Atlas: Automate Online Service Configuration in Network Slicing

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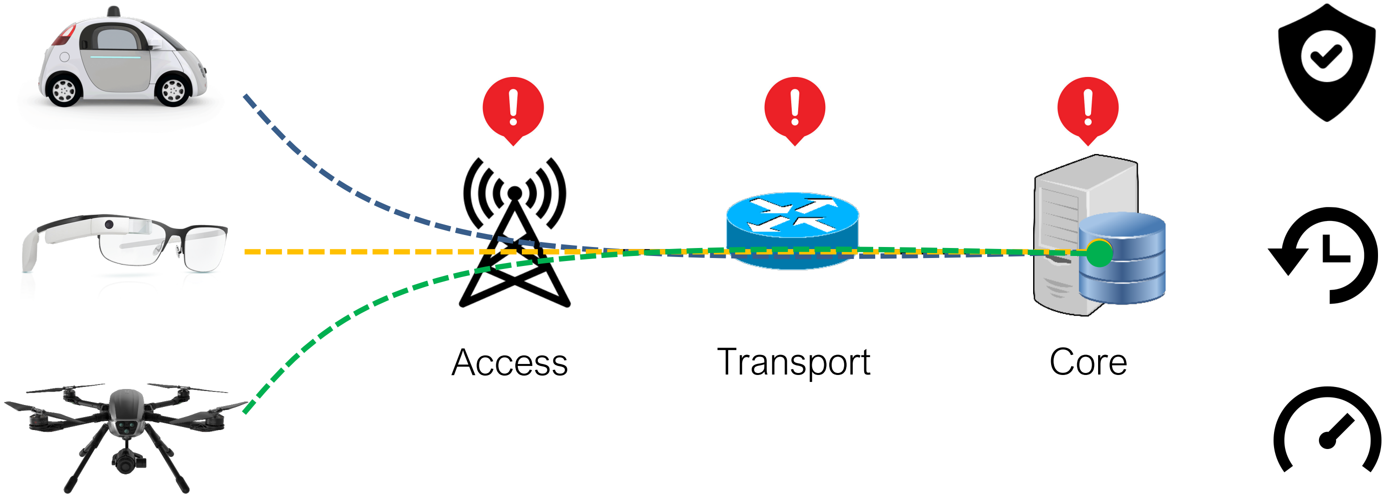
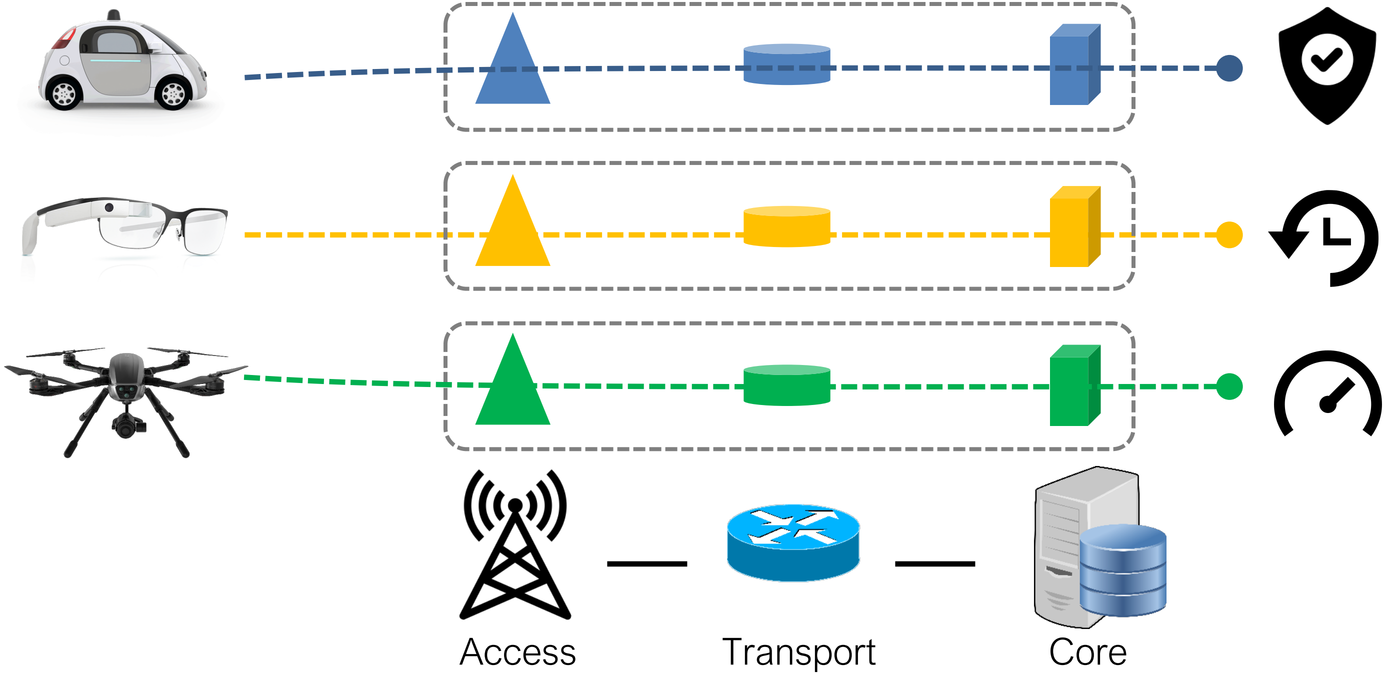
Emerging Applications

