## iSwitch: Accelerating Distributed Reinforcement Learning with In-Switch Computing

# Youjie LiIou-Jen LiuYifan YuanDeming ChenAlexander SchwingJian Huang

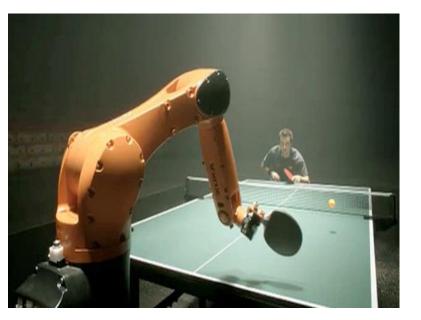
### **I** University of Illinois at Urbana-Champaign

Electrical & Computer Engineering

### AI Applications are Increasingly Operating in Dynamic Environments



Autonomous Driving



**Robotics** 



Games





### AI Applications are Increasingly Operating in Dynamic Environments



Autonomous Driving



Robotics



Games

ECE ILLINOIS

Reinforcement Learning Empowers AI Applications to Take Real-Time Intelligent Actions



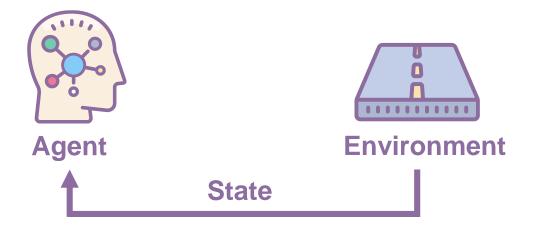




**Environment** 

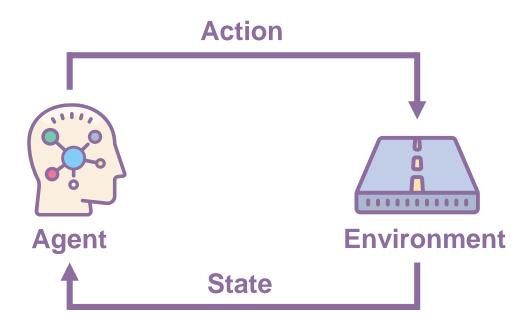




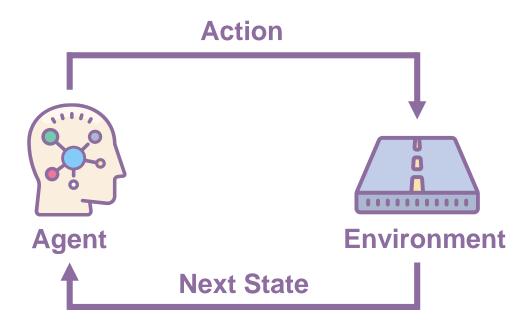






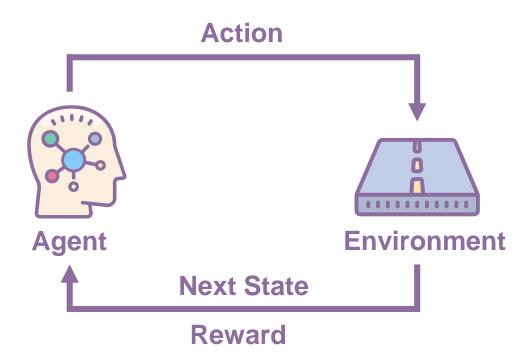






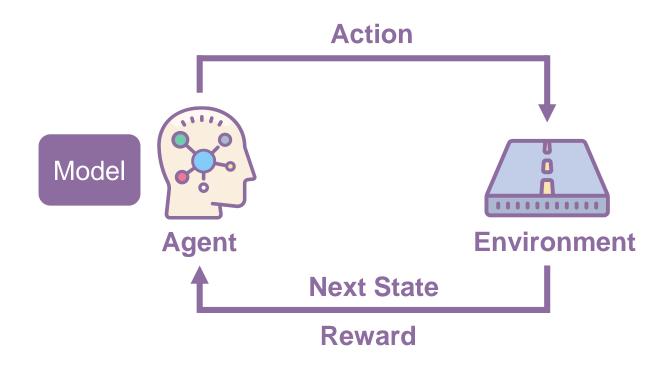




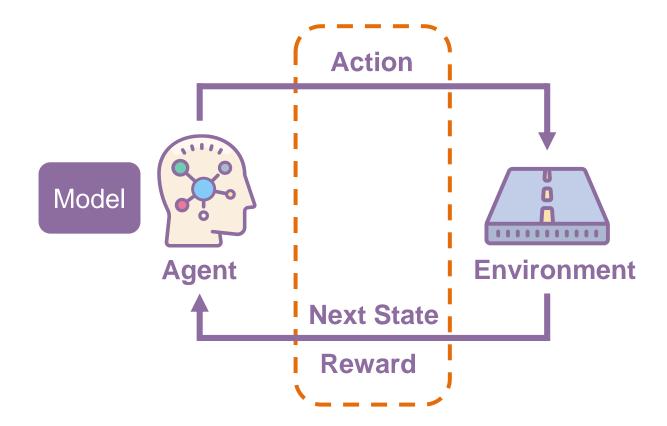




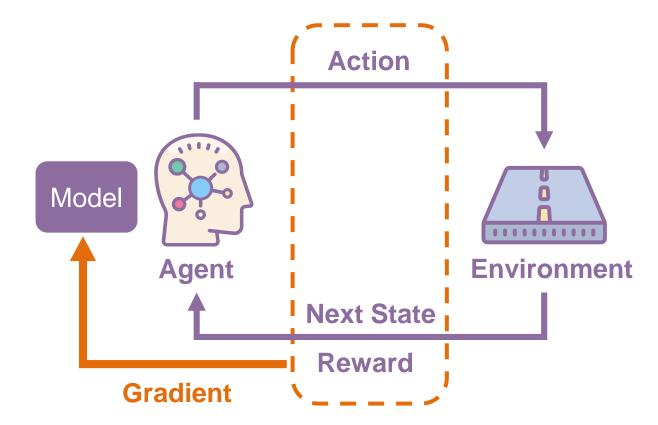




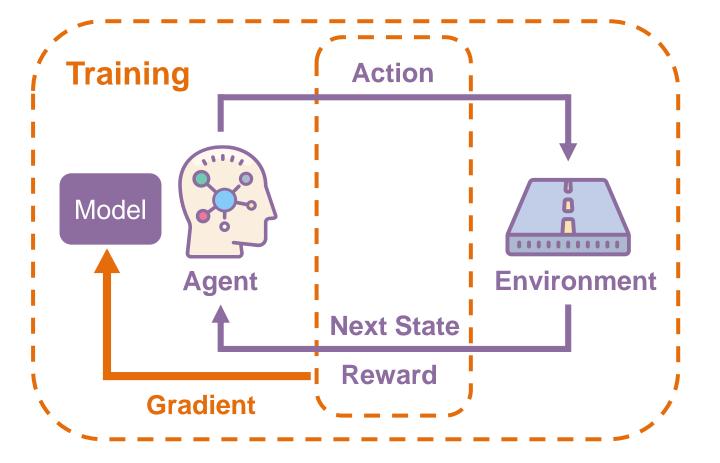




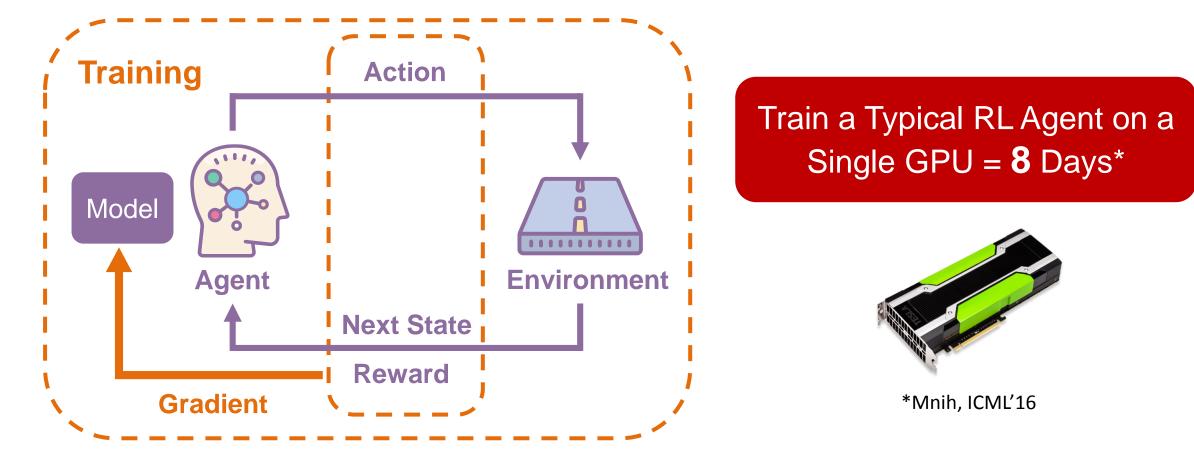




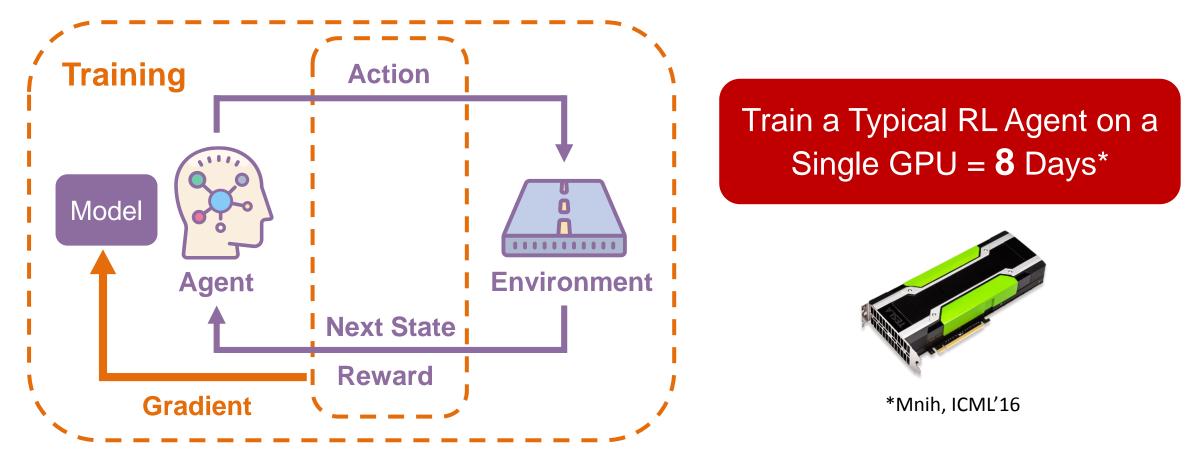






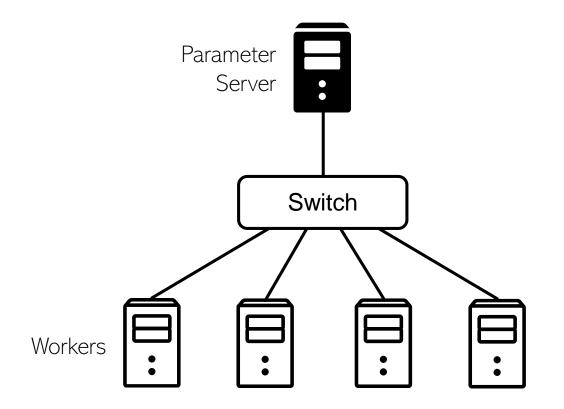






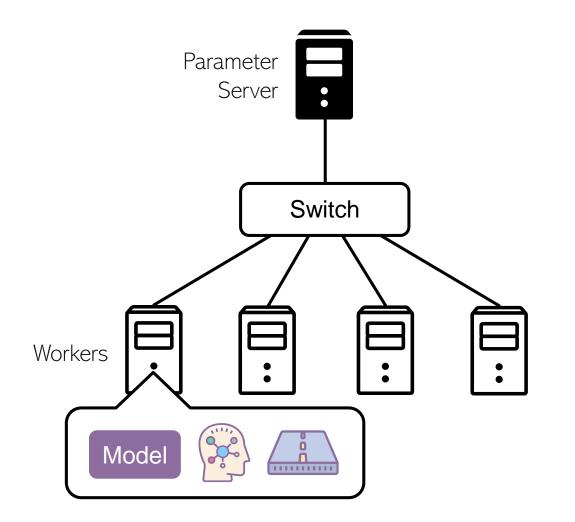
**RL** Requires Distributed Training for Improved Performance



