ChannelMAE: Self-supervised learning assisted online adaptation of neural channel estimators

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University of Edinburgh

My Random Walk

PACKET
ROUTE
SIGNAL

01 Nanjing

東南大學
SOUTHEAST UNIVERSITY

Southeast University, Bachelor

(2020)

02 Hong Kong

THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

Hong Kong Polytechnic University, Exchange (2018)

03 Shanghai

上海交通大學
SHANGHAI JIAO TONG UNIVERSITY

Shanghai Jiao Tong University, PhD, supervised by Prof. Xudong Wang

(graduated Sep. 2025)

04 London

Imperial College London

Imperial College London, Visiting PhD, supervised by Prof. Geoffrey Y. Li

(Aug. 2023 – Jan. 2025)

05 Edinburgh

THE UNIVERSITY of EDINBURGH

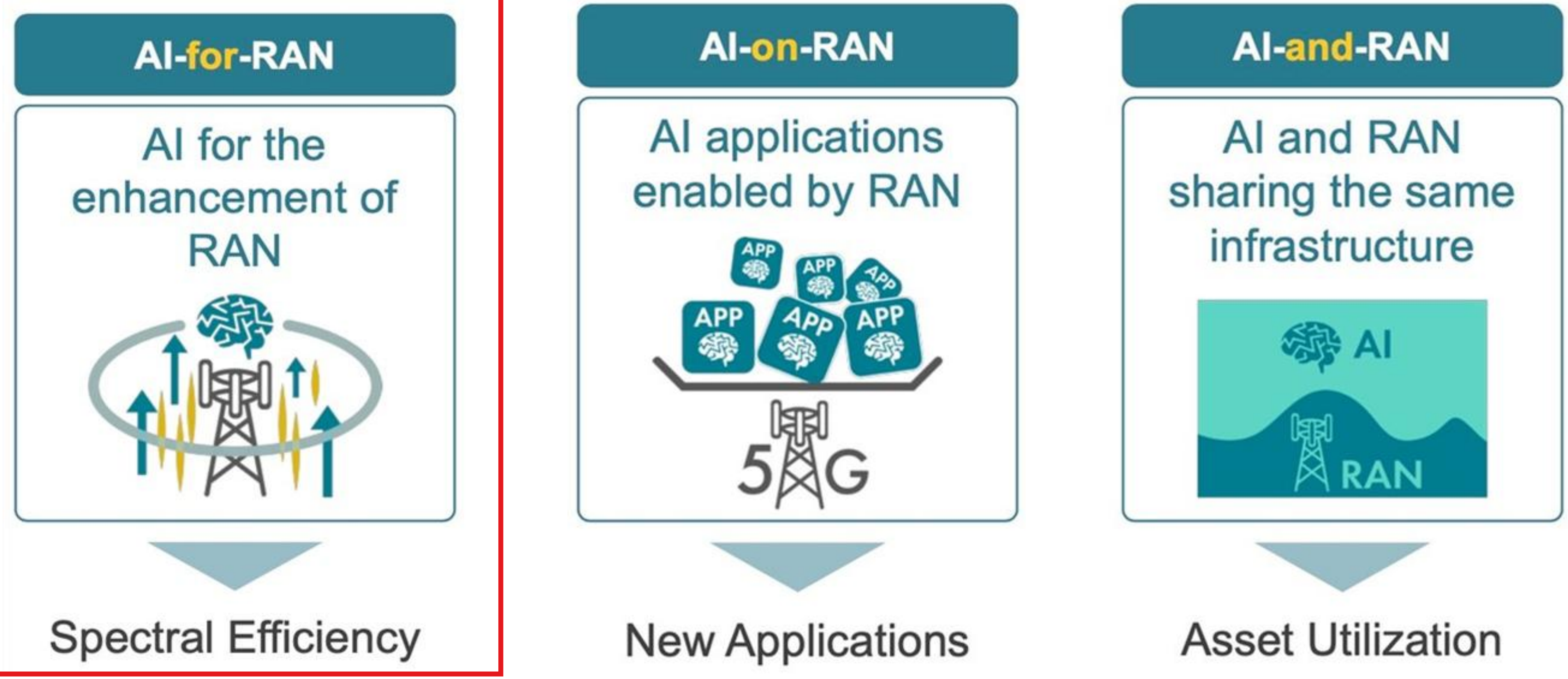
University of Edinburgh, Postdoctoral Research Associate

(Oct. 2025 – Present)

