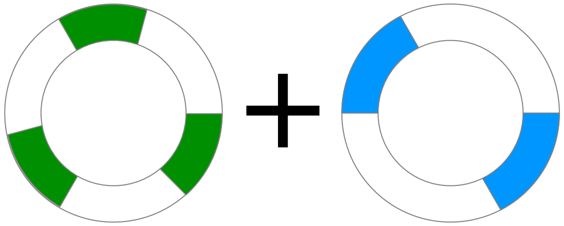


- Step 3. For each link in the network:
    - Overlays the circles of jobs going through the link and rotates them
    - Find a configuration that minimizes the total bandwidth demand
    - This gives us a set of relative shifts in time

- 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 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.