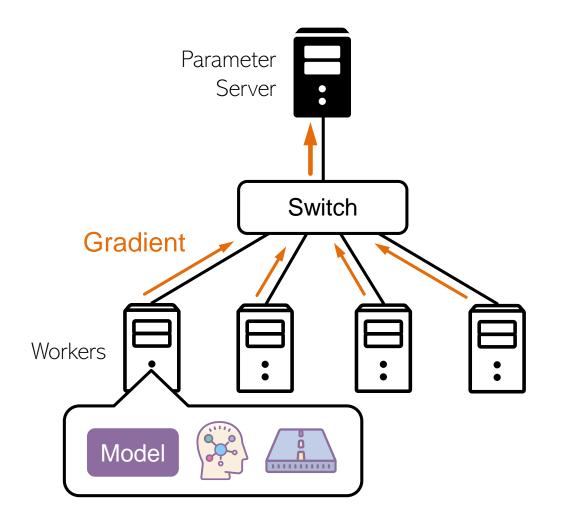


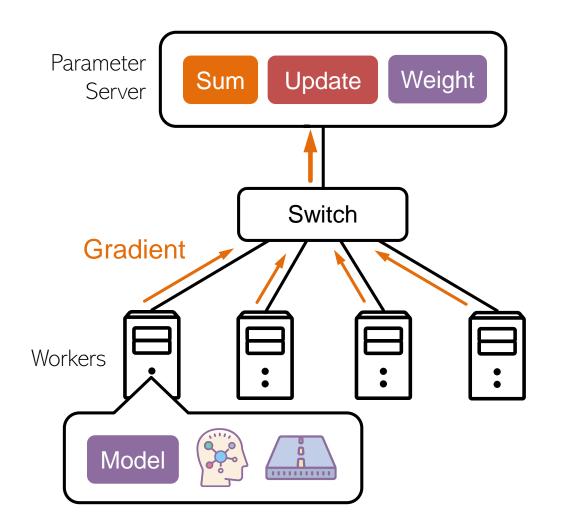




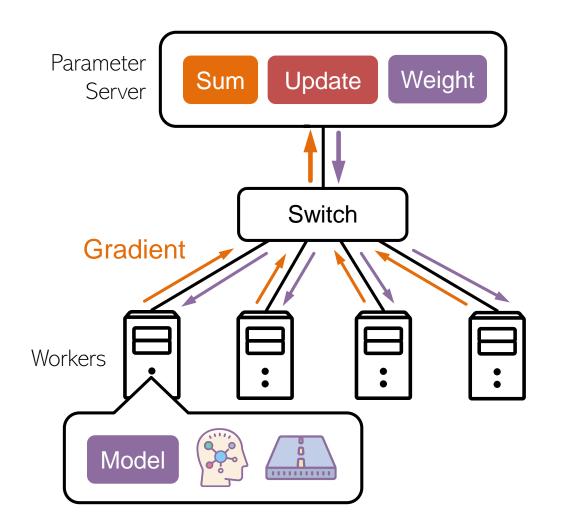




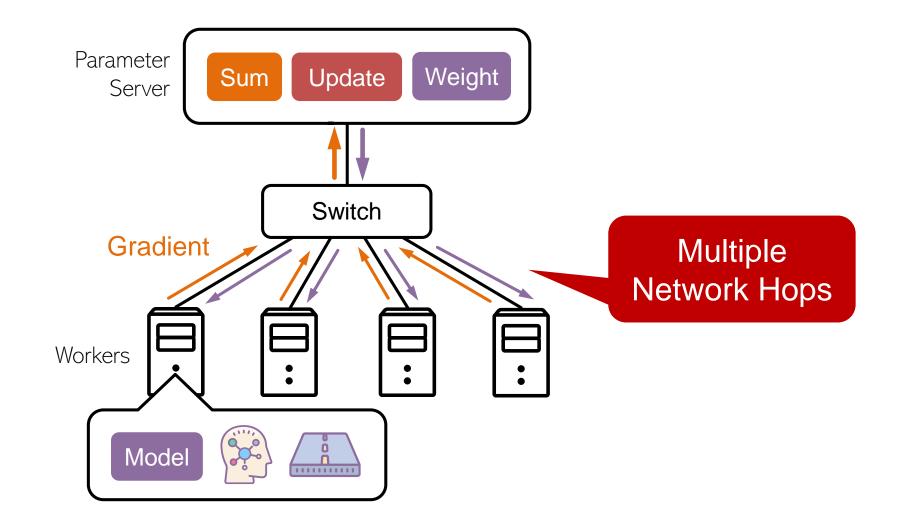




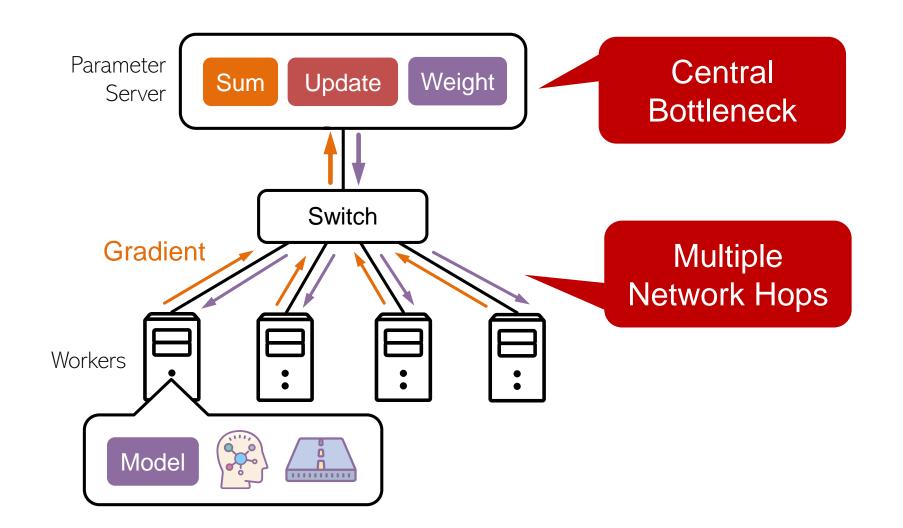




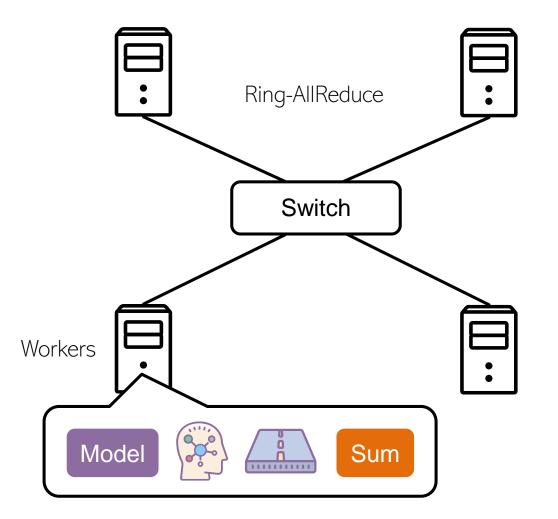




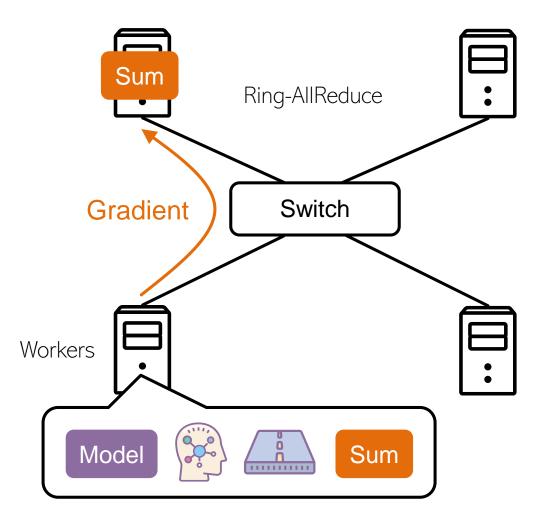




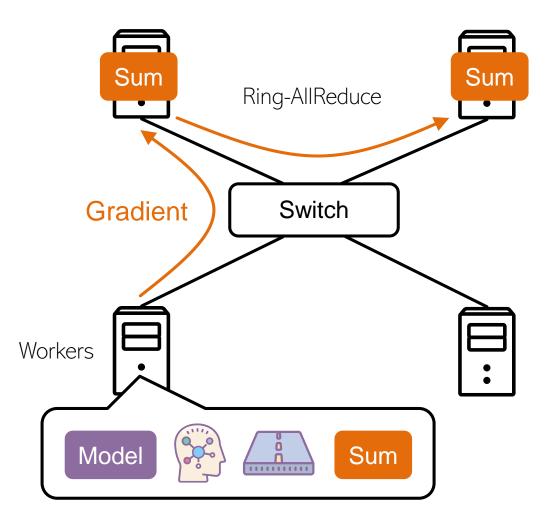




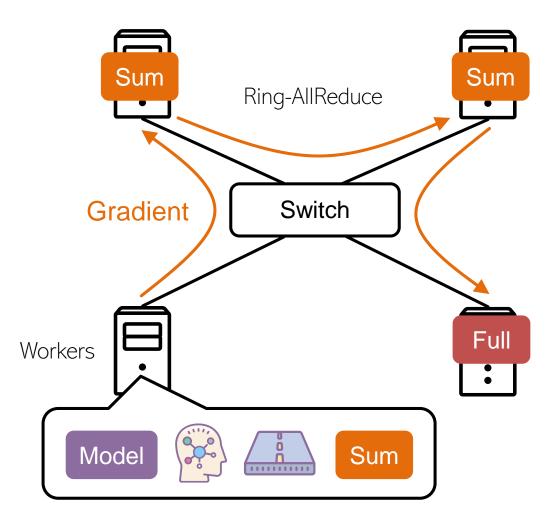




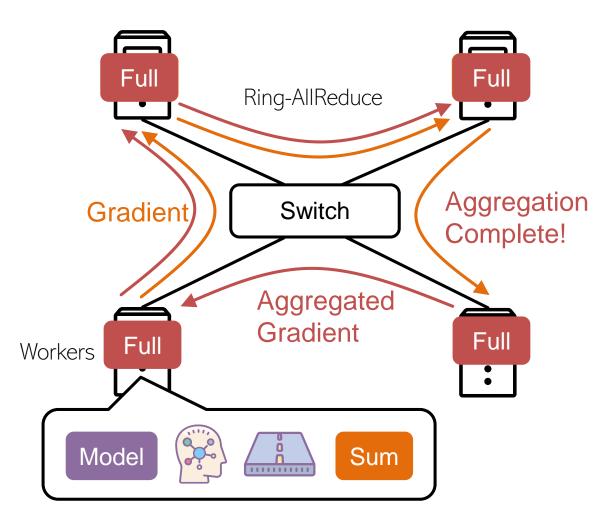




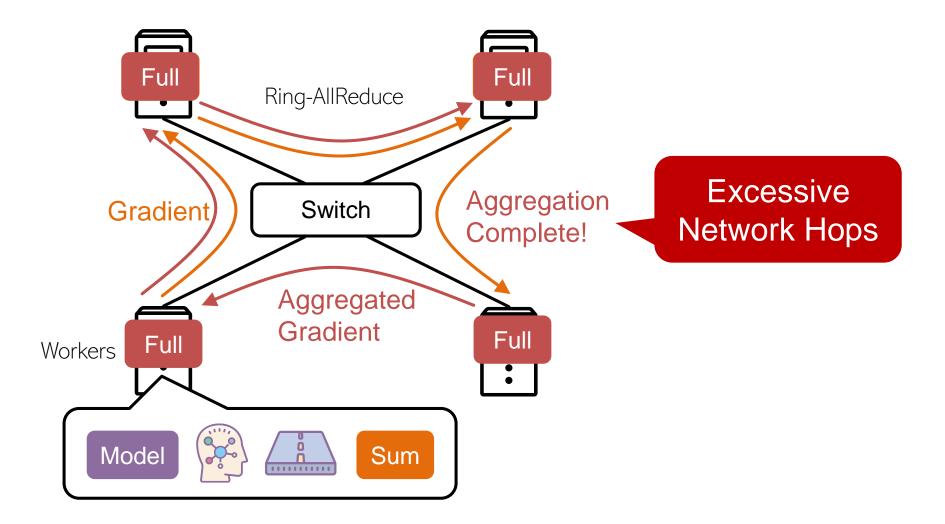






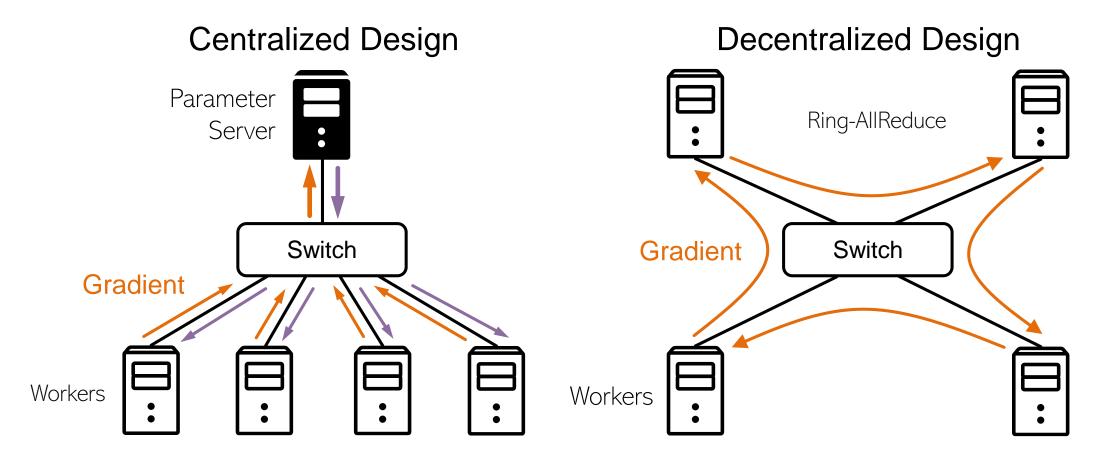






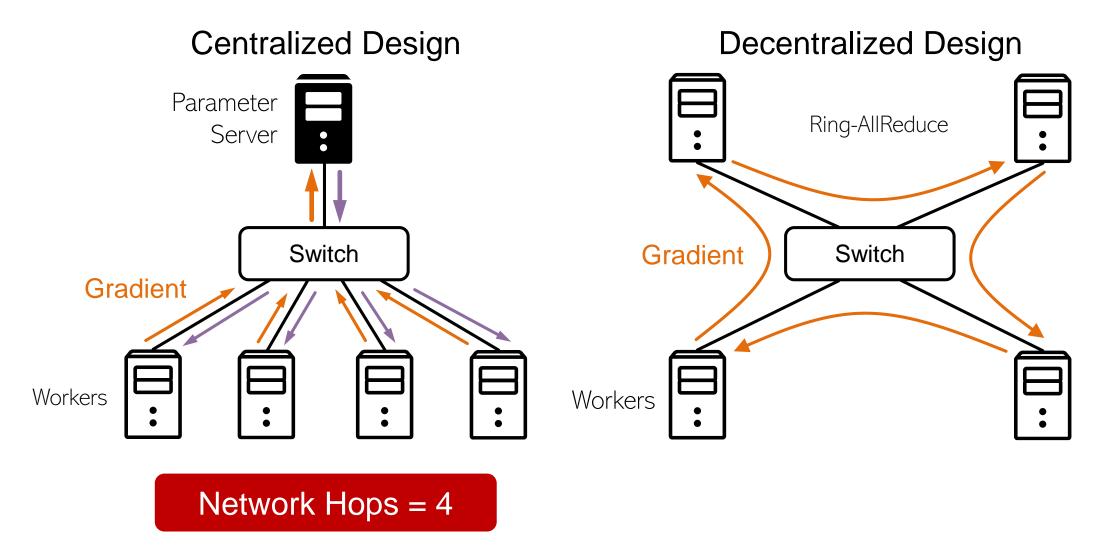


### **Network Communication is the Bottleneck in Distributed RL Training**



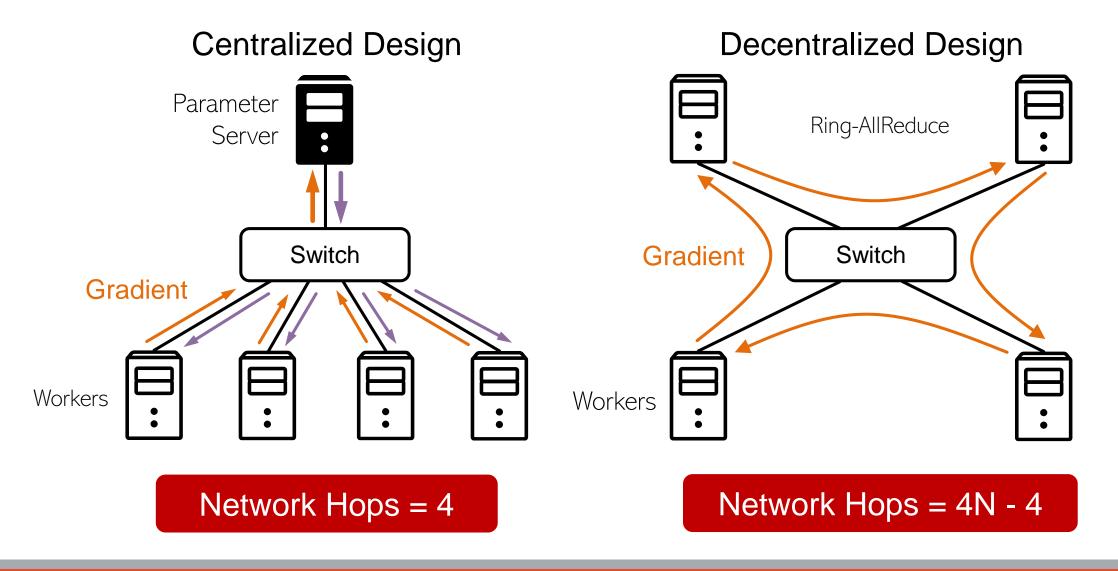


### **Network Communication is the Bottleneck in Distributed RL Training**





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<b>RL</b> Benchmark	DQN- Atari	A2C- Atari	PPO- MuJoCo	DDPG- MuJoCo
Gradient Size	6 MB	3 MB	40 KB	158 KB
Training Iterations	200 M	2 M	0.2 M	3 M

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<b>DNN</b> Benchmark	AlexNet- ImageNet	ResNet50- ImageNet	VGG16- ImageNet	MLP- MNIST
	,,			





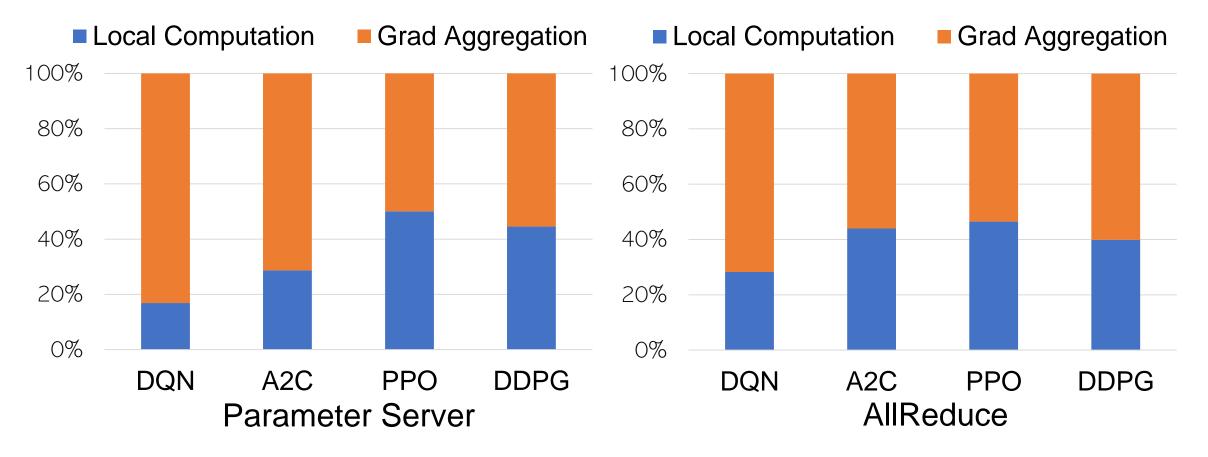
<b>RL</b> Benchmark	DQN- Atari	A2C- Atari	PPO- MuJoCo	DDPG- MuJoCo	88x Smaller
Gradient Size	6 MB	3 MB	40 KB	158 KB	Gradient Size
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**Distributed RL Training is Latency Critical** 

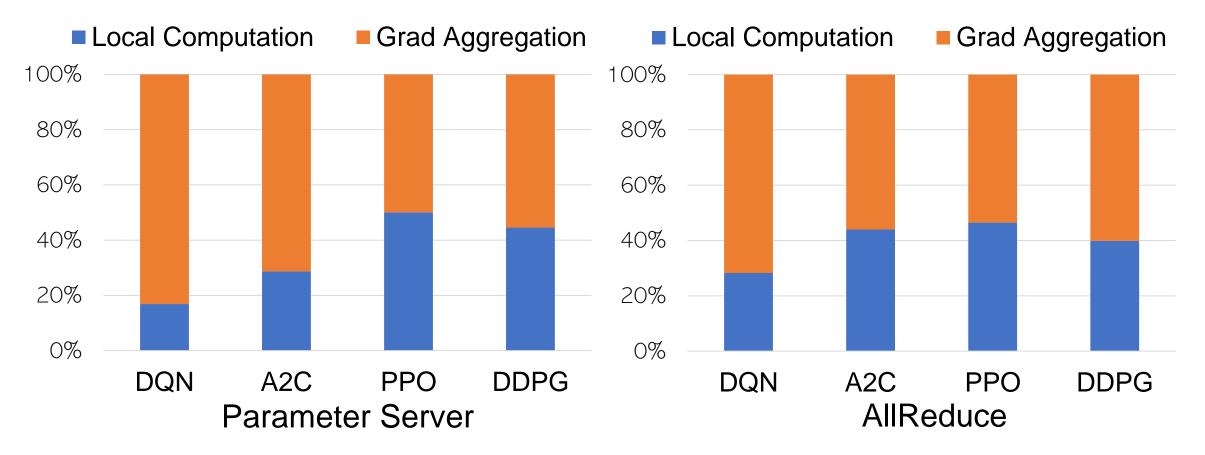


### **Quantifying the Network Overhead in Distributed RL Training**





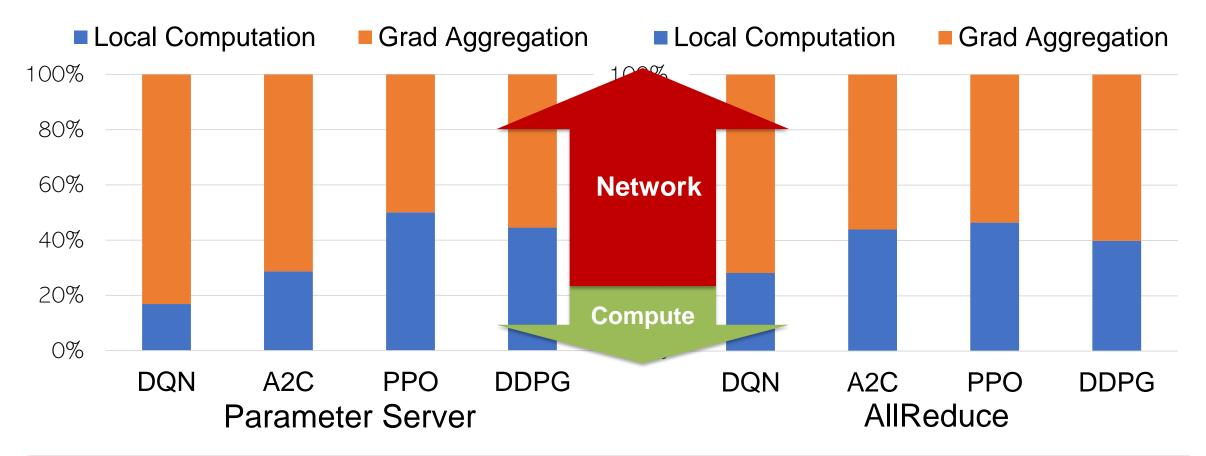
### **Quantifying the Network Overhead in Distributed RL Training**



### Gradient Aggregation over the Network Dominates the Training Time (50~83%)

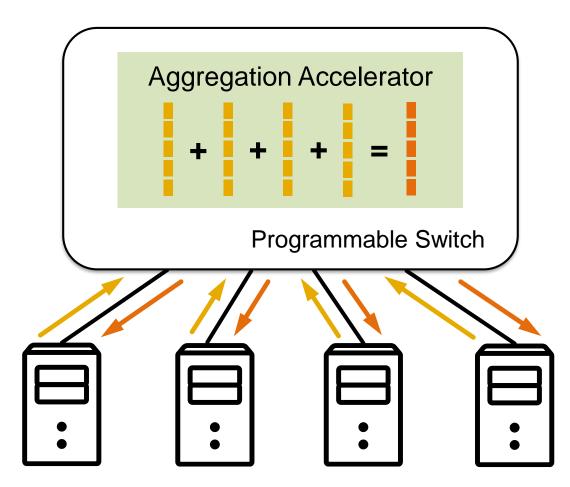


# **Quantifying the Network Overhead in Distributed RL Training**

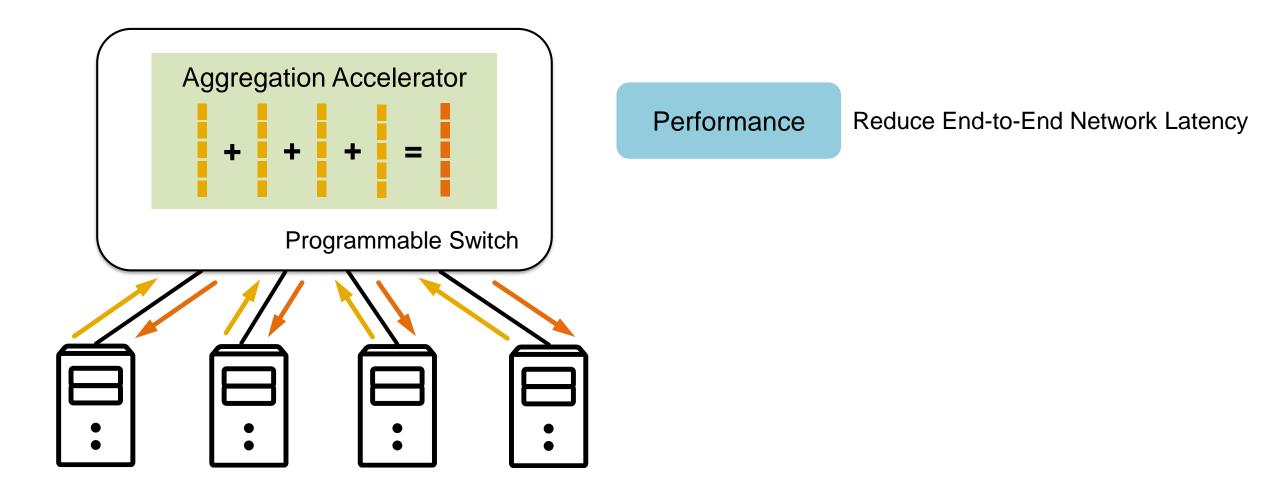


Gradient Aggregation over the Network Dominates the Training Time (50~83%)

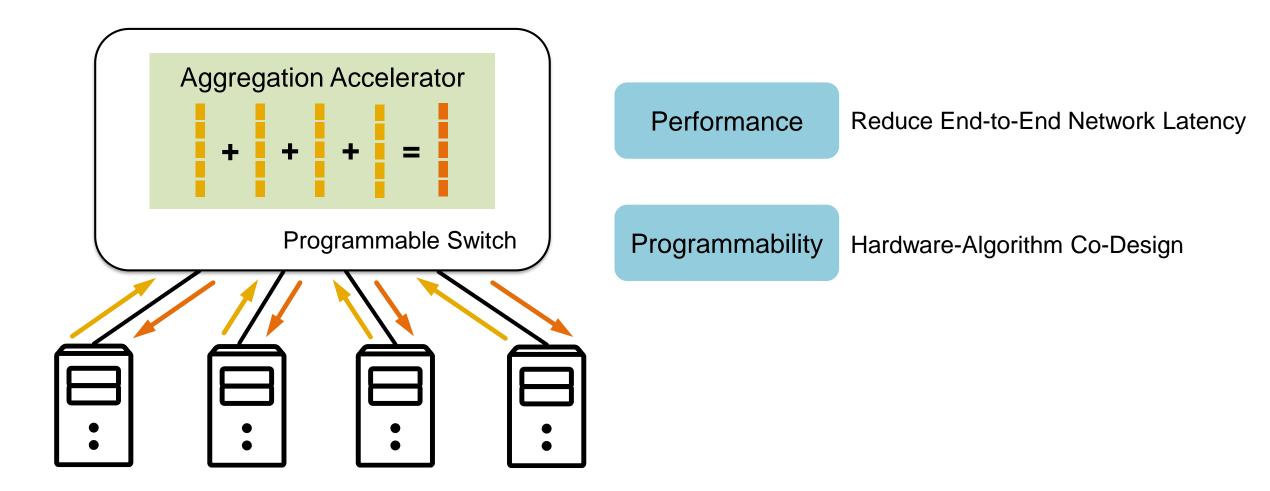




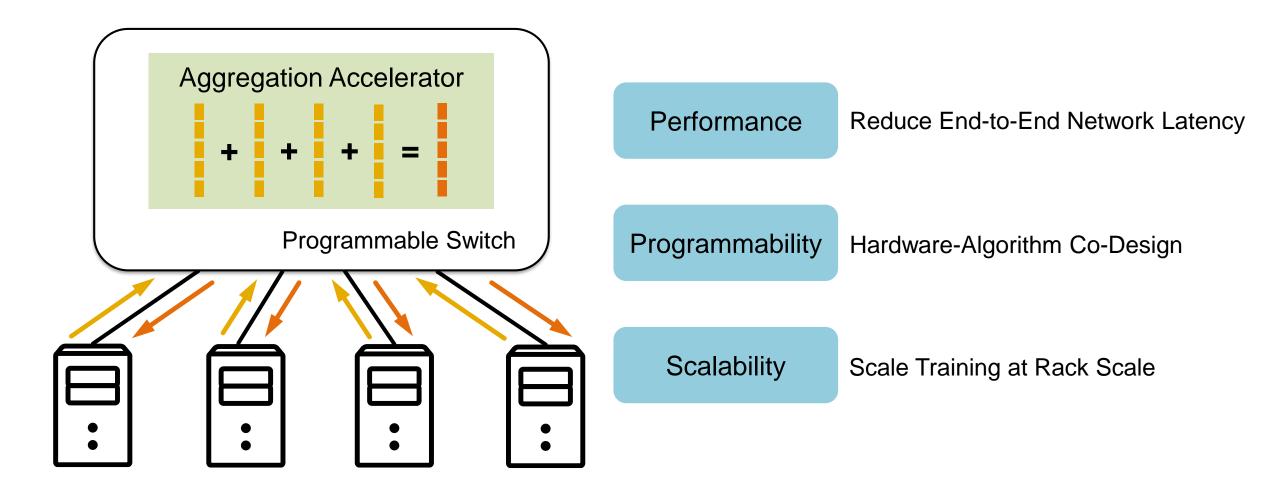














## **Challenges of In-Switch Acceleration**

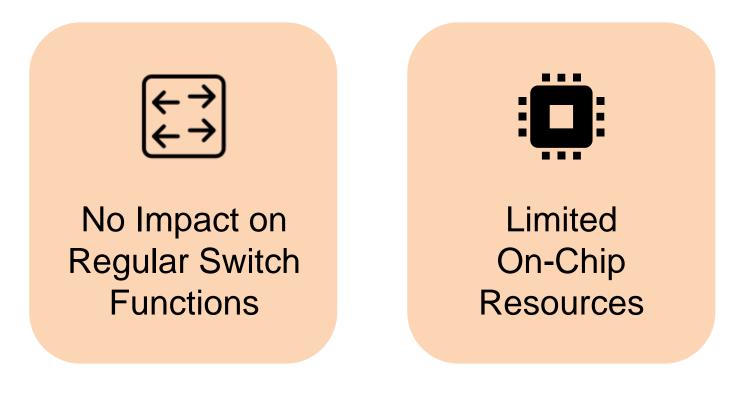


No Impact on Regular Switch Functions



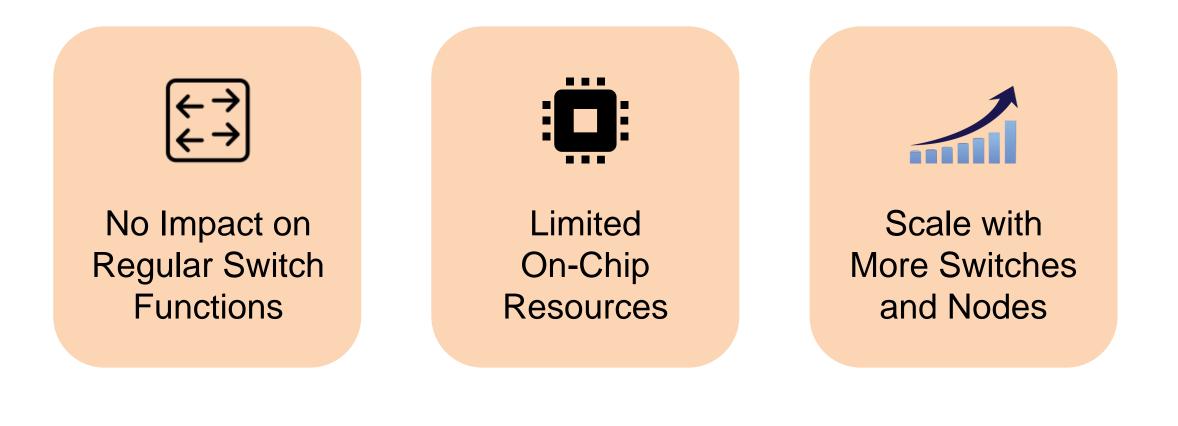


## **Challenges of In-Switch Acceleration**





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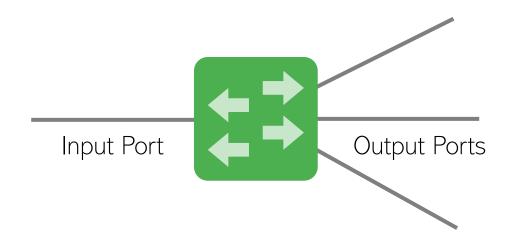
**Control Plane** 







**Control Plane** 

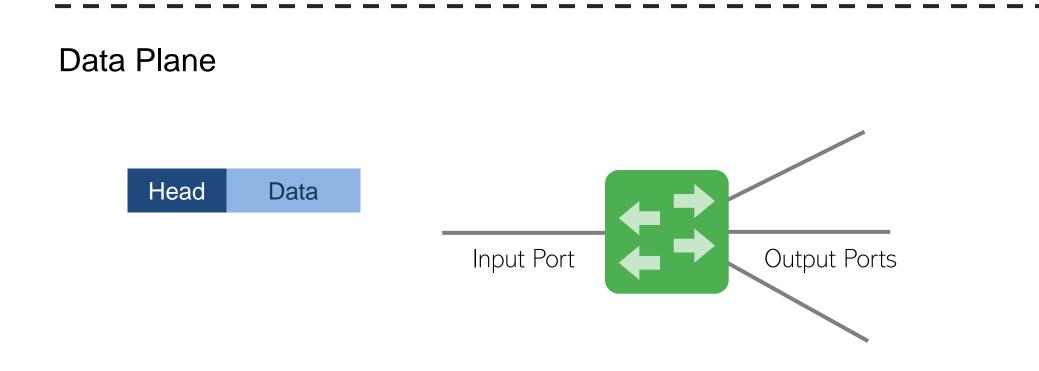








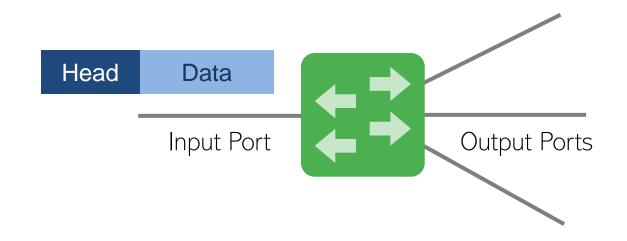
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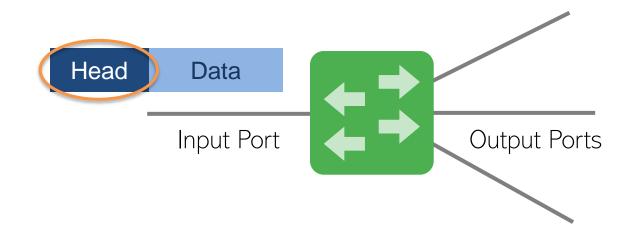
**Control Plane** 

Data Plane





**Control Plane** 

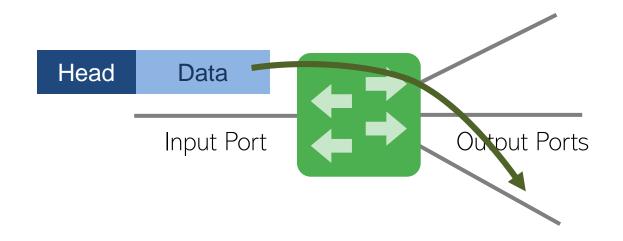








**Control Plane** 

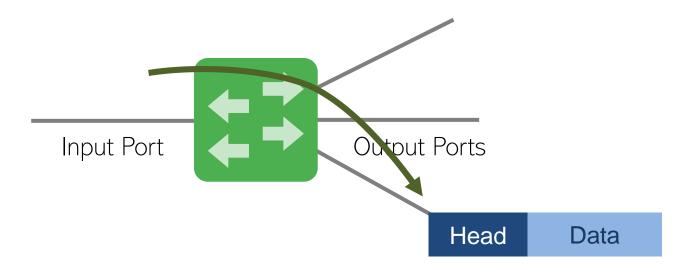








**Control Plane** 

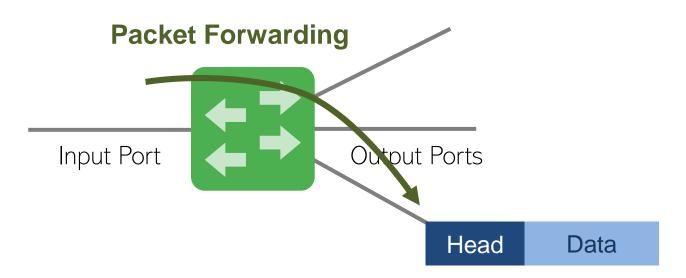






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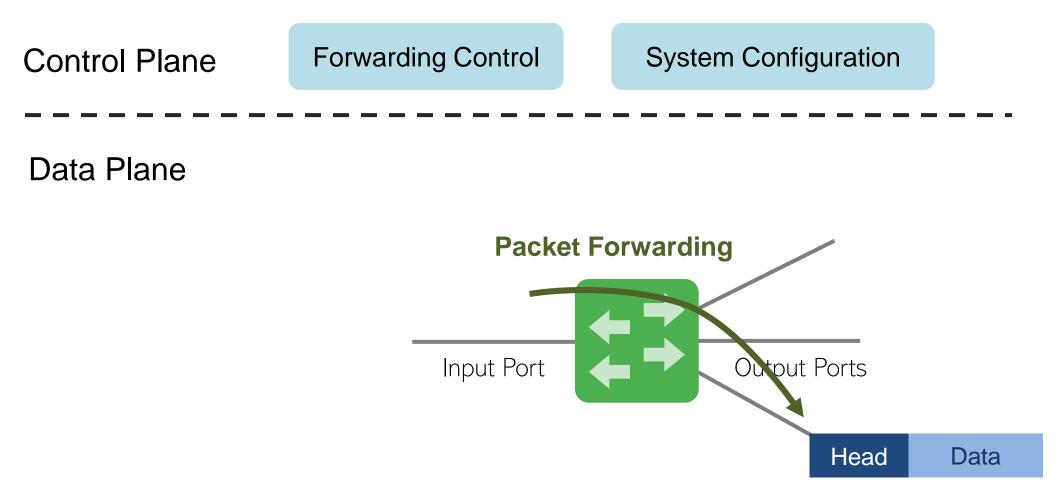
Data Plane