PACKET CREATED → ROUTE SELECTED → PACKET FORWARDED → SIGNAL RECEIVED → DESTINATION REACHED

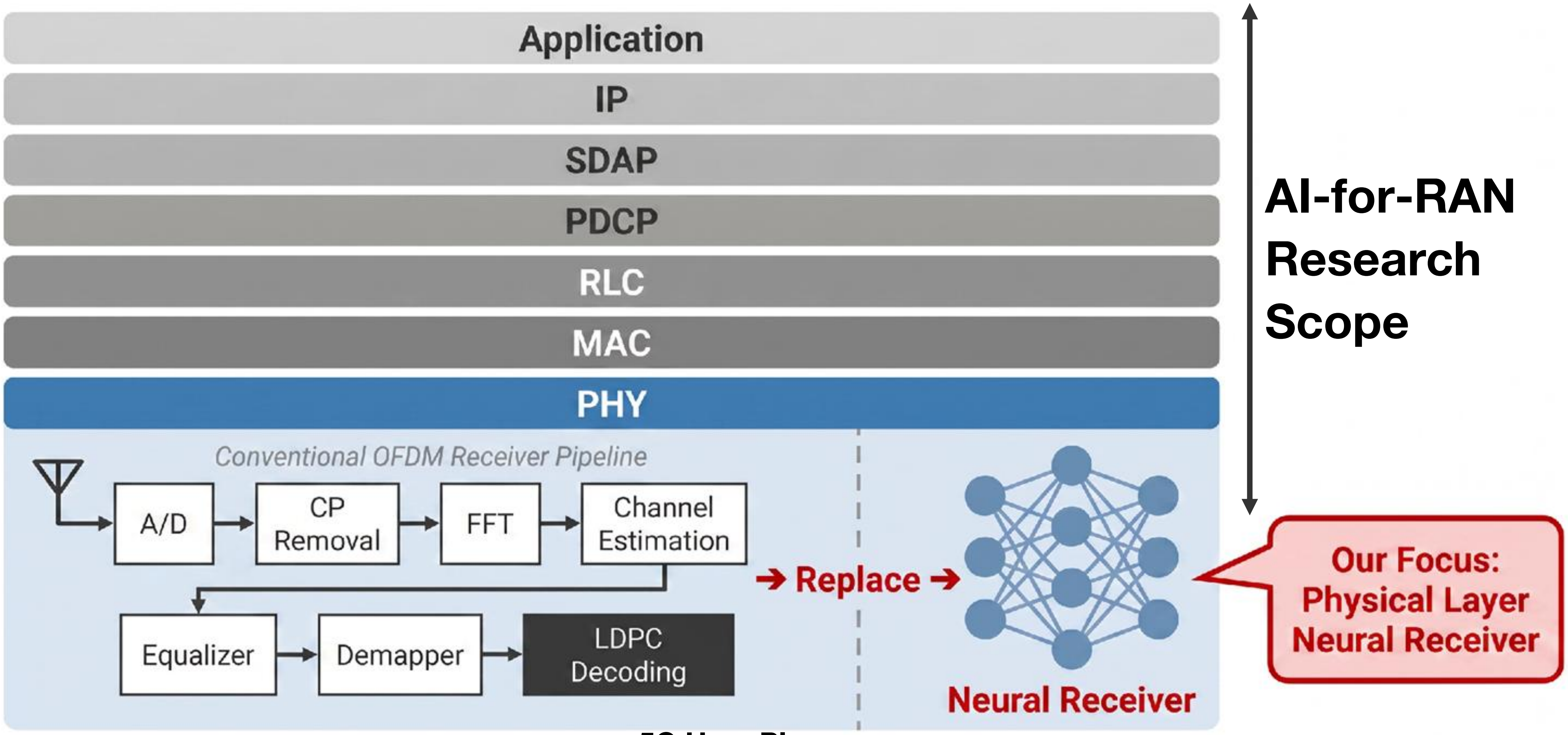
AI for Radio Access Network (RAN)

AI-RAN Alliance founded in 2024



https://ai-ran.org/

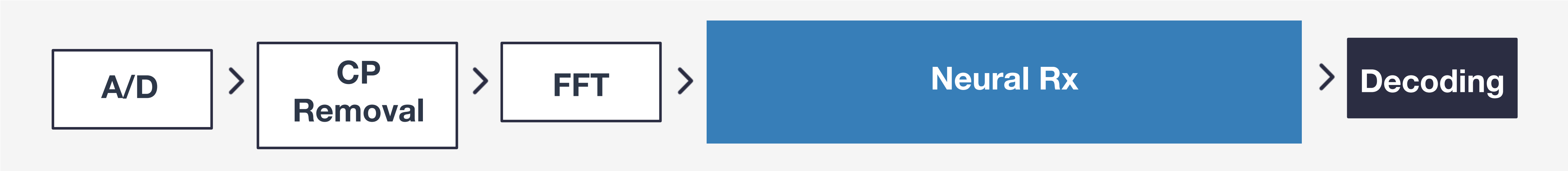
AI for RAN



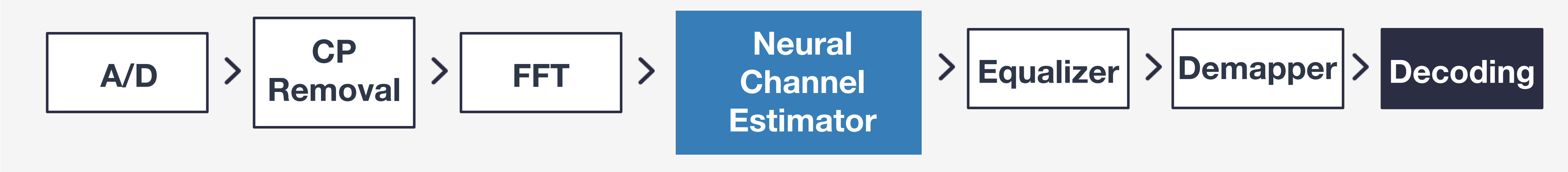
5G User Plane

Neural Receiver

Fully Learned Neural Rx



Partially Learned Neural Rx



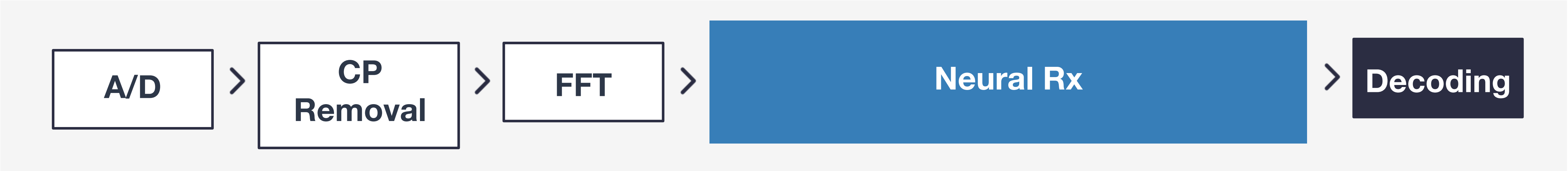
My previous works on fully learned neural Rx:

- [INFOCOM’25] GraphRx (collaborative neural Rx)
- [INFOCOM’25] FedPDA (on-device neural Rx)

Scan ME

Neural Receiver

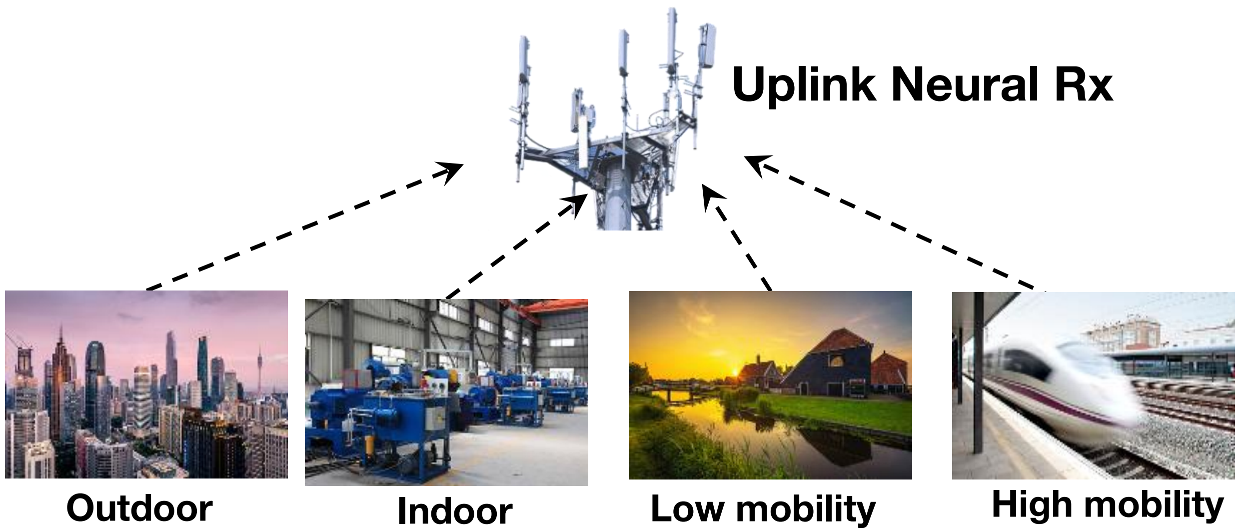
Fully Learned Neural Rx



Partially Learned Neural Rx

- Implicit & accurate modeling of real-world channels
- Superior tradeoff between receiver complexity and performance compared to classical methods

Necessity of Online (Test-Time) Adaptation

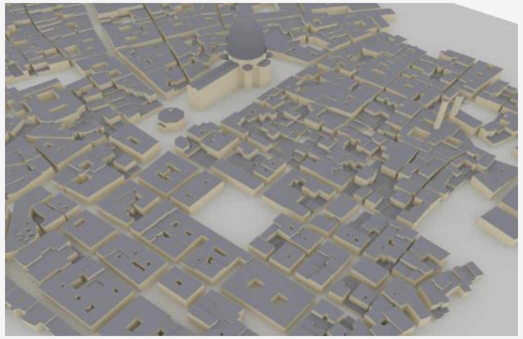


Impractical to host a neural Rx that covers all types of channel environments

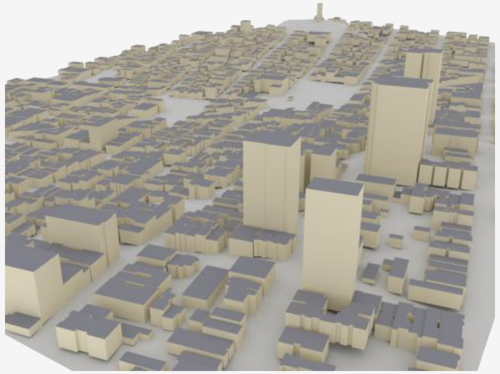
Therefore: A two-step methodology

Offline Pretraining → Test-Time Adaptation Based on Real-World Data

Necessity of Online (Test-Time) Adaptation

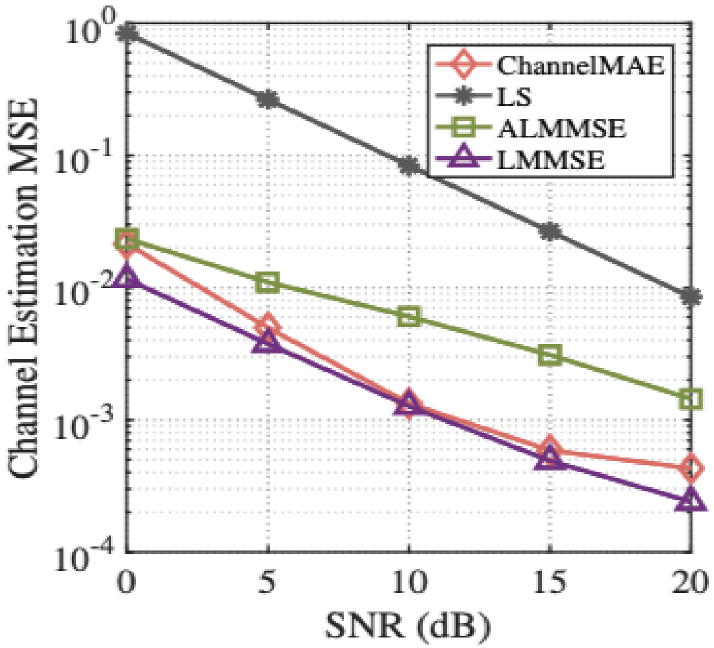


Low-rise buildings,
flat terrain
(Florence)



