

Scalable Routing with Deep Reinforcement Learning

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October 23, 2019





Unix Approach: Do one thing and do it well

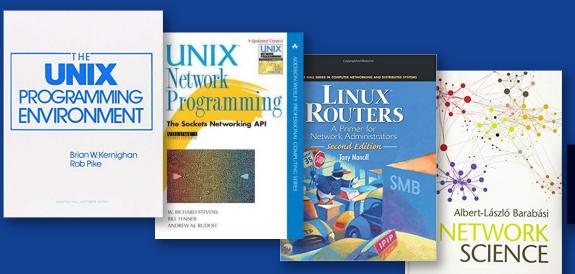
Unix Approach: Do one thing and do it well
Write programs to work together

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Unix Success: Shift from centralized mainframes to small decentralized computers*

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Large-Scale Networking



Routing Challenges in Large-Scale Networks

Route Computation Complexity



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Service Diversity (Delay, rate, ...)



Large State Space

Routing Challenges in Large-Scale Networks

Route Computation Complexity



Scalability

Service Diversity (Delay, rate, ...)



Large State Space

Demand Uncertainty and Dynamism



Need for Adaptive Routing

Distributed Approaches (e.g., BGP)

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(No Global Overview)

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Centralized Approaches (e.g., PCE)

Distributed Approaches (e.g., BGP)
(No Global Overview)

Centralized Approaches (e.g., PCE)
(Global View)

Prior Art & Our Approach

Distributed Approaches (e.g., BGP) (No Global Overview)

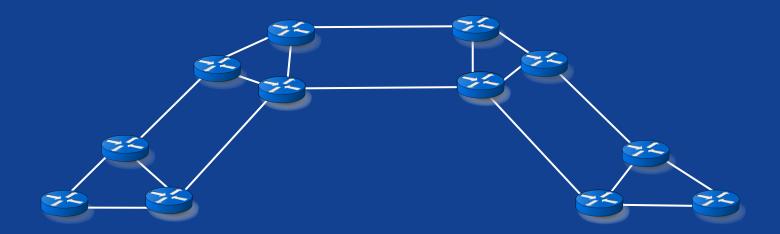
Centralized Approaches (e.g., PCE)
(Global View)

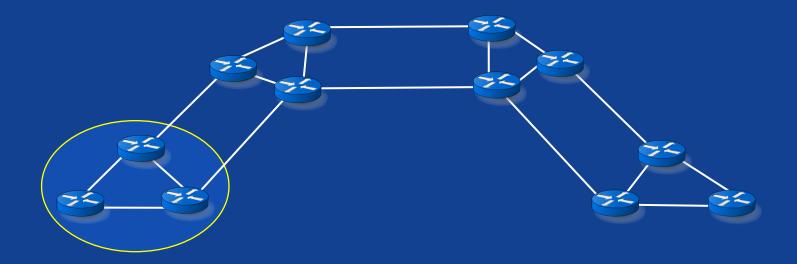
Our Approach: Cluster Oriented Scalable Routing

