



# A Semantic-Aware Multiple Access Scheme for Distributed, Dynamic 6G-Based Applications

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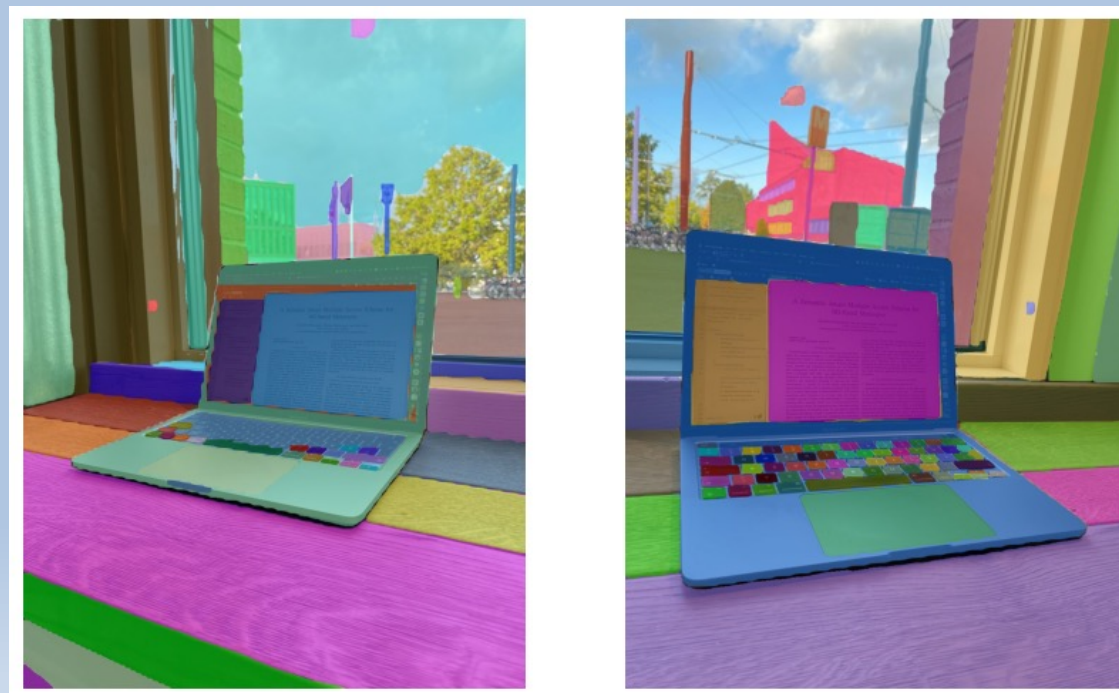
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# Introduction

- ❑ Paradigm Shift in Communication systems
  - ❑ from the traditional **bit-oriented** model, to a **semantic-aware** paradigm, where:
    - ❑ the semantic value of various system components is **quantified** and subsequently **integrated** into the transmission process
    - ❑ Examples: messages, users, and resources
- ❑ Significant **opportunities** for innovative services
  - ❑ particularly in the context of the **6G-based Metaverse**

# Introduction

- ❑ Various tools for capturing meaningful understanding from user data
  - ❑ Examples: Segment Anything Model (SAM), FastSAM
- ❑ Sample scenario: a group of nearby users engaged in a holographic meeting with a **partially shared background and environmental sounds.**