- Resource competition degrades end-to-end performance
  - independent optimization, e.g., RAN and TN, fails in guaranteed performance



Network Slicing

- Enable customized end-to-end slice for each application
  - performance and functional isolation, SLA guarantee
  - customization in performance, function, security, etc.



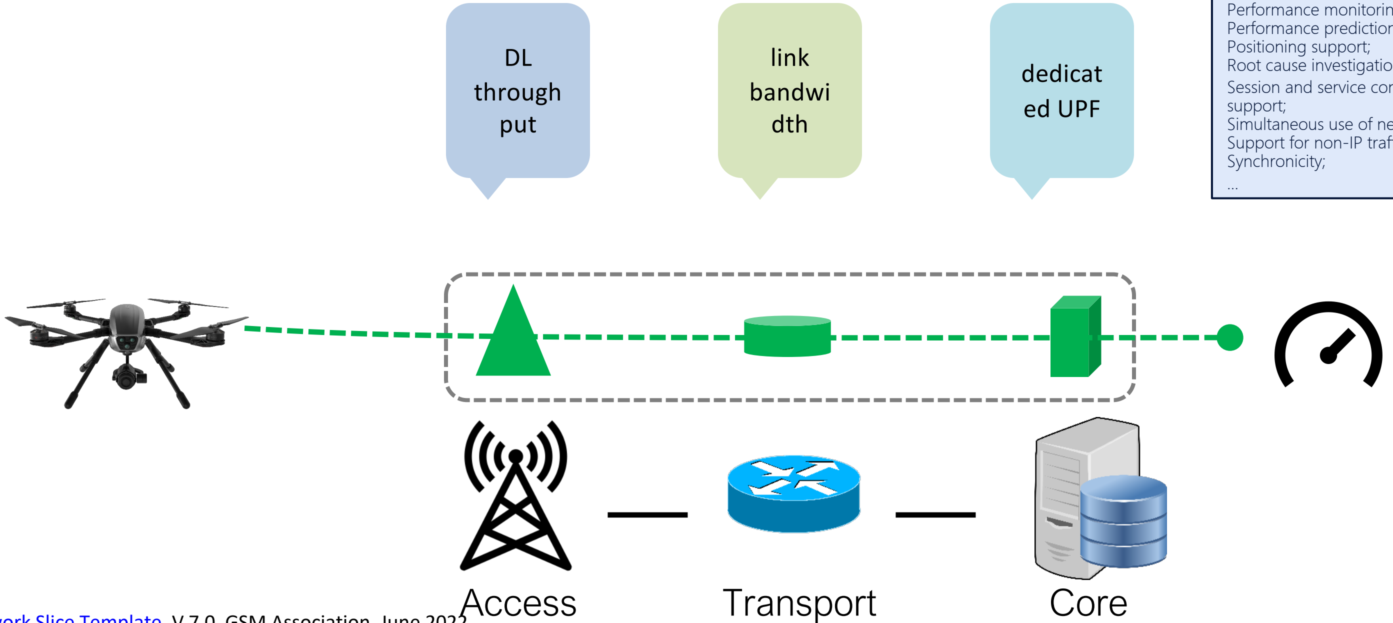
Service Configuration

❖ Configure individual slice settings to maintain SLA

- for example, cross-domain resources, attributes*
- High-dim contextual states, e.g., traffic, users
- long configuration interval, e.g., hours (non-markov)