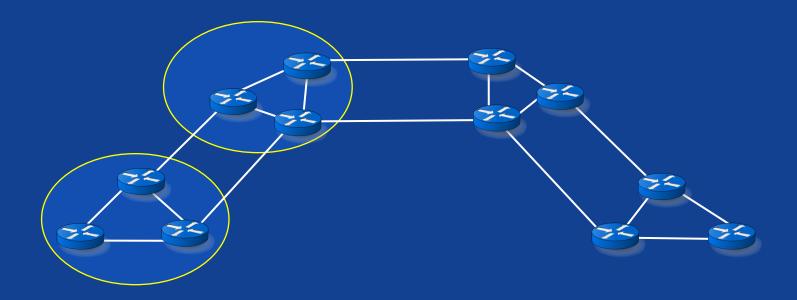
Distributed with Global View

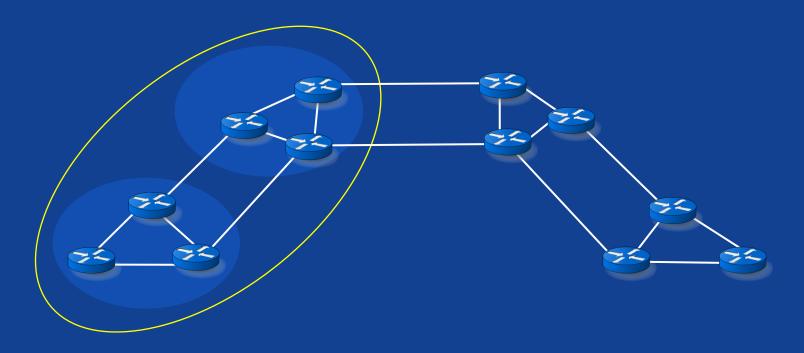
Patent pending

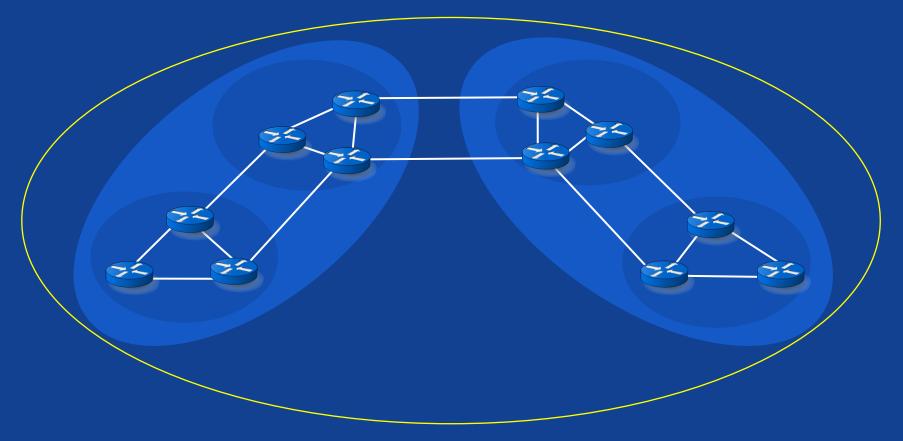
Cluster Oriented Scalable Routing

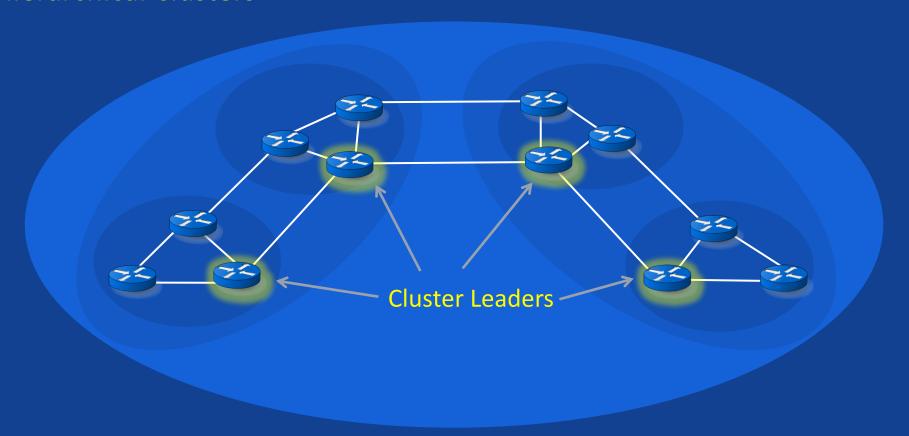










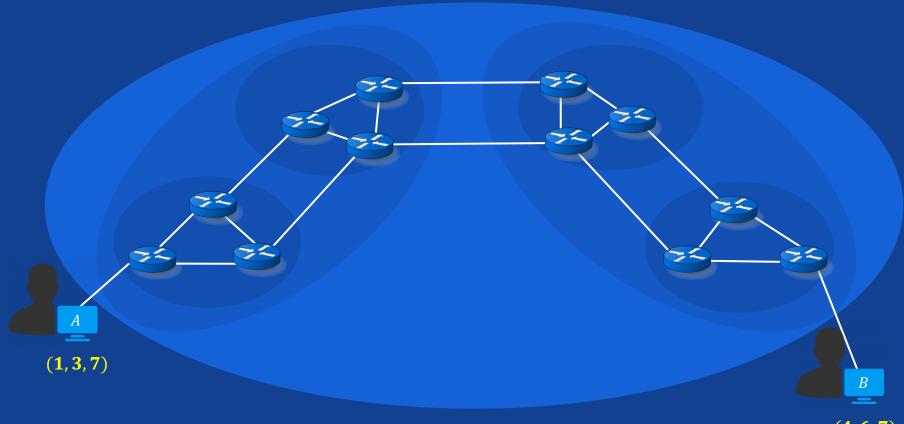


Network Identifiers (1, 3, 7)