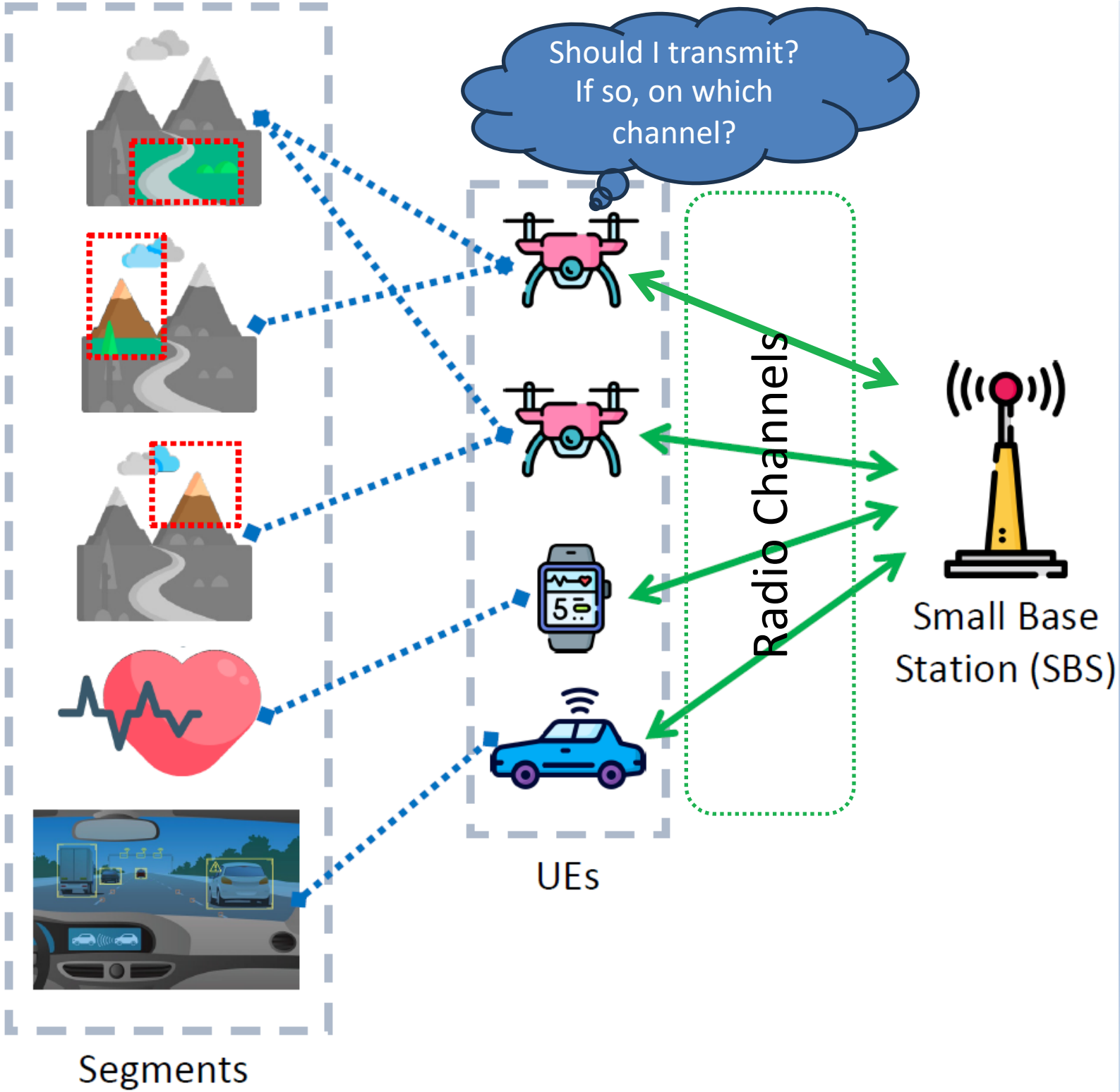
# Introduction

- ❑ Network-wide semantic awareness:
  - ❑ The incorporation of semantics into **decision-making processes** at various network layers,
  - ❑ including Medium Access Control (MAC) protocols
  
- ❑ **Key idea:** Utilization of limited radio resources by eliminating redundant data transmission
  
- ❑ State of the art:
  - ❑ dedicating a portion of resources to **transmit shared information** among users (e.g., MDMA protocol [7])
  - ❑ **joint semantic encoding** of data from multiple users
  - ❑ Unsuitable for **distributed** 6G-based applications

# Our Focus

- ❑ **A novel formulation** for the multiple-access problem
  - ❑ optimize the trade-off between utilization and fairness
- ❑ Semantic-Aware Multi-Agent Double and Dueling Deep Q-Learning (SAMA-D3QL) method
  - ❑ Semantic-Aware: to be explained later
  - ❑ Multi-agent: based on VDN architecture [20]
  - ❑ Double and Dueling Deep Q-Learning (our previous works [16-19])

# System model



# Problem Formulation

$$\max_{\mathbf{M}} \sum_{t \in \{0, \dots, \mathcal{T}\}} \mathbf{U}_{\alpha}(\mathbb{X}^t) \quad \text{s.t.}$$

**Maximizing  $\alpha$ -Fairness among user throughputs**

$$\mathbf{U}_{\alpha}(\mathbb{X}^t) = \begin{cases} \sum_{i \in \mathbb{N}} \log(x_i^t) & \text{if } \alpha = 1 \\ (1 - \alpha)^{-1} \cdot \sum_{i \in \mathbb{N}} (x_i^t)^{1-\alpha} & \text{if } \alpha \neq 1 \end{cases}$$

$$\sum_{c \in \{0, \dots, \mathcal{C}\}} m_{i,c}^t \leq 1 \quad \text{UE } i \text{ sending on channel } c \text{ at time slot } t$$

**Transmission constraints**

$$z_i^t = \sum_{c \in \{0, \dots, \mathcal{C}\}} m_{i,c}^t \cdot \prod_{j \neq i} (1 - m_{j,c}^t)$$