slice attributes*

Deterministic communication;
Group communication support;
Location based message delivery;
Isolation level;
Mission critical support;
MMTel support;
Network slice customer network functions;
Performance monitoring;
Performance prediction;
Positioning support;
Root cause investigation;
Session and service continuity support;
Simultaneous use of network slice
Support for non-IP traffic;
Synchronicity;
...

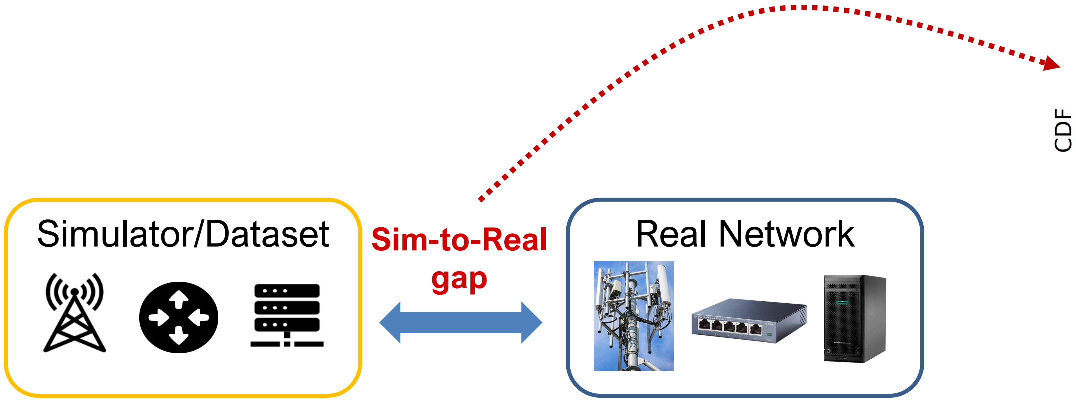


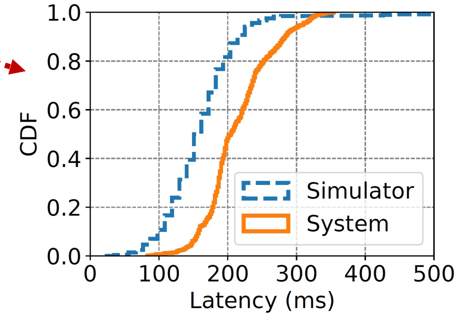
*Generic Network Slice Template, V 7.0, GSM Association, June 2022

State-of-the-Art

❖ Offline approaches

- design the policy in offline environments, e.g., simulator or dataset
- offline approaches [1, 2] suffer simulation-to-reality discrepancy
- the discrepancy between offline simulators and real-world networks



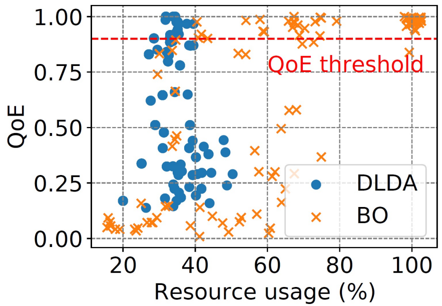


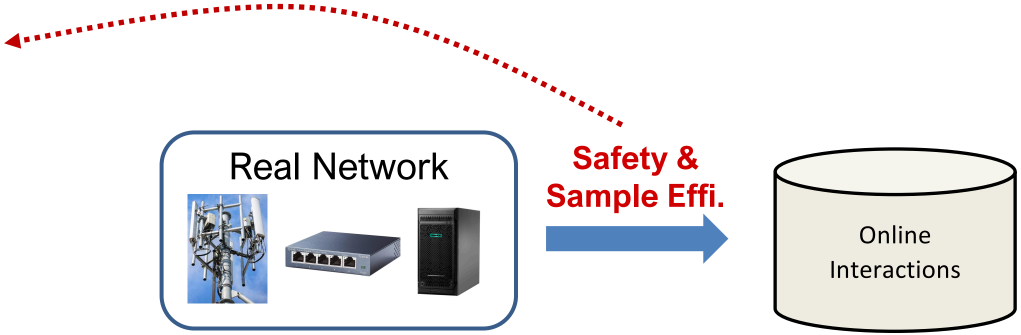
[1] Marquez, C., et. al. How should I slice my network? A multi-service empirical evaluation of resource sharing efficiency. Mobicom 2018 (pp. 191-206).
[2] Salvat, J.X., et. al. Overbooking network slices through yield-driven end-to-end orchestration. CoNEXT *2018* (pp. 353-365).

