LoRAT: Low Rank Adaptation and Transfer for Multi-environment Channel Estimations

Qi Wang∗, **Xubo Li**∗, Yong Xiao∗†‡
∗School of Elect. Inform. & Commun., Huazhong Univ. of Sci. & Tech., Wuhan, China
†Peng Cheng Laboratory, Shenzhen, China
‡Pazhou Laboratory (Huangpu), Guangzhou, China

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Outline

- Background and Motivation
- System Model
- LoRAT Architecture
- Experiments and Simulation Results
- Conclusion

Background and Motivation

Autonomous vehicles

E-healthcare

VR/AR

- Accurate channel estimation is a foundational requirement for B5G and 6G applications.

Background and Motivation

Fig. An environmental layout

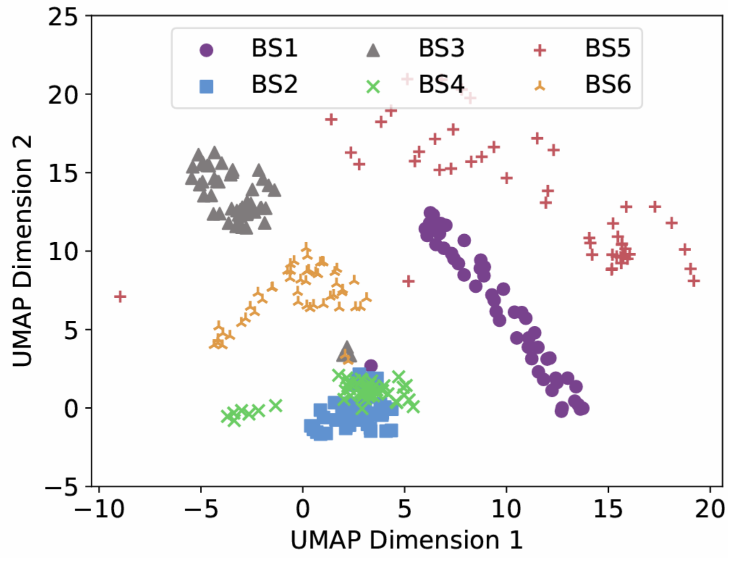


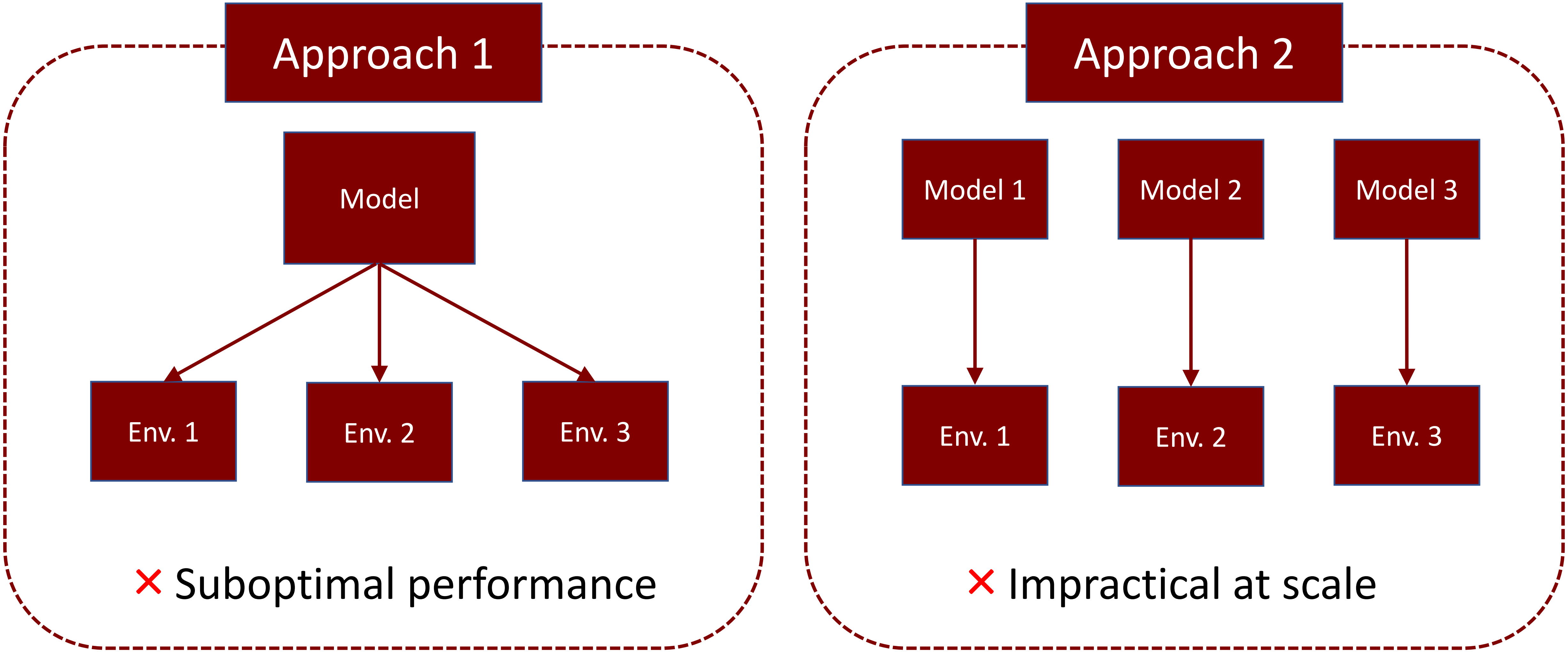
Fig. CSI data distribution

■ The channel state information (CSI) exhibits distinct statistical distribution characteristics across different environments.

