Mobile Task Offloading Under Unreliable Edge Performance

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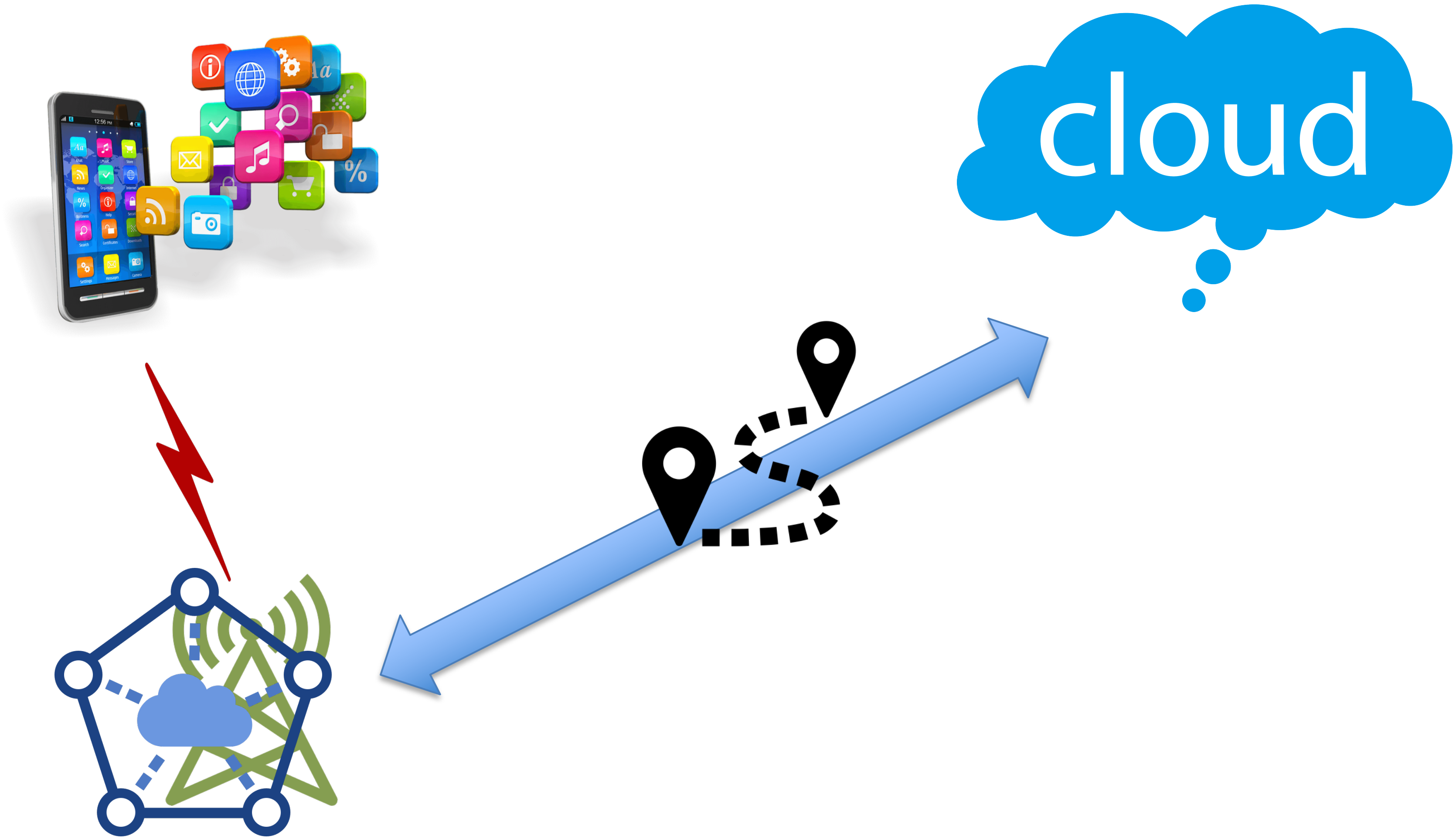
Edge Offloading

What and Why



Edge Offloading

Pros and Cons

Energy savings

Faster processing

- However, edge offloading incurs delay and consumes energy for data transmission
- We need to decide when and which tasks to offload

Edge Offloading

Current Studies

- Optimize latency and energy for offloaded tasks
- Consider single/multiple devices
- However, existing works assume offloaded task will always be processed at edge