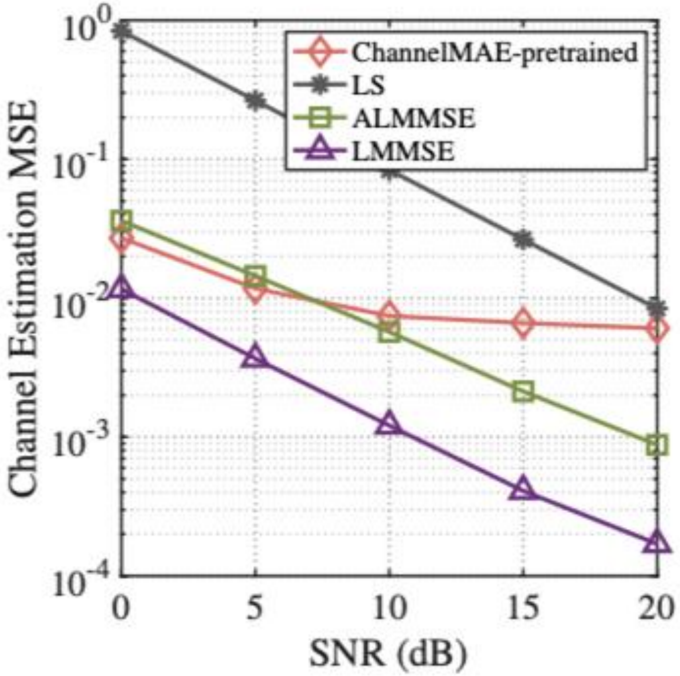
High-rise buildings,
unflat terrain
(San Francisco)

Offline Env.



Test pretrained model in online Env.

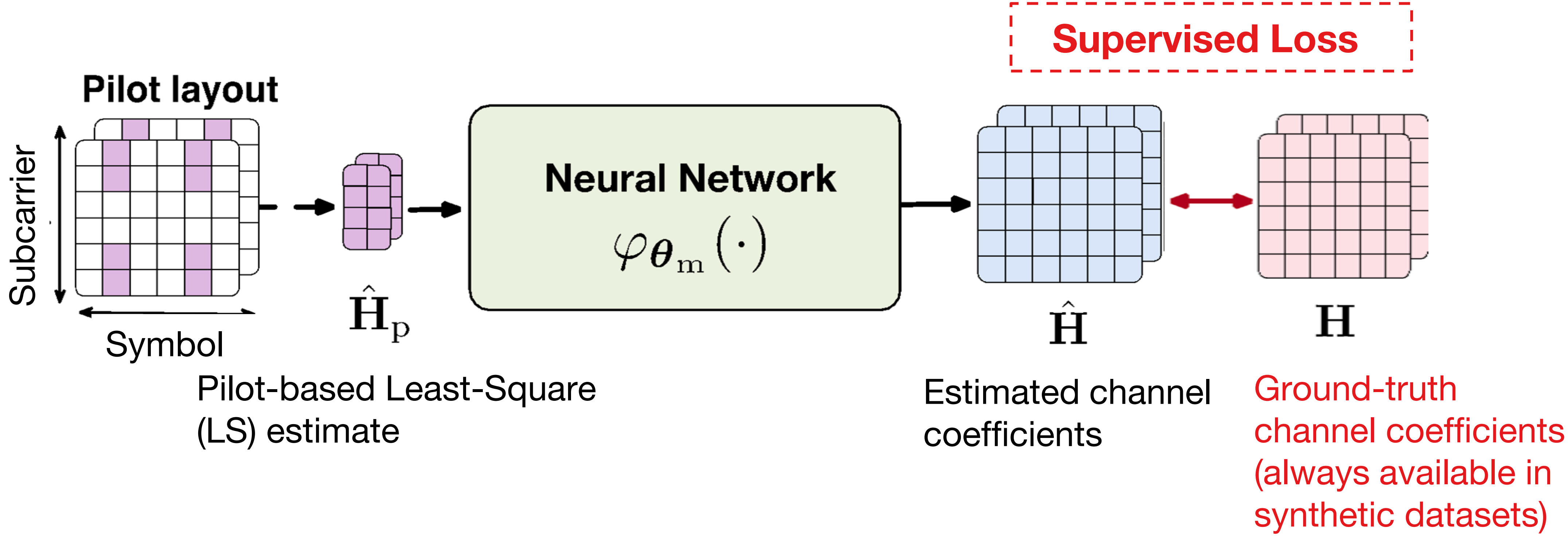
Online Env.



Online degradation

But How to Do Online Adaptation?

First let's see how to do offline pretraining in a supervised way:



However, NO ground-truth channel coefficients online

Related Work

True channel coefficients are **NOT** known online

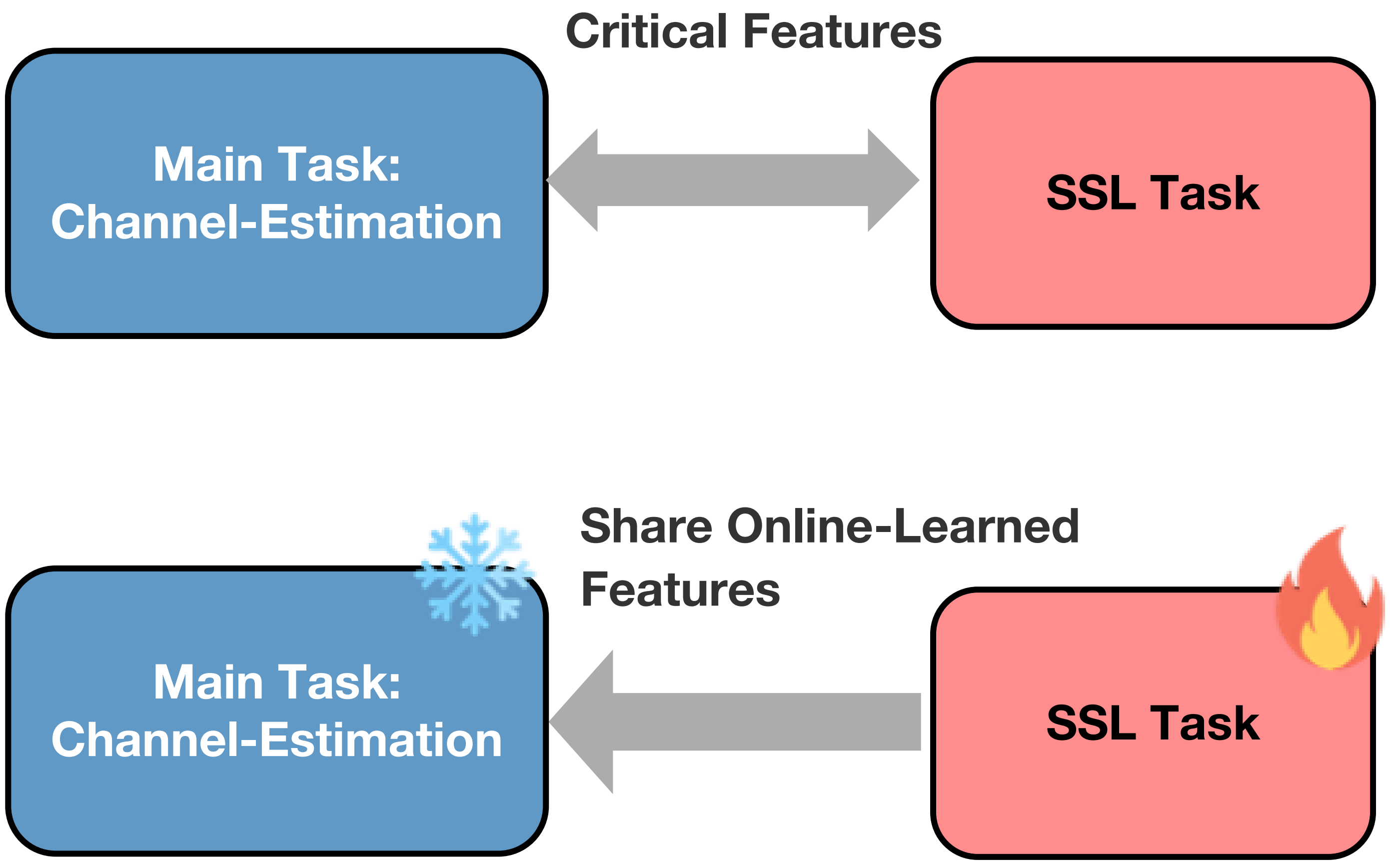
Methods	Assume prior channel stat.	Incur extra pilot overhead	OFDM	Model Arch.
HA03 [TWC' 23]	Yes	Yes	Yes	Transformer+Fully-connected + CNN
FedPDA [INFOCOM' 25]	No	Yes	Yes	CNN
CLCE [TWC' 25]	No	Yes	Yes	Transformer+Fully-connected + CNN
DnCNN [TWC' 24]	Yes	No	No	CNN
Our work	No	No	Yes	Transformer + ResNet

- ***Incur extra pilot overhead or assume prior knowledge of channel statistics***

Requirements of Test-Time Adaptation of Neural Channel Estimators

- **Not using ground-truth channel coefficients** (not available online)
  → Normal supervised learning is not applicable
- **Not incurring extra pilot overhead**
  = Non-intrusive to data transmission
- **No prior channel statistics known in advance**

Introduction of a Self-Supervised Learning (SSL) Task

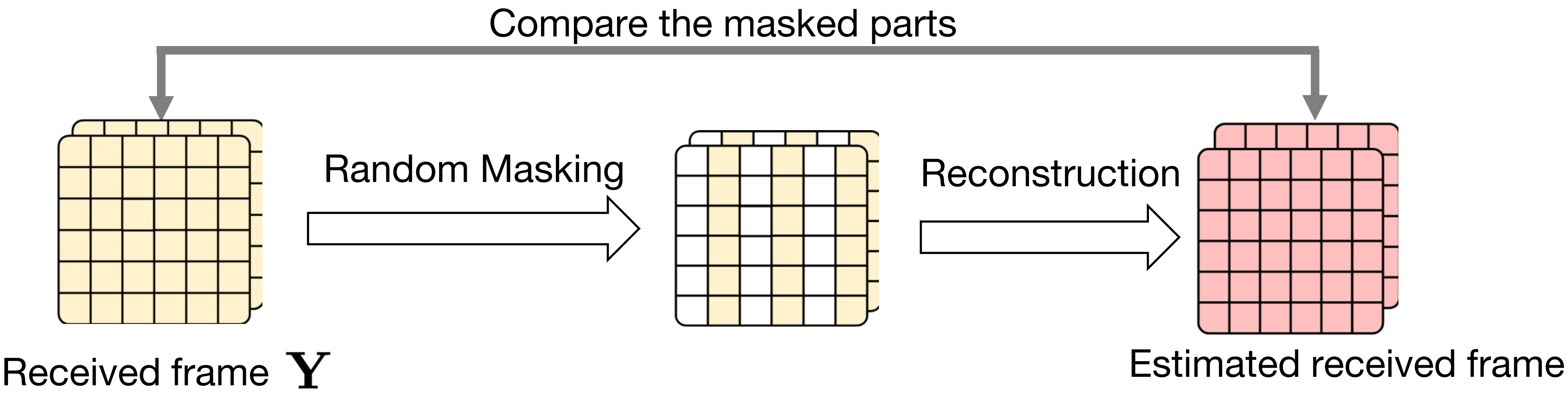


> ***The SSL task learns the critical features that benefit the main task without labels***

> **SSL-task should satisfy:**
> - No additional pilot overhead
> - No prior channel statistics