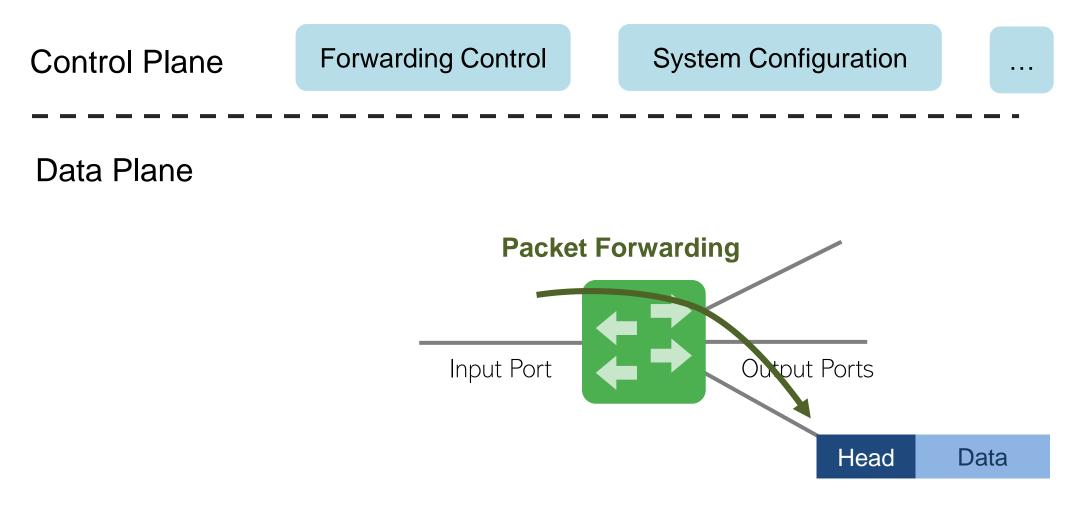


Forwarding Control **Control Plane** Data Plane **Packet Forwarding** Output Ports Input Port Head Data