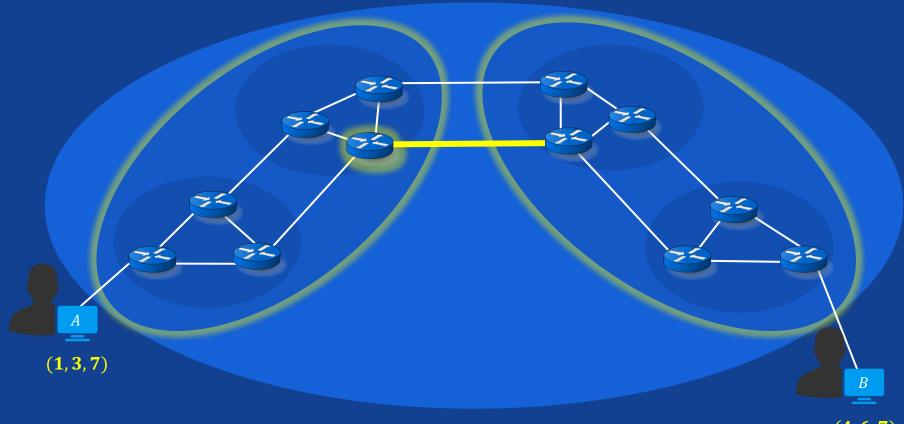




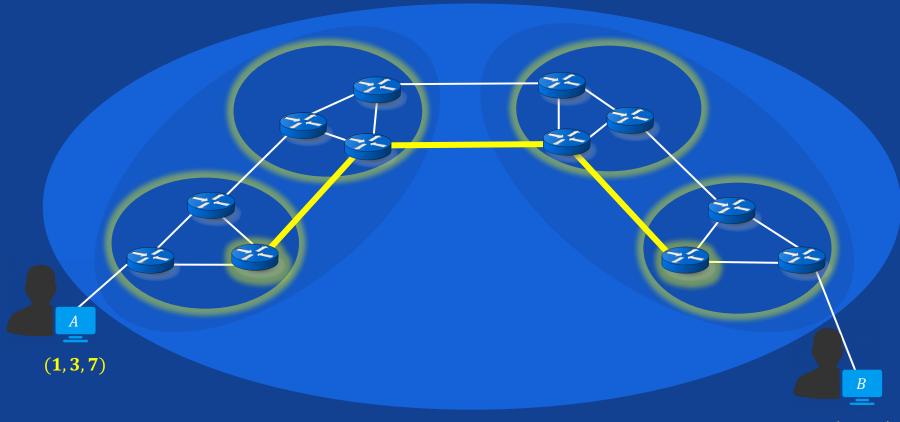
Leader Assistance



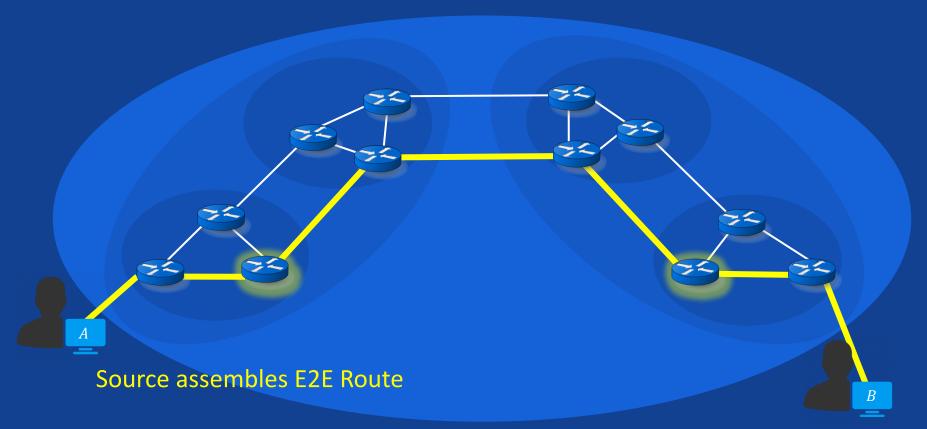
Leader Assistance