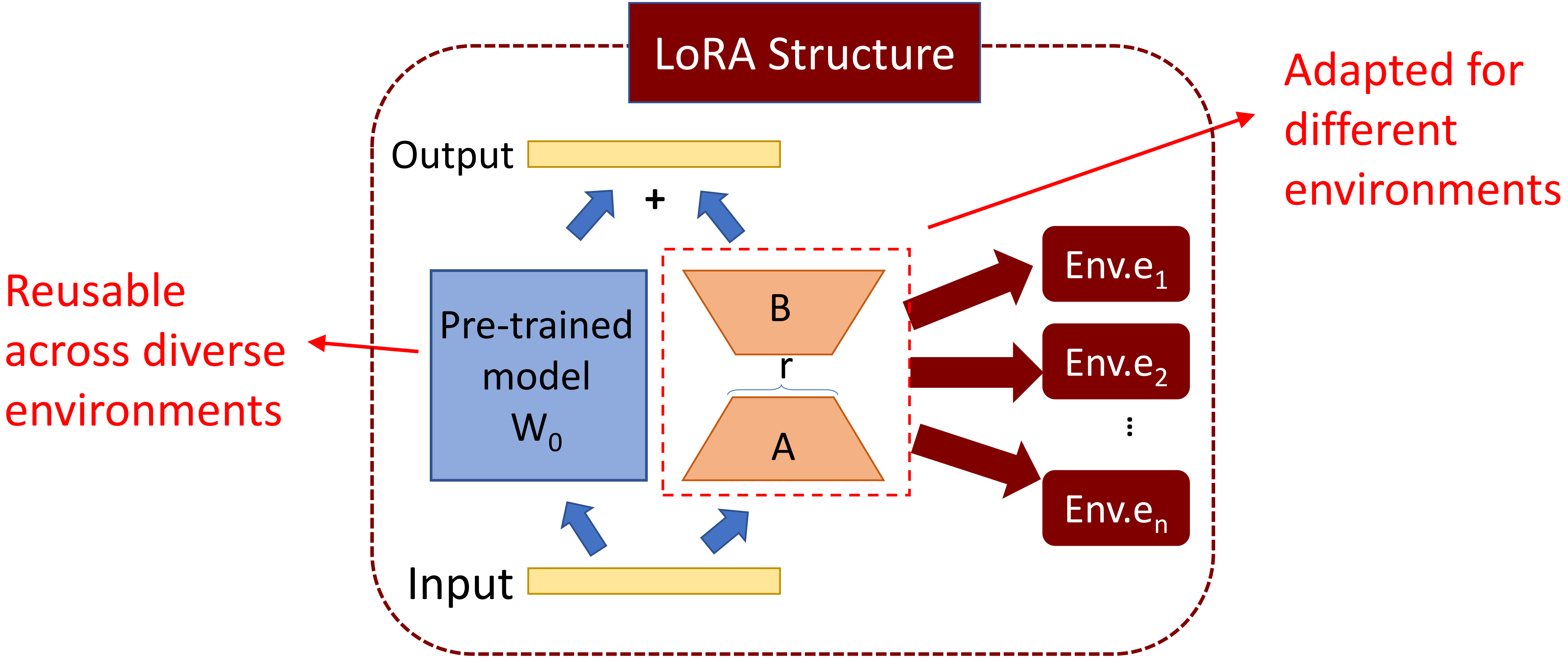
■ Challenges

- Traditional methods often fail to capture the channel dynamics in complex scenarios.
- Deep learning methods is computationally expensive and lacks generalizability.