$$x_i^t = \dot{x}_i^t + \ddot{x}_i^t \quad \star$$

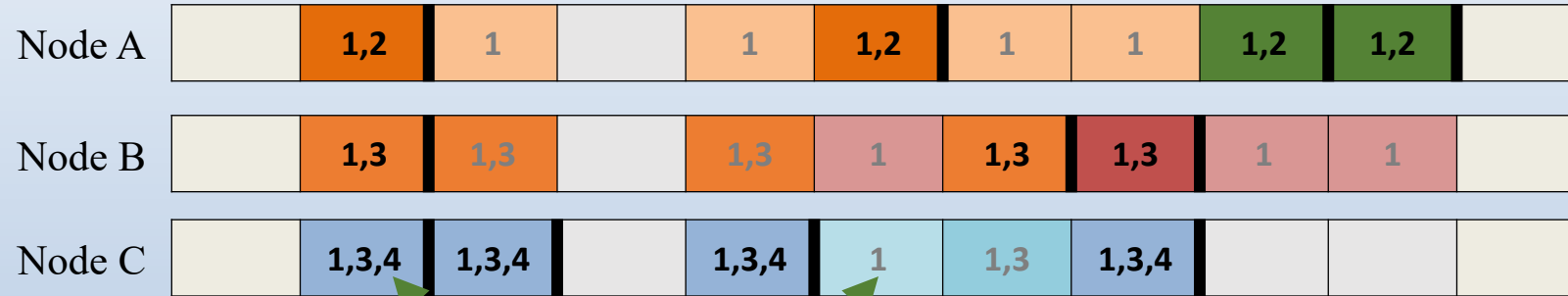
**To be explained...**





# Sample Scenario

(a) Successful transmissions of nodes, with segment numbers for each node



**Self Throughput**

**Assisted Throughput**

★  $x_i^t = \dot{x}_i^t + \ddot{x}_i^t$

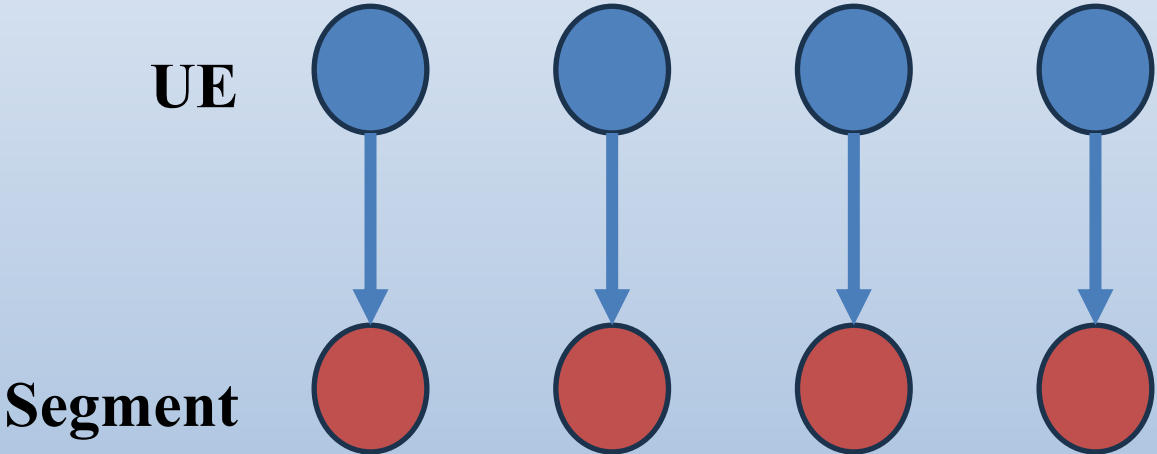
$$\dot{x}_i^t = \Omega_i^t \cdot \sum_{k,t \in \mathbb{K}, \mathbb{W}^t} a_{i,k}^t \cdot z_i^t$$

$$\ddot{x}_i^t = \Omega_i^t \cdot \sum_{k,t \in \mathbb{K}, \mathbb{W}^t} \left( a_{i,k}^t \cdot (1 - z_i^t) \cdot y_k^{t,-i} \right)$$

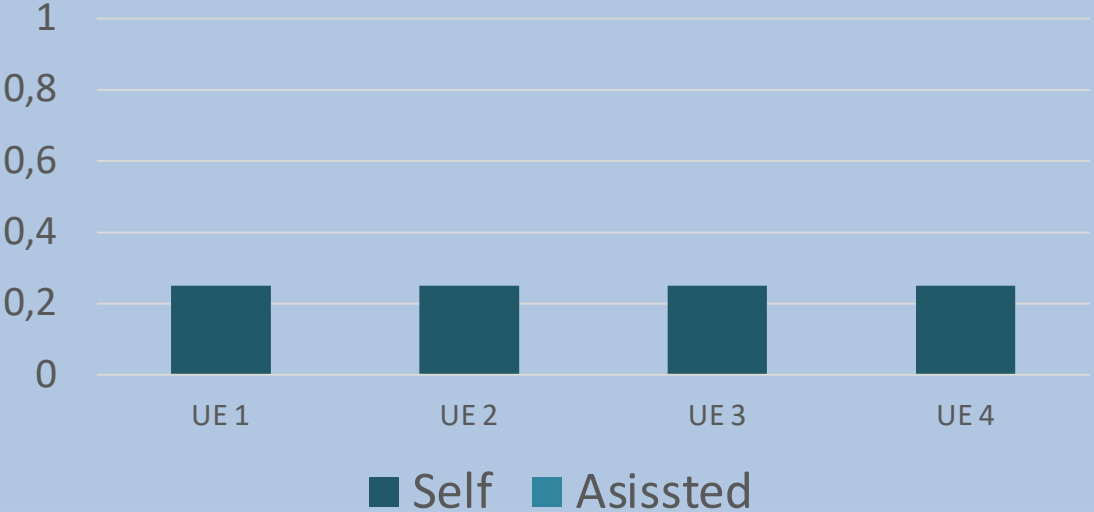
Here,  $y_k^{t,-i} = \min \left\{ 1, \sum_{j \in \mathbb{N} \setminus \{i\}} a_{j,k}^t \cdot z_j^t \right\}$ .

# Optimal Solutions

Bit-Oriented Example (with any  $\alpha$ )