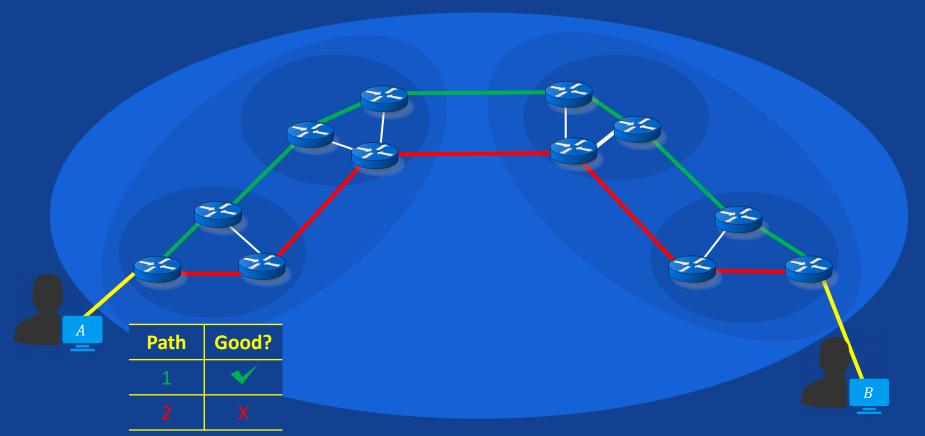
Leader Assistance



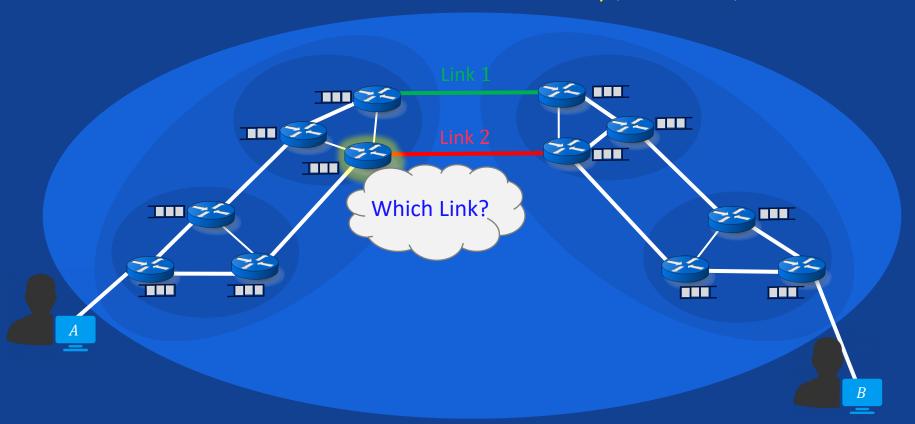
Segment Routing



Source Intelligence (Global View)