State-of-the-Art

❖ Online approaches

- learn the policy via interacting with real-world networks
- online ML methods [3] suffer safety and sample-efficiency issue
- **sample-efficiency**: long configuration interval in real-world networks
- **safety**: unpredictable configuration actions from DNN-parameterized policies



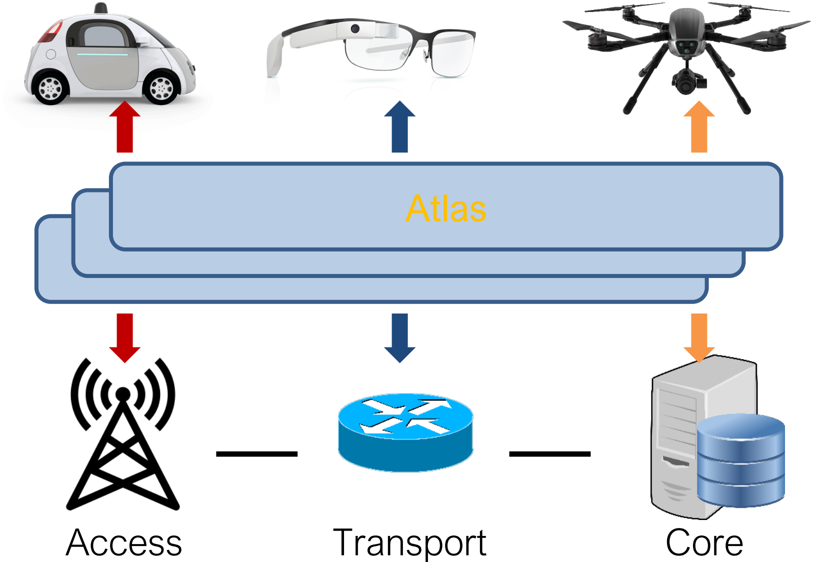


[3] Shi, J., et. al. Adapting wireless mesh network configuration from simulation to reality via deep learning based domain adaptation. *NSDI* 2021 (pp. 887-901).

Atlas

❖ The first integrated offline-online network slicing

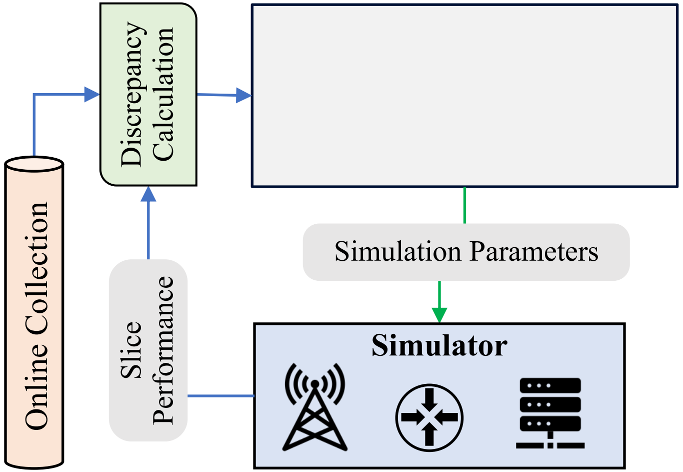
- Atlas automates service configuration of individual slices
- Atlas achieves safe and sample-efficient learn-to-configure in three integrated stages
- **stage 1: learning-based simulator**, for reducing sim-to-real discrepancy
- **stage 2: offline training**, for training an offline policy
- **stage 3: online learning**, for learning the online policy