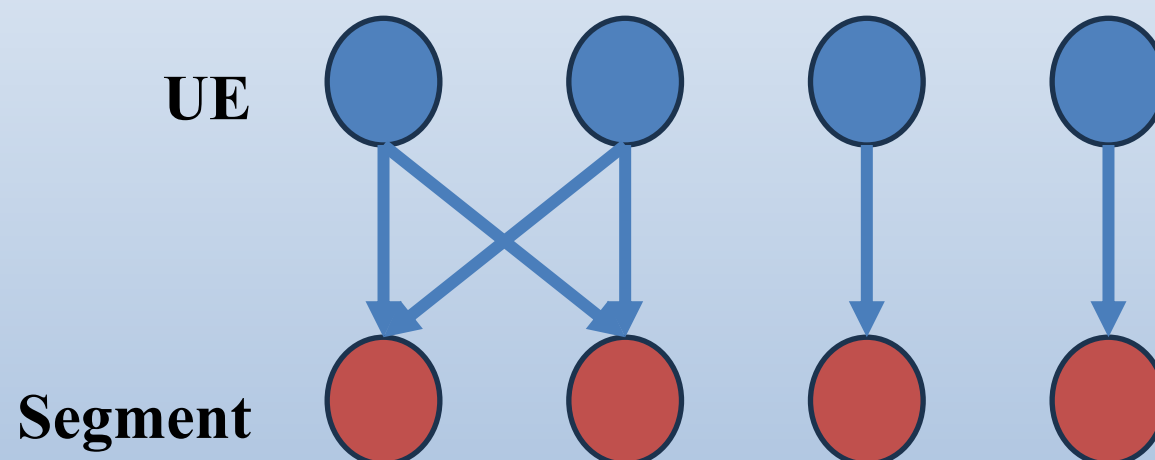


Optimal User Throughputs

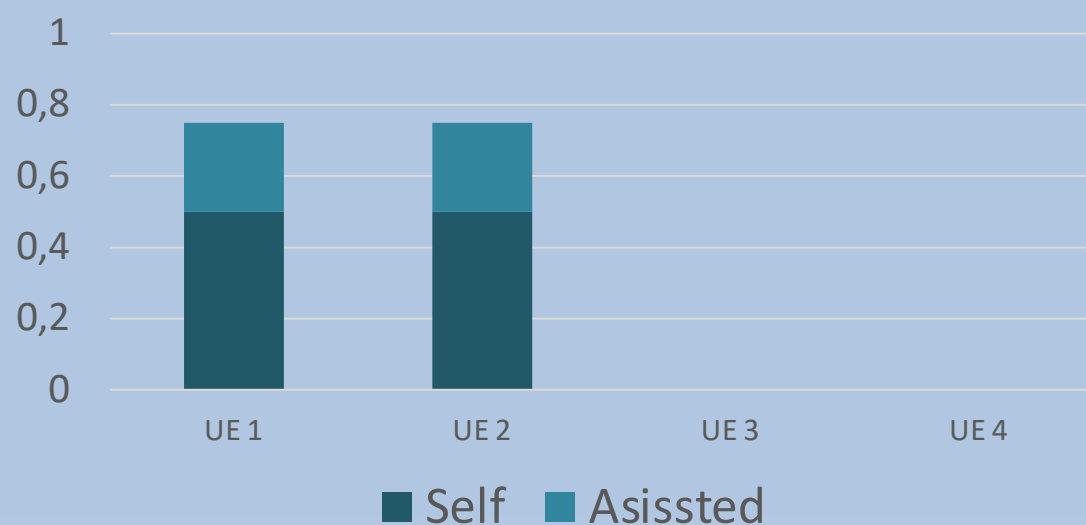


# Optimal Solutions

Semantic-Aware Example ( $\alpha = 0$ , No Fairness)

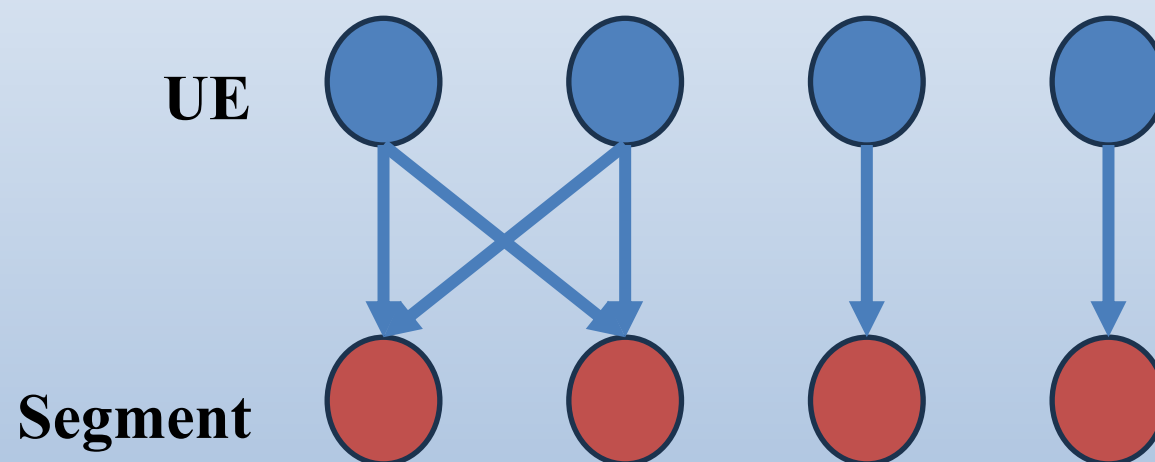


Optimal User Throughputs

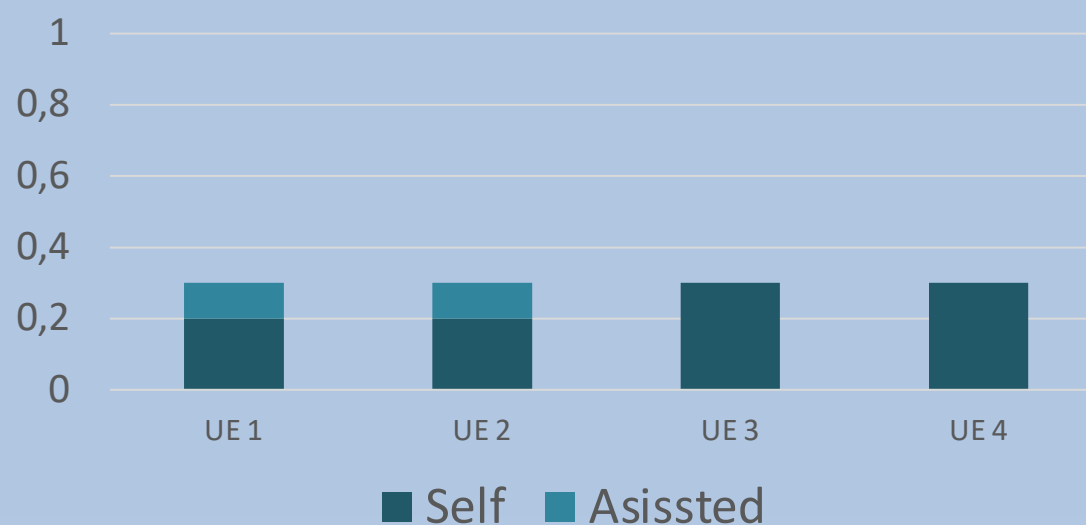


# Optimal Solutions

Semantic-Aware Example ( $\alpha = \infty$ , Only Fairness)



Optimal User Throughputs



# Why MADRL?

- ❑ Optimization problem is non-linear and challenging
  - ❑ Number of UEs
  - ❑ Number of channels
  - ❑ Number of segments
- ❑ No access to the information of future time slots
- ❑ UEs are unaware of each other's decisions or associations
- ❑ Dynamic associations (future work)

# SAMA-D3QL

State space of UE  $i$  ( $= s_i^t$ )

$\bar{v}_i^{t-W}$	$\dot{o}_i^{t-W}$	$\ddot{o}_i^{t-W}$	$\rho_i^{t-W}$
...			
$\bar{v}_i^{t-1}$	$\dot{o}_i^{t-1}$	$\ddot{o}_i^{t-1}$	$\rho_i^{t-1}$
$\bar{v}_i^t$	$\dot{o}_i^t$	$\ddot{o}_i^t$	$\rho_i^t$