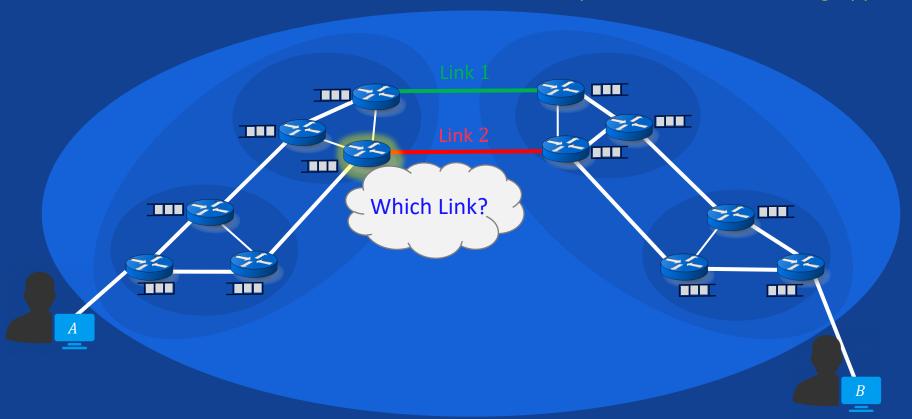


Based on transmission delays, queuing delays, utilizations,



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Deep Reinforcement Learning Approach



Reinforcement Learning

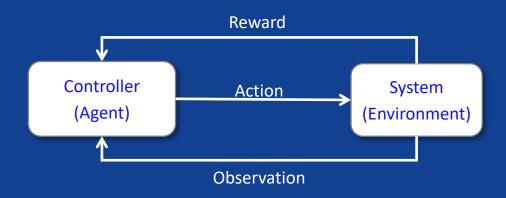
Powerful

DeepMind's AI beats world's best Go player in latest face-off

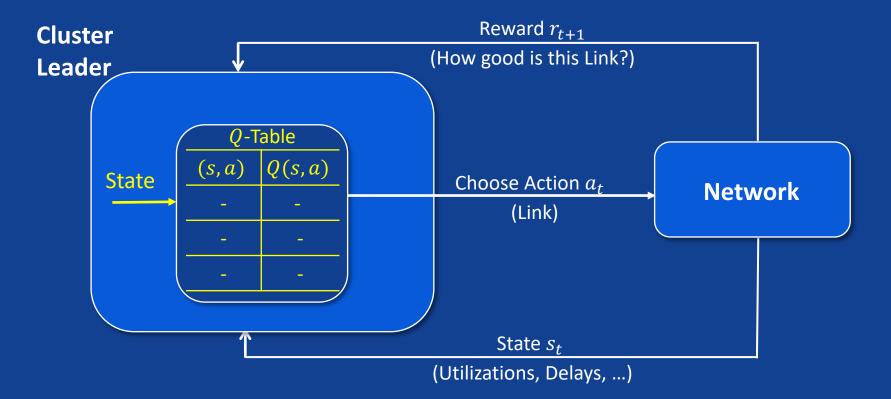
Challenging

Convergence is not universally guaranteed Needs time to experiment – like a human

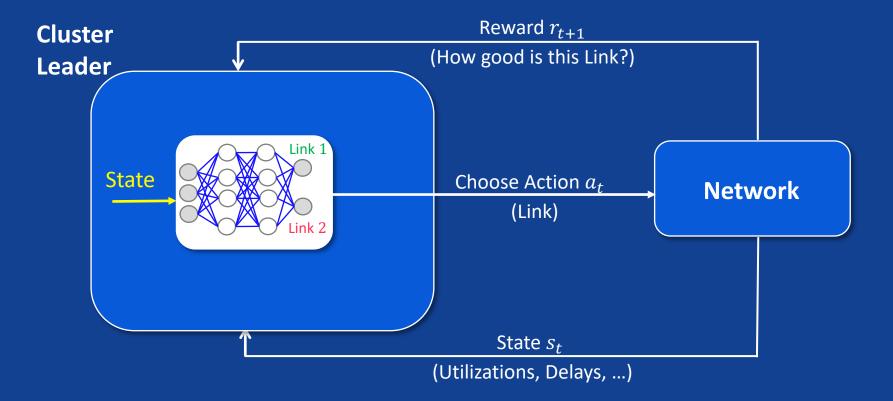
Ke Jie, who once boasted he would never be beaten by a computer at the ancient Chinese game, said he had 'horrible experience'