Challenge 1: How to Design an Appropriate SSL Task

Masked reconstruction



Direct reconstruction NOT feasible

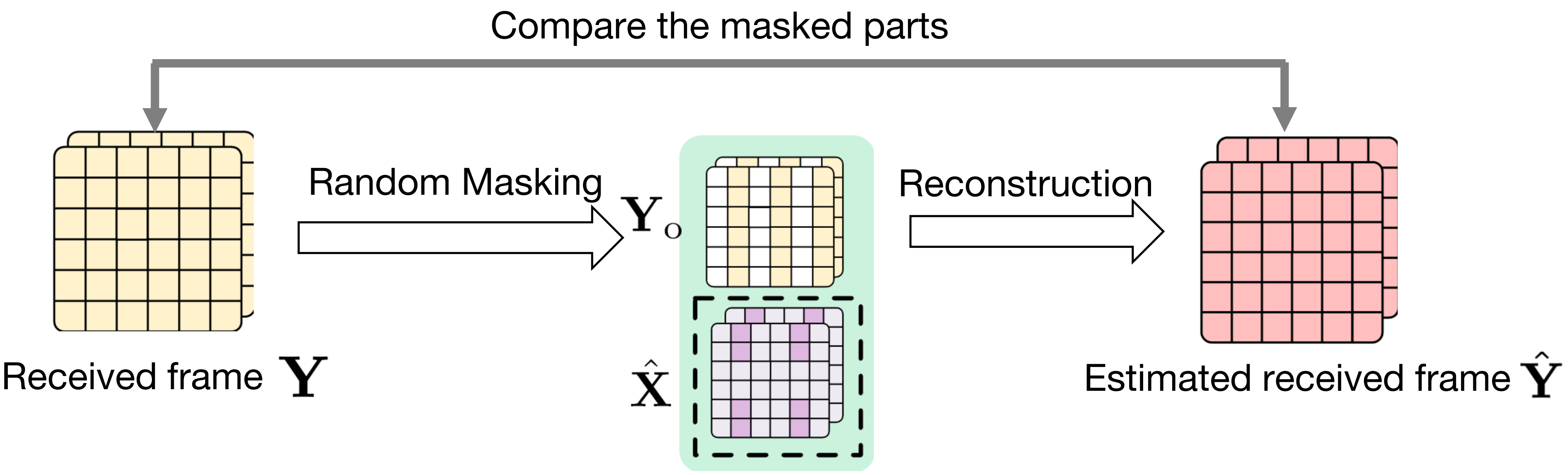
$$\boxed{\mathbf{Y}} = \mathbf{H} \odot \boxed{\mathbf{X}} + \mathbf{N}$$

Gaussian noise

Randomness **Randomness**

Challenge 1: How to Design an Appropriate SSL Task

Masked reconstruction



Enable reconstruction by incorporating estimated data-symbols

$$\hat{\mathbf{Y}} = \phi_{\boldsymbol{\theta}_{\mathrm{s}}}\left(\mathbf{Y}_{\mathrm{O}}, \hat{\mathbf{X}}\right)$$

Challenge 2: How to Design a Model Architecture to Consolidate Two Tasks

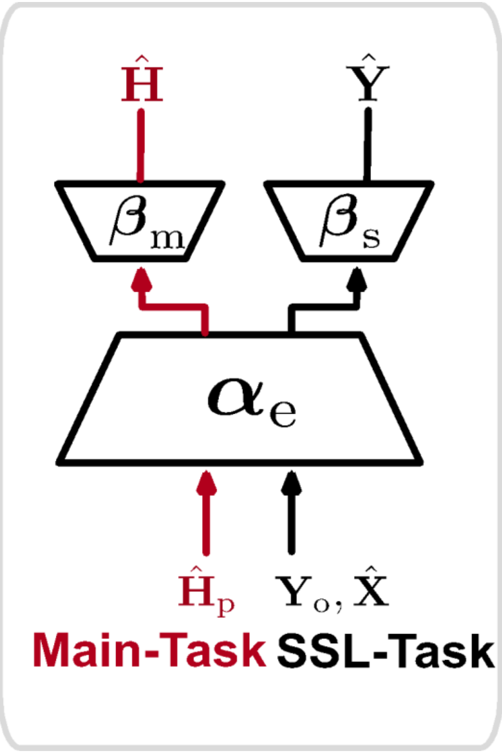
ChannelMAE: Two-Branch Masked Auto-Encoder (MAE)