Background and Motivation

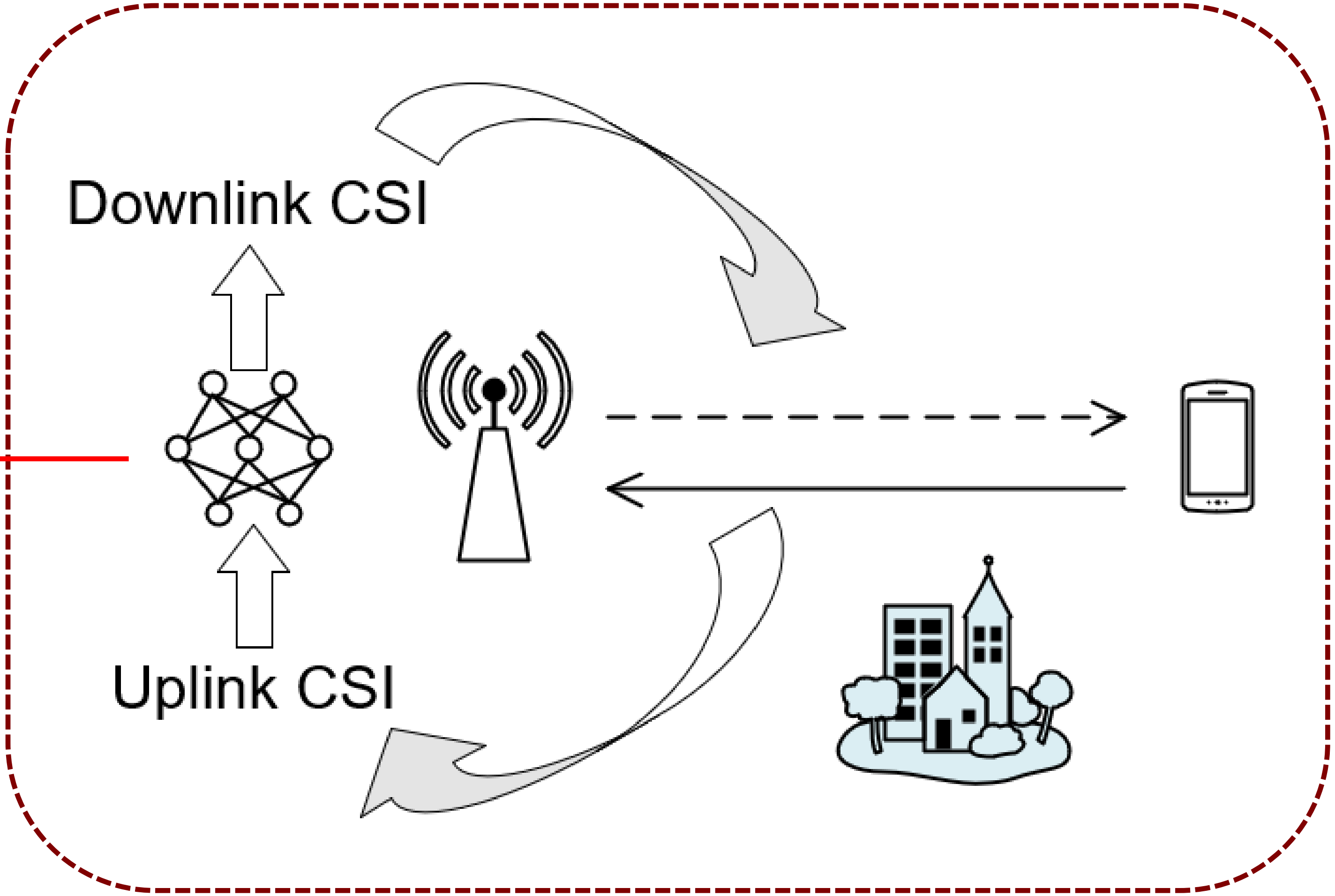


Background and Motivation



Background and Motivation

Uplink-to-downlink mapping



Background and Motivation

- Key Contribution

  - **Proposes LoRAT**: A novel framework for efficient multi-environment CSI estimation without requiring labeled downlink data in new environments.
  - **Data-to-model mapping**: Learns to predict environment-specific model adaptations using only unlabeled uplink CSI, eliminating the need for costly retraining.
  - **Low-rank adaptation**: Uses a shared foundation model with lightweight, low-rank updates to capture environment-specific features, reducing computational and communication overhead.
  - **Scalable for wireless foundation models**: Enables rapid deployment across diverse environments, making it ideal for B5G/6G intelligent networks.

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System Model

- In environment e_i , the received signal at subcarrier k is

$$\mathbf{Y}_{e_i}[k] = \mathbf{H}_{e_i}[k]\mathbf{X}[k] + \mathbf{N}_{e_i}[k]$$

where H is complex channel matrix modeled as a sum over propagation paths:

$$\mathbf{H}_{e_i}[k] = \sum_{p \in \mathcal{P}_{e_i}} a_{e_i,p} e^{\frac{-j2\pi f_k d_{e_i,p}}{c} + j\phi_{e_i,p}},$$

System Model

- Optimization Objective

Model parameter

Environment-specific distribution

$$
\begin{aligned}
\min_{\boldsymbol{\omega}_{e_j}=\mathcal{T}(\boldsymbol{\omega}_S)} \quad & \mathcal{L}_{e_j}(\boldsymbol{\omega}_{e_j}) = \mathbb{E}_{h_{e_j,n}\sim\Psi_{e_j}}\left[\ell(\boldsymbol{\omega}_{e_j}; h_{e_j,n})\right], \\
\text{s.t.} \quad & \hat{h}^{\mathrm{dl}}_{e_j,n} = f_{\boldsymbol{\omega}_{e_j}}(h^{\mathrm{ul}}_{e_j,n}),
\end{aligned}
$$