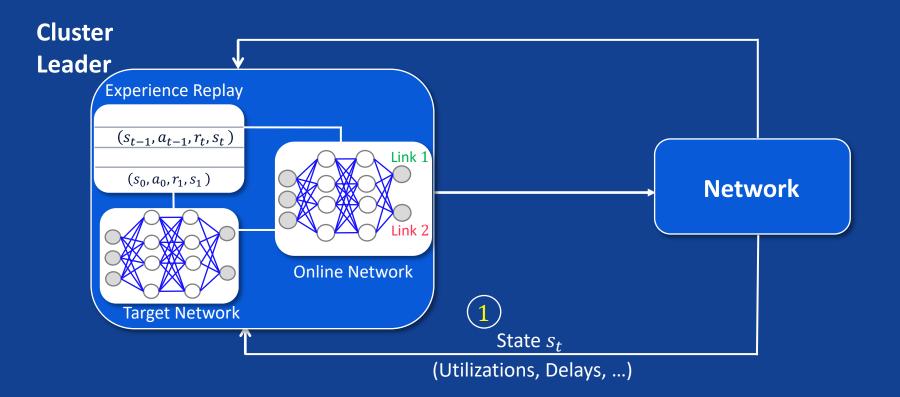
Q-Learning



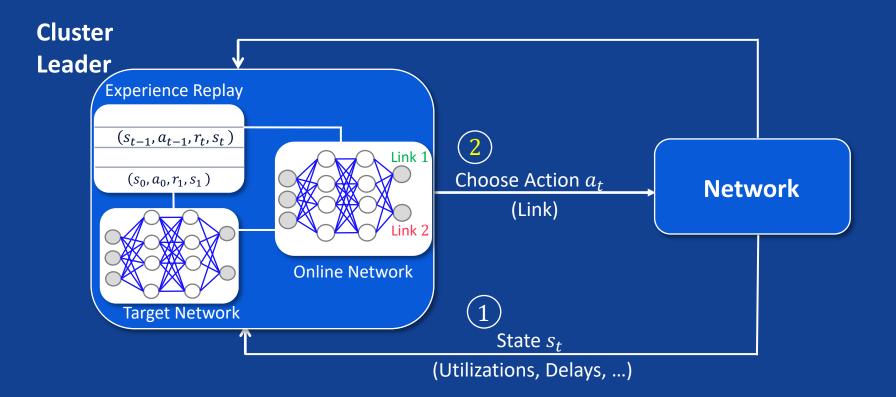
Deep Q-Learning

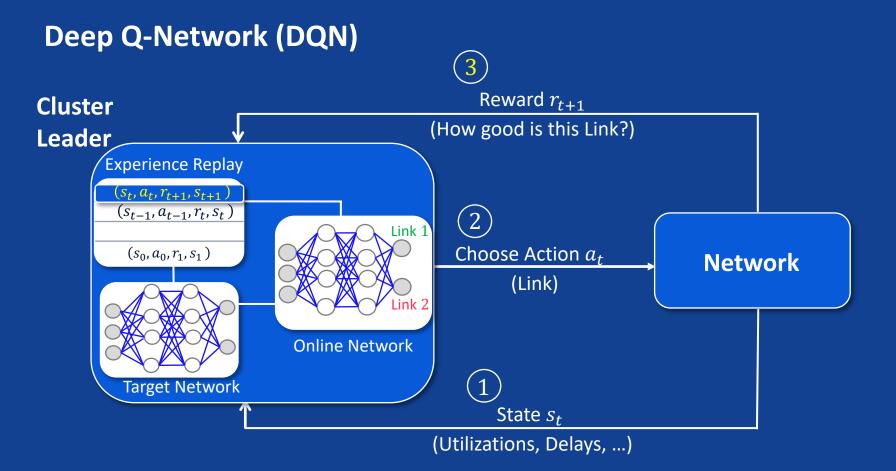


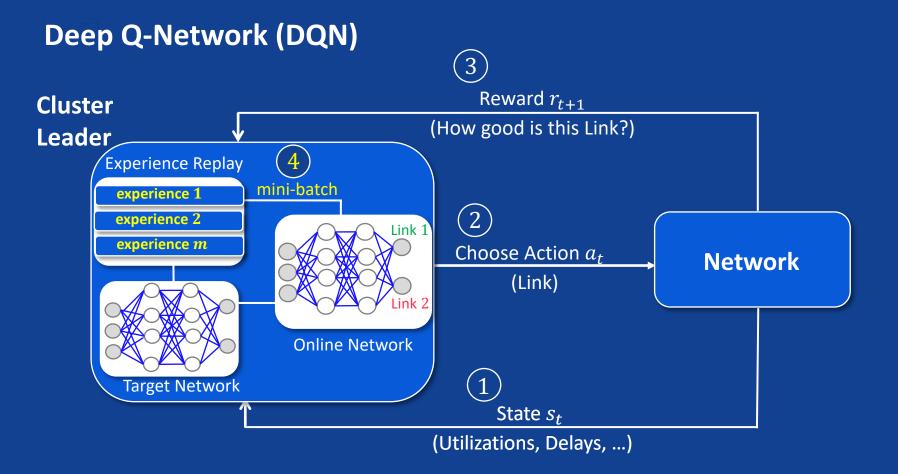
Deep Q-Network (DQN)



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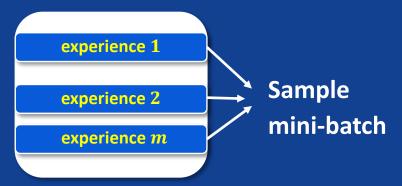






Experience Replay & Deep Double Q-Network (DDQN)

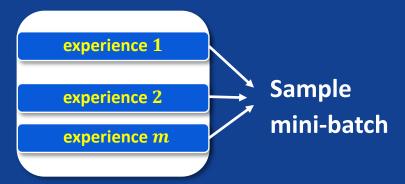
Prioritized Experience Replay



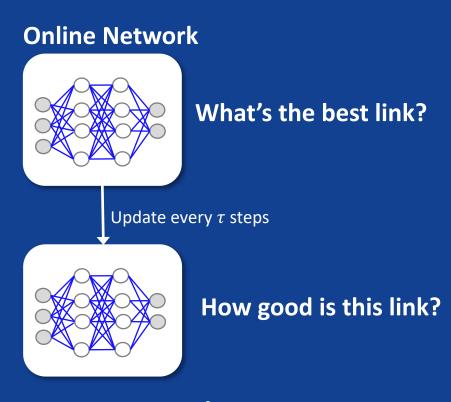
Priority ∝ **How surprising?**