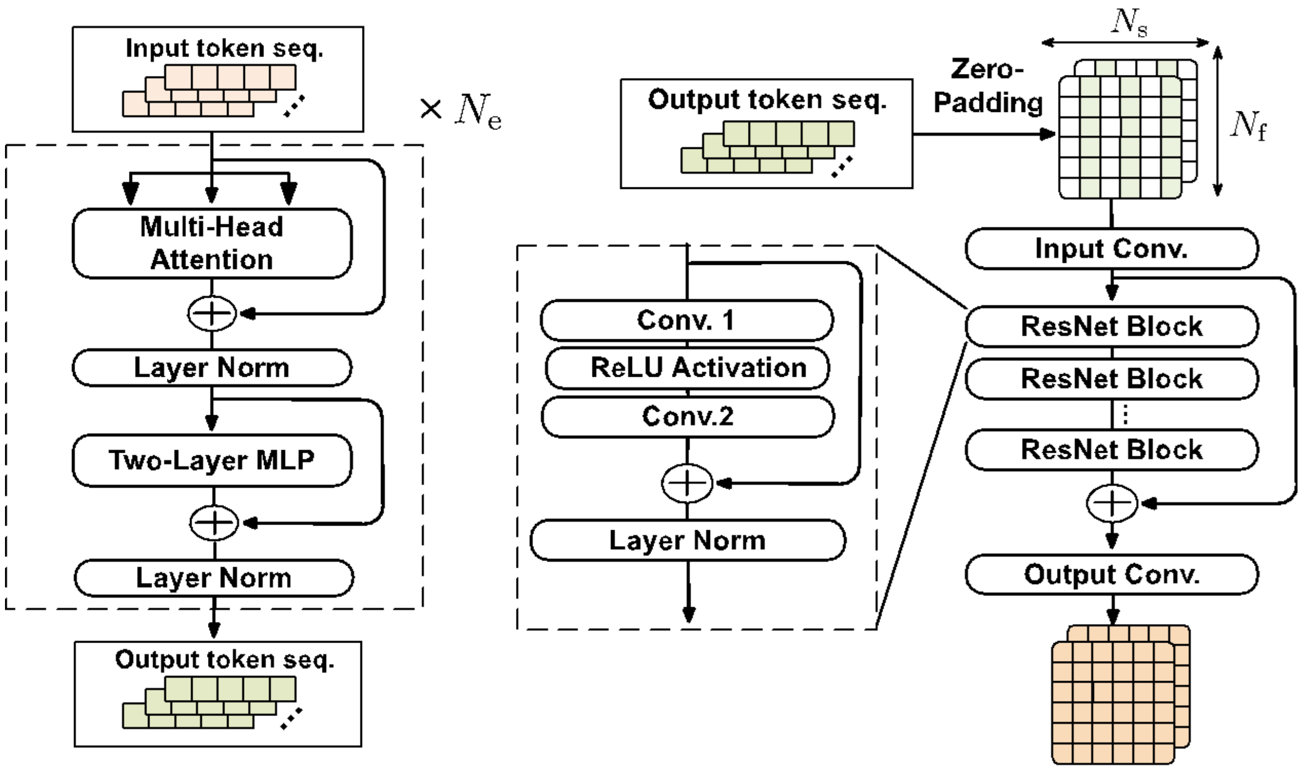
$$\hat{\mathbf{H}} = \varphi_{\boldsymbol{\theta}_{\mathrm{m}}}(\hat{\mathbf{H}}_{\mathrm{p}}) \qquad \hat{\mathbf{Y}} = \phi_{\boldsymbol{\theta}_{\mathrm{s}}}\left(\mathbf{Y}_{\mathrm{o}}, \hat{\mathbf{X}}\right)$$

$$\boldsymbol{\theta}_{\mathrm{m}} = \{\boldsymbol{\alpha}_{\mathrm{e}}, \boldsymbol{\beta}_{\mathrm{m}}\} \qquad \boldsymbol{\theta}_{\mathrm{s}} = \{\boldsymbol{\alpha}_{\mathrm{e}}, \boldsymbol{\beta}_{\mathrm{s}}\}$$

Decoders

Shared enc.





Encoder

Decoder

Asymmetric Model Arch.

Challenge 3: How to Design an Efficient Training Strategy

Two-Phase Training Strategy

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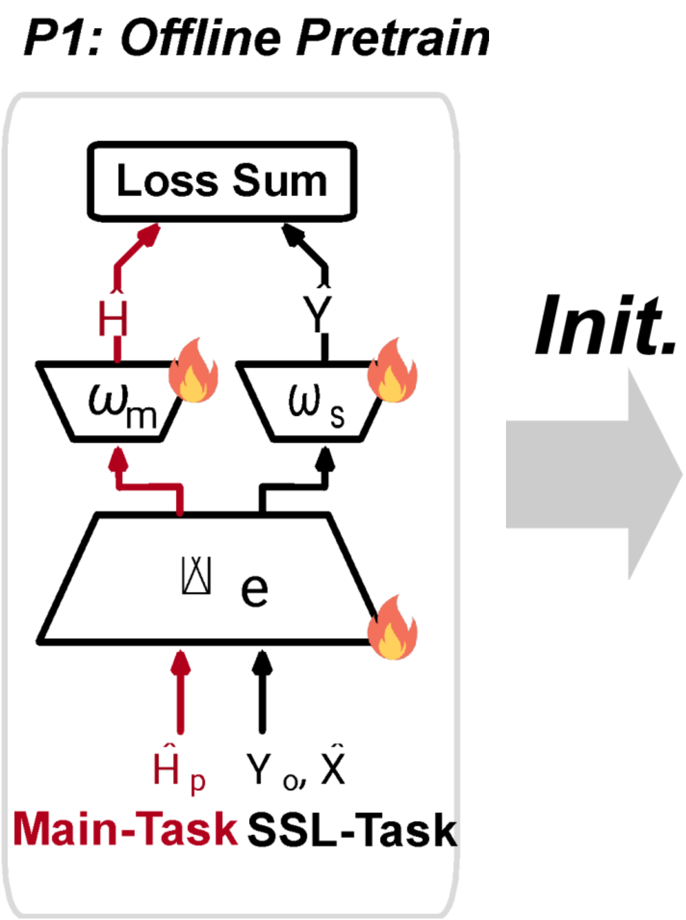
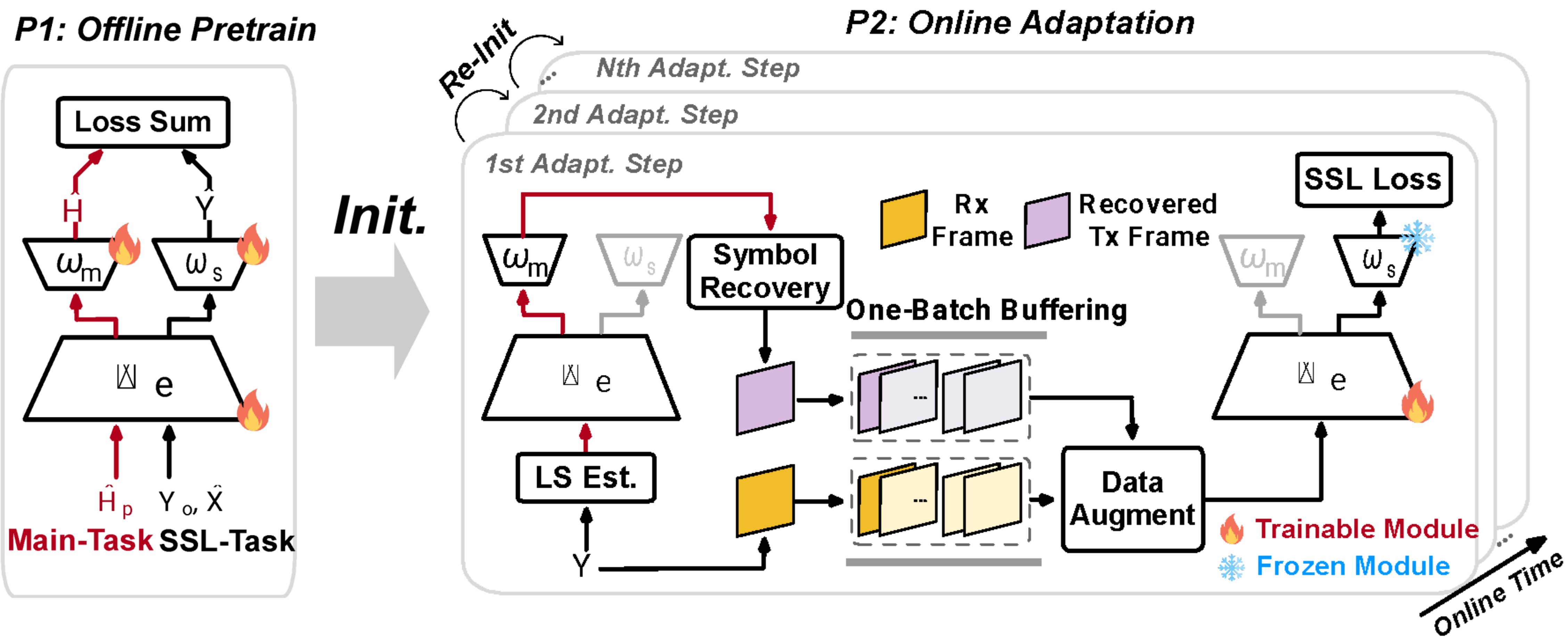
Two-Phase Training Strategy