} History Size (W)

Normalized delay to  
last successful transmission (D2LT)  
metric [14]

Observation  $\{B, I, S, C\}$

Assisted transmission

- Action:
- Transmission on channel  $c$
  - Sensing channel  $c$

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**Algorithm 1: SAMA-D3QL**

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**Input:**  $\mathcal{T}$ ,  $\epsilon'$ , and  $\tilde{\epsilon}$

1  $\mathcal{W} \leftarrow \mathbf{0}$ ,  $\mathcal{W}^- \leftarrow \mathbf{0}$ ,  $\epsilon \leftarrow 1$ ,  $memory \leftarrow \{\}$

2 **foreach**  $t$  in  $\{0, \dots, \mathcal{T}\}$  **do**

3     ★ Decentralized Execution (4-15)

4     **foreach**  $i$  in  $\mathbb{N}$  **do**

5          $\zeta \leftarrow$  generate a random number from  $[0 : 1]$

6         **if**  $\zeta > \epsilon$  **then** Local observation

7              $(\phi, c) \leftarrow \operatorname{argmax}_{\rho \in \rho_i} Q(s_i^t, \rho, \mathcal{W}_i)$

8         **else**

9             select a random  $(\phi, c)$  from  $\rho_i$

10         **if**  $\phi = 1$  **then**

11             transmit packet on channel  $c$

12         **else**

13             sense channel  $c$

14             receive  $\dot{o}_i^t$  and  $\ddot{o}_i^t$  from the SBS

15             construct  $s_i^{t+1}$

16     ★ Centralized Training (17-20)

17     calculate  $\mathbf{R}^t$  according to (7)

18      $memory \leftarrow \{\mathbf{R}^t\} \cup \{(s_i^t, (\phi, c), s_i^{t+1}) \mid i \in \mathbb{N}\}$

19     choose a batch of samples from  $memory$

20     train the agent according to (9)

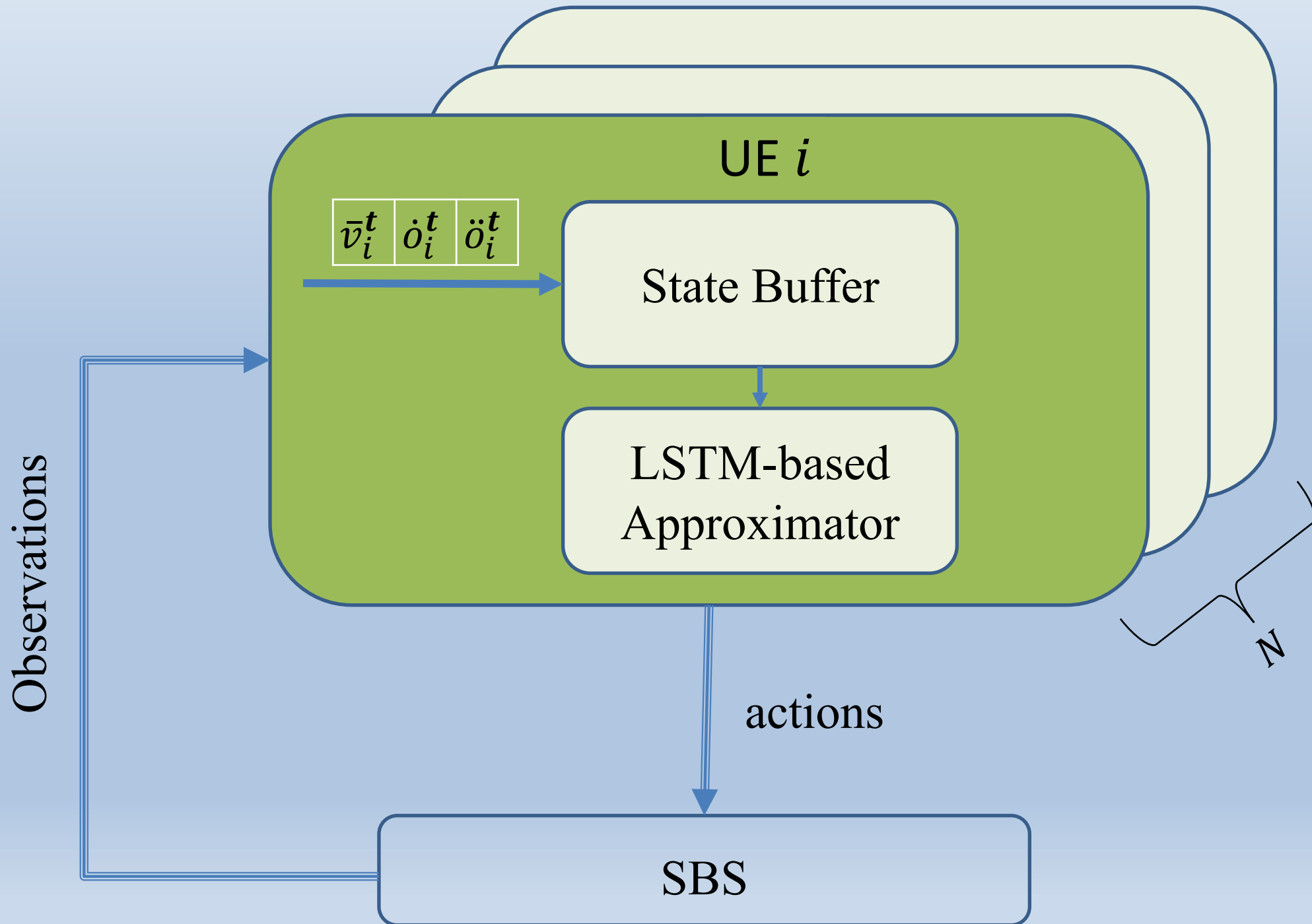
21     **if**  $\epsilon > \tilde{\epsilon}$  **then**