Experience Replay & Deep Double Q-Network (DDQN)

Prioritized Experience Replay



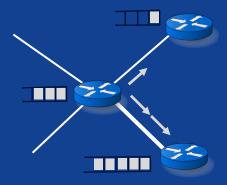
Priority ∝ **How surprising?**



Target Network

How to design the reward?

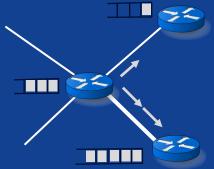
Local Reward



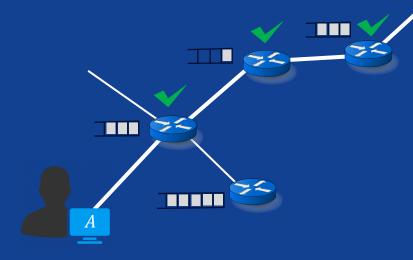
Assigned individually (Distributing load, Delay, Loss, ...)

How to design the reward?

Local Reward +



Global Reward



Assigned individually (Distributing load, Delay, Loss, ...)

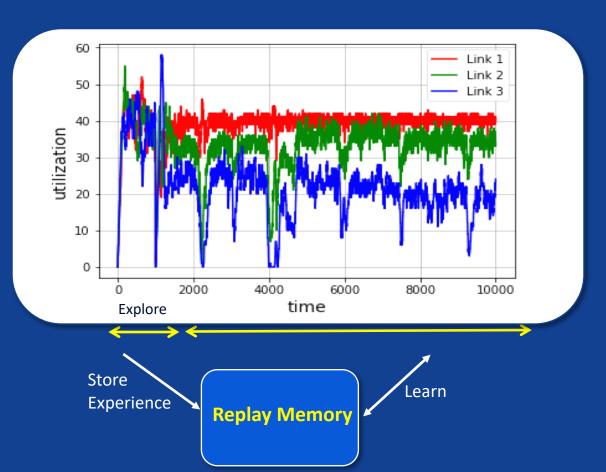
Assigned to all (End-to-end Delay, ...)