Neural network

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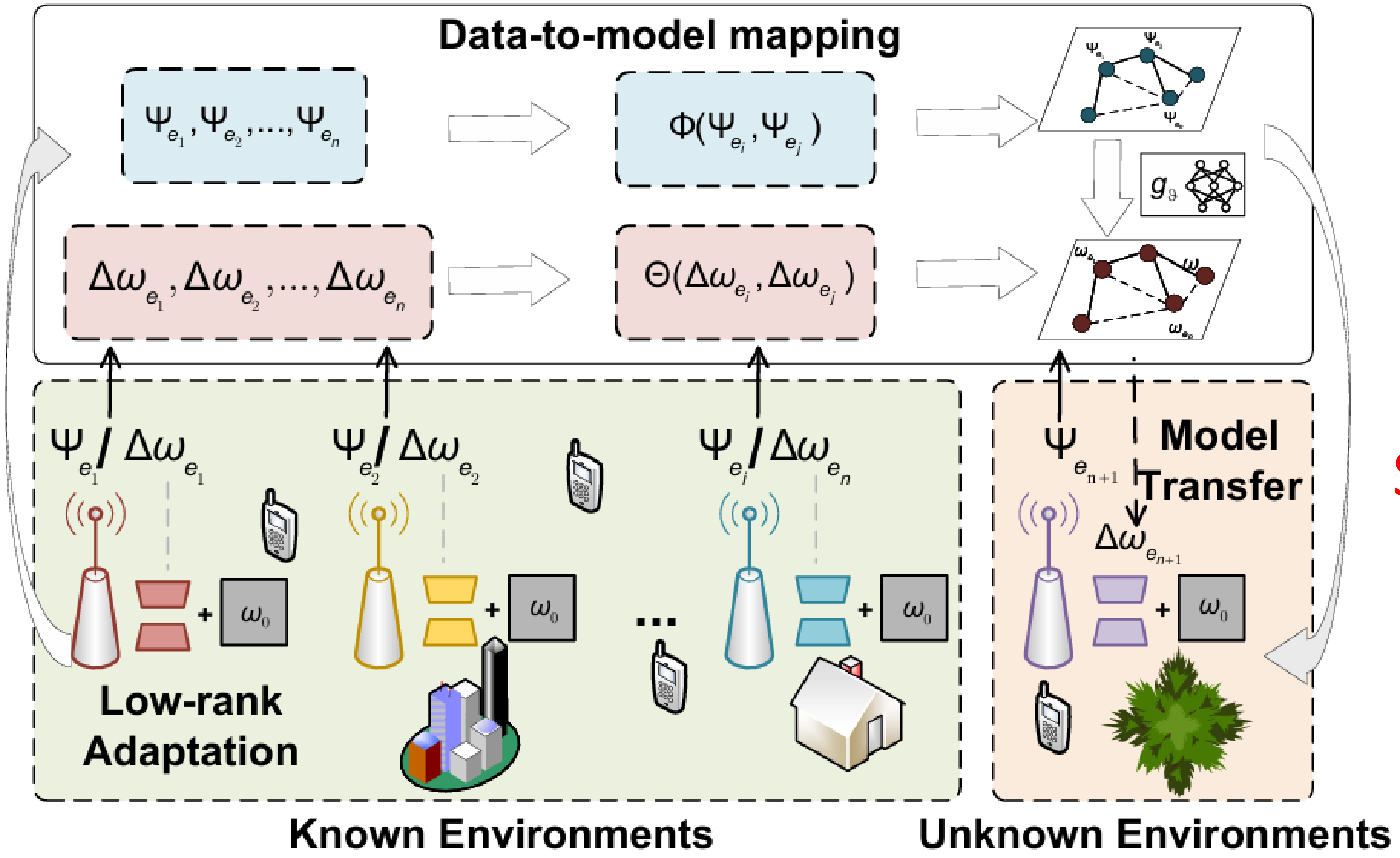
LoRAT Architecture