Stage 1

Learning-based Simulator

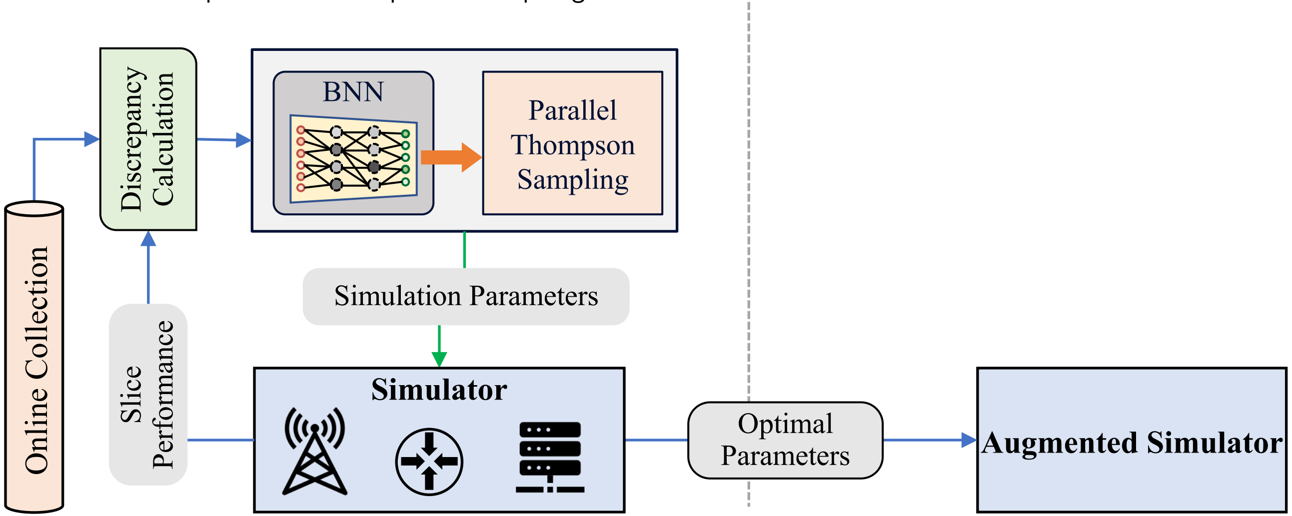
- **objective**: automatically reduce the simulation-to-reality discrepancy
- **action**: adjust the simulation parameters, e.g., base pathloss
- **rationale**: these parameters might not accurate enough



Stage 1

❖ Learning-based Simulator

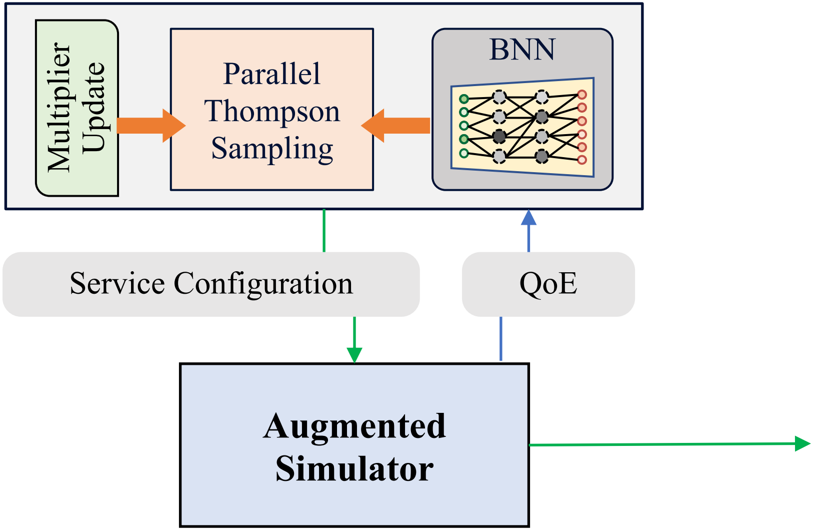
- problem: minimize KL divergence between simulation and system measurement
- challenge: unknown correlation between KL divergence and high-dim simulation parameters
- solution: new Bayesian learning method
    - scalable Bayesian neural network
    - parallel Thompson sampling