Results

Global reward

Path	Good?
1	Best
2	Ok
3	Worst

Two-layer DNN,
Huber Loss,
Batch Size=32,
Replay Memory =1000



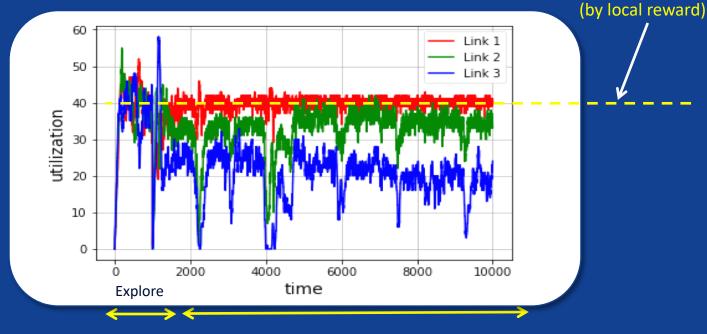
Results

Utilization threshold= 40

Global reward

Path	Good?
1	Best
2	Ok
3	Worst

Two-layer DNN,
Huber Loss,
Batch Size=32,
Replay Memory =1000



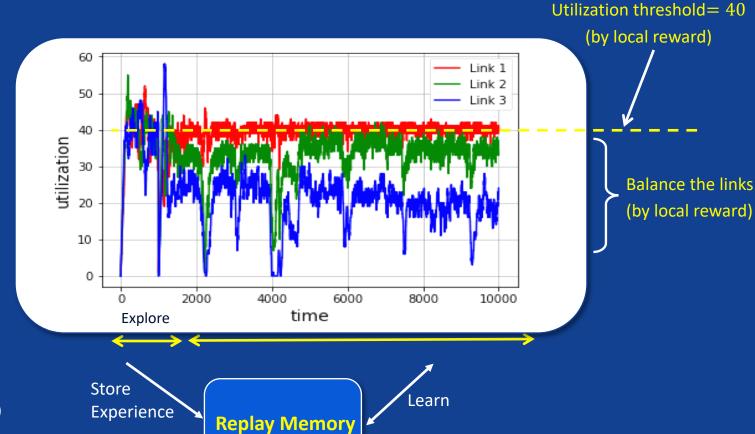
Store Experience Replay Memory Learn

Results

Global reward

Path	Good?
1	Best
2	Ok
3	Worst

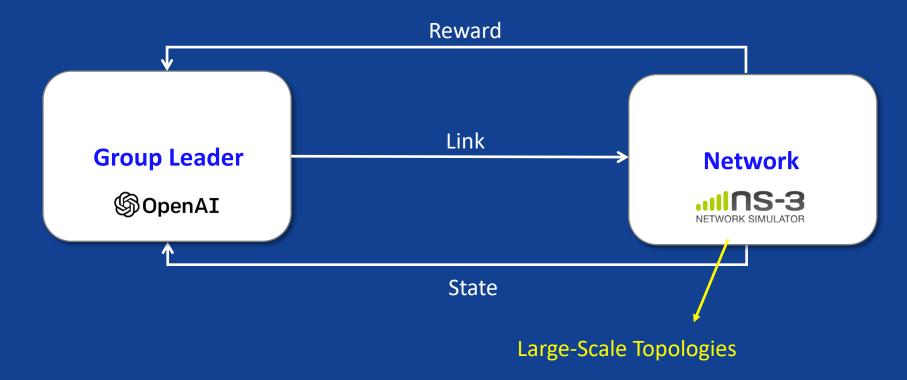
Two-layer DNN,
Huber Loss,
Batch Size=32,
Replay Memory =1000



What's Next?



What's Next?



Questions? Thank you

Paper: Hierarchical Deep Double Q-Routing https://arxiv.org/pdf/1910.04041.pdf

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