Step 2

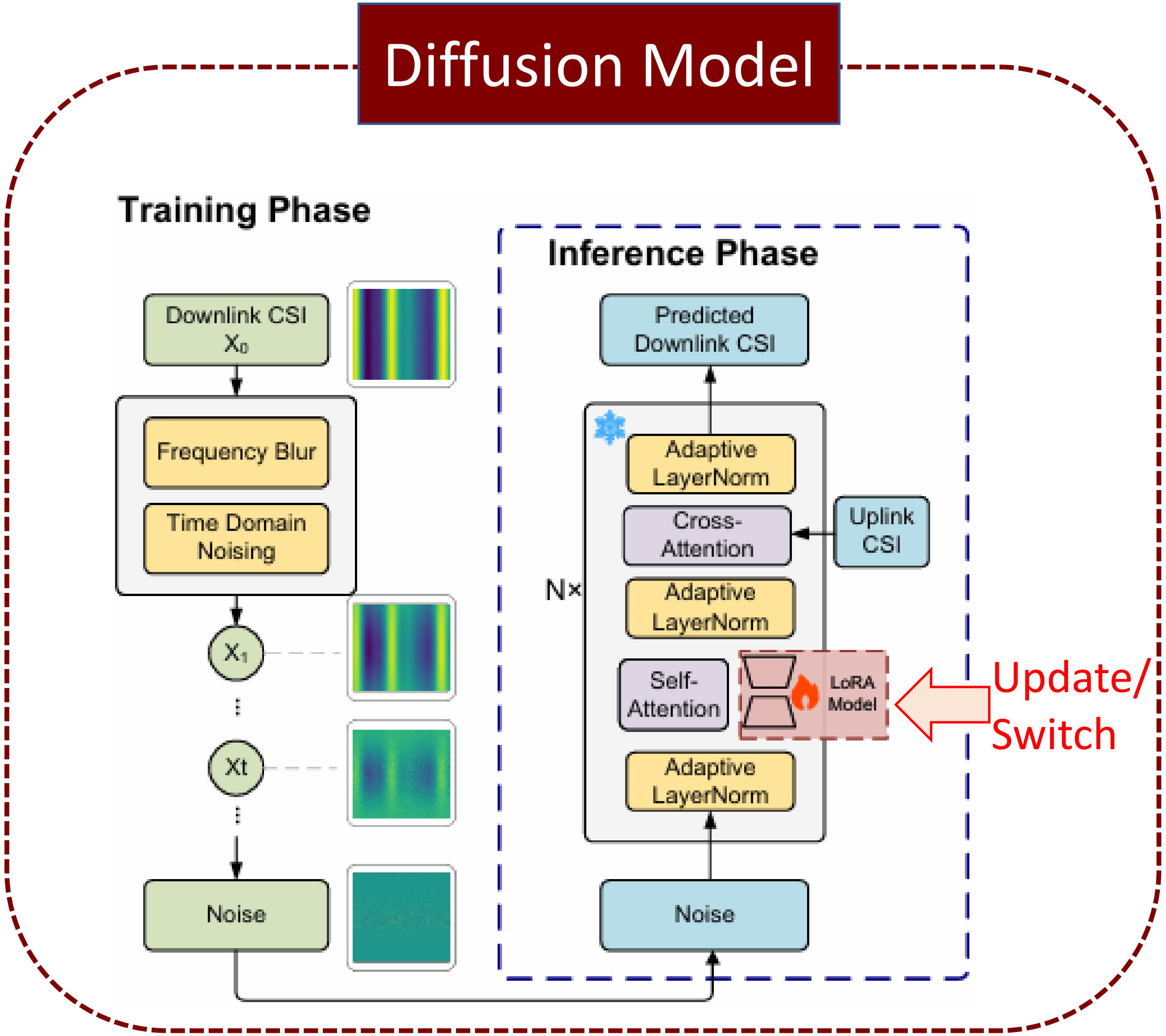


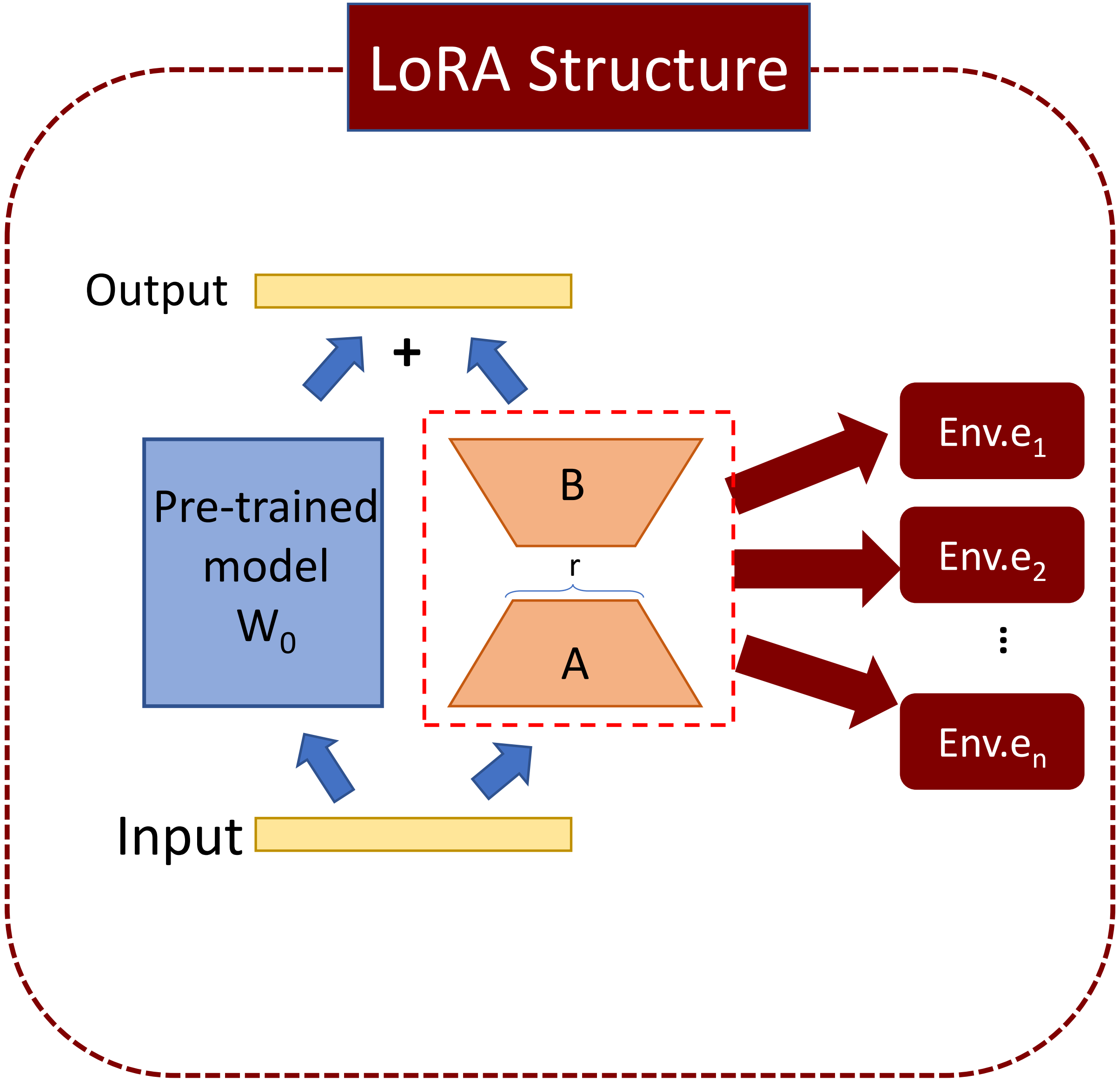
Step 1

Step 3

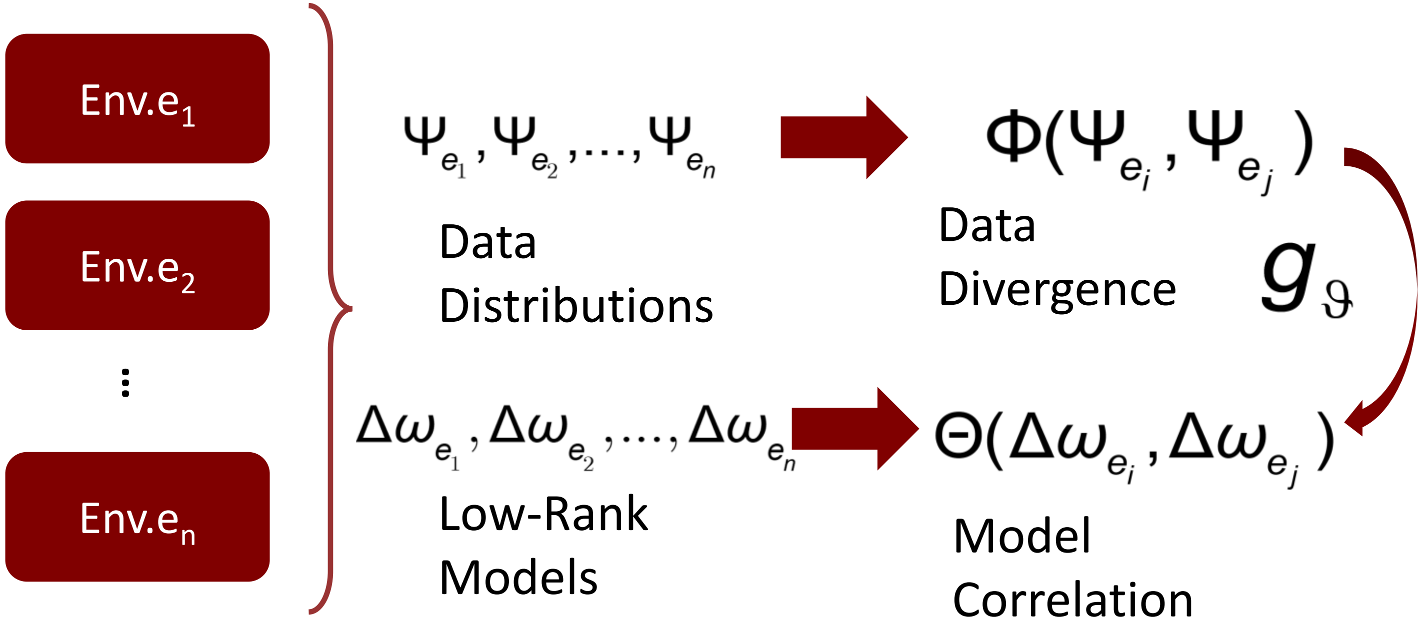
Fig. Overview

LoRAT Architecture





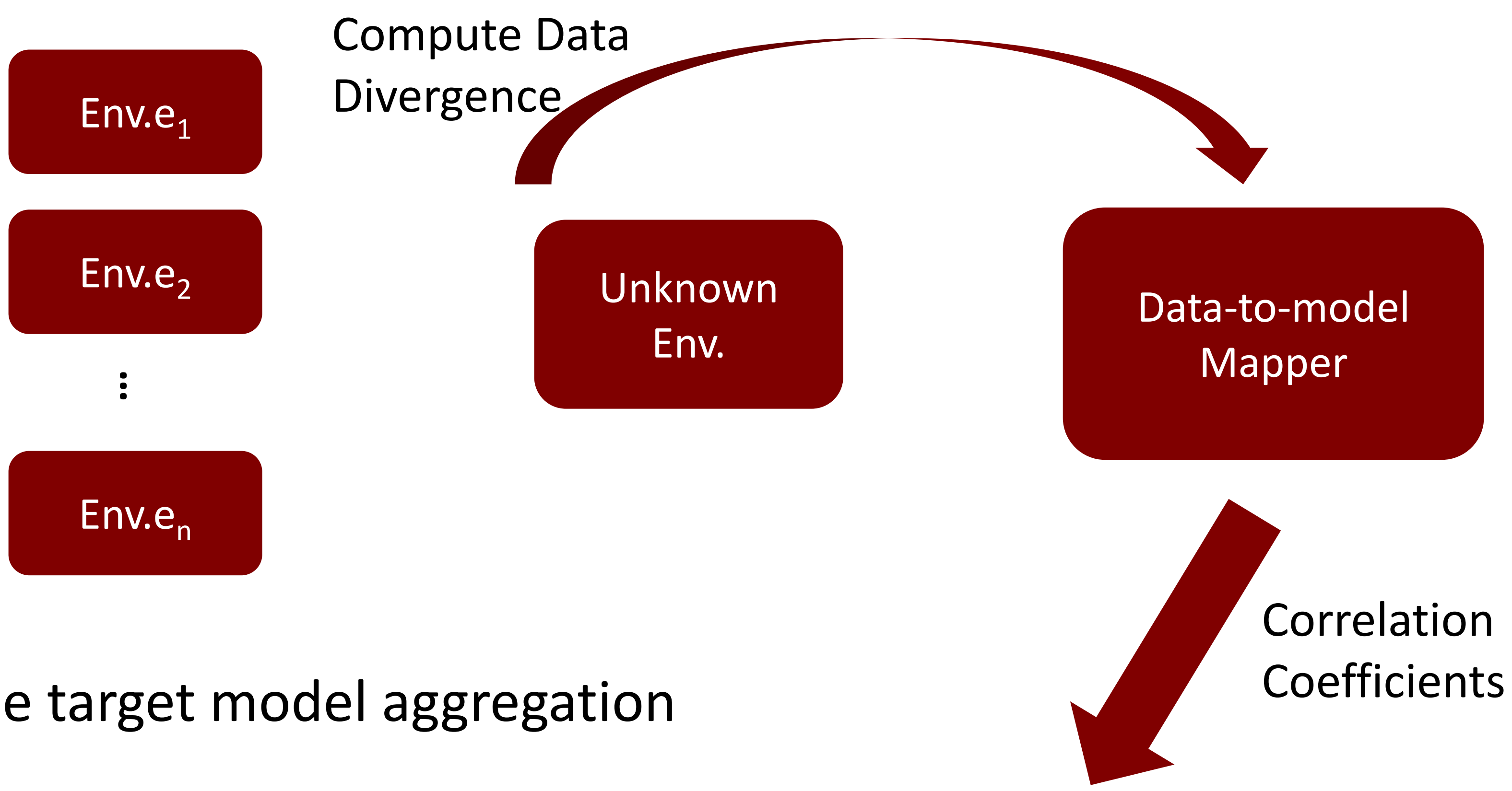
LoRAT Architecture



- Optimization Objective：

$$\min_{\vartheta} \ \mathcal{L}_{\text{map}}(\vartheta) = \sum_{\substack{\forall e_i, e_j \in \mathcal{E}^S, \\ i \neq j}} \left\| g_\vartheta(\Phi(\Psi_{e_i}, \Psi_{e_j})) - \Theta(\Delta\mathbf{W}_{e_i}, \Delta\mathbf{W}_{e_j}) \right\|^2$$

LoRAT Architecture



- The target model aggregation

$$\mathbf{W}_{e_j} = \mathbf{W}_0 + \sum_{e_i \in \mathcal{E}^S} \frac{\lambda_{e_i e_j}}{\sum_{e_i \in \mathcal{E}^S} \lambda_{e_i e_j}} \Delta \mathbf{W}_{e_i}.$$

LoRAT Architecture

- Advantages
  - LoRAT requires no labeled data in the target environment.
  - LoRAT has very low communication and computation overhead.
  - LoRAT is highly scalable.
  - LoRAT is model-agnostic.

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Experiments and Simulation Results