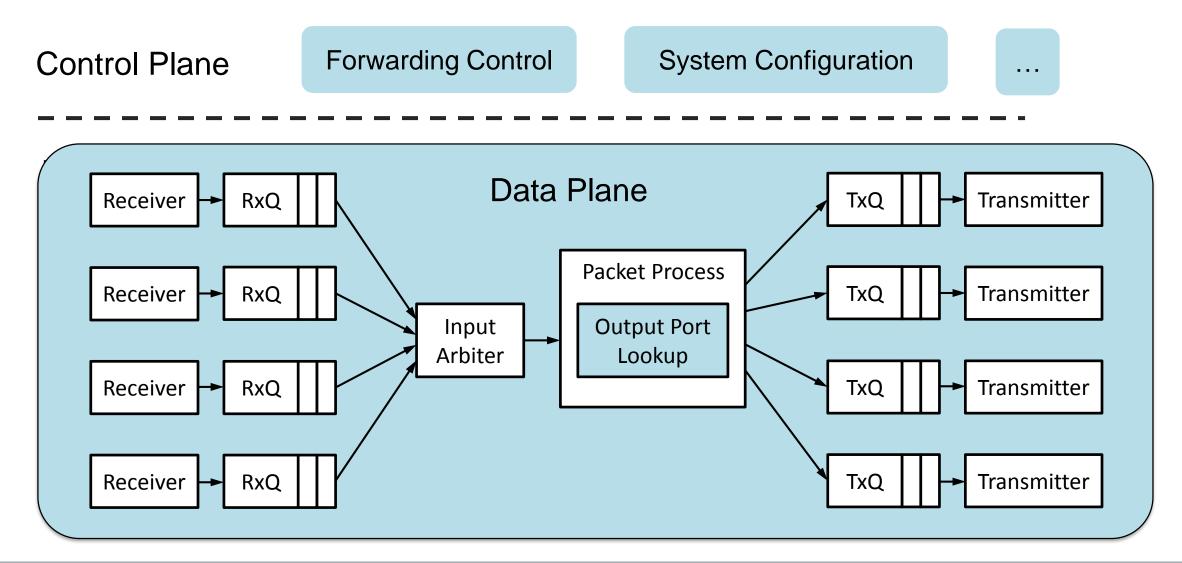


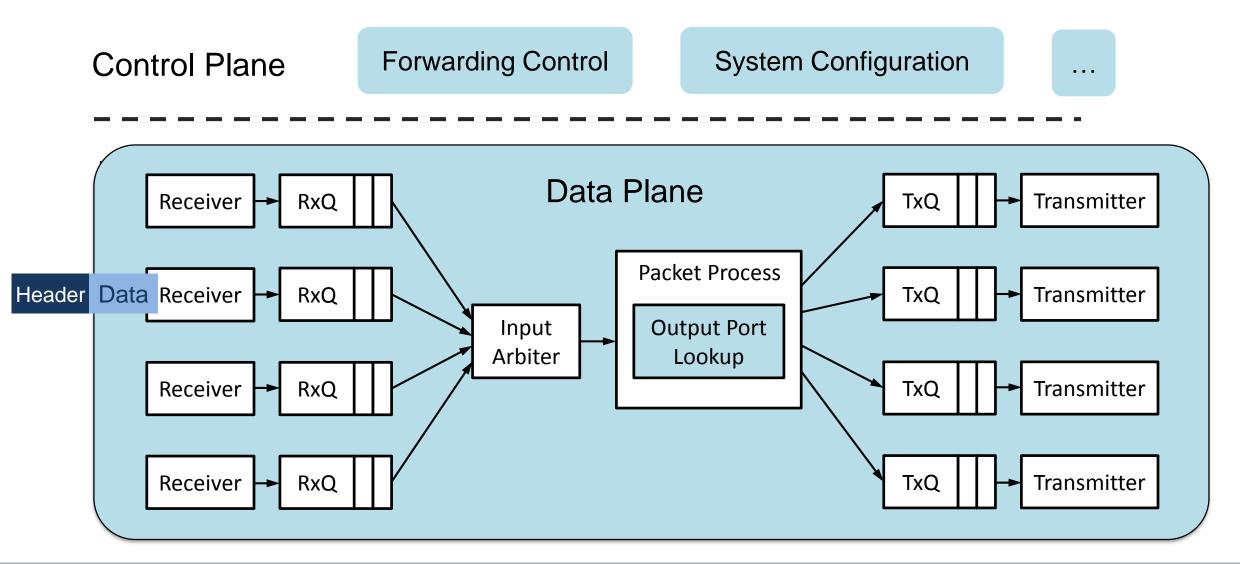


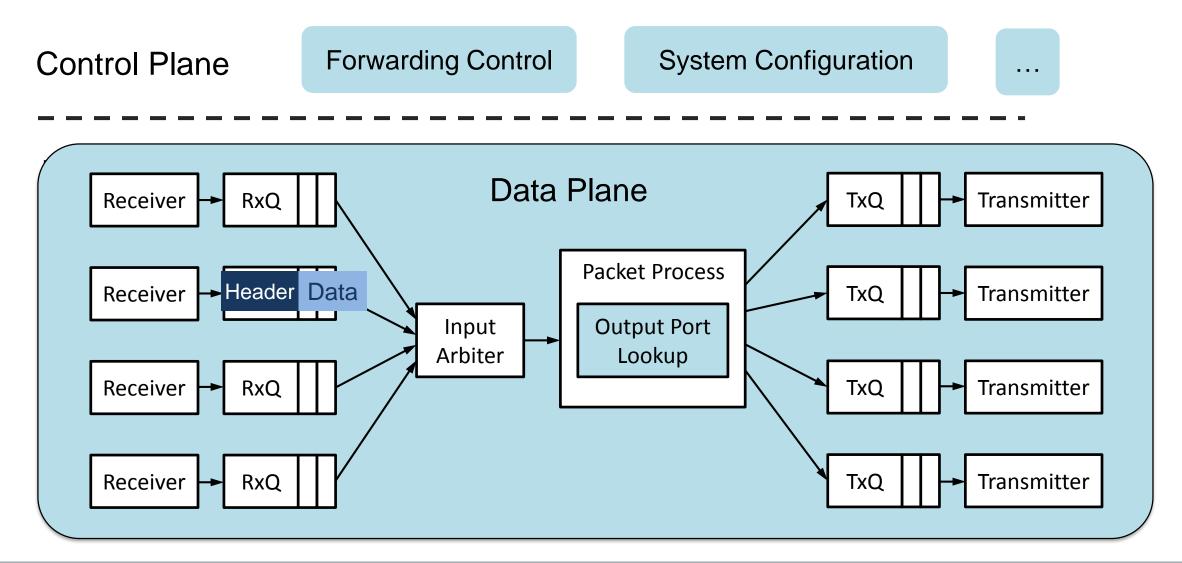


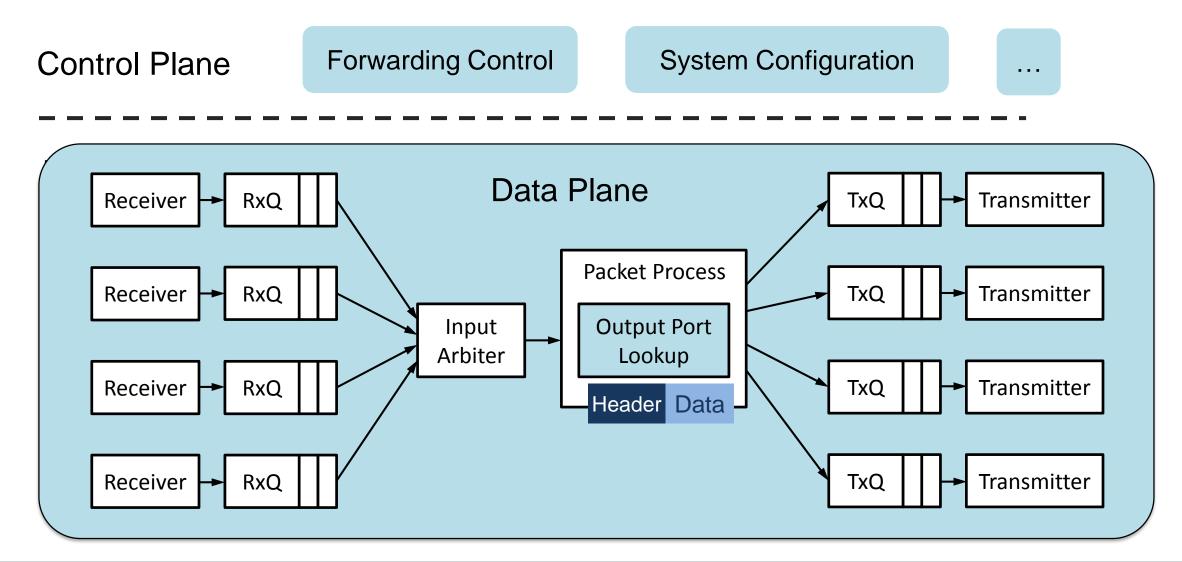


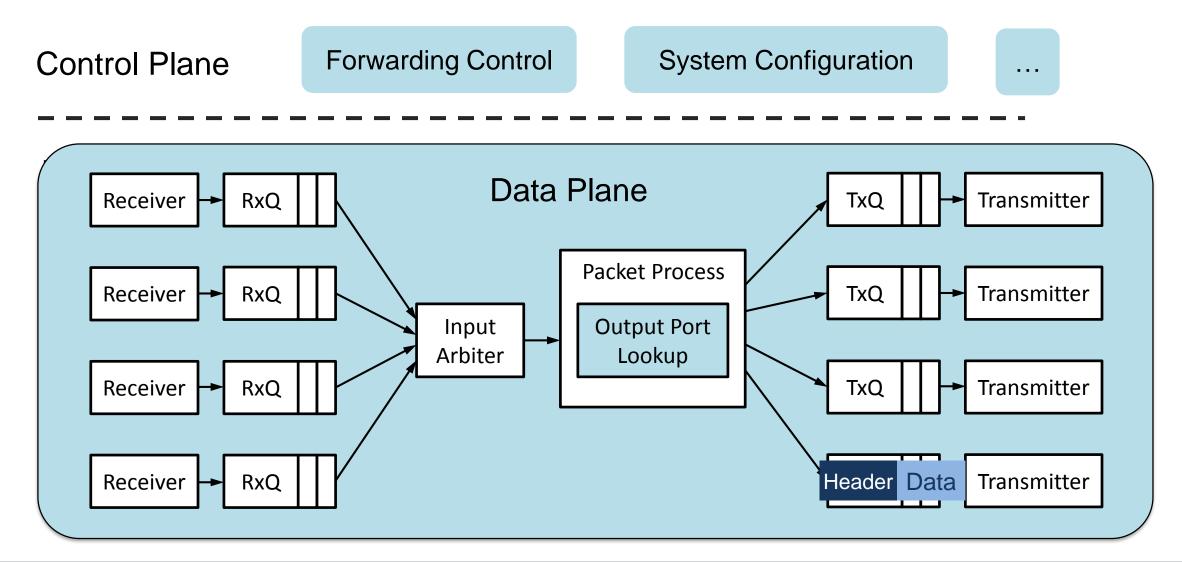


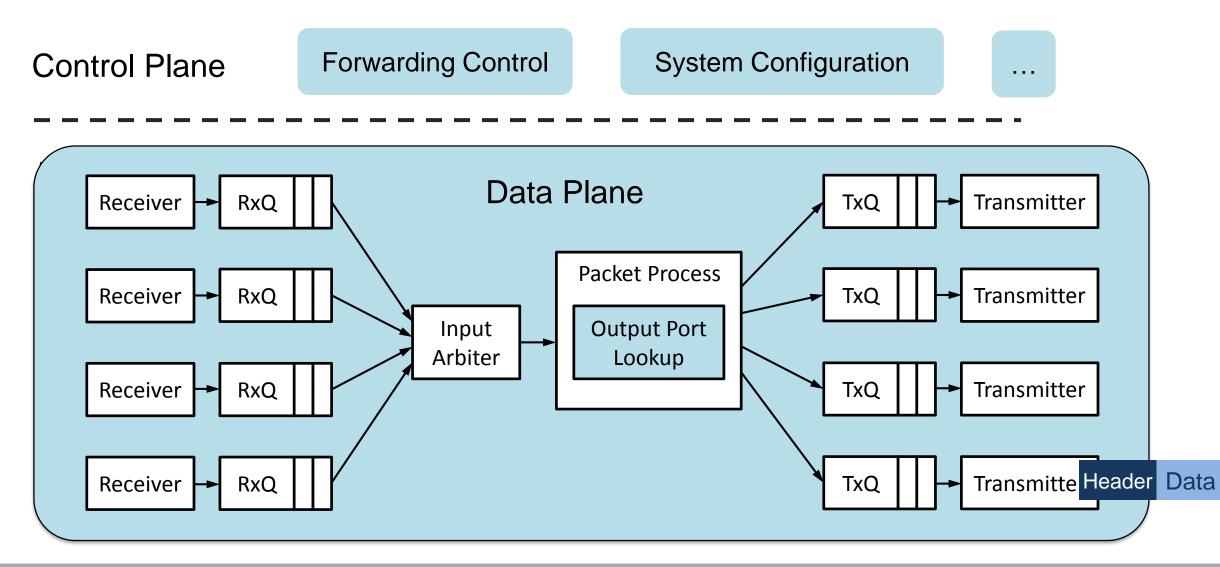


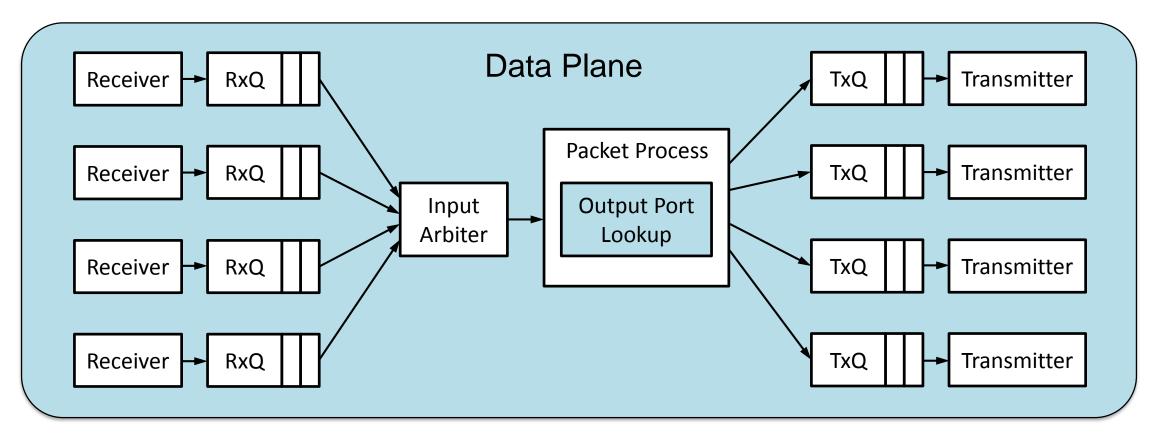




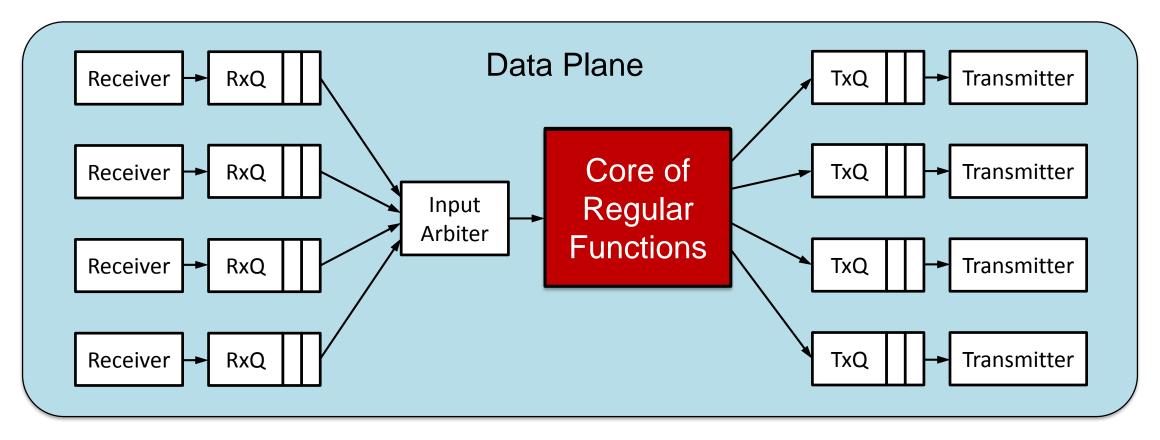




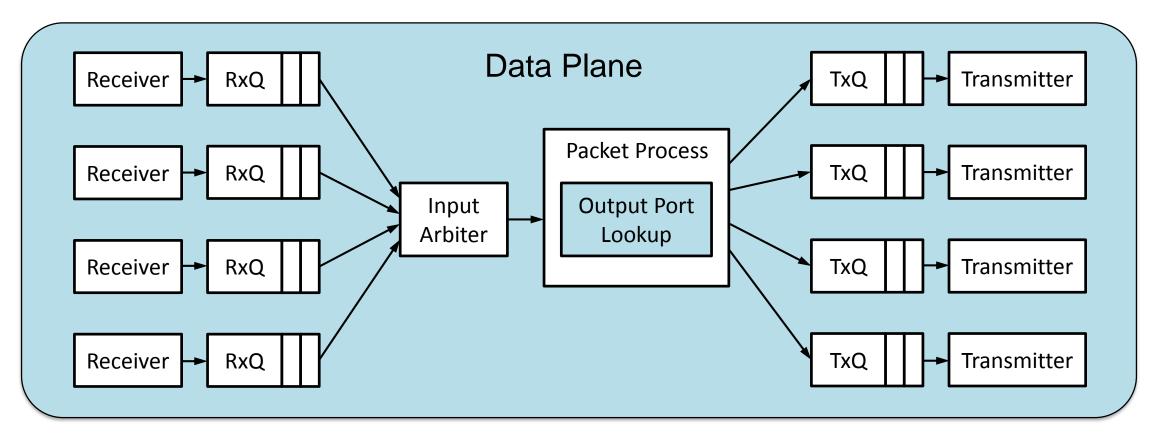




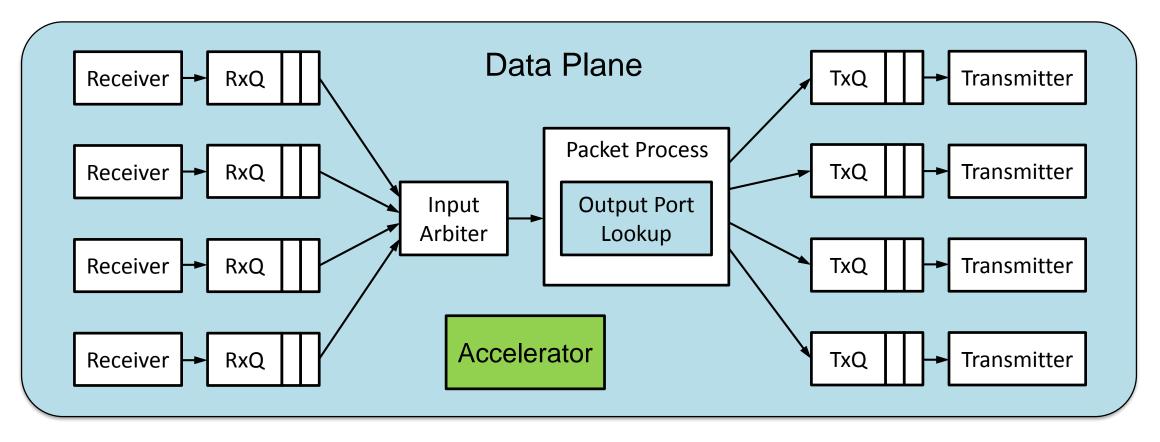




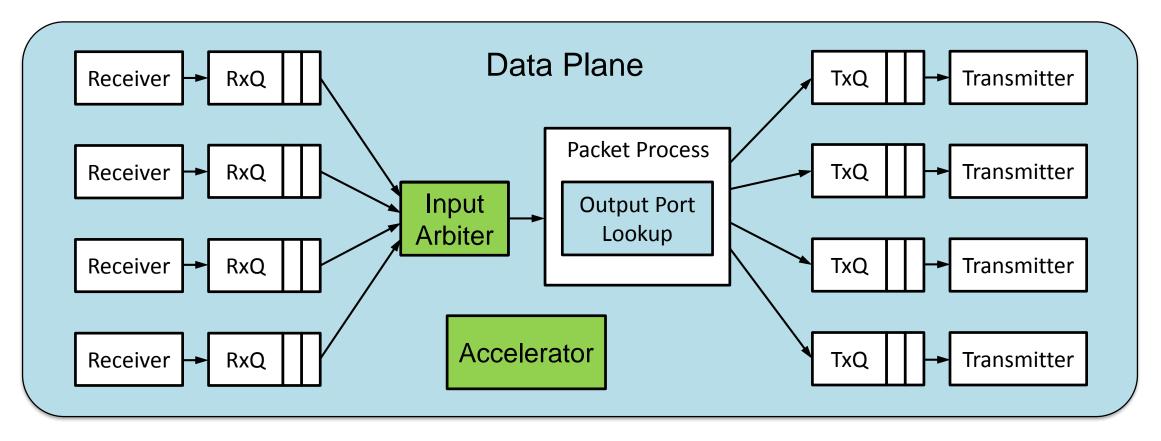




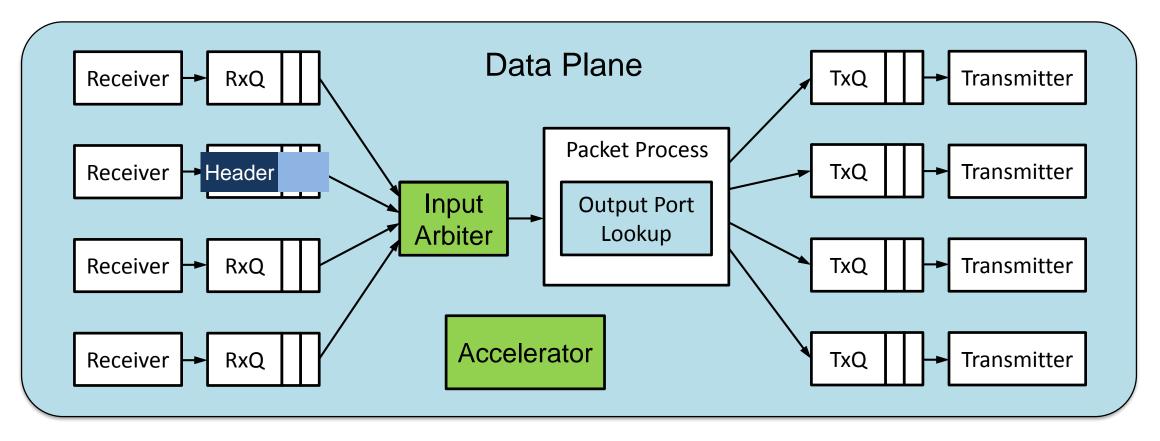




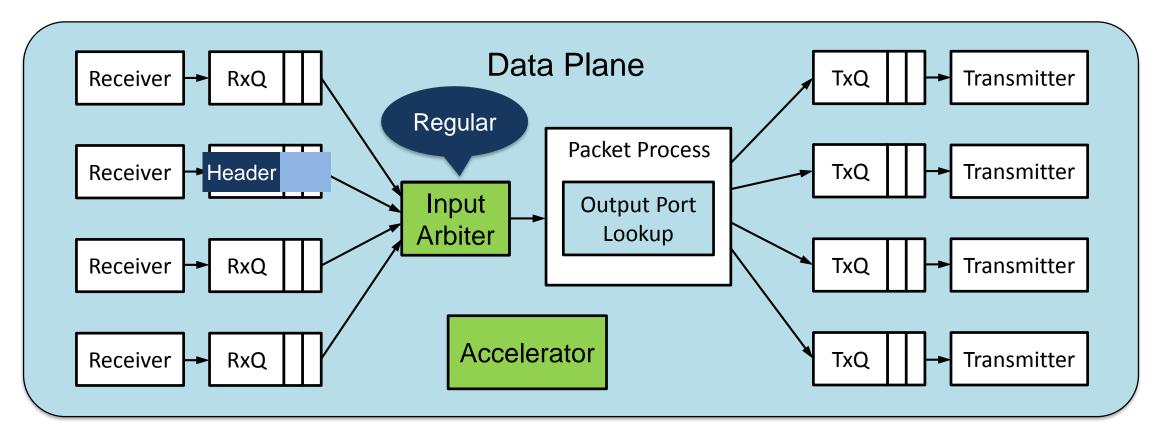




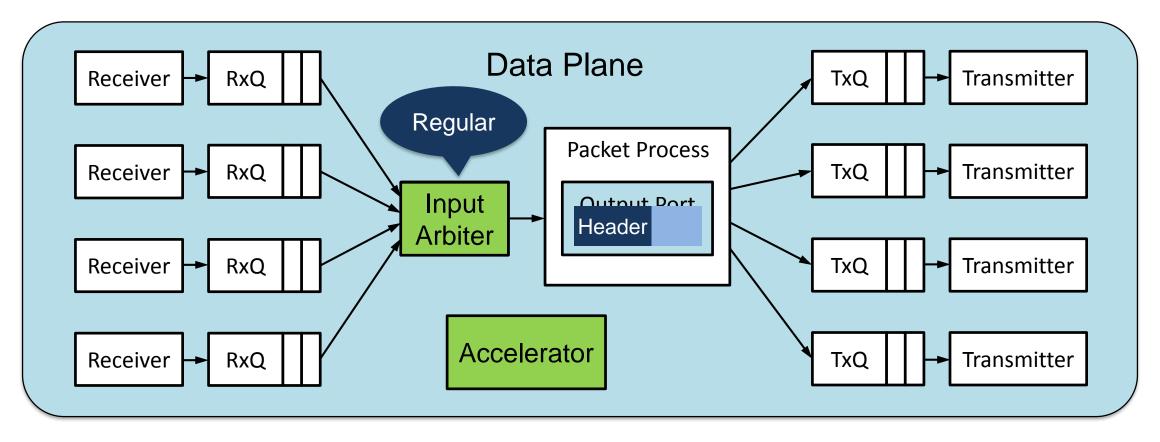




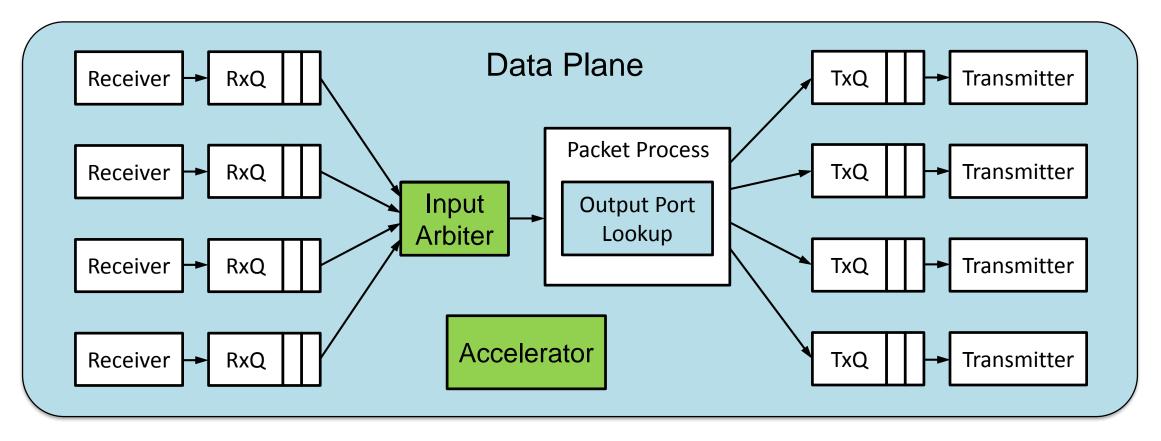




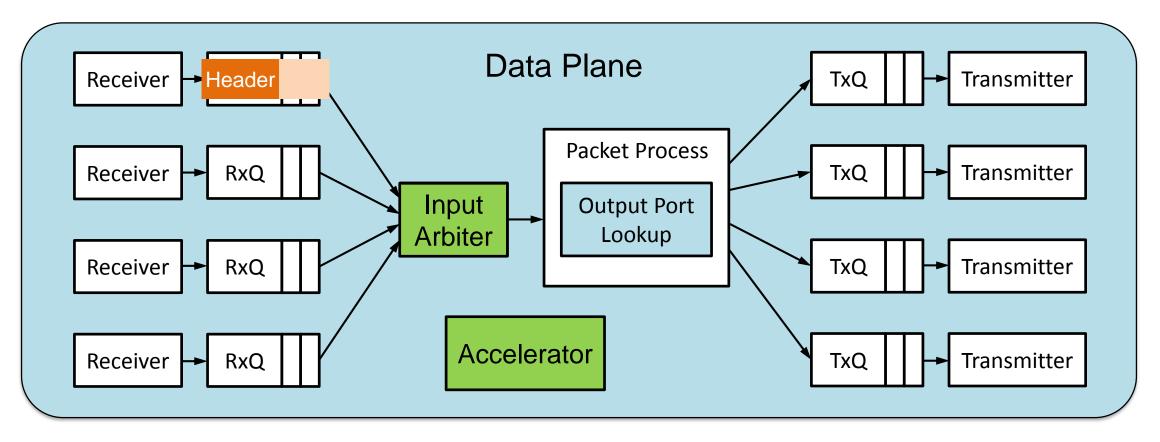




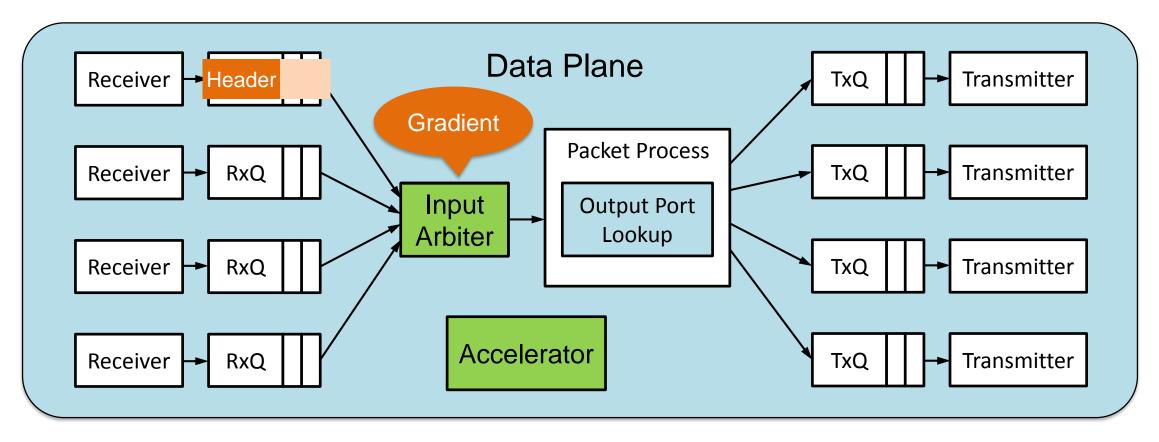




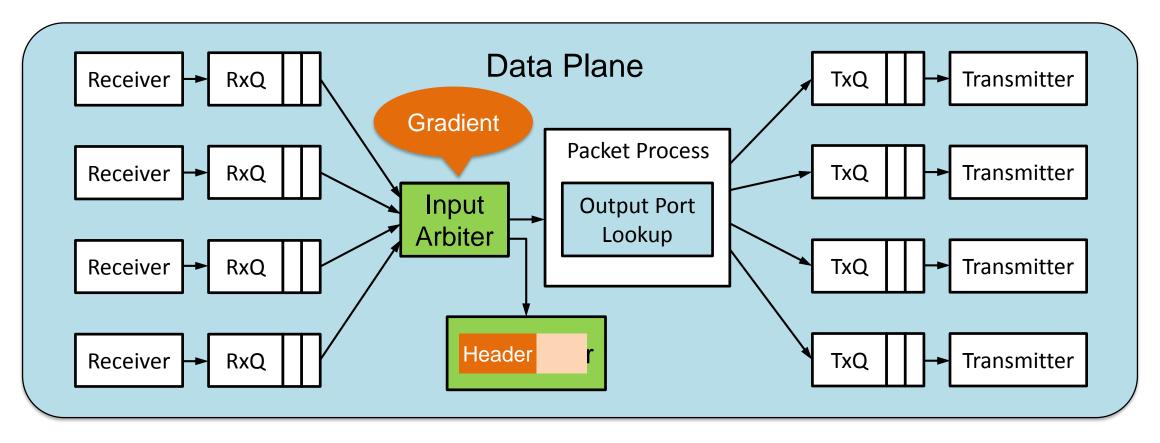