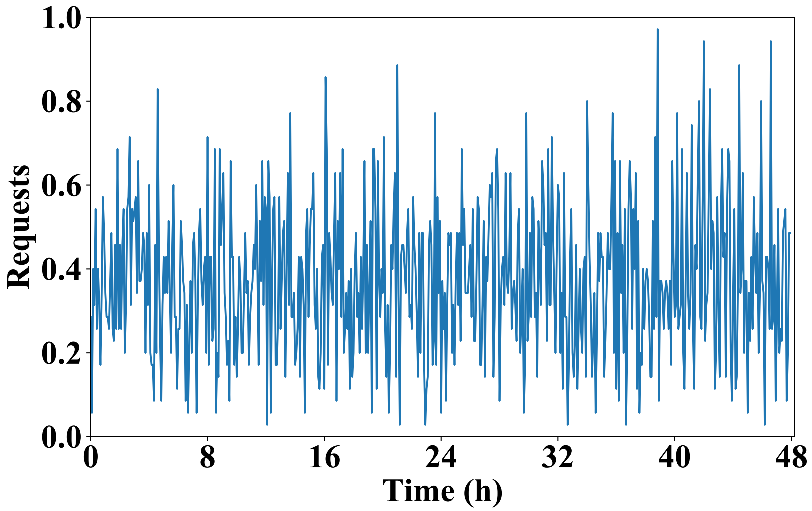
- K. Zhang, Y. Zhu, S. Leng, Y. He, S. Maharjan, andY. Zhang. Deep learning empowered task offloading for mobile edge computing in urban informatics. IEEE Internet of Things Journal, 6(5):7635{7647, 2019.
- Ali Shakarami, Mostafa Ghobaei-Arani, and Ali Shahidinejad. A survey on the computation offloading approaches in mobile edge computing: a machine learning-based perspective. Computer Networks, page 107496, 2020.