Stage 2

❖ Offline Training

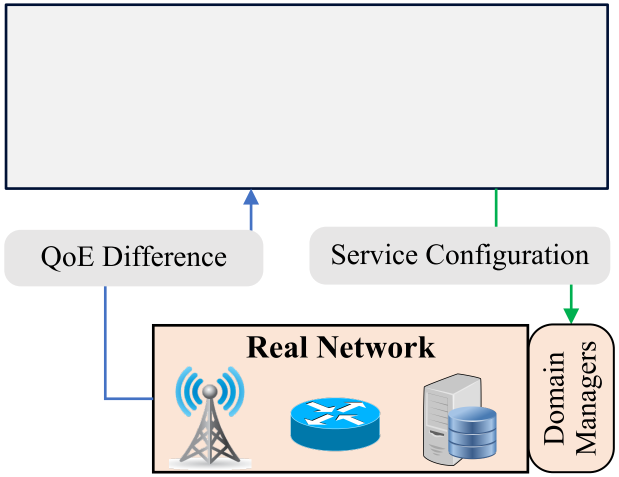
- **objective**: offline train a policy in the augmented simulator
- **problem**: minimize resource usage under requirement of percentile QoE
- **challenge**: unknown correlation between slice QoE and configuration parameters
- **solution**: constraint-aware method and Bayesian learning method



Stage 3

❖ Online Learning

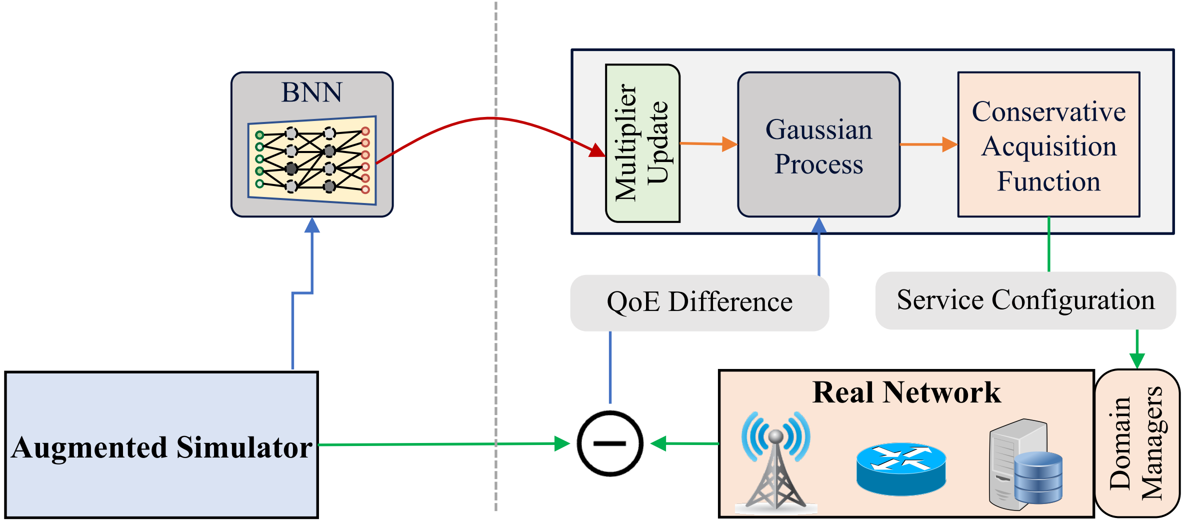
- **objective**: online learn the policy in real-world networks
- **rationale**: resolve the sim-to-real discrepancy eventually
- **problem**: minimize resource usage under requirement of percentile QoE



Stage 3

❖ Online Learning

- **challenge**: assure safety (SLA violation) under limited online transitions
- **solution:**
  - sample-efficient GP model to learn sim-to-real gap only
  - conservative acquisition function with regret bound
  - hybrid multiplier update with both offline and online transitions