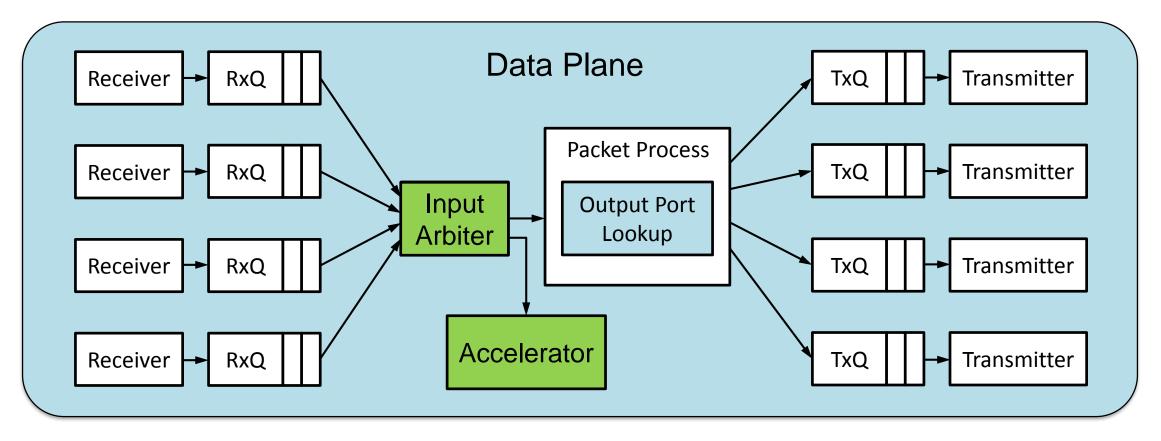




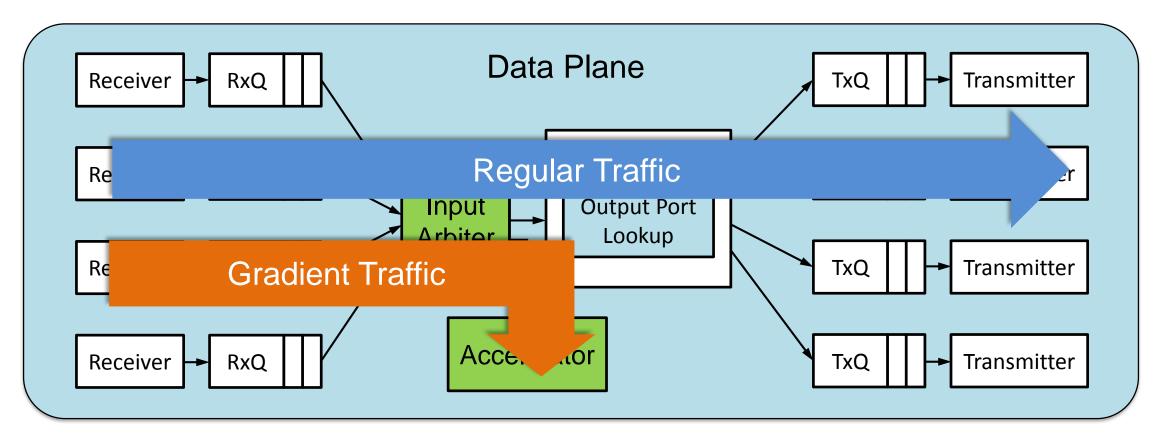




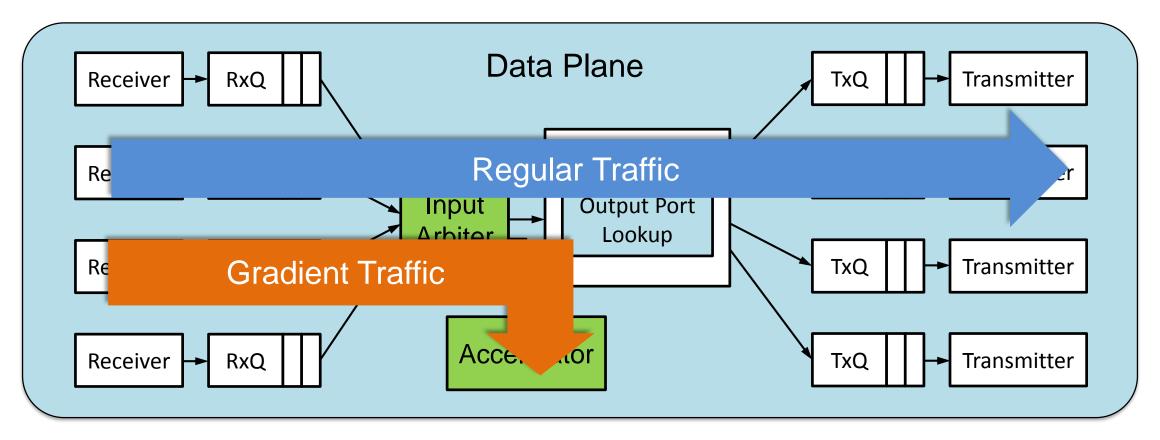






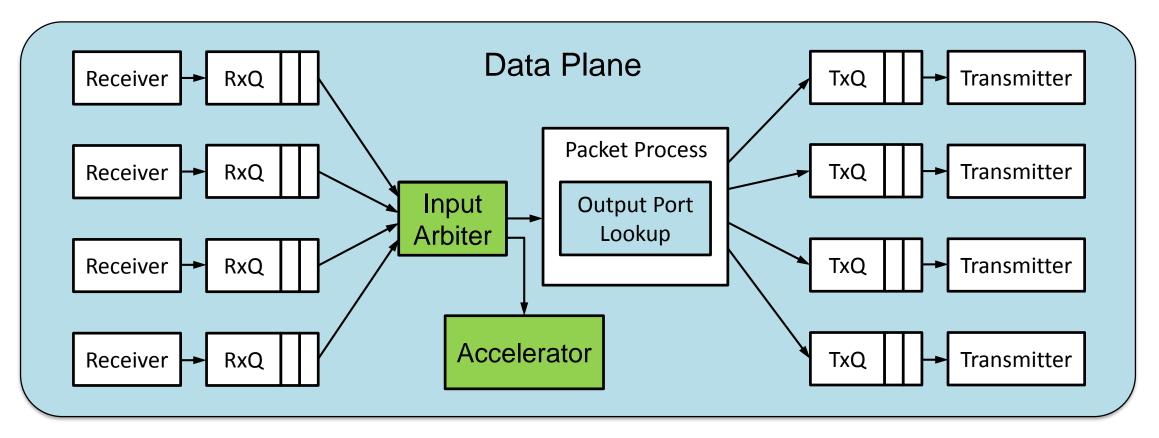






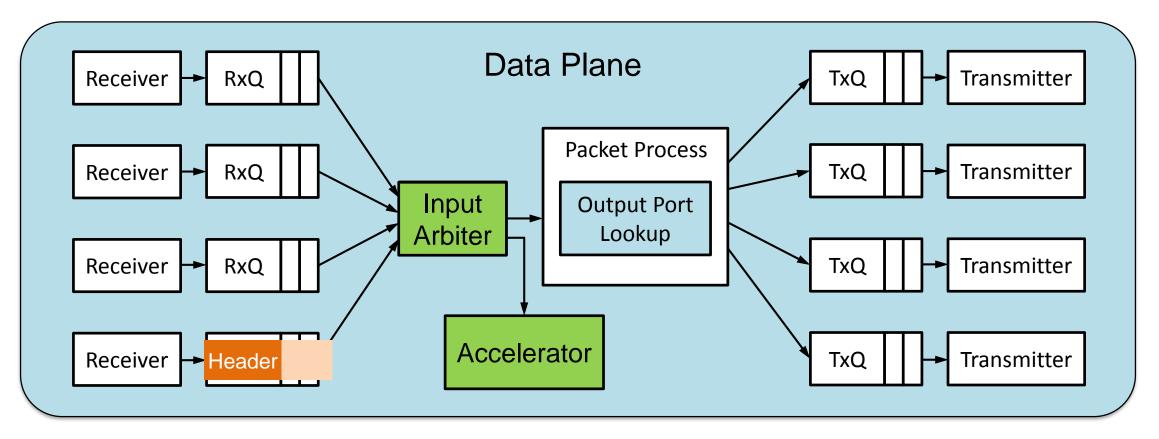
Hardware Acceleration Isolated From Regular Switch Function





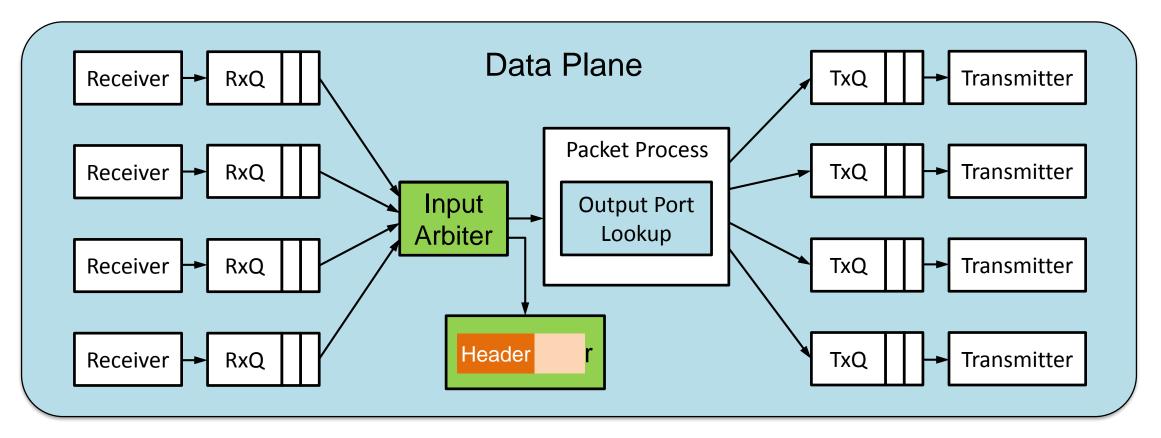
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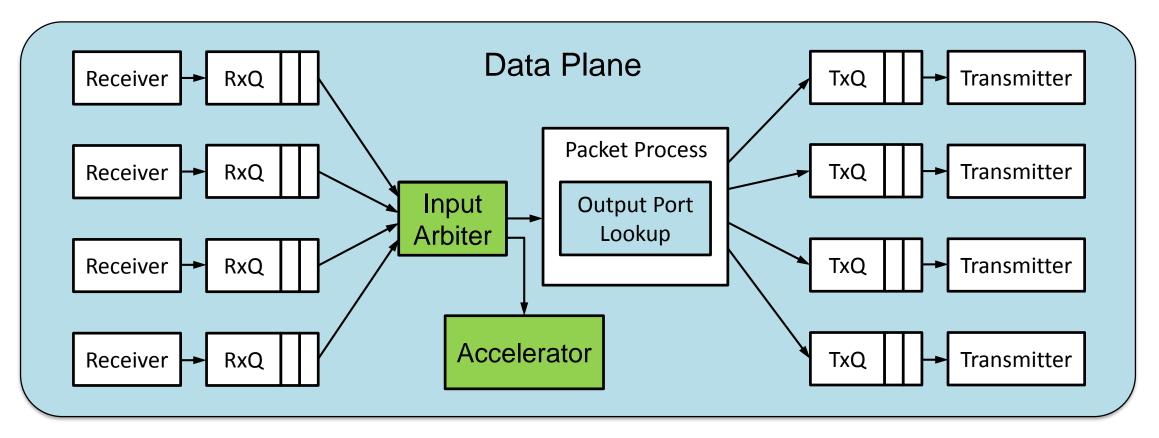
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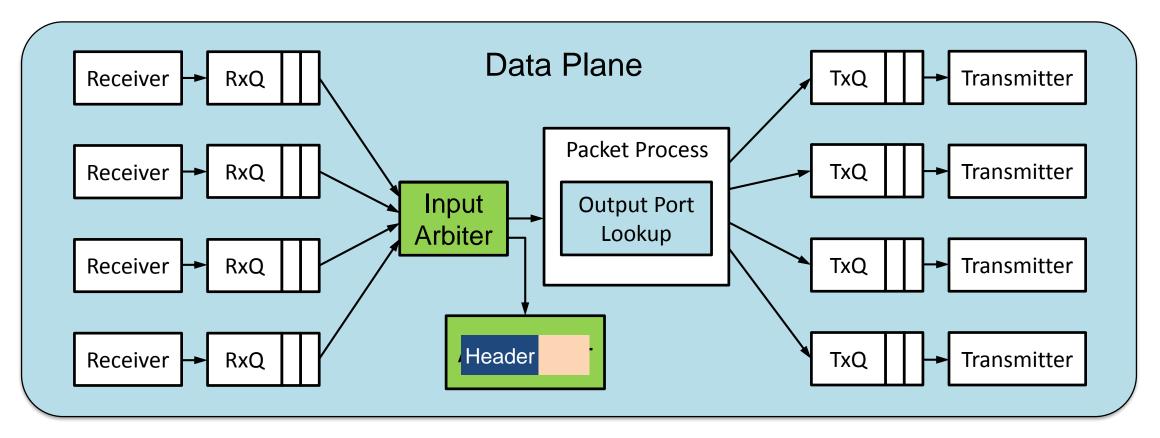
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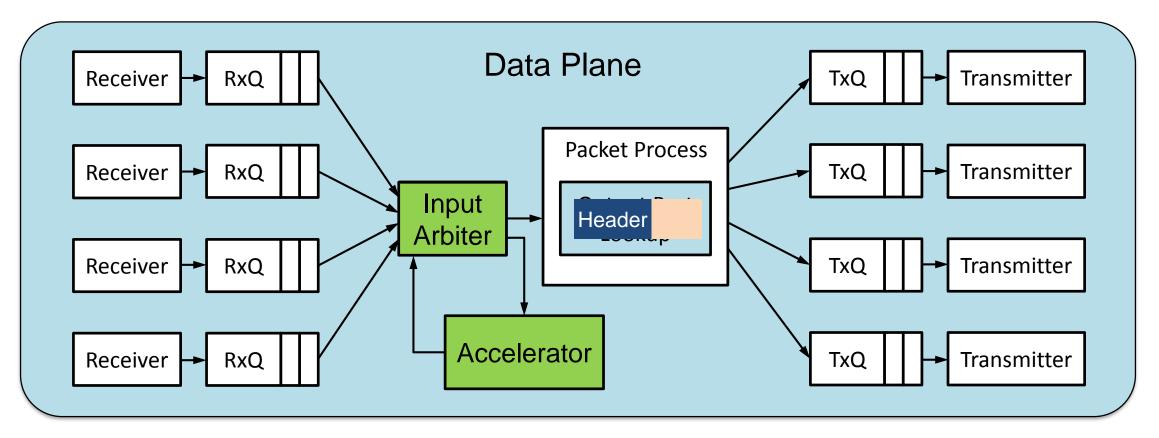
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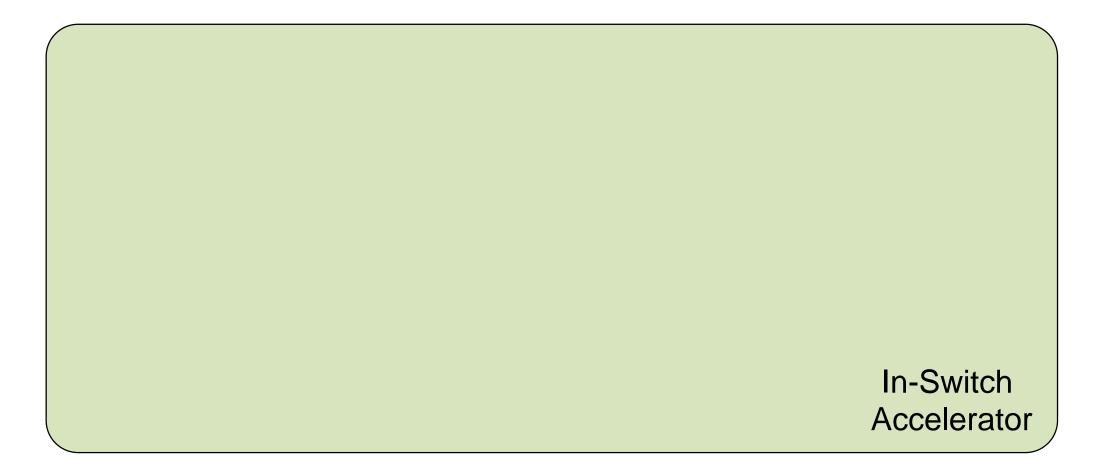
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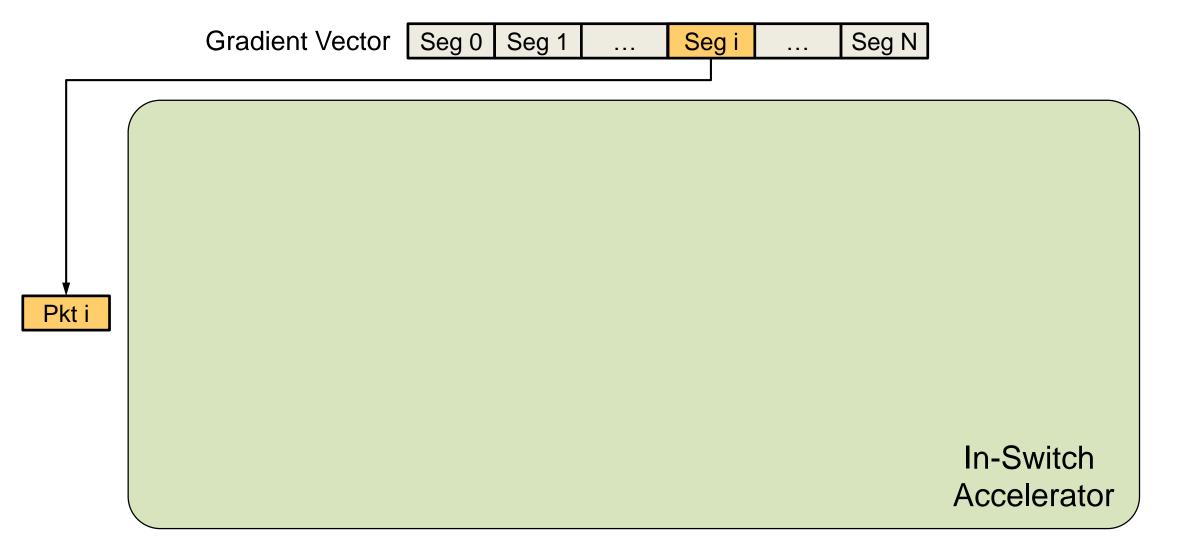