Edge Offloading

Challenges

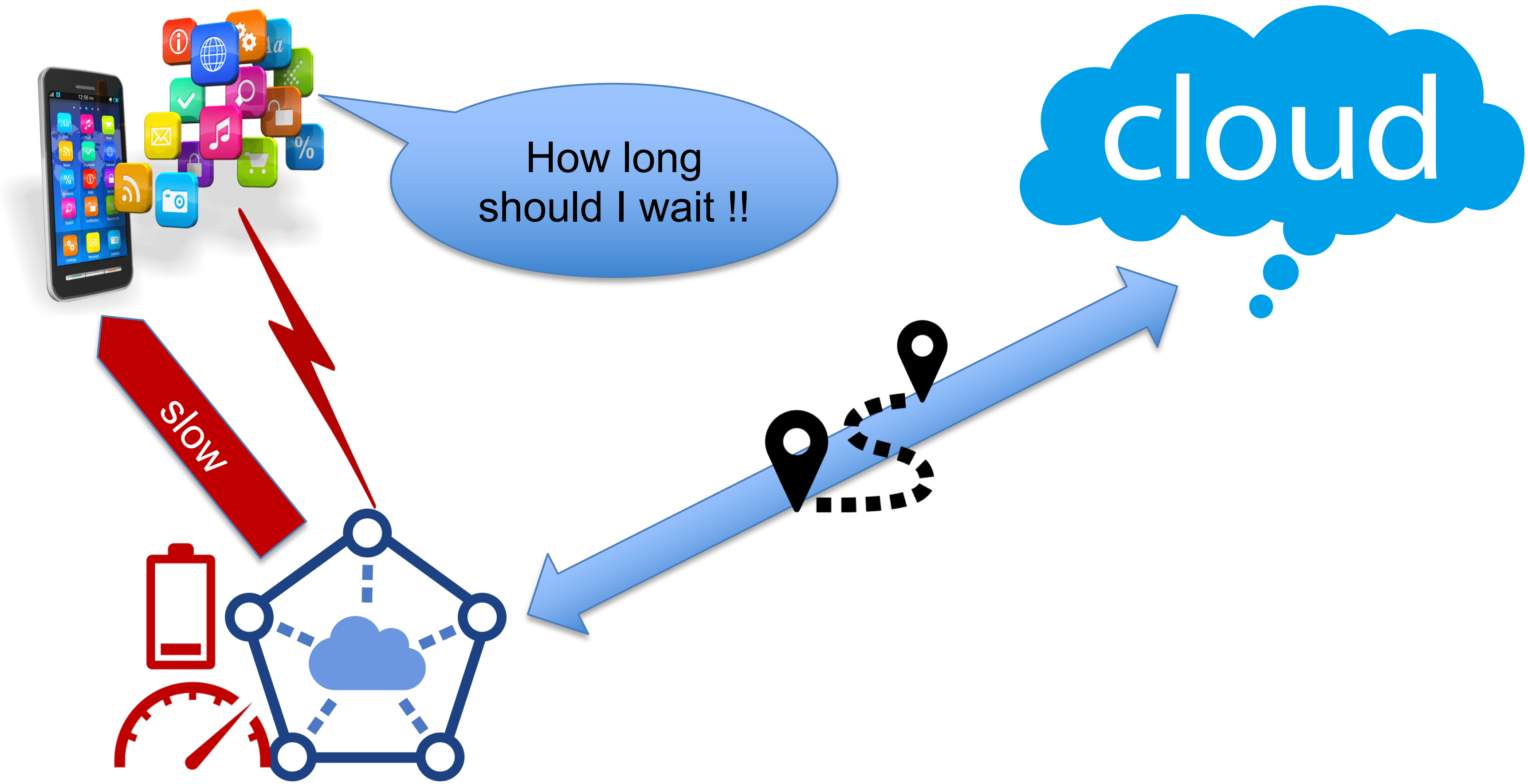
- Intermittent capacity

- Rapidly changing workload



Edge Offloading

Edge Offload to Cloud



Our Approach

- We optimize mobile energy and task completion time
- We consider unreliability in the edge
- We use “learning” to navigate the unknown environment

Objective

OPTO: $\min_{x_k} \sum_k (t_k + w \cdot e_k)$

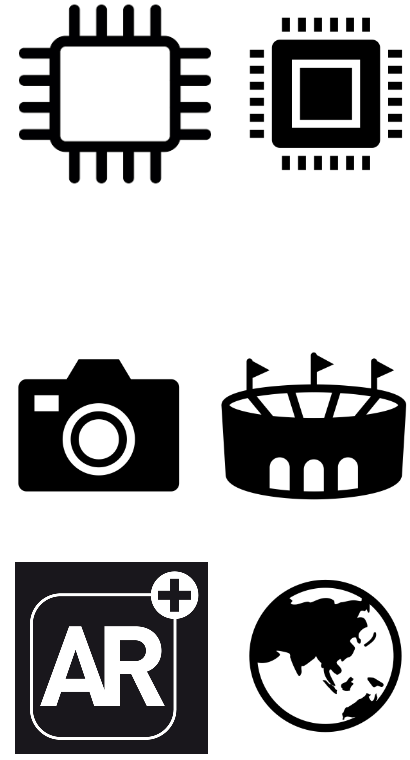
Where,

- t_k is task completion time
- e_k is energy consumption
- w is the weight variable
- x_k is the decision variable

Why Learning?

Model Free Solution

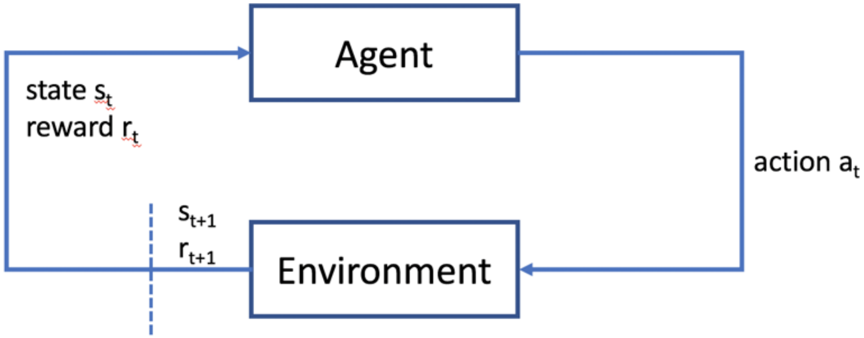
OPTO: $\min_{x_k} \sum_k (t_k + w \cdot e_k)$



- All offloading decisions are tied together
- t_k and e_k are hard to estimate
- Difficult to generalize energy & latency
- Different area may have different resource requirements
- We use MDP with Reinforcement Learning