System Implementation

Testbed

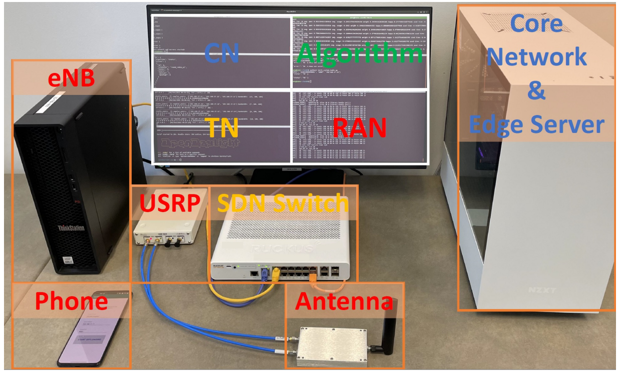
User: OnePlus 9 5G	Agent: PyTorch 1.5 (128x64x32)
RAN: OpenAirInterface w/ USRP (LTE B7)	TN: OpenDayLight w/ SDN switch
CN: OpenAir-CN w/ CUPS	Edge: Dockers collocated with SPGW-U

Virtualization

- RAN: FlexRAN (exclusive PRB assignment) + customized MCS offset
- TN: OpenFlow with configurable bandwidth via “meter”
- CN: isolated SPGW-U container per slice
- EN: docker container via “docker update”

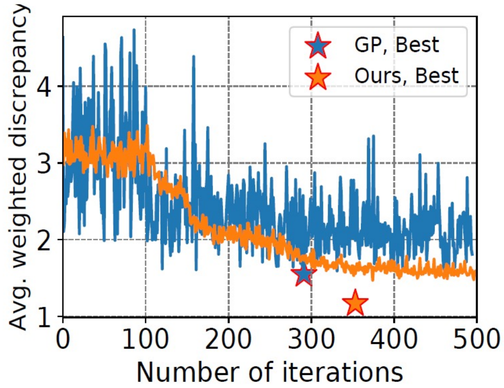
Applications

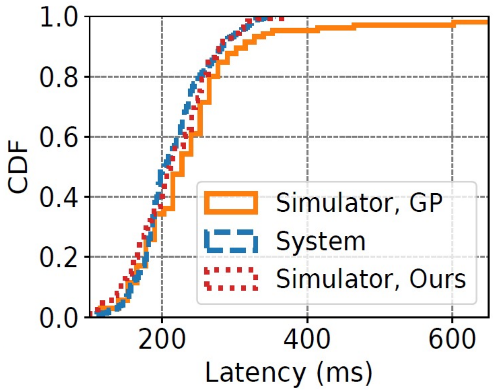
- Video analytics at the edge
- send 540p image to edge server
- the server run ORB to extract features
- requirement: 300ms round-trip latency



Stage 1 Performance

- Atlas reduces sim-to-real discrepancy
  - obtains 81.2% discrepancy reduction under 0.12 parameter distance
  - more than 24.5% reduction than existing Bayesian optimization method (GP)





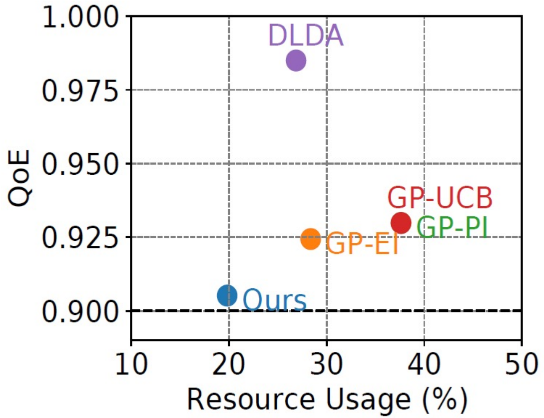
Methods	Sim-to-Real Discrepancy	Parameter distance	Best simulation parameters
Original Simulator	1.38	0	[38.57, 5.0, 9.0, 0.0, 0.0, 0.0, 0.0]
Aug. Simulator, GP	0.31	0.16	[38.57, 1.44, 7.48, 5.07, 9.23, 6.02, 6.47]
Aug. Simulator, Ours	0.26	0.12	[38.76, 0.68, 8.93, 5.03, 8.93, 2.16, 3.10]

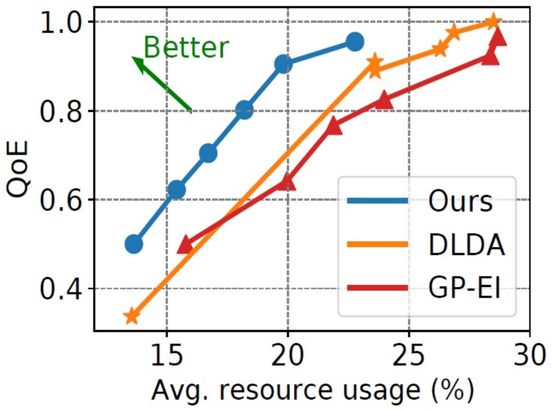
Table 4: Details of offline learning-based simulator