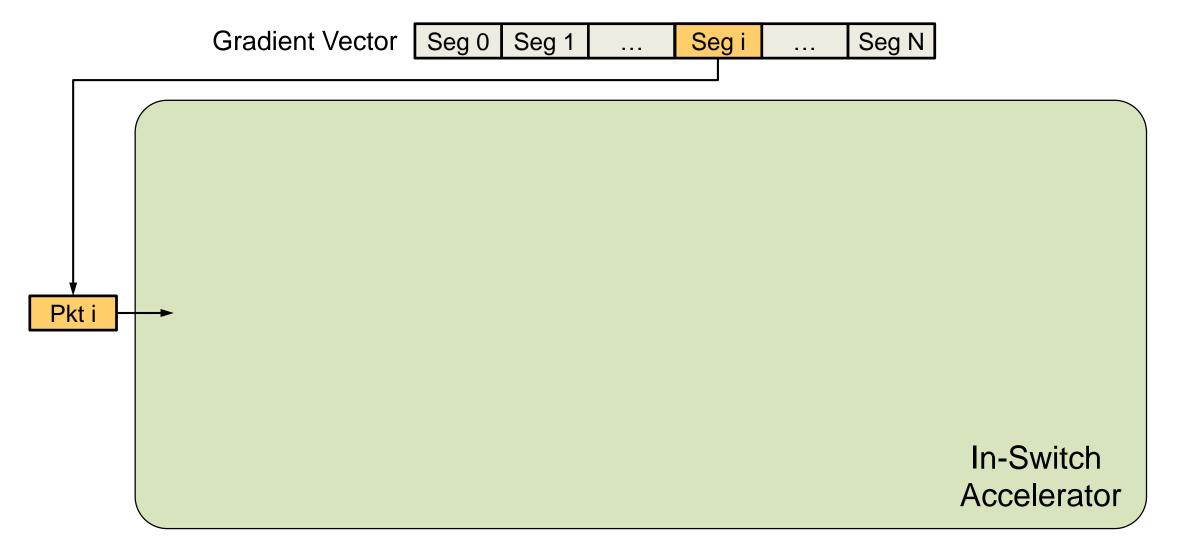


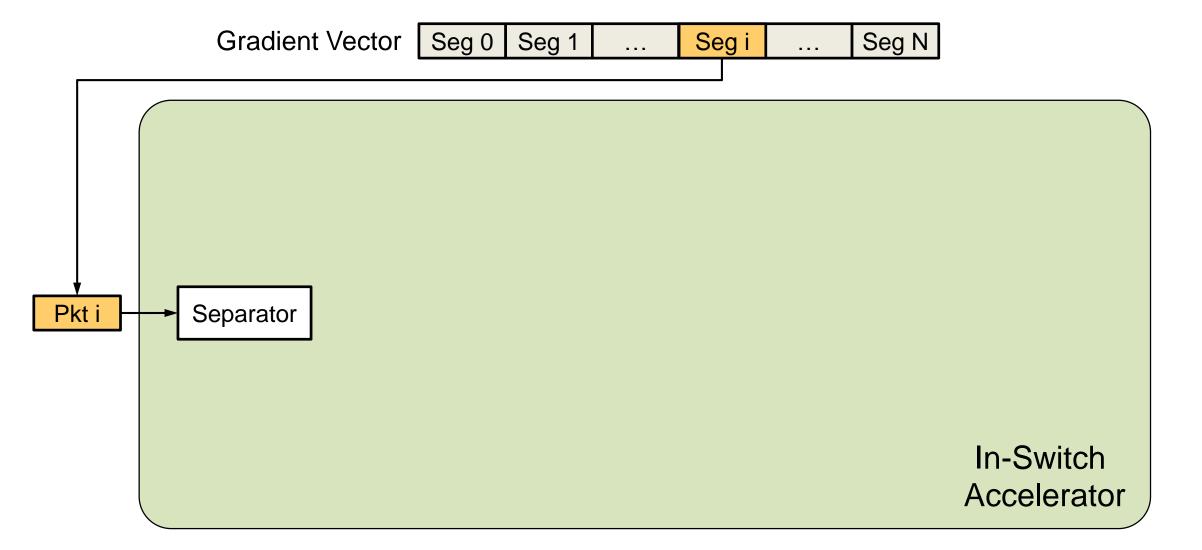


Gradient Vector	Seg 0	Seg 1	 Seg i	 Seg N
		_	_	

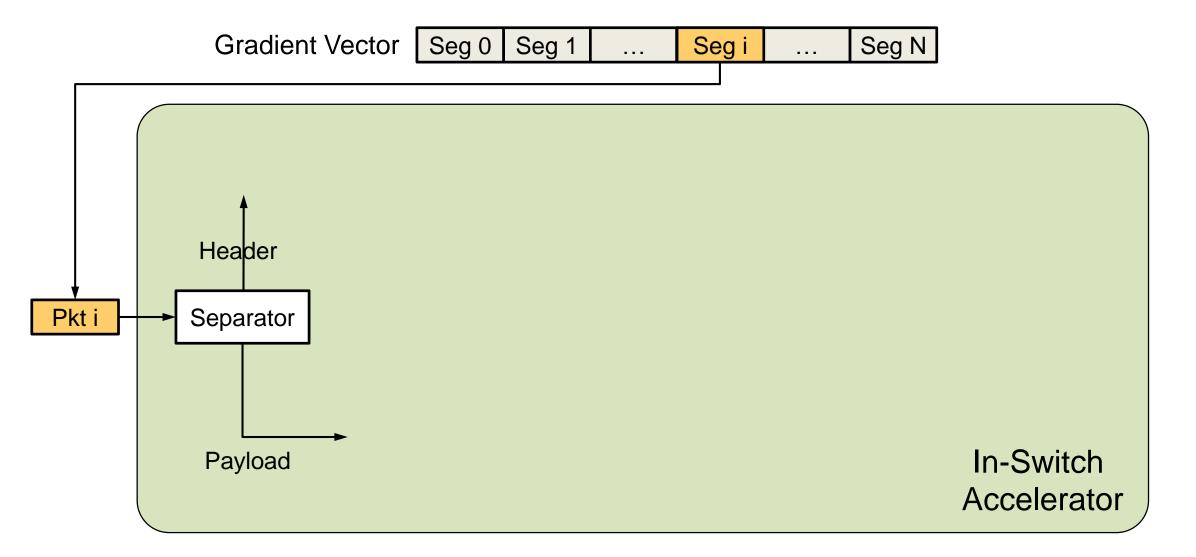




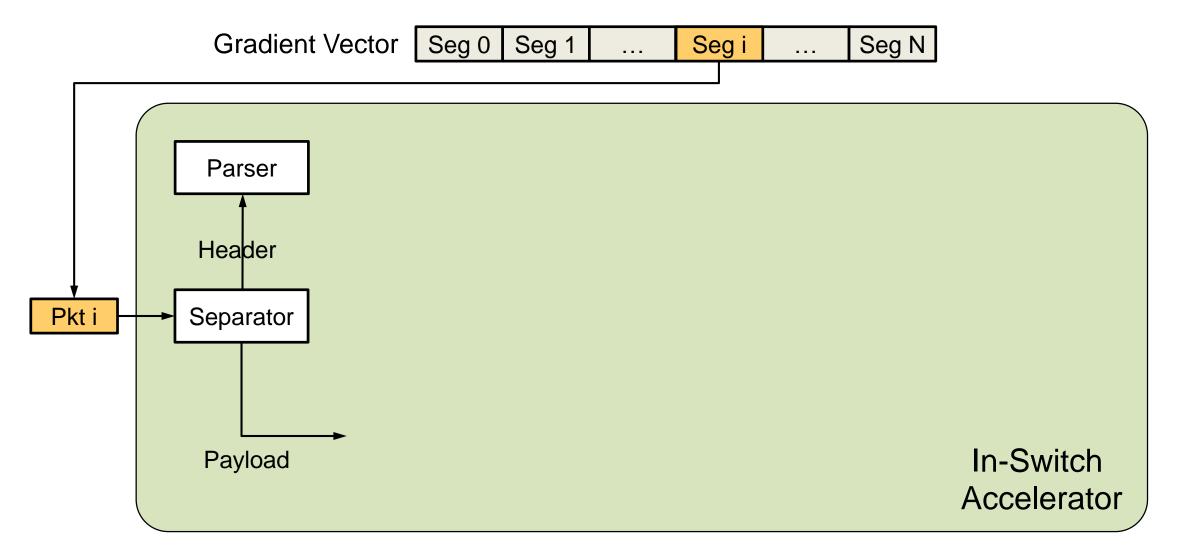




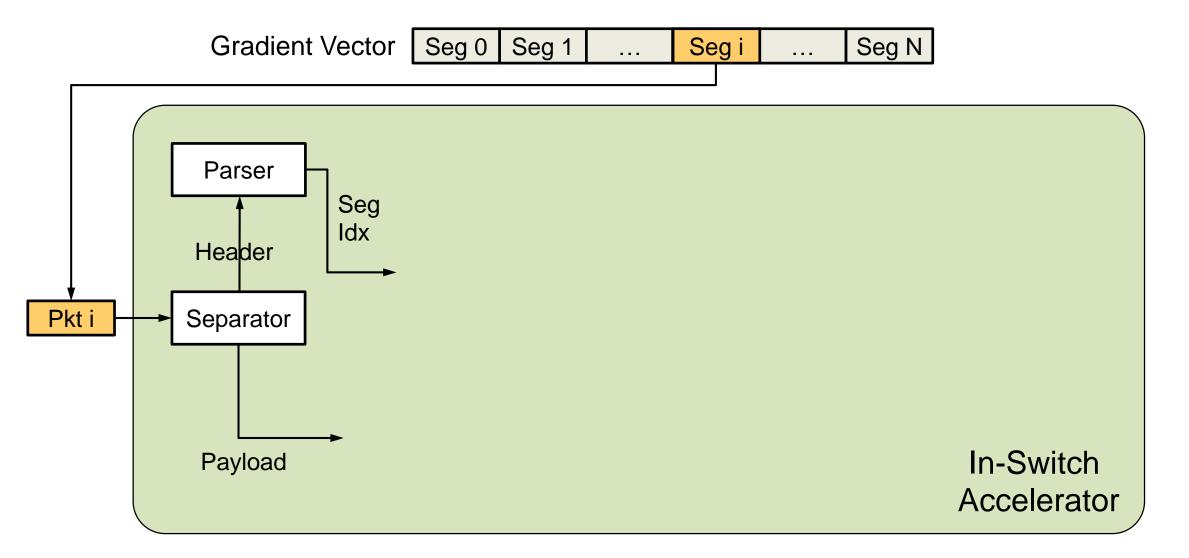




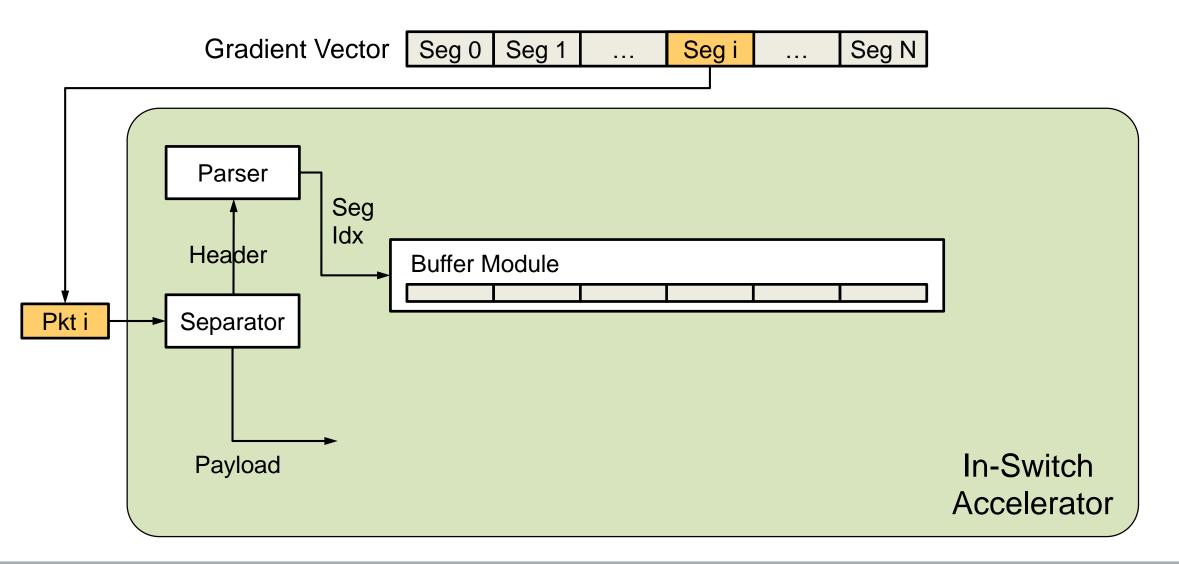




#### Π

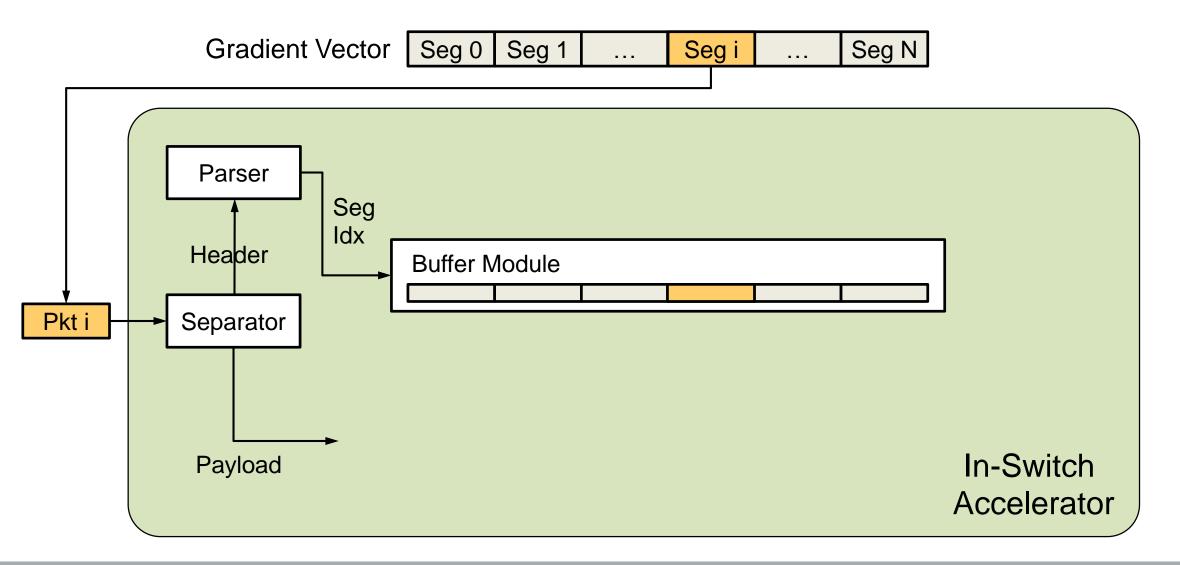


#### Π

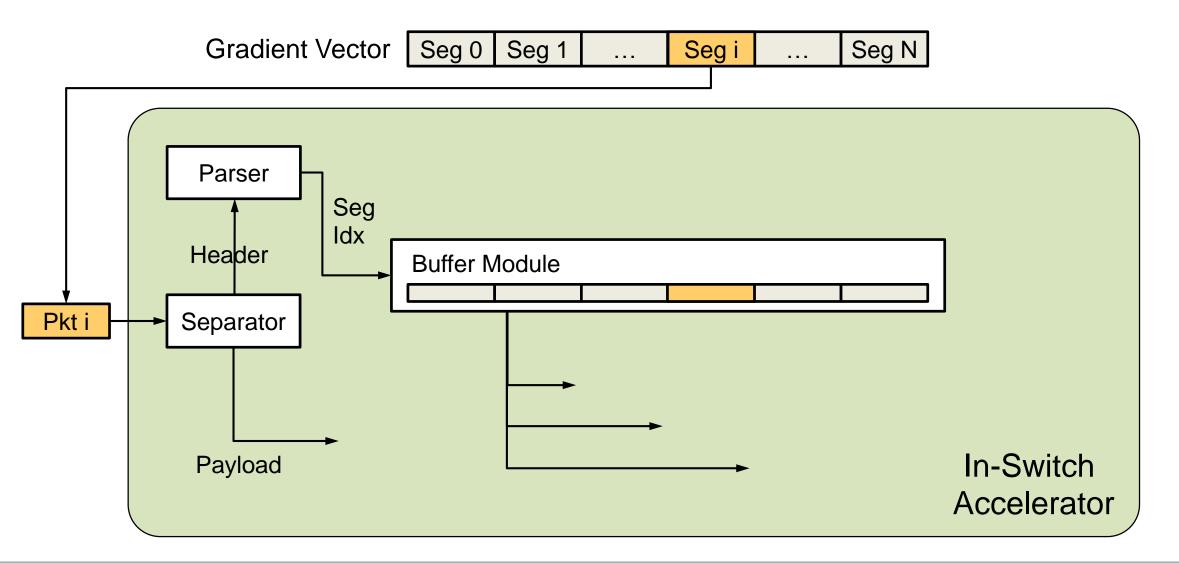




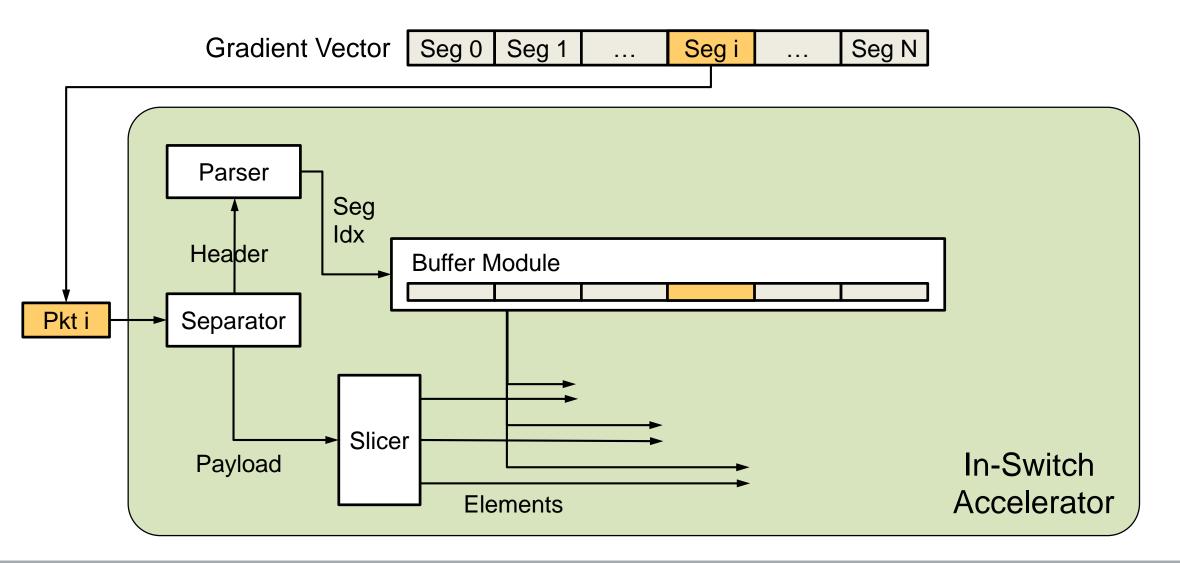




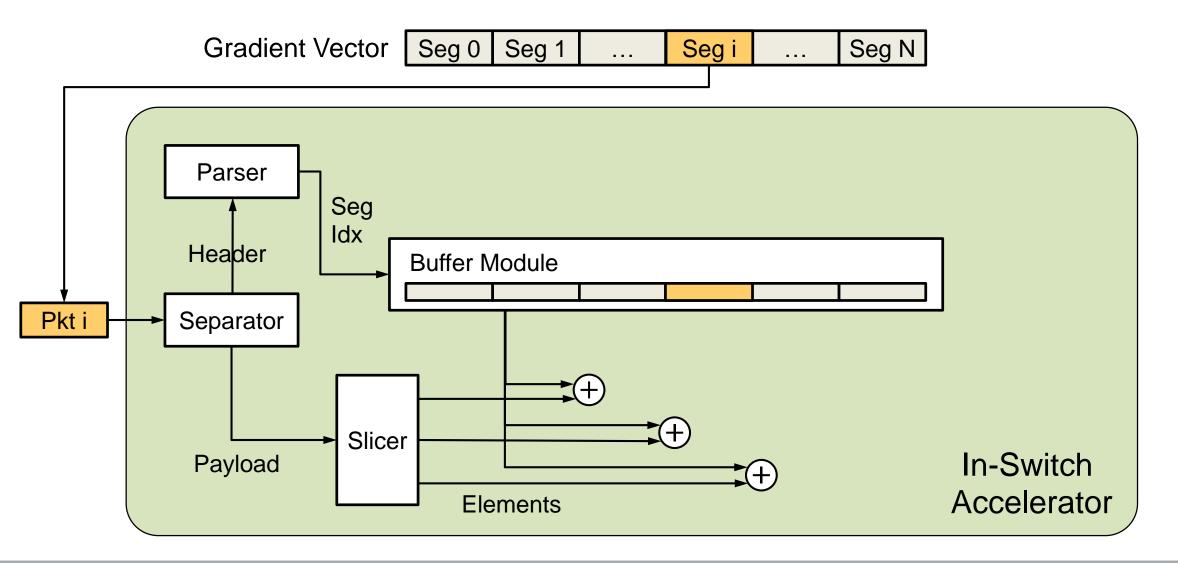




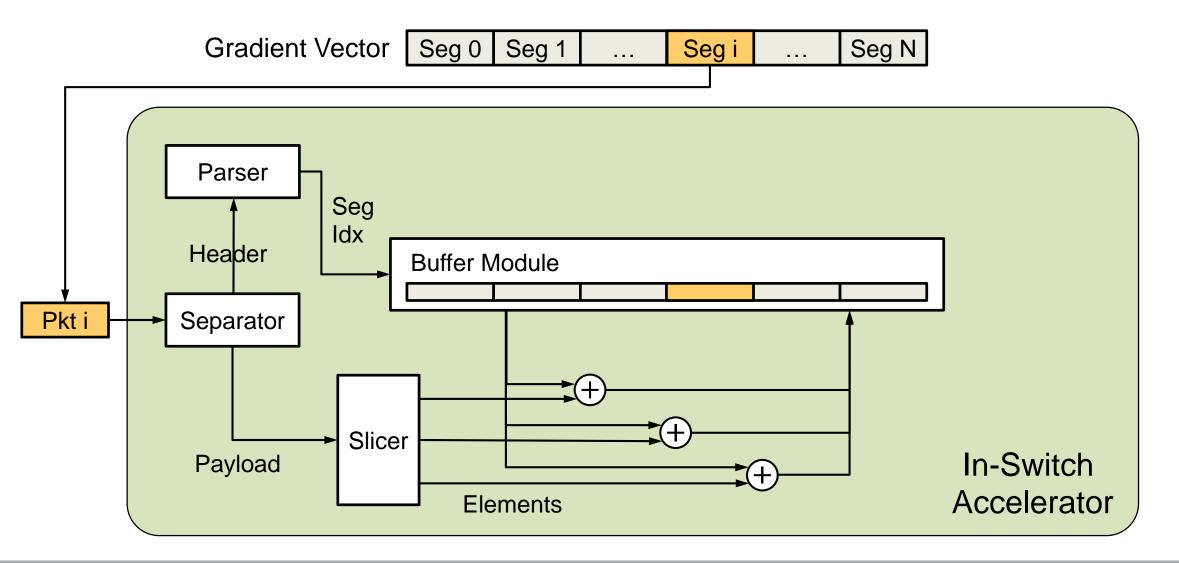




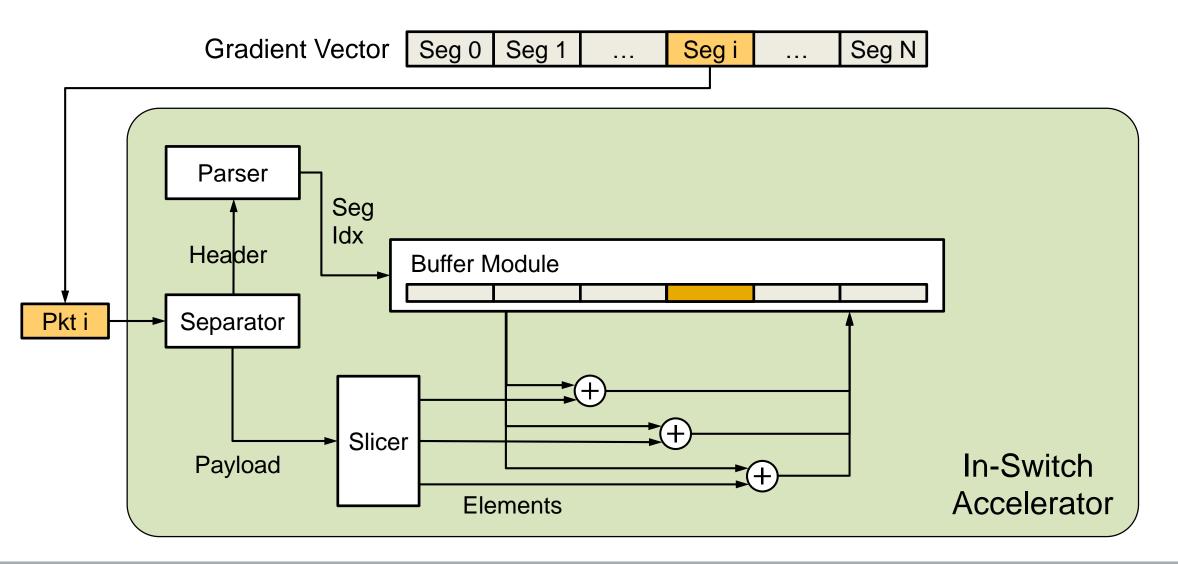




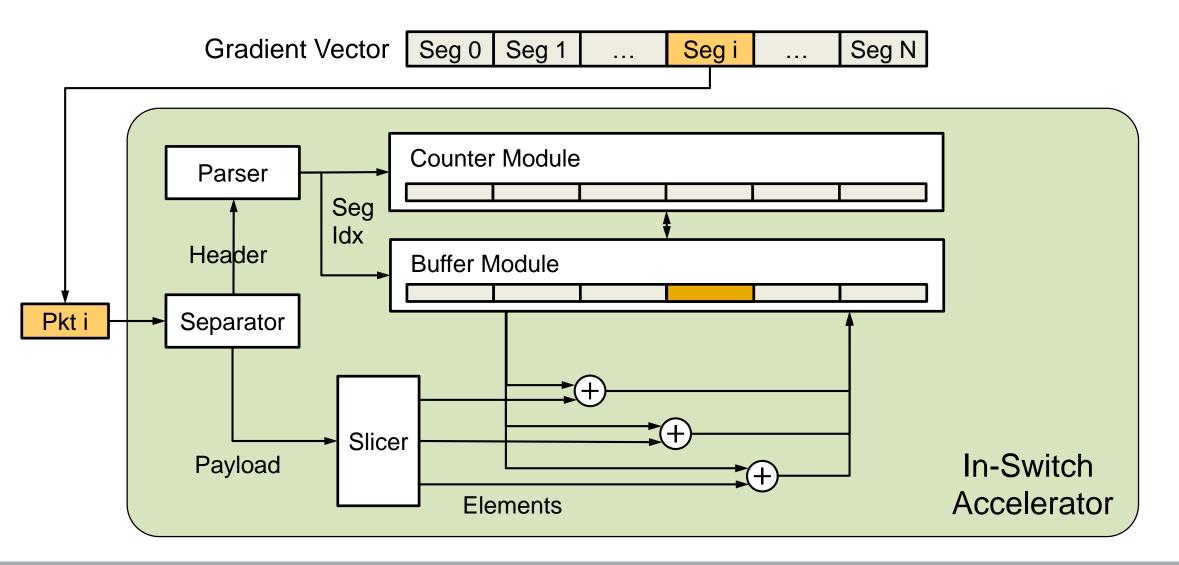




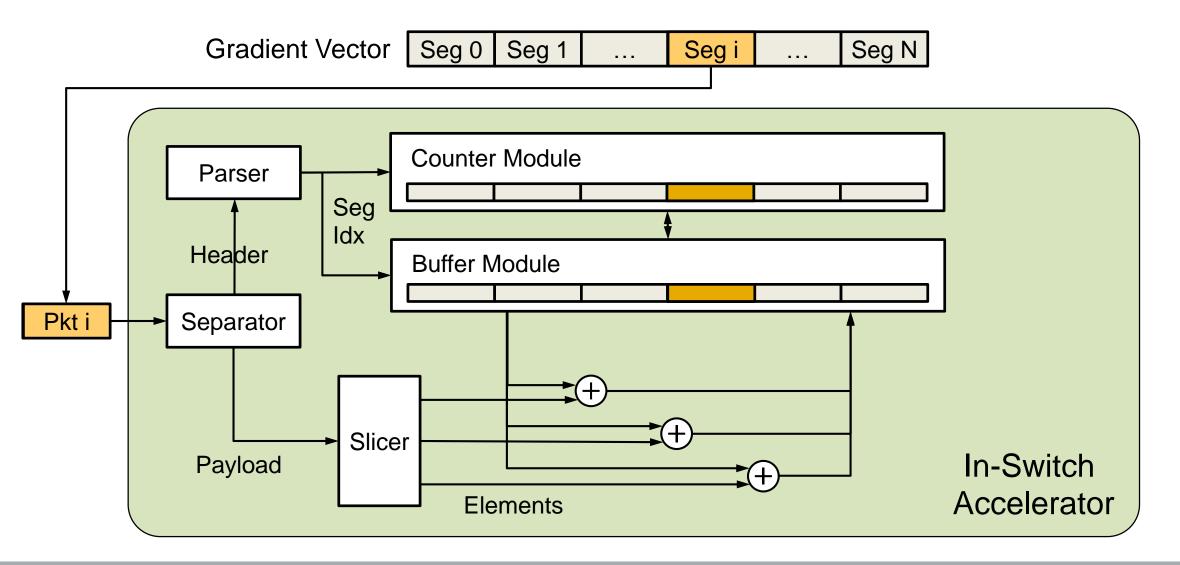




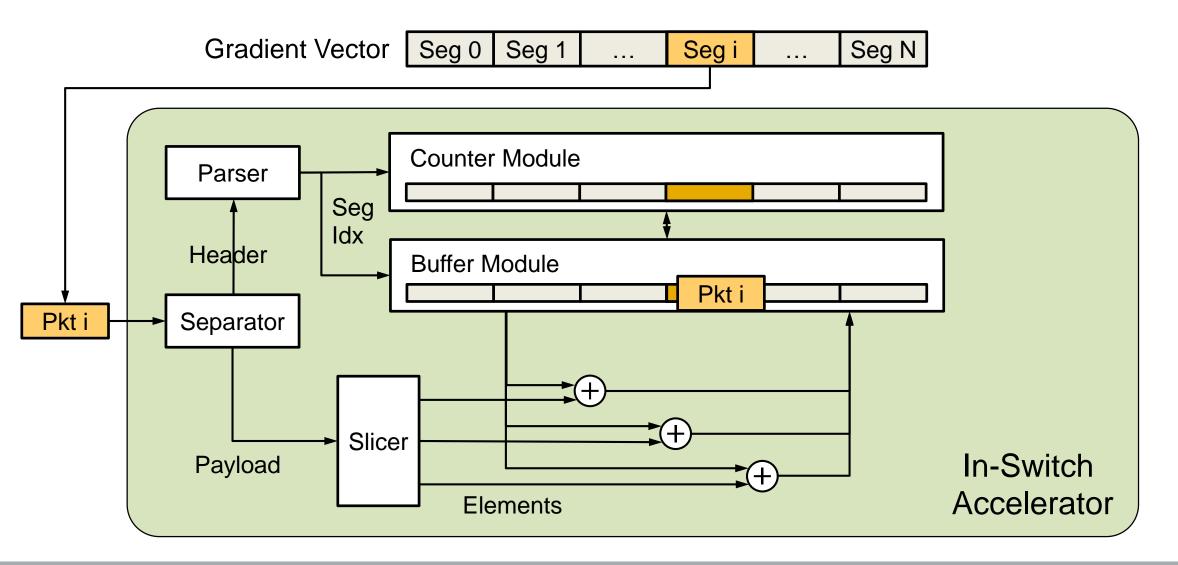




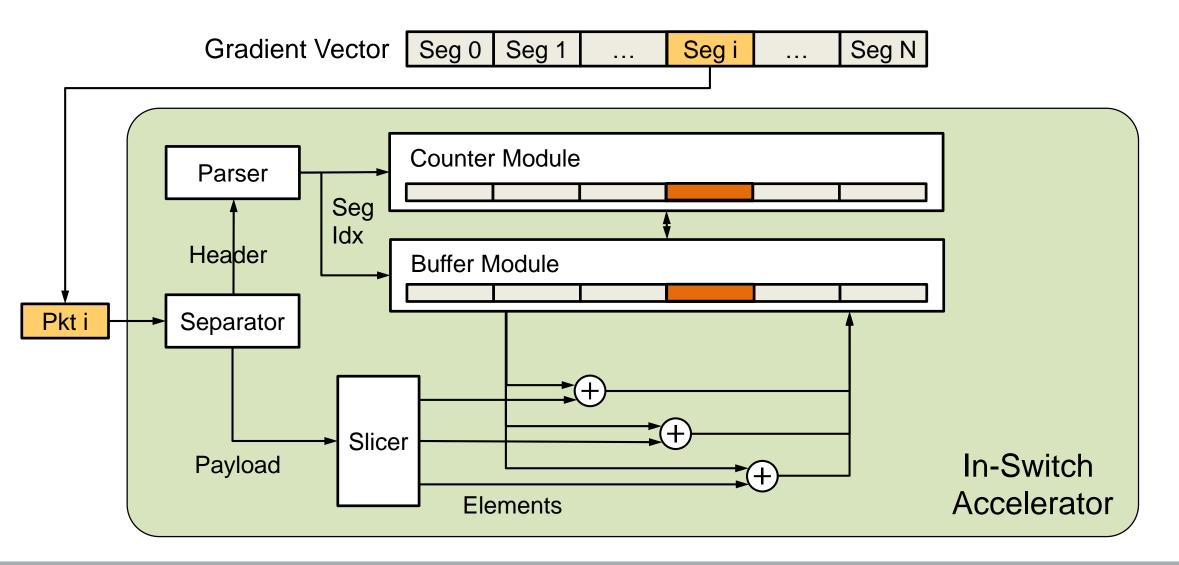




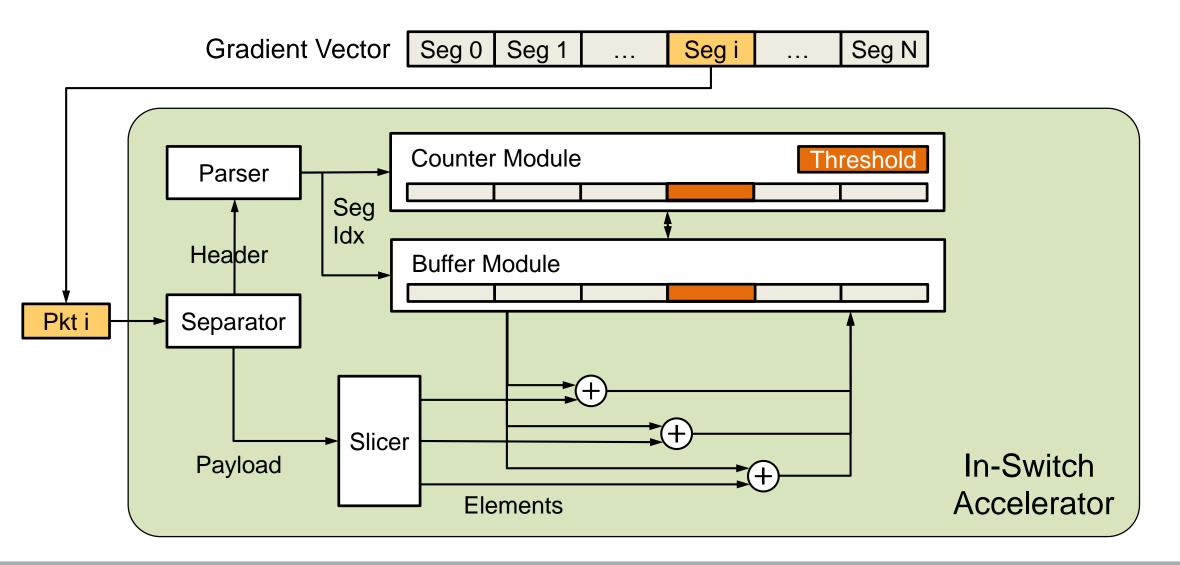




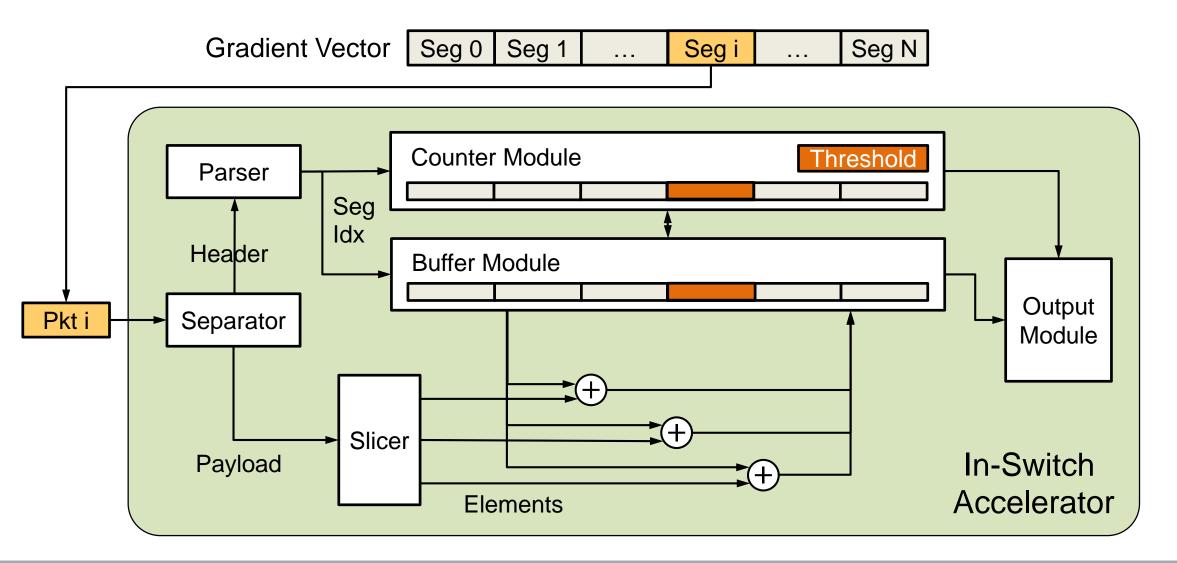




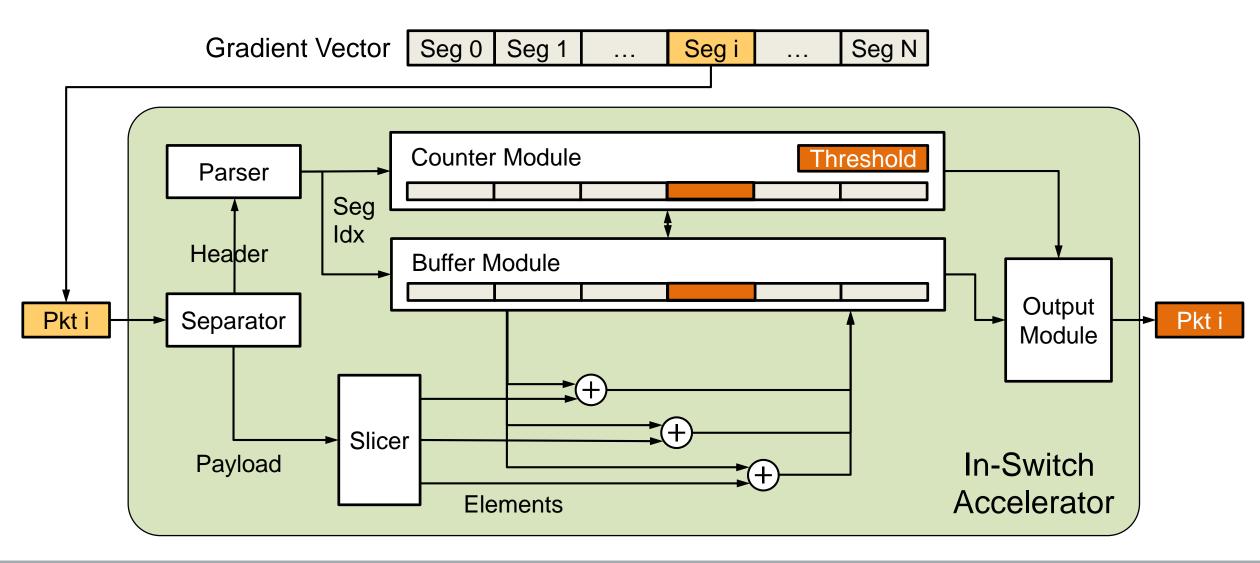




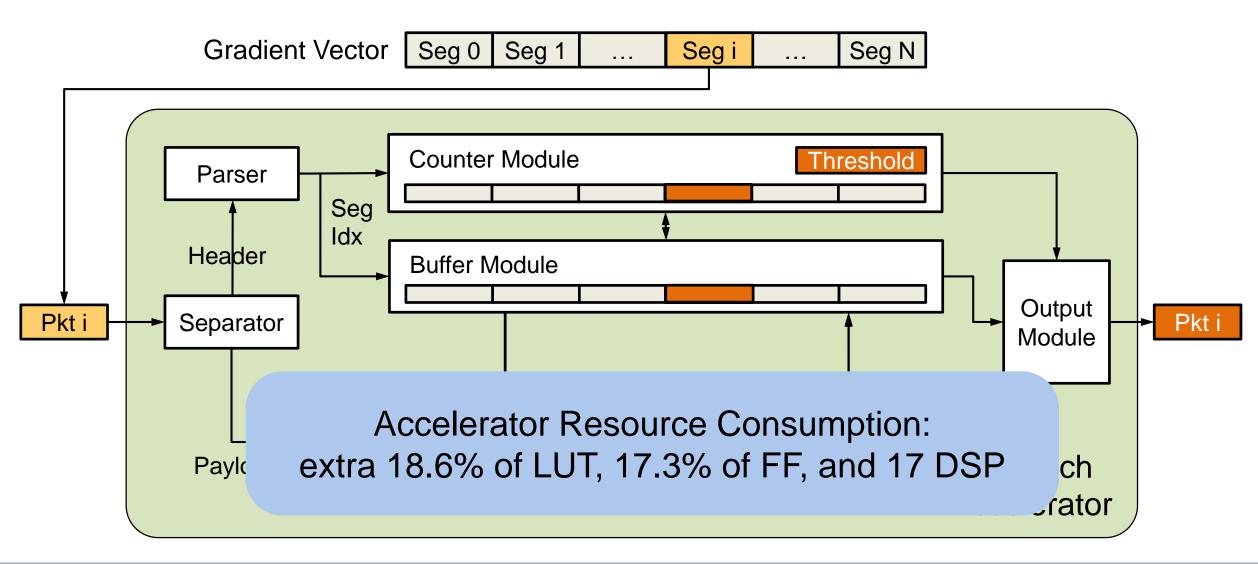
#### Π





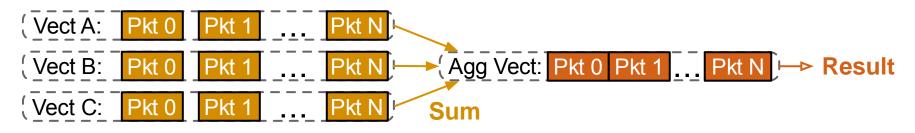








### Aggregating Gradient at Packet-Level for Improved Parallelism



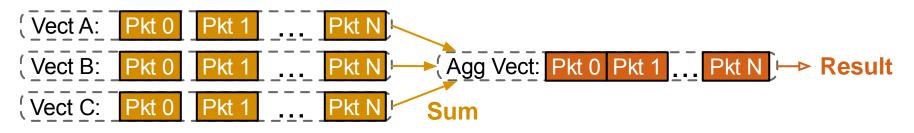
**Conventional Vector-Level Aggregation** 



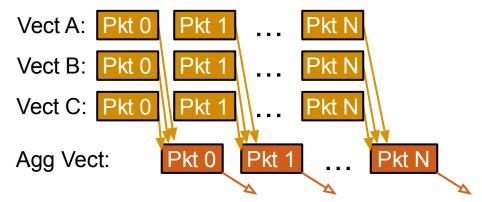




### Aggregating Gradient at Packet-Level for Improved Parallelism



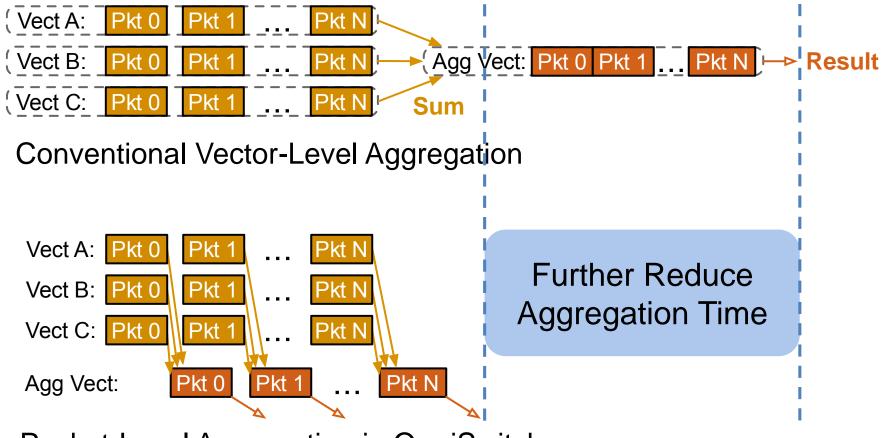
Conventional Vector-Level Aggregation



Packet-Level Aggregation in Our iSwitch



# Aggregating Gradient at Packet-Level for Improved Parallelism



Packet-Level Aggregation in Our iSwitch



Regular Packet:

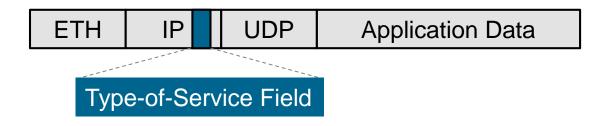
ETH IP	UDP	Application Data
--------	-----	------------------

Data Packet of iSwitch:

ETH IP	UDP	Application Data
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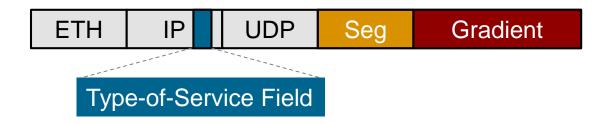


Data Packet of iSwitch:



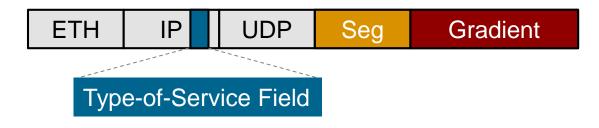


Data Packet of iSwitch:





Data Packet of iSwitch:

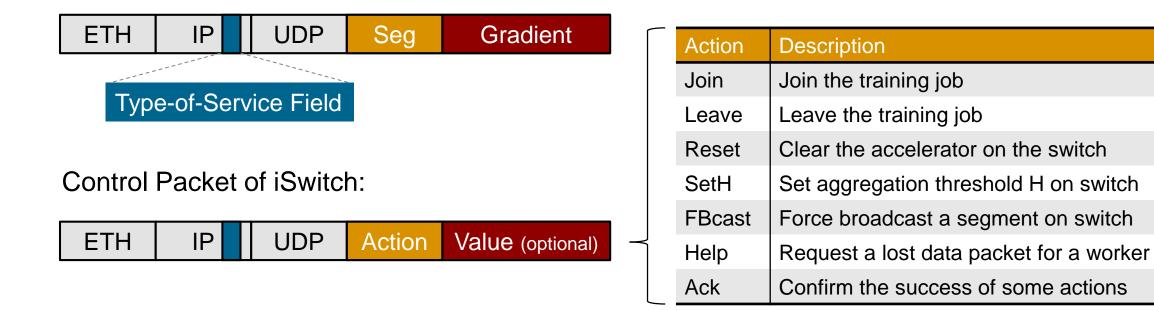


Control Packet of iSwitch:





#### Data Packet of iSwitch:





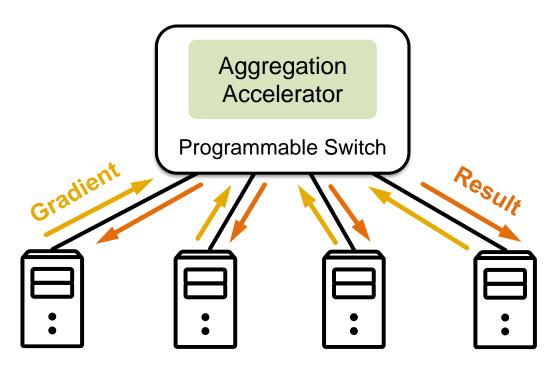
#### Data Packet of iSwitch:

ETH IP UDP Seg Gradient	$\left[ \right]$	Action	Description
		Join	Join the training job
Type-of-Service Field		Leave	Leave the training job
		Reset	Clear the accelerator on the switch
Control Packet of iSwitch:		SetH	Set aggregation threshold H on switch
		FBcast	Force broadcast a segment on switch
ETH IP UDP Action Value (optional)		Help	Request a lost data packet for a worker
		Ack	Confirm the success of some actions