22          $\epsilon \leftarrow \epsilon \cdot \epsilon'$

$$\mathbf{R}^t = \frac{1}{\mathcal{N}} \cdot \sum_{i \in \mathbb{N}} \bar{v}_i^t \cdot \mathbb{1}(\dot{o}_i^t = S) \quad (7)$$

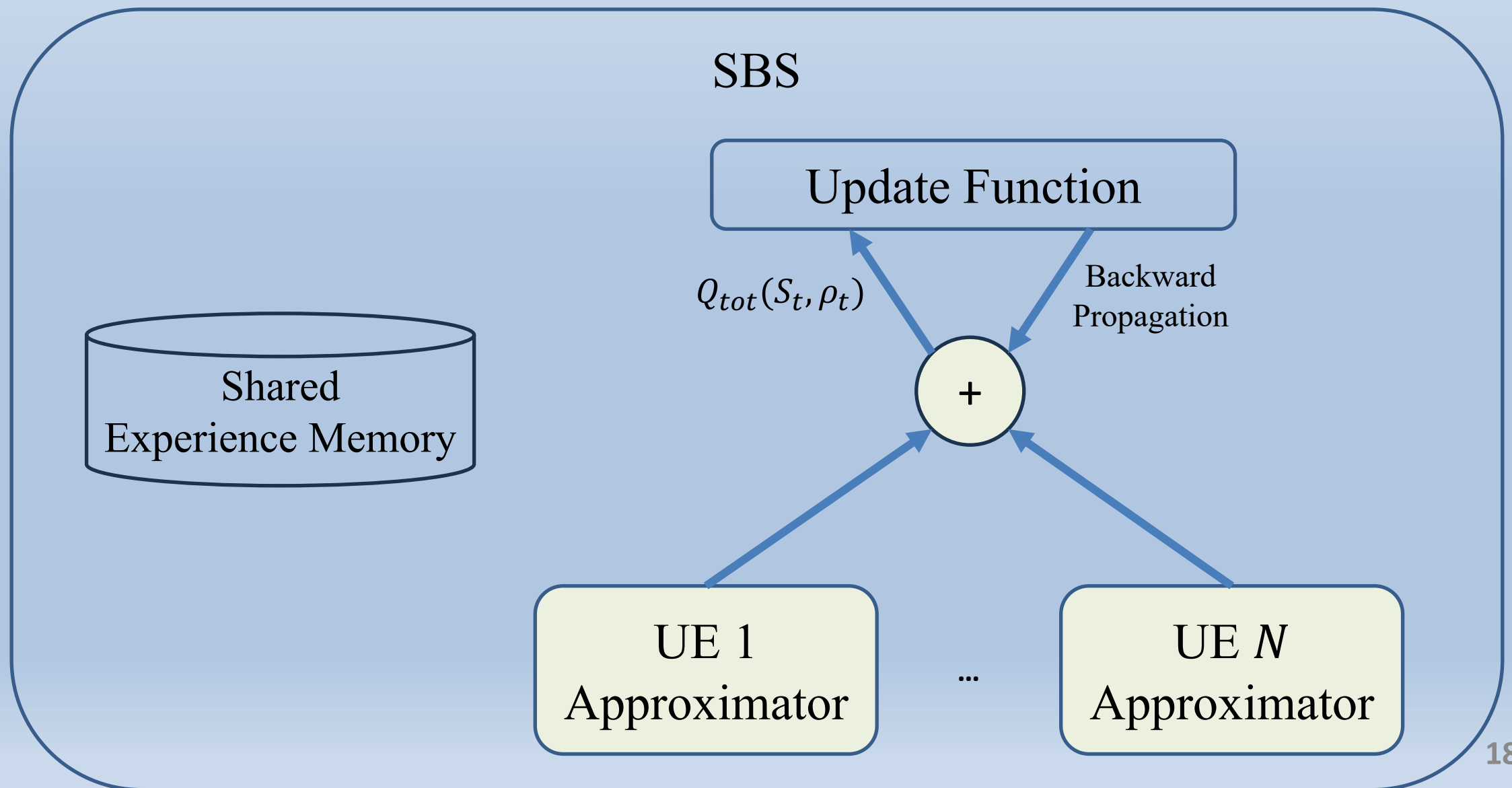
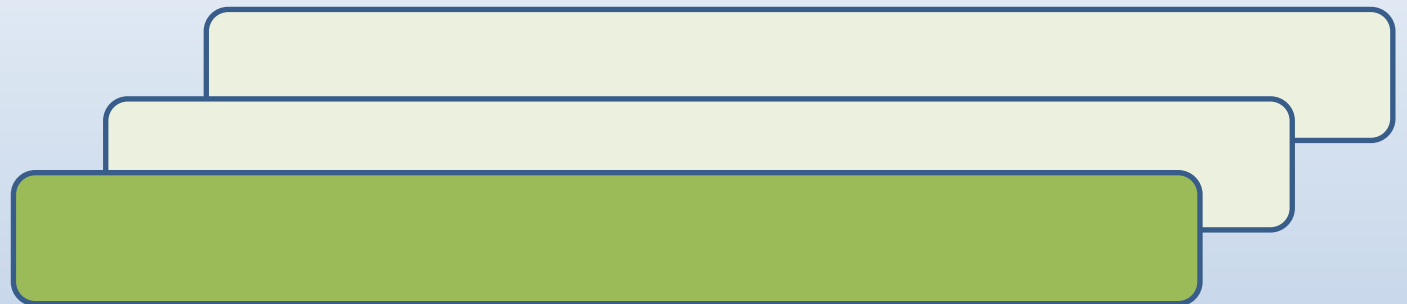
# SAMA-D3QL