Stage 2 Performance

❖ Atlas trains the policy with reduced resource usage

- obtains up to 47.5% usage reduction than existing solutions
- better Pareto boundary performance



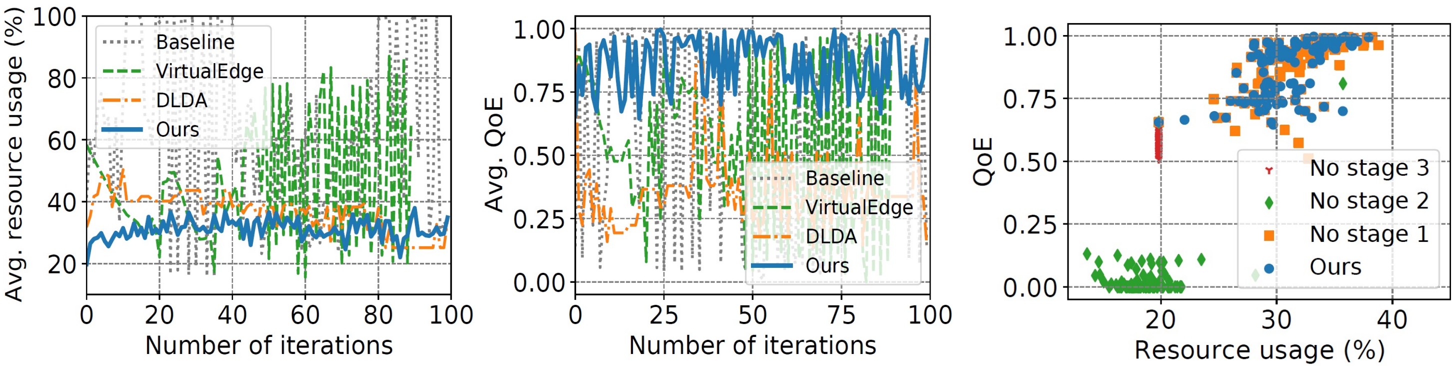


Shi, J., Sha, M. and Peng, X., 2021. Adapting wireless mesh network configuration from simulation to reality via deep learning based domain adaptation. *NSDI 21*.

Stage 3 Performance

❖ Atlas reduces usage and QoE regret

- obtains up to 63.9% reduction on the regret of resource usage
- obtains up to 85.7% reduction on the regret of slice QoE
- results show the necessity of integrating three stages



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Summary

- End-to-end slicing is necessitated to assure diversified performance of slices
- We proposed Atlas, the first integrated offline-online network slicing system that automates the service configuration of individual slices
- Atlas addressed practical challenges of online machine learning, i.e., safety and sample-efficiency, by designing three interrelated stages.
- We prototype Atlas in end-to-end slicing testbed with extensive performance evaluation
- GitHub: https://github.com/int-unl/Atlas.git

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Simulation and Configuration Space

- Simulation Space
  - selected according to its impact on the sim-to-real discrepancy
- Configuration Space
  - selected according to its impact on the performance of slice users
- Atlas can handle more simulation and configuration space

Configuration	Meaning	Range
bandwidth_ul	maximum uplink PRBs	[0, 50]
bandwidth_dl	maximum downlink PRBs	[0, 50]
mcs_offset_ul	uplink MCS offset [24]	[0, 10]
mcs_offset_dl	downlink MCS offset [24]	[0, 10]
backhaul_bw	transport bandwidth (Mbps)	[0, 100]
cpu_ratio	CPU ratio of docker	[0, 1.0]

Table 2: Network configuration space

Parameters	Meaning
baseline_loss	base loss in pathloss model (dBm)
enb_noise_figure	noise by non-ideal transceivers (dBm)
ue_noise_figure	noise by non-ideal transceivers (dBm)
backhaul_bw	additional transport bandwidth (Mbps)
backhaul_delay	additional transport delay (ms)
compute_time	additional server compute time (ms)
loading_time	additional loading time in UE (ms)

Table 3: Simulation parameter space