#### iSwitch extension will NOT affect regular network functions

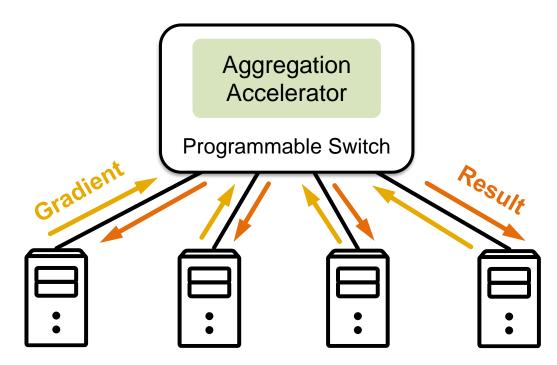


Synchronous Distributed Training



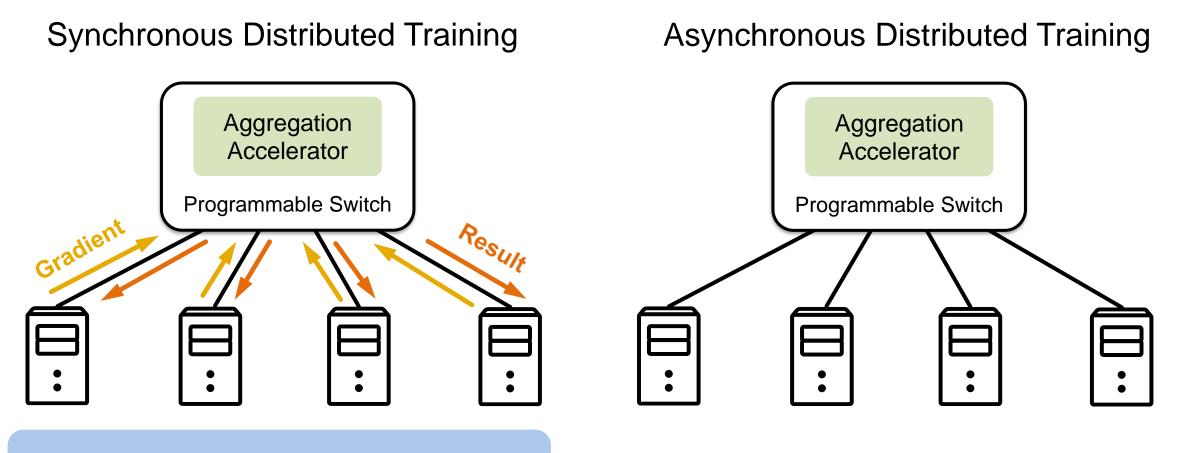


Synchronous Distributed Training



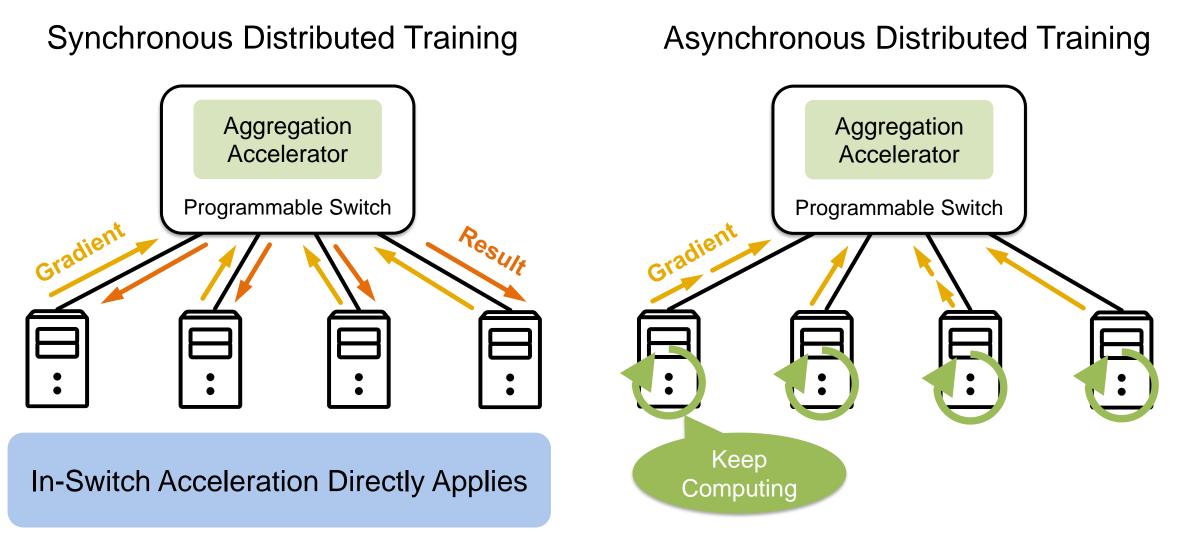
In-Switch Acceleration Directly Applies



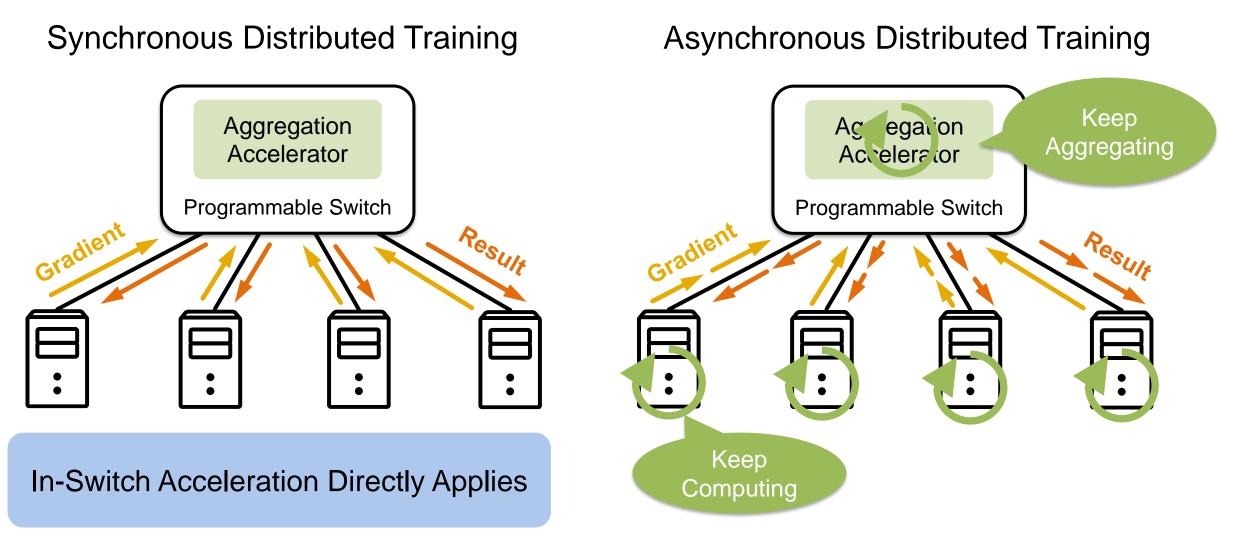


In-Switch Acceleration Directly Applies

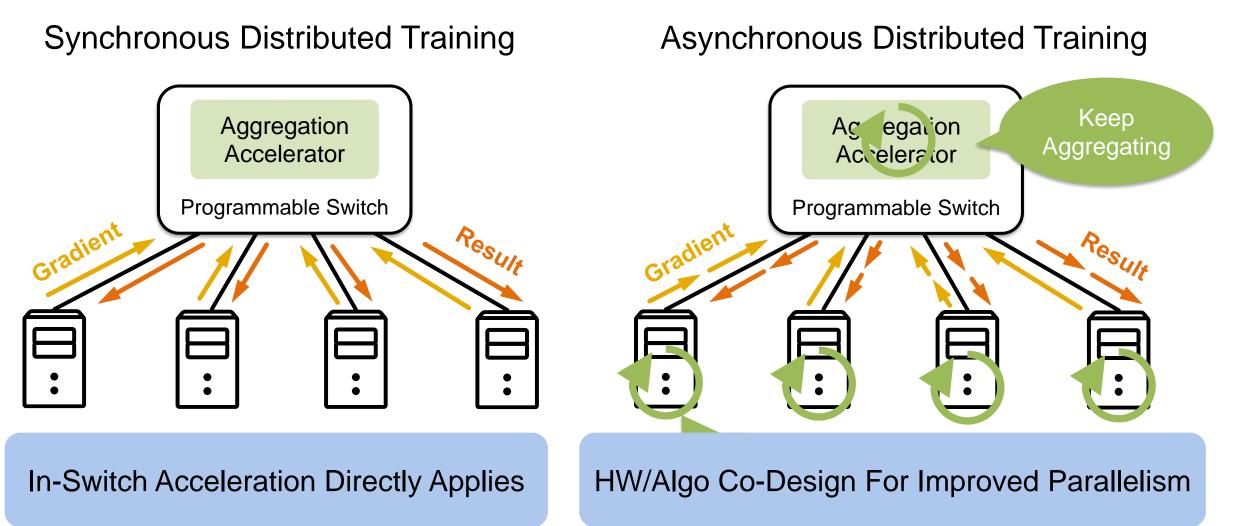


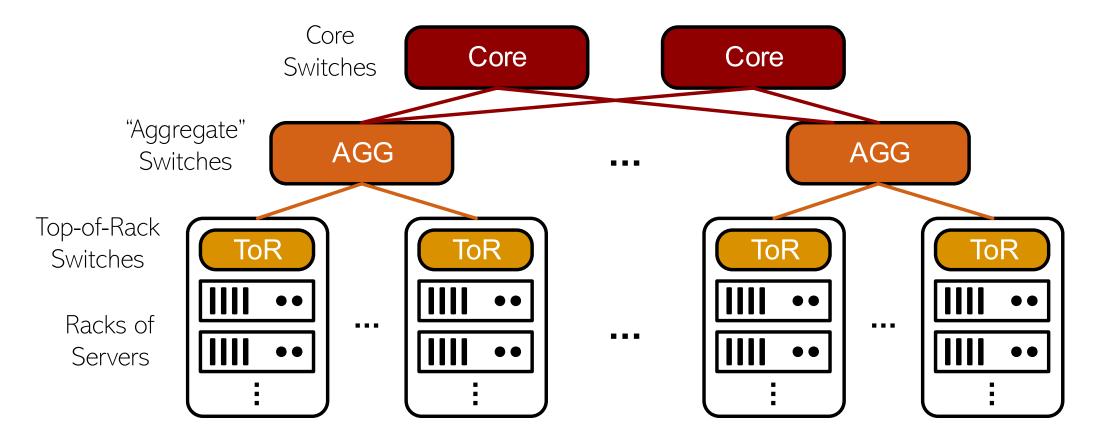






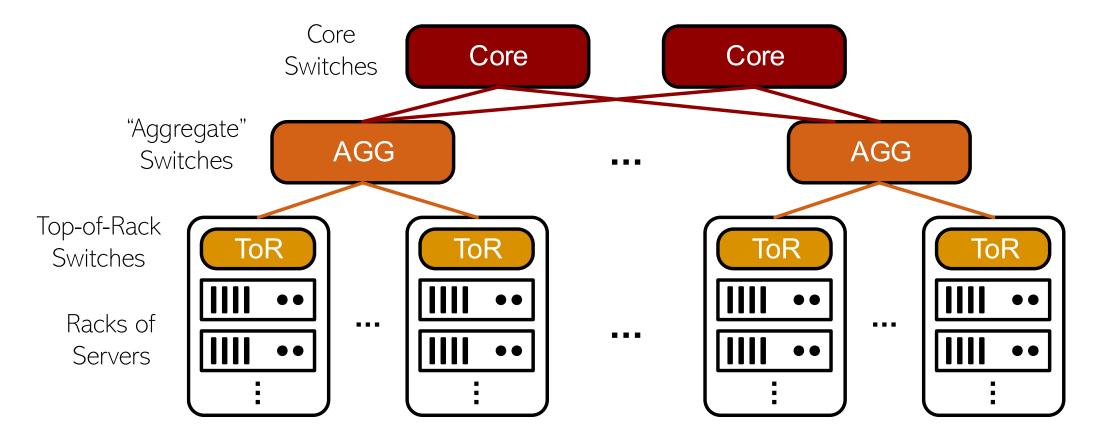






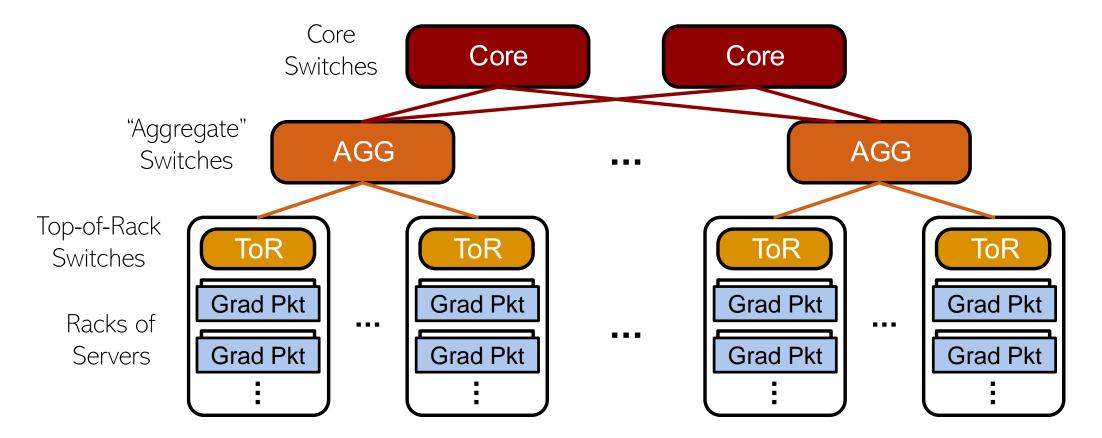
The Typical Network Architecture at Data Center