Reinforcement Learning

Model Free DQN Solution



- No previous knowledge needed
- Q-learning, DQN, DDPG

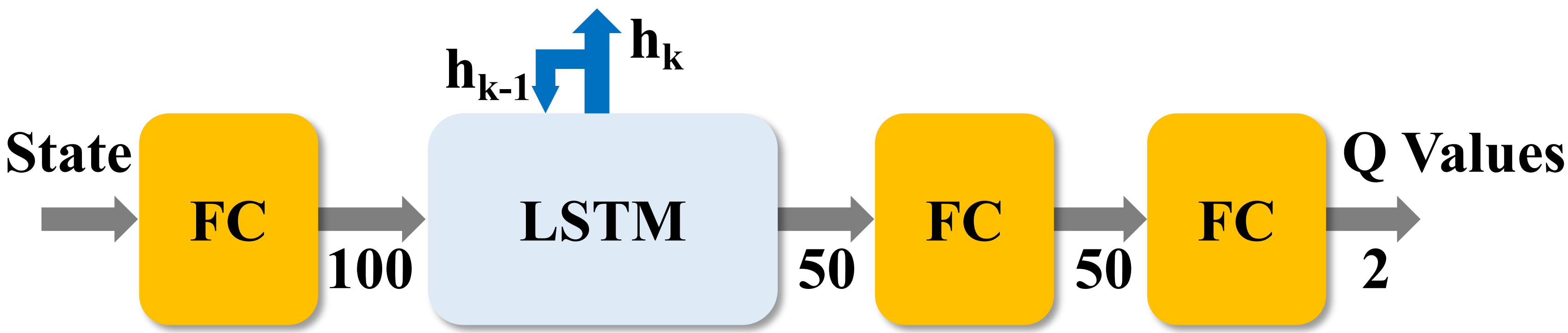
DeepTO

Markov Decision Process

- System State: $s_k = \left(a_k, e_k^b, \mu_k^m, \mu_k^e, u_k\right)$
    - $a_k = Task(data, cpu\ cycle), e_k^b = available\ energy$
    - $\mu_k^m = mobile\ capability,\ \ \mu_k^e = edge\ capability,$
    - $u_k = uplink\ rate$
- Action: $x_k \in \mathrm{A}(s_k) \in [0,1]$
- Reward: $r_k = R(s_k, x_k, s_{k+1})$
- Q-learning poor performance
    - DQN
- User request arrival is not Markovian
    - Long Short-Term Memory (LSTM) to estimate user request and state transition