## Decentralized Execution



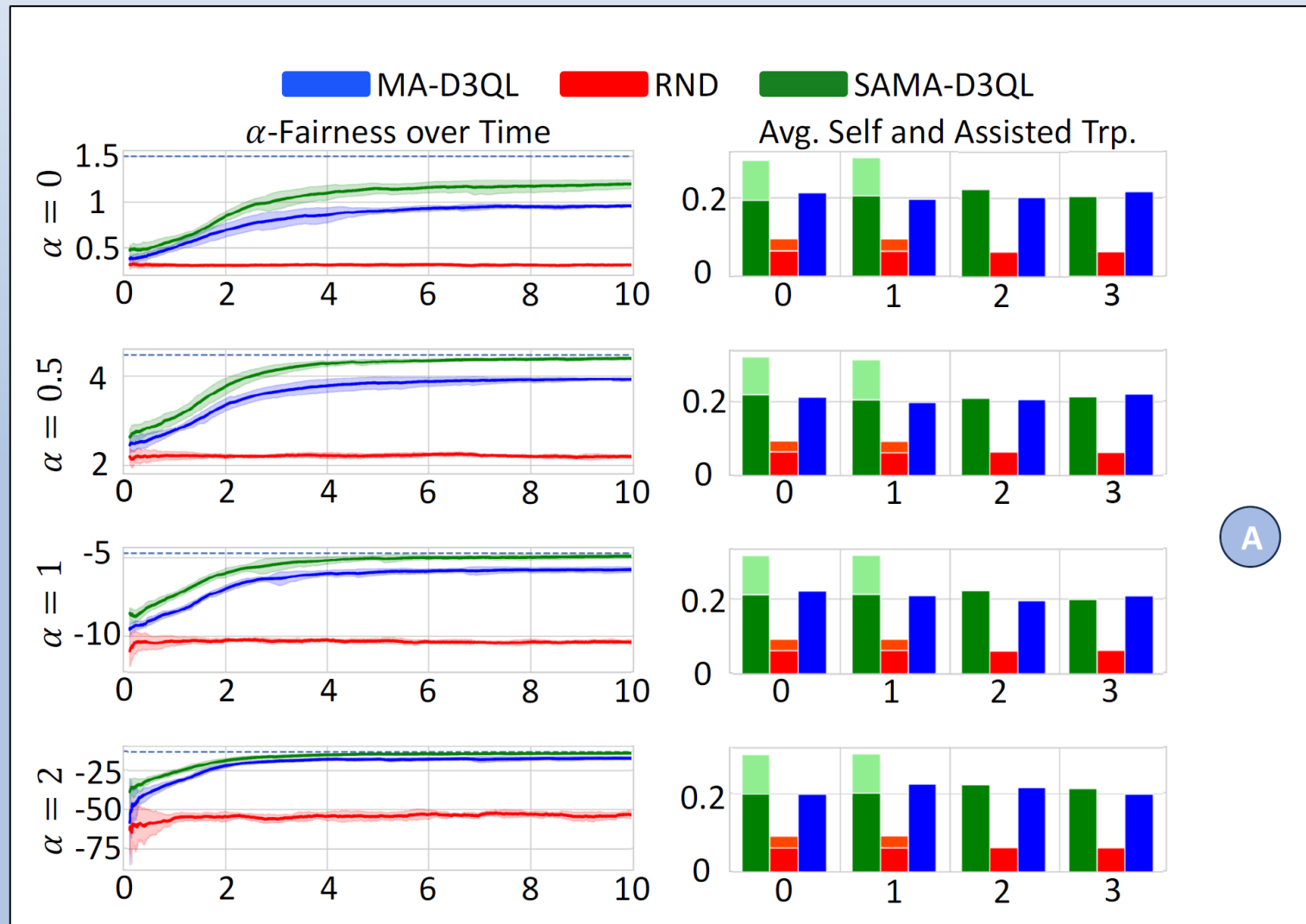
# SAMA-D3QL

## Centralized Training

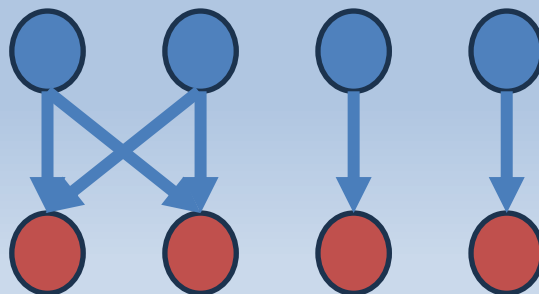


# Results

## Single Channel Setting

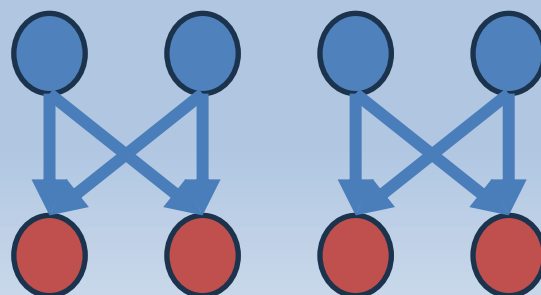
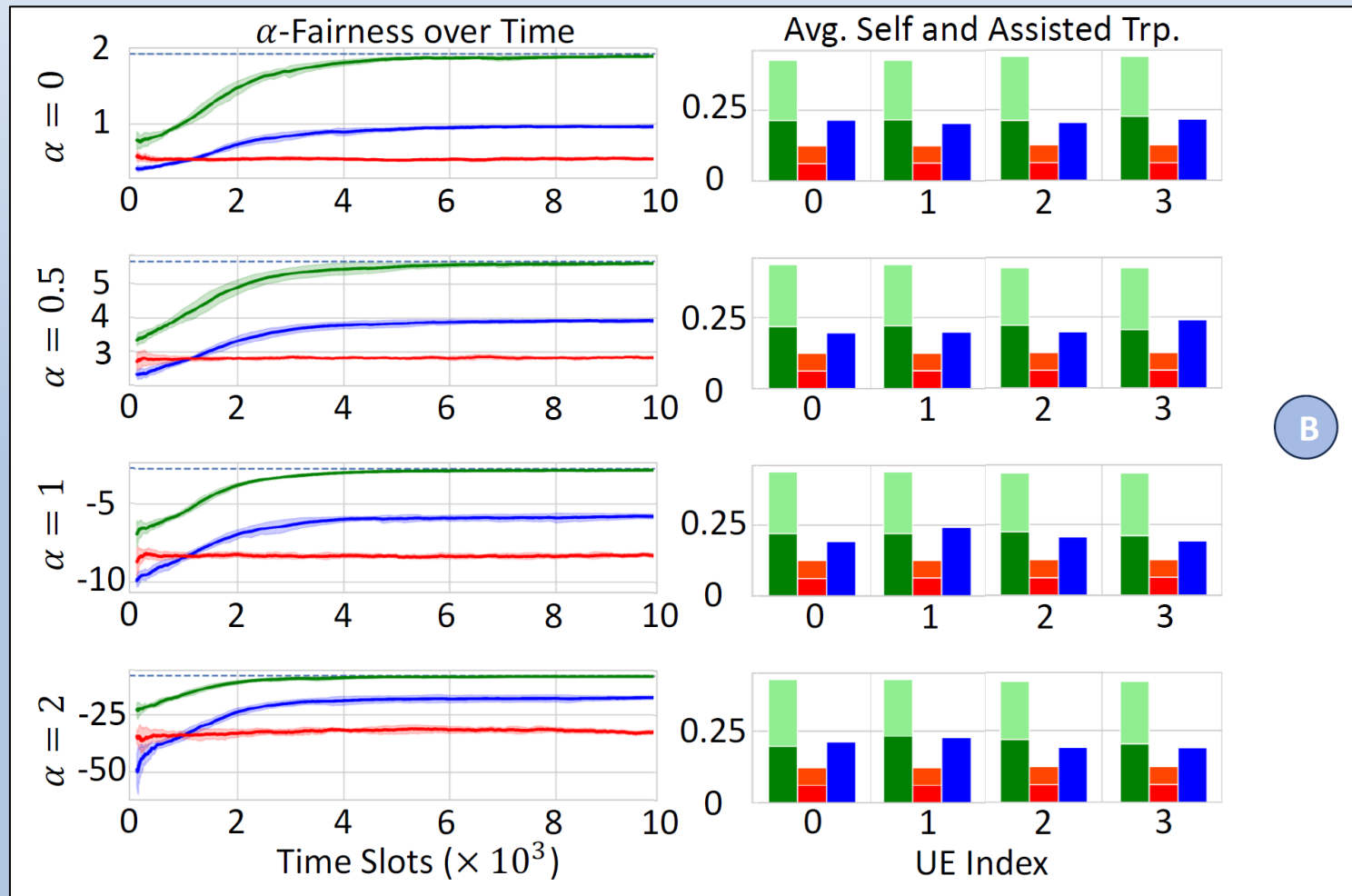


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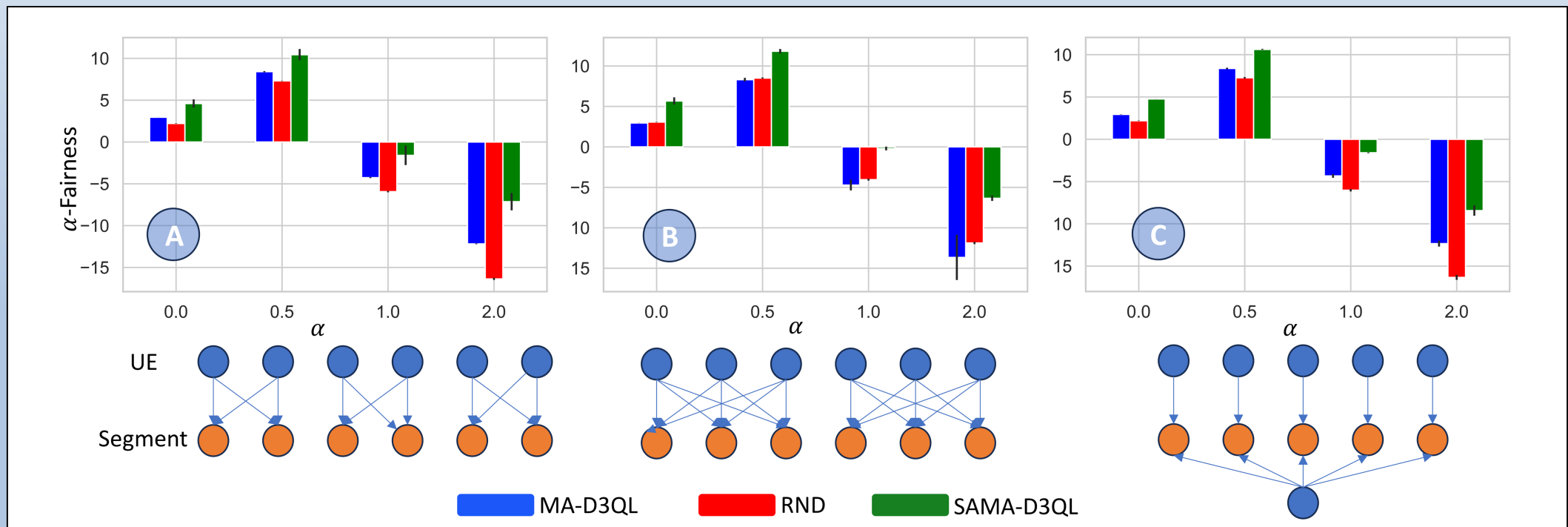
# Results

## Single Channel Setting



# Results

## Multi Channel Setting



# Conclusion

- ❑ Addressing the challenges of multiple access in distributed and dynamic 6G-based applications
- ❑ A structured and adaptable formal framework that leverages the semantic relationships between users
- ❑ SAMA-D3QL algorithm with decentralized decision-making
- ❑ For future: more realistic and practical scenarios
  - ❑ varying and non-binary UE-segment associations
  - ❑ variable packet-size scenarios
  - ❑ more advanced MADRL algorithms
  - ❑ Evaluate in real-world settings

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