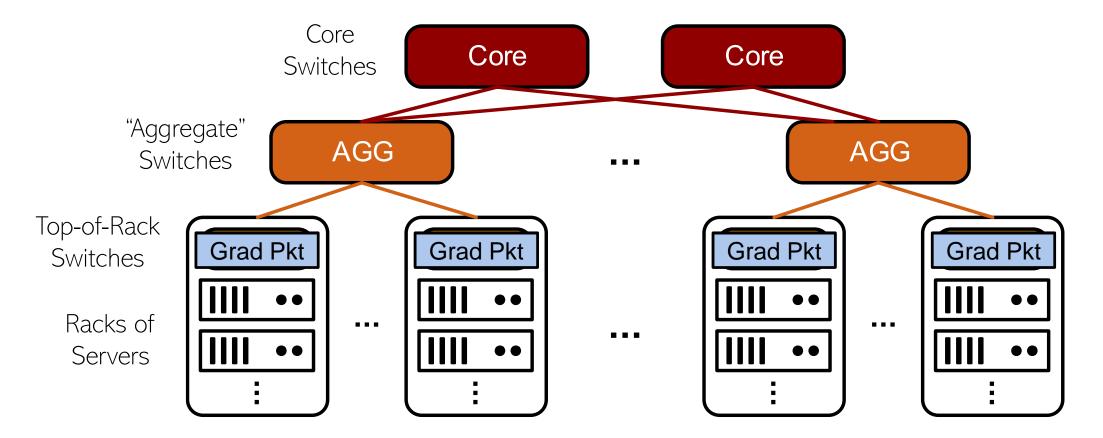
The Hierarchical Aggregation of iSwitch





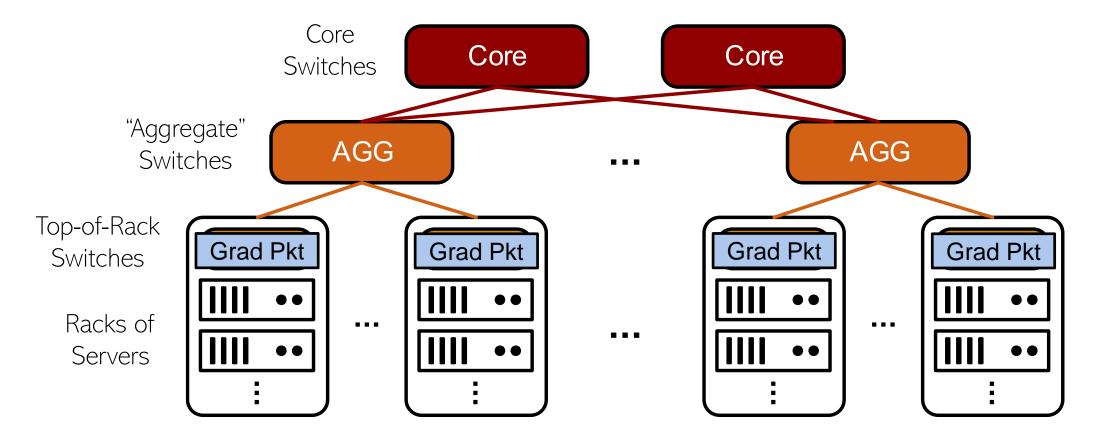
The Hierarchical Aggregation of iSwitch





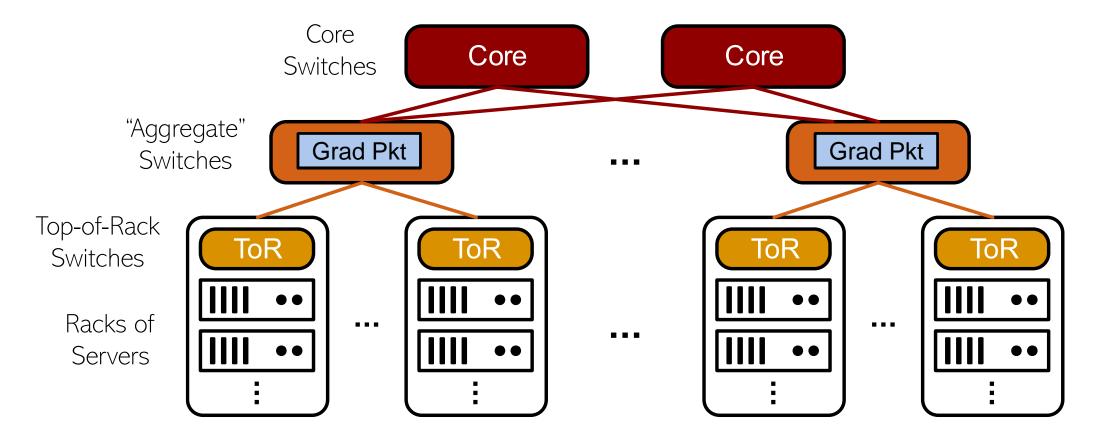
The Hierarchical Aggregation of iSwitch





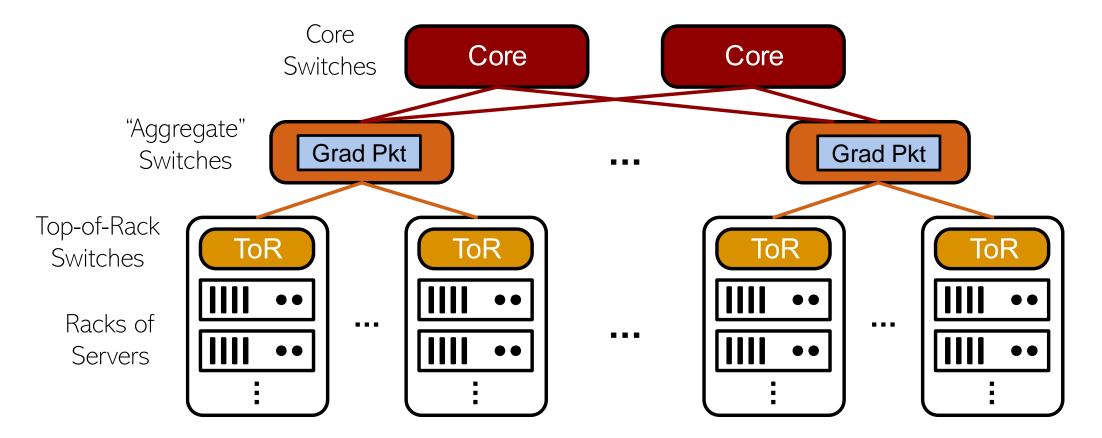
The Hierarchical Aggregation of iSwitch





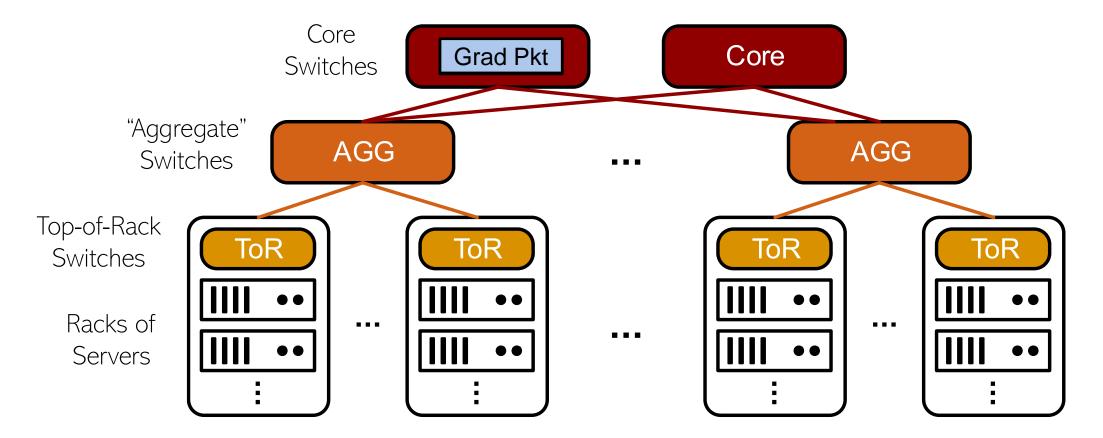
The Hierarchical Aggregation of iSwitch





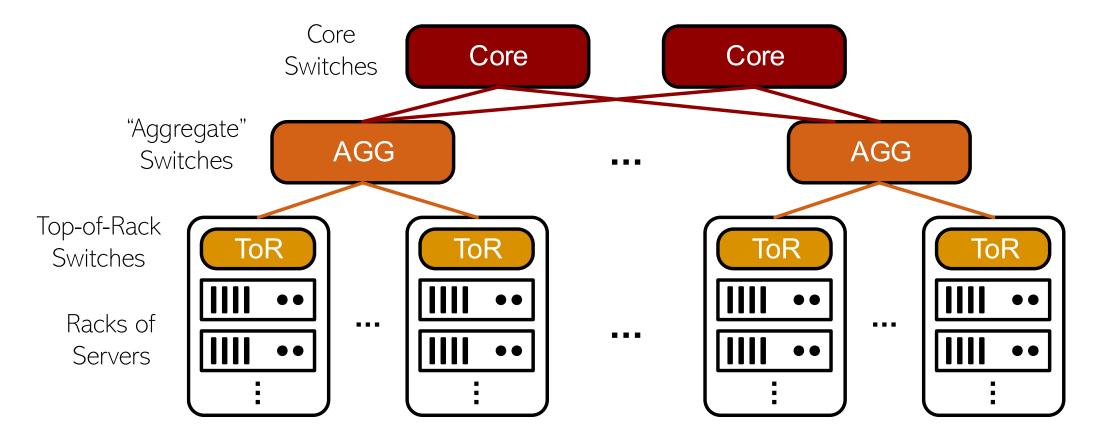
The Hierarchical Aggregation of iSwitch





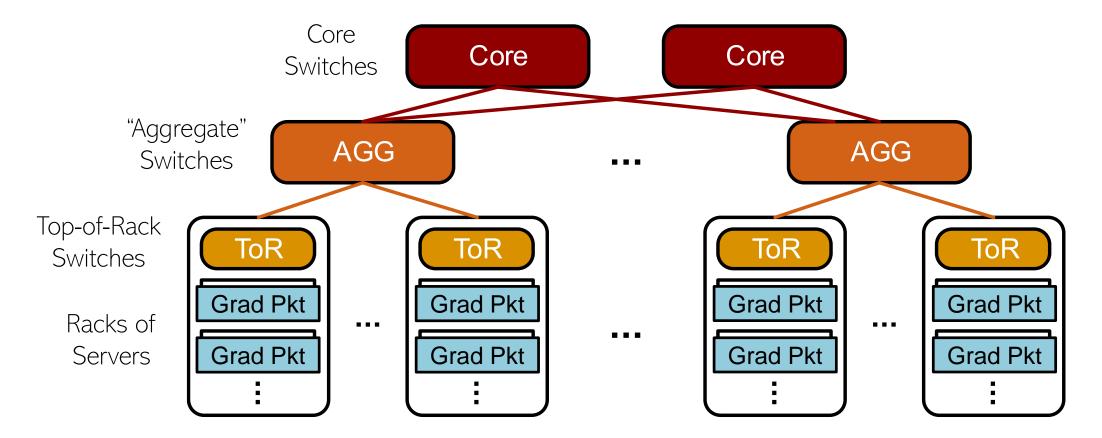
The Hierarchical Aggregation of iSwitch





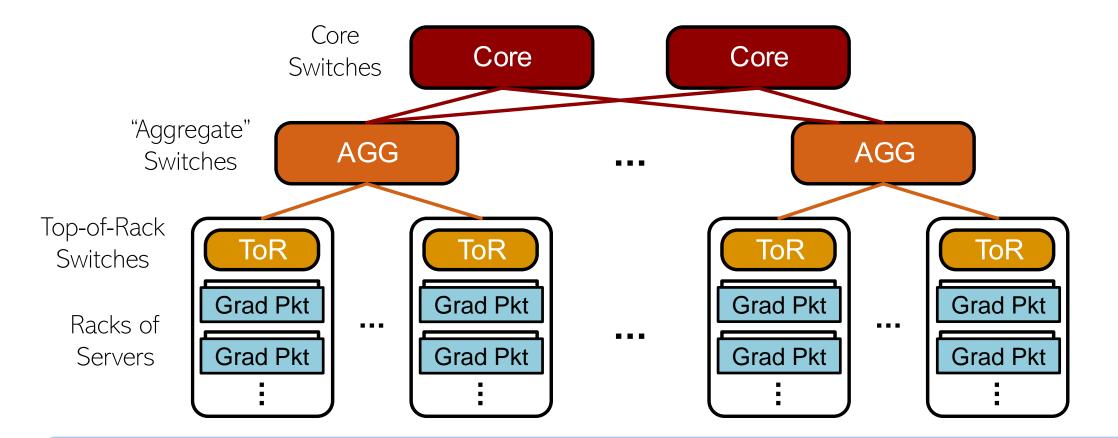
The Hierarchical Aggregation of iSwitch





The Hierarchical Aggregation of iSwitch





No Additional Cost or Topology Change for Scaling In-Switch Computing



#### In-Switch Computing Implementation



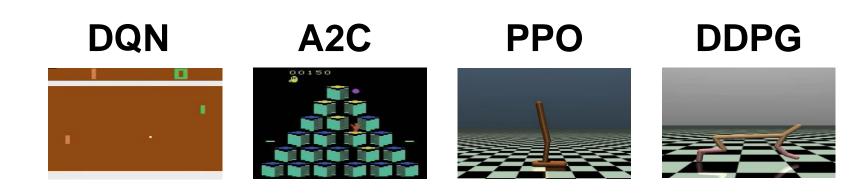
NetFPGA-SUME Board



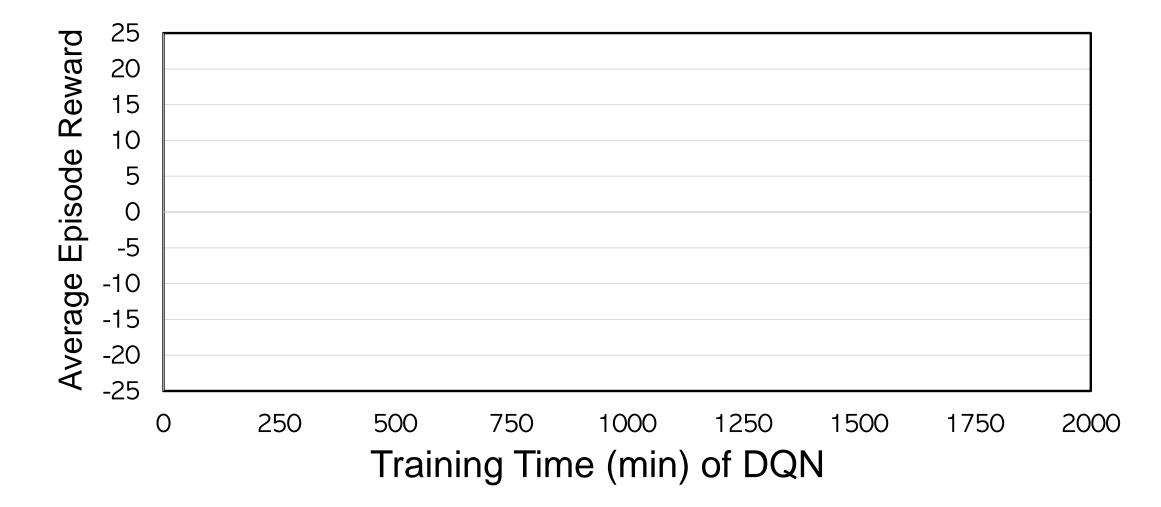
GPU Cluster

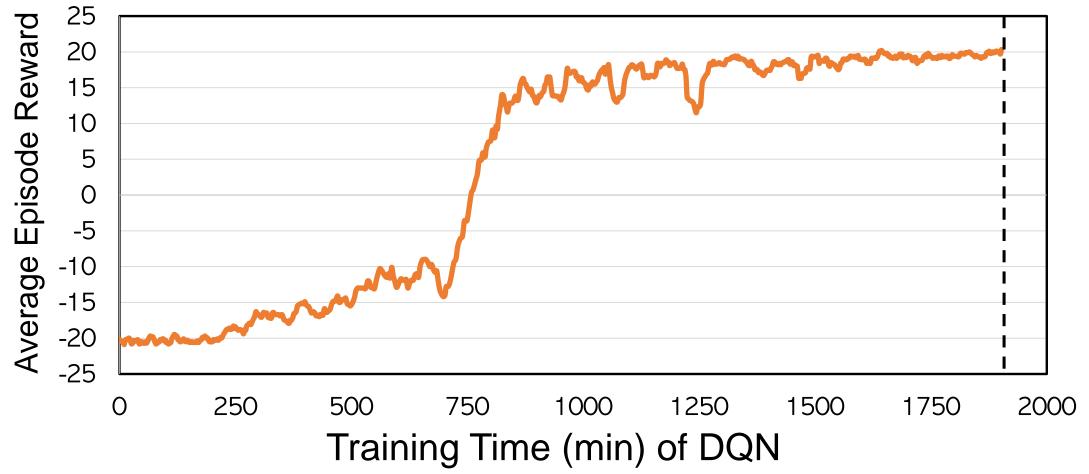
**ECE ILLINOIS** 

### **RL Training Benchmarks**

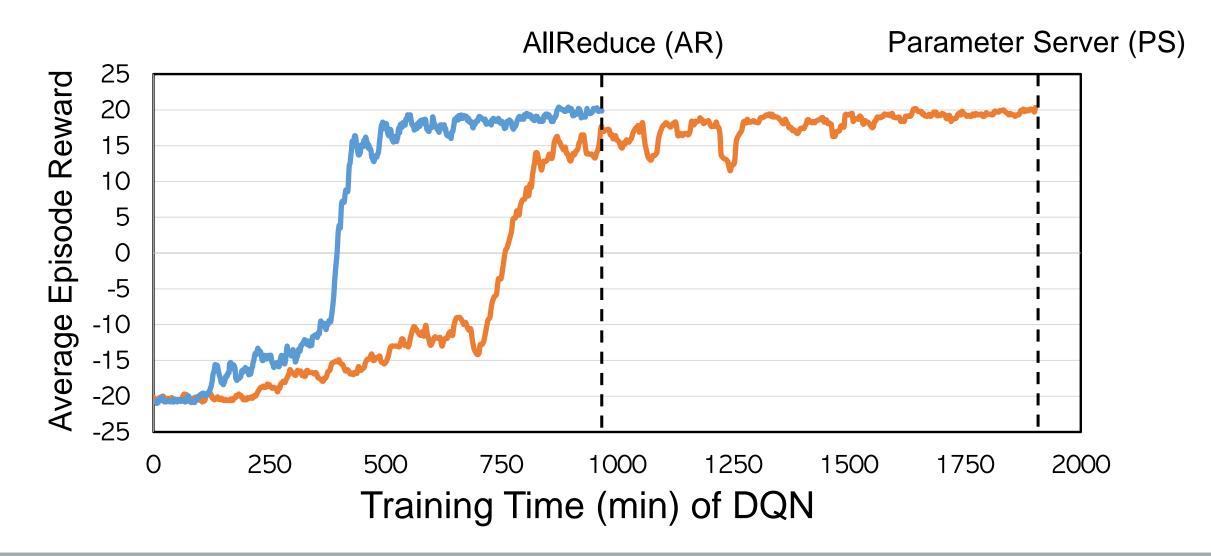


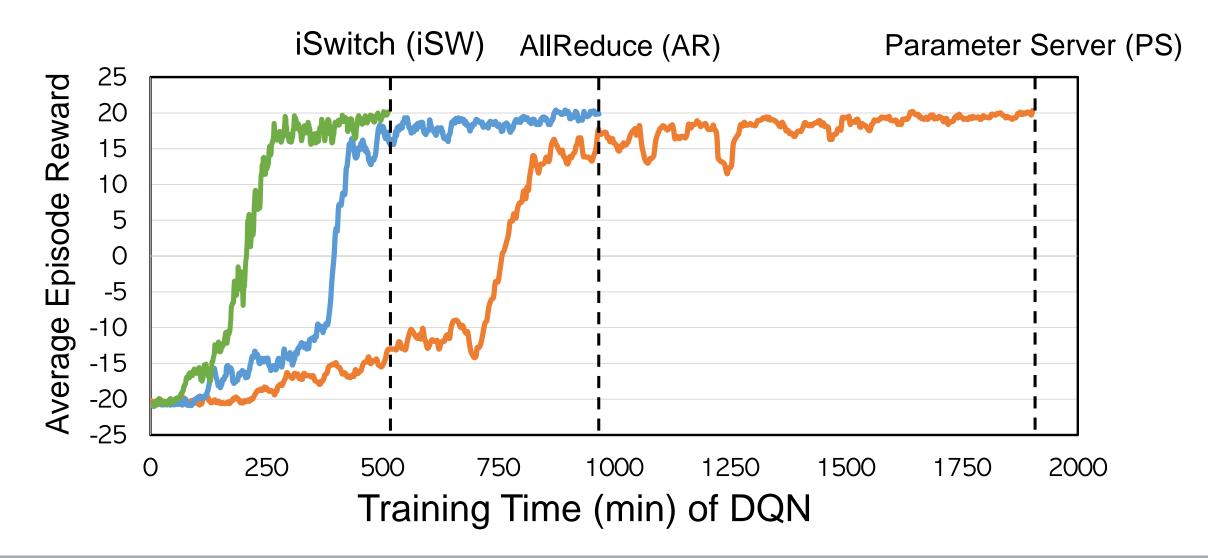




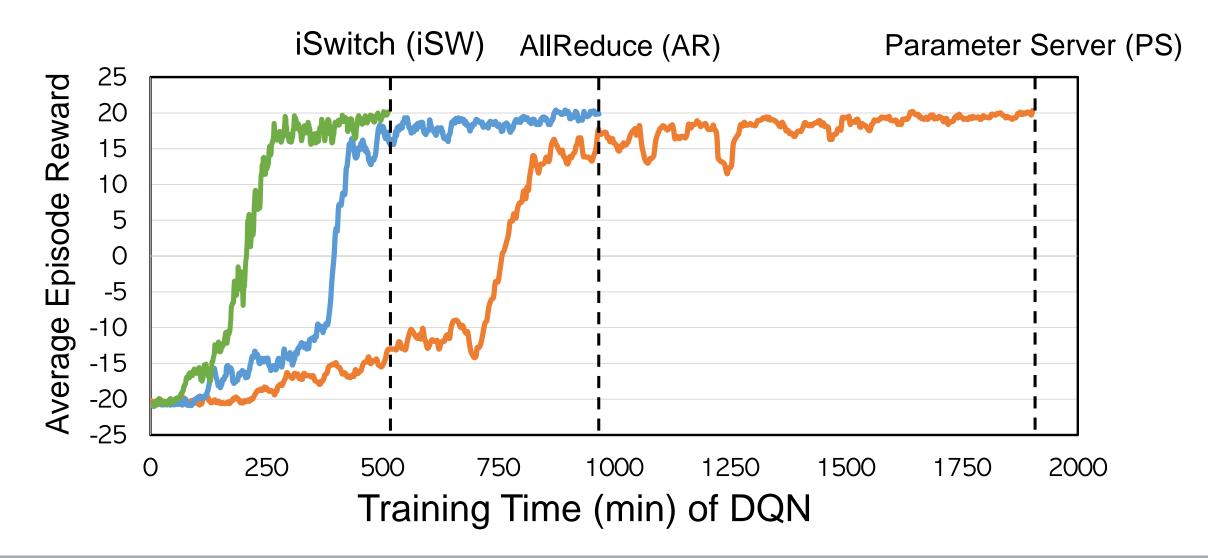


Parameter Server (PS)

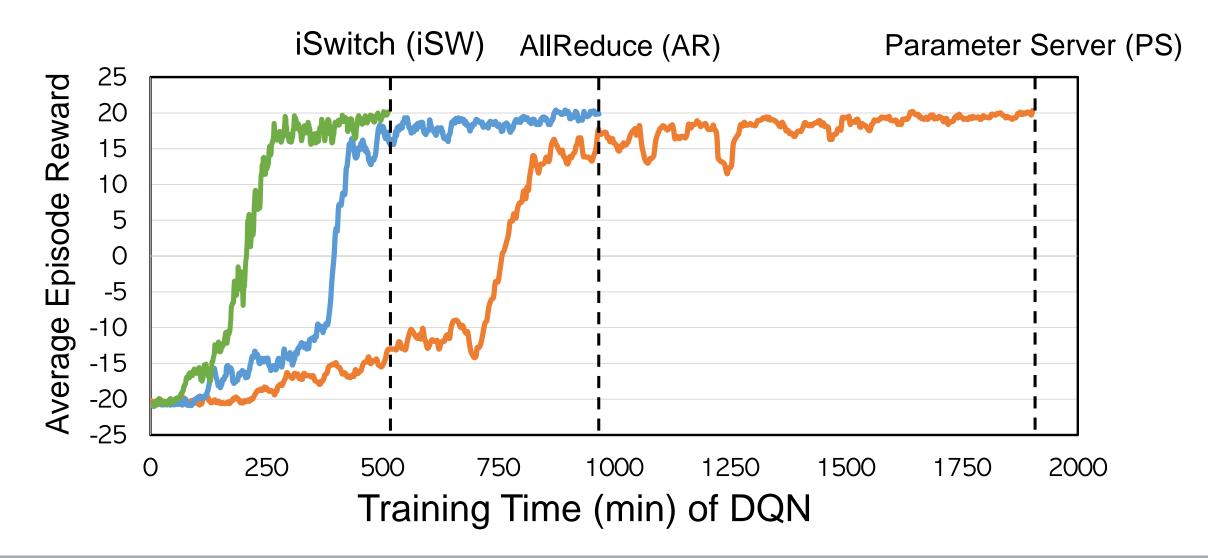




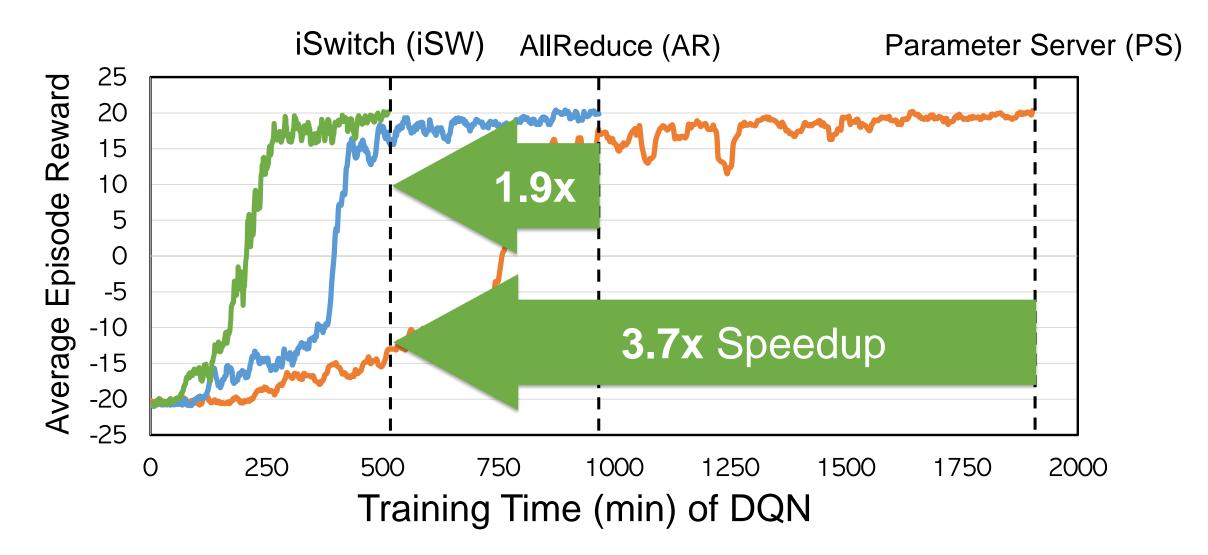
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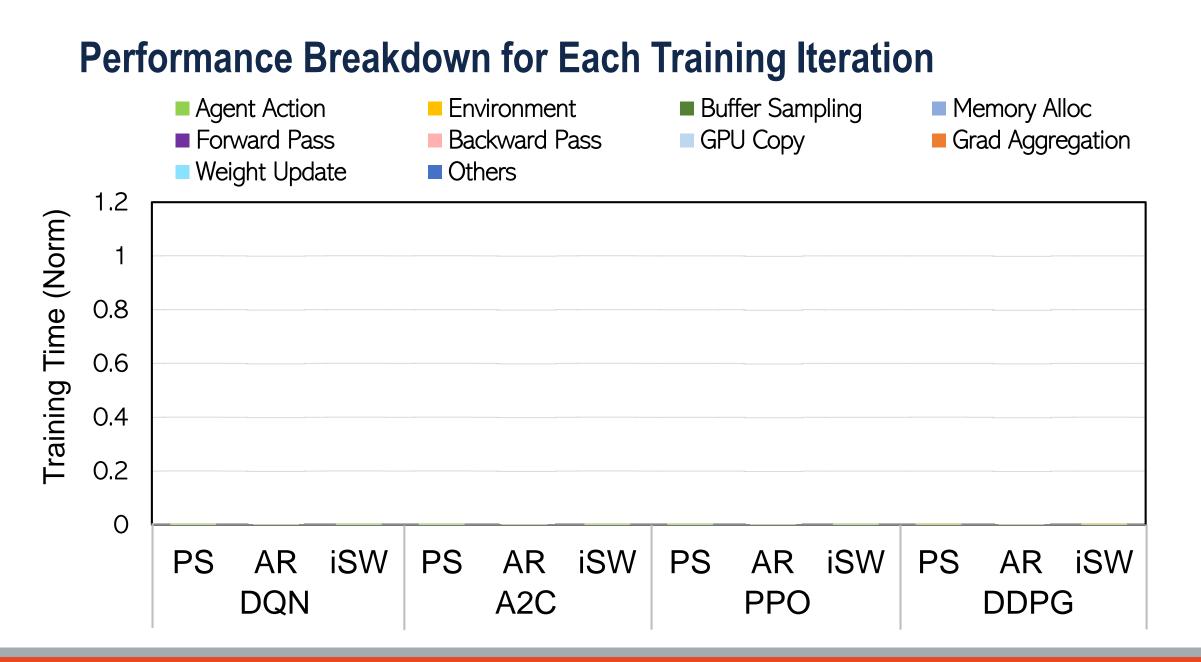
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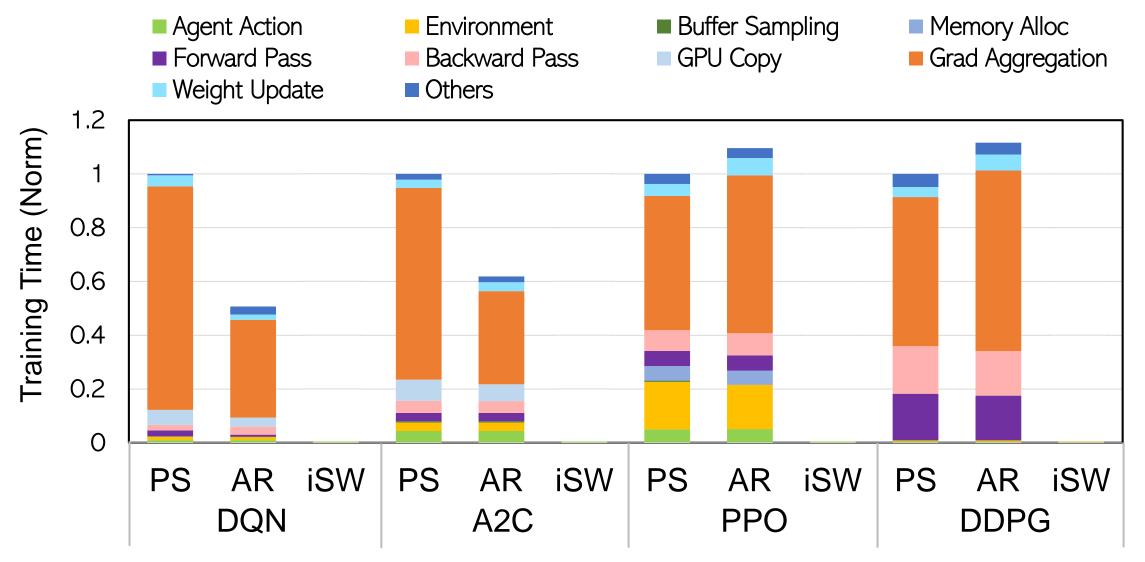
#### ECE ILLINOIS

20

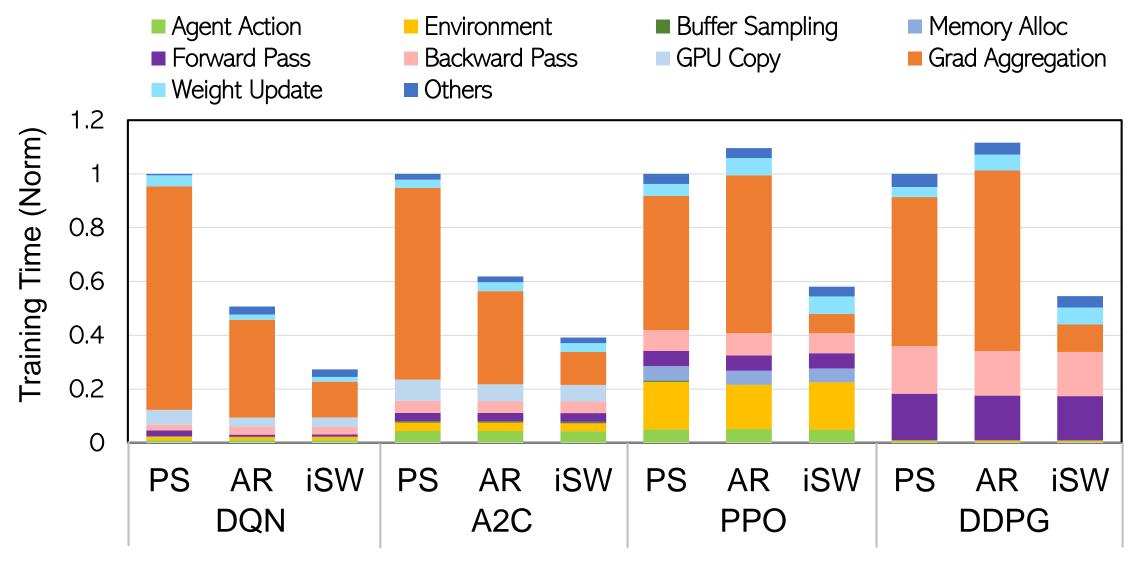
#### **Performance Breakdown for Each Training Iteration** Agent Action Environment Buffer Sampling Memory Alloc Forward Pass Grad Aggregation GPU Copy Backward Pass Weight Update Others 1.2 Training Time (Norm) 1 0.8 0.6 0.4 0.2 0 PS PS PS PS AR iSW AR iSW AR iSW AR iSW DQN A2C **PPO** DDPG



#### **Performance Breakdown for Each Training Iteration**

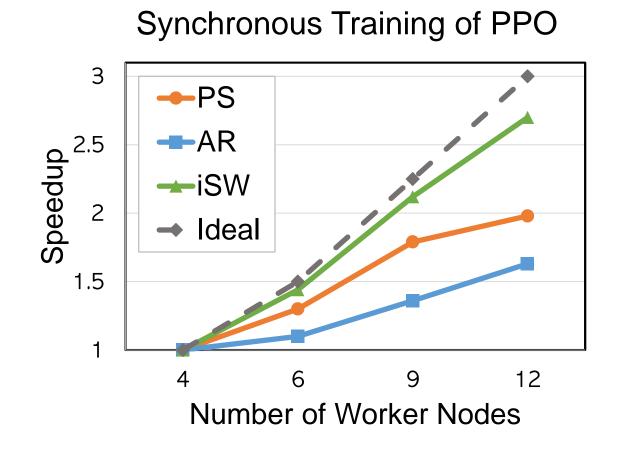


#### **Performance Breakdown for Each Training Iteration**



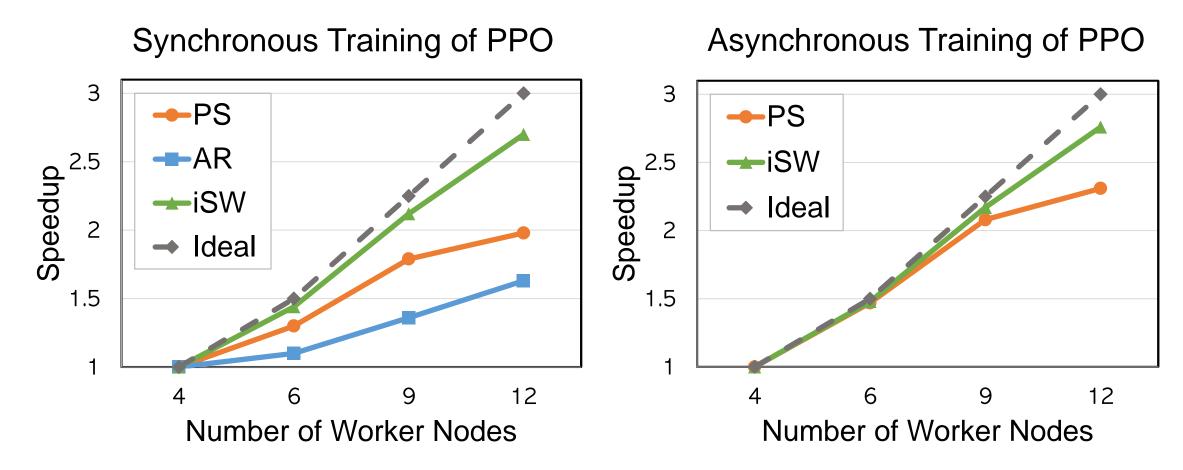


#### Improved Training Scalability with In-Switch Computing



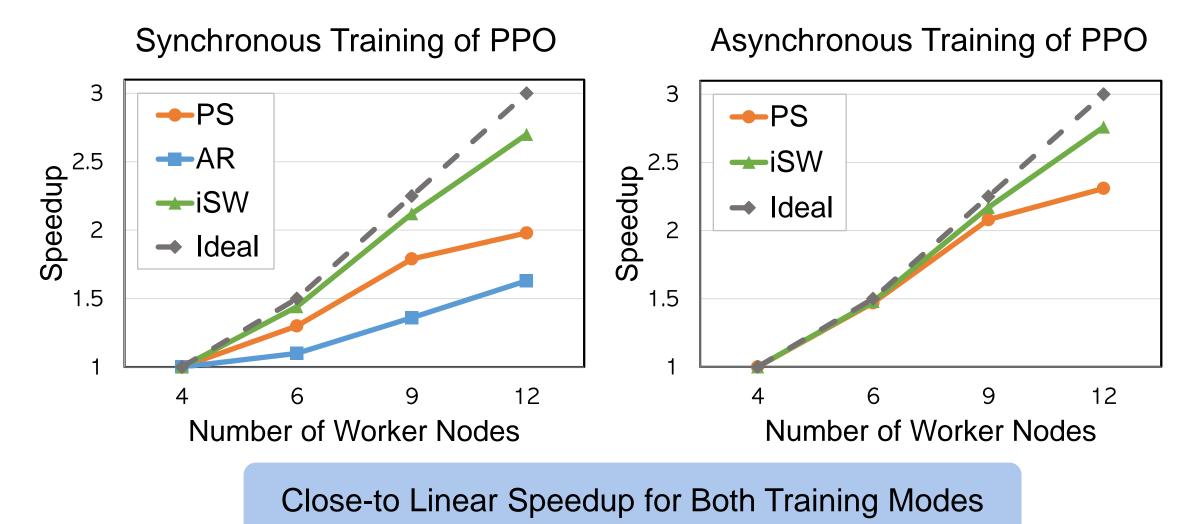


### Improved Training Scalability with In-Switch Computing



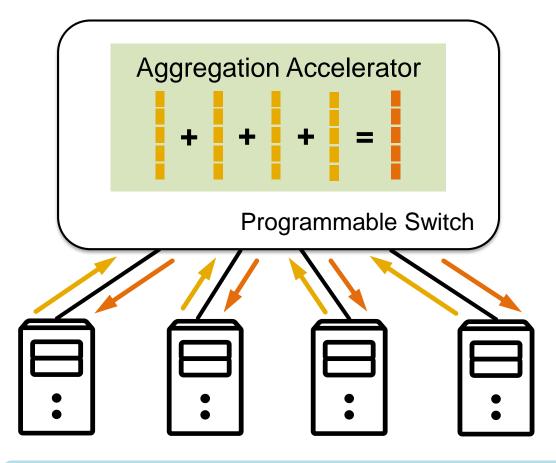


### Improved Training Scalability with In-Switch Computing





In-Switch Computing Summary



**3.7x** Speedup for Both Sync/Async Training

Scales at Rack-Scale Clusters



# Thanks!

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# Iou-Jen Liu Yifan Yuan Deming Chen Alexander Schwing Jian Huang

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