DeepTO

Network Architecture



Experimental Settings

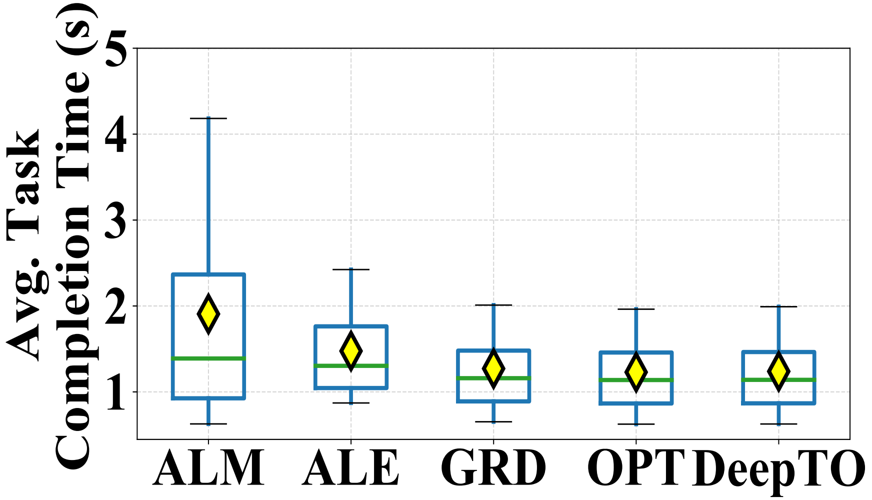
Real World & Synthetic

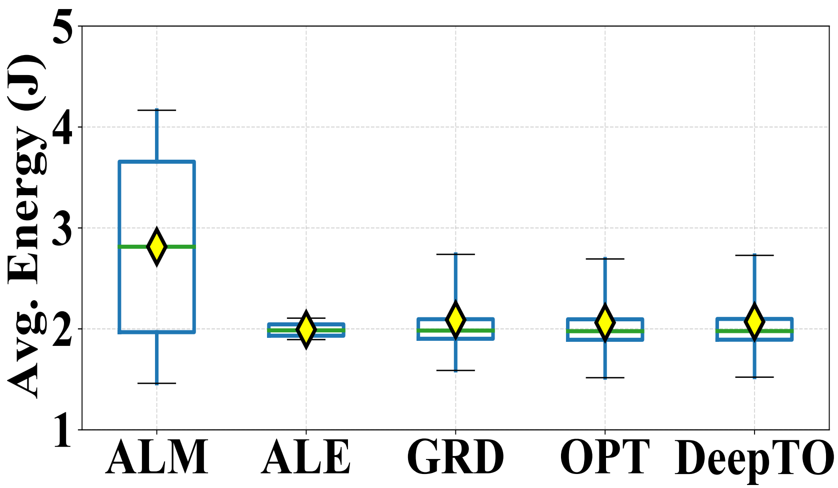
- Edge workload – uber trace
- Edge-to-cloud additional latency – cloud ping test
- Data sizes [500 KB-1 MB] randomly distributed
- CPU cycle 500 M – 2000 M
  - 500 M / 1.5 GHz = 0.33 sec
- Battery capacity 120 J
- Transmission power 500 mW
- Mobile capacity 1.5 GHz [20%-100%]
- Edge and Cloud 3.6 GHz

Results

Comparison of Algorithms

ALM – All Mobile
ALE – All Edge
GRD – Greedy
OPT – Optimum
DeepTo – Our approach

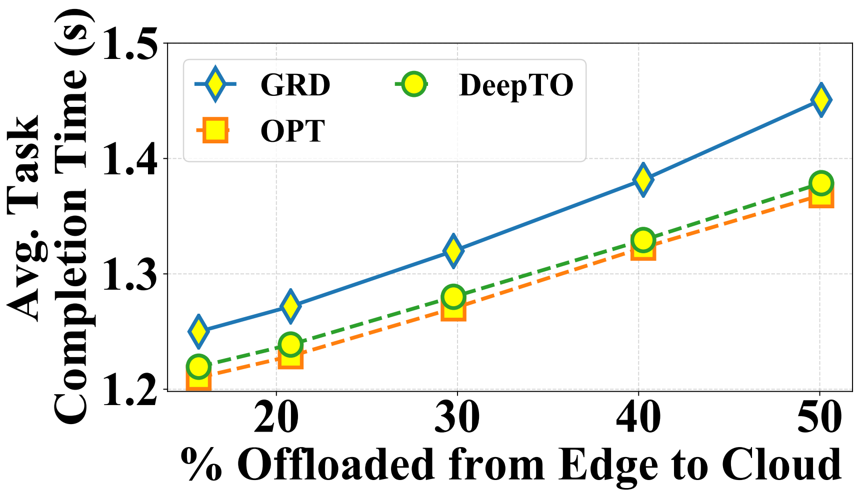


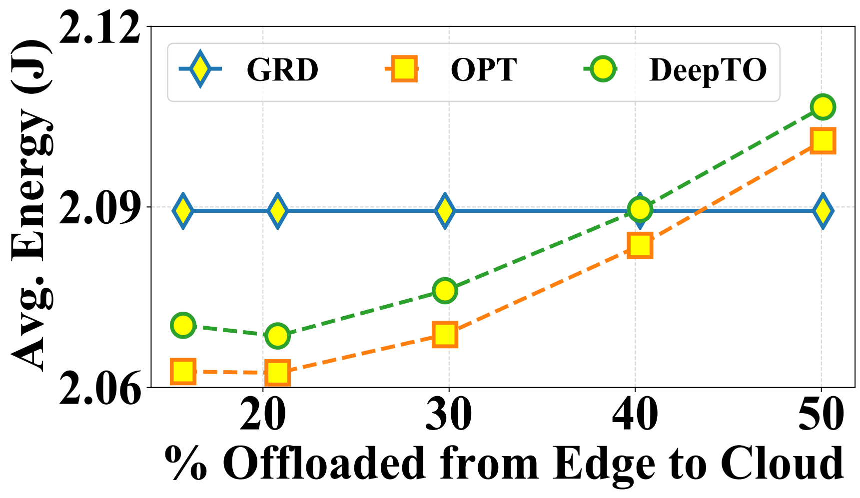


Results

Impact of Offloading from Edge

GRD – Greedy
OPT – Optimum
DeepTo – Our approach





Future Works

- Training time
  - Use federated learning
  - Use pre-trained model
- Use real world mobile user data

Thank you!

Questions?