■ Experimental Setup

Fig. An environmental layout

Metric

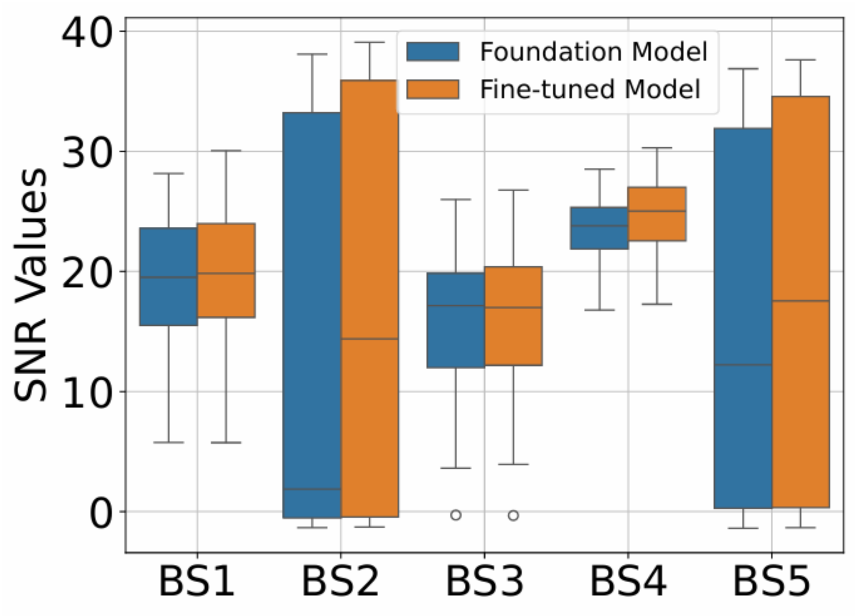
Predicted Value

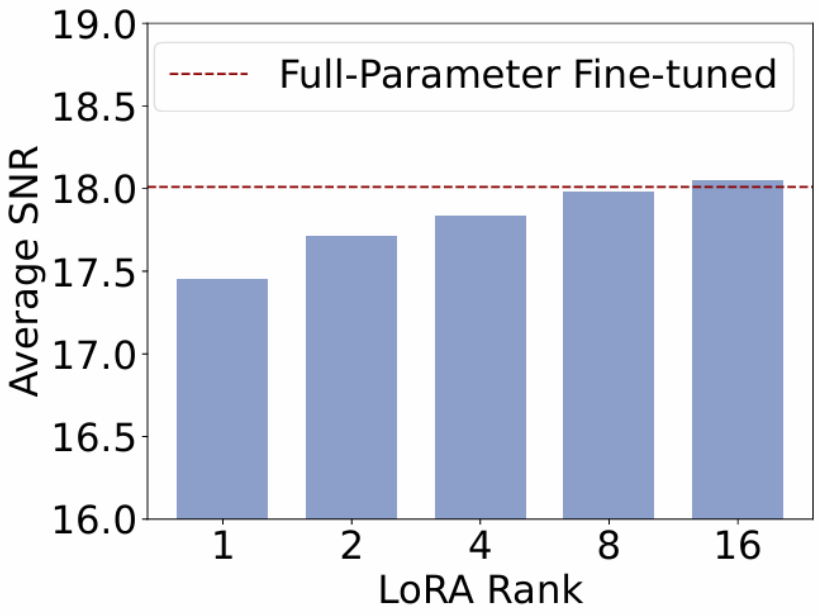
Ground Truth

$$\mathrm{SNR} = -10\log_{10}\left(\frac{\|\hat{h}^{\mathrm{dl}} - h^{\mathrm{dl}}\|^2}{\|h^{\mathrm{dl}}\|^2}\right)$$

Environments Number	Subcarriers Number	Antennas Number	Frames Number
6	52	96	5026

Experiments and Simulation Results





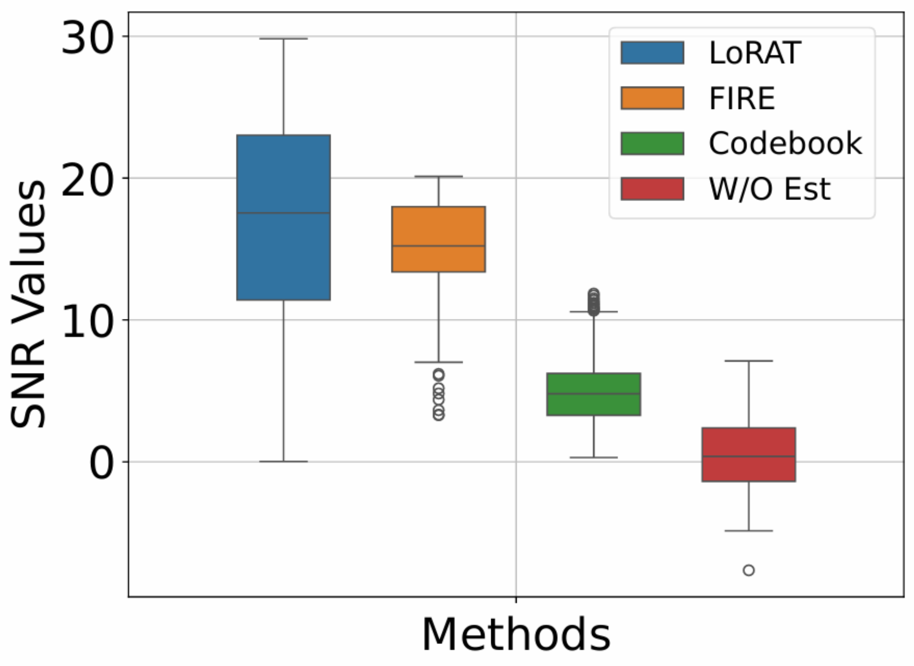
Observation

The fine-tuned model consistently achieves performance gains in all scenarios.

Observation

As the rank increases, LoRA approaches the performance of full-parameter fine-tuning.

Experiments and Simulation Results



Model transfer performance under different metrics. Performance is tested by SNR in dB.

Measure	Cosine Similarity	L1 Norm	L2 Norm
KL Divergence	16.36±7.47	**16.45±7.46**	16.29±7.39
JS Divergence	16.37±7.47	**16.45±7.46**	**16.45±7.46**

Observation

LoRAT significantly outperforms state-of-the-art baselines

Observation

Across all combinations, LoRAT consistently achieved SNR values around **16.4 dB**.

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Conclusion

- **LoRAT Framework**: Proposed LoRAT for efficient, label-free channel estimation across unseen environments.
- **Low-Rank Adaptation & Data-to-Model Mapping**: Combines low-rank adaptation with a learned data-to-model mapping to enable rapid transfer using only unlabeled uplink data.
- **Significant Accuracy Gains**: Achieves up to 15% improvement over learning-based methods and 265% over traditional codebook approaches in real-world measurements (Argos dataset).
- **Reduced Overhead**: Drastically reduces computational and communication costs compared to full fine-tuning or retraining.
- **Foundation Models for Wireless Systems**: Paves the way for scalable foundation models that can be efficiently adapted to diverse deployment scenarios—accelerating the development of intelligent, 6G-ready networks.

Thank You!

For more information, please contact:

Yong Xiao
(yongxiao@hust.edu.cn)
Qi Wang
(wang77@hust.edu.cn)