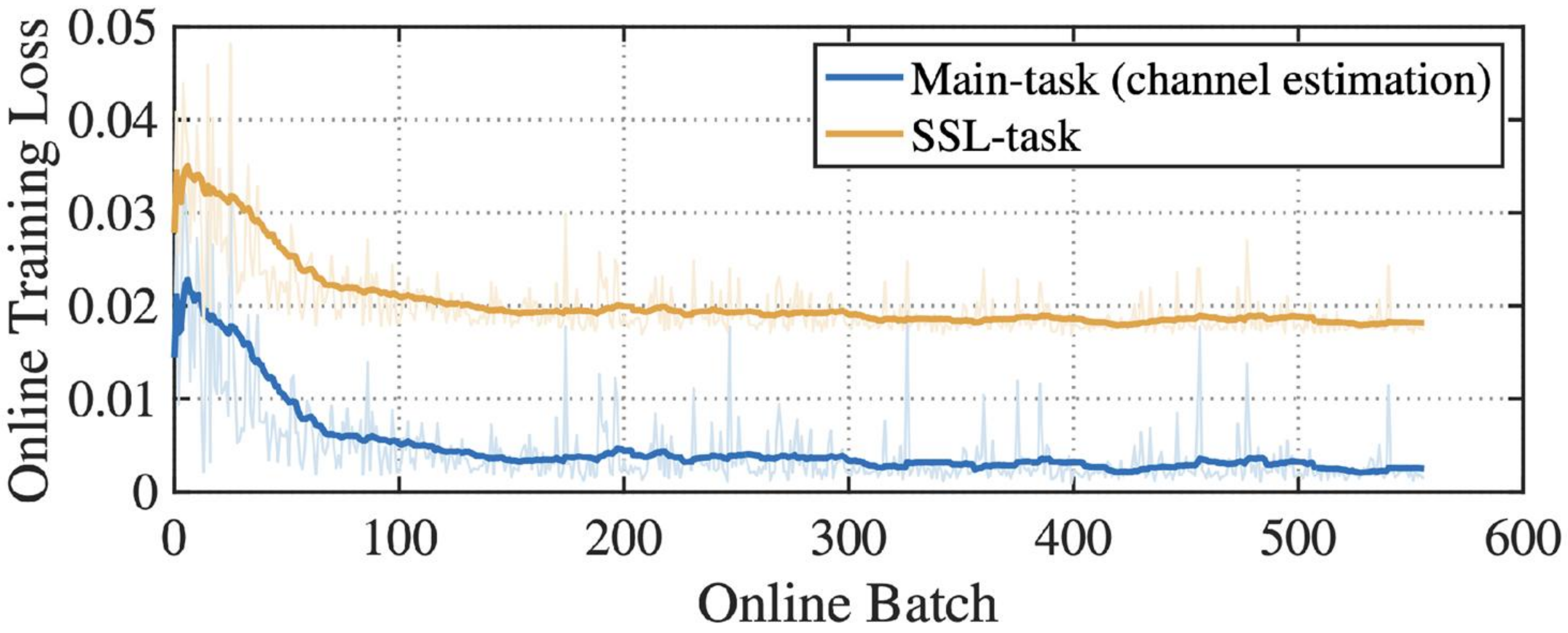
Challenge 3: How to Design an Efficient Training Strategy

Two-Phase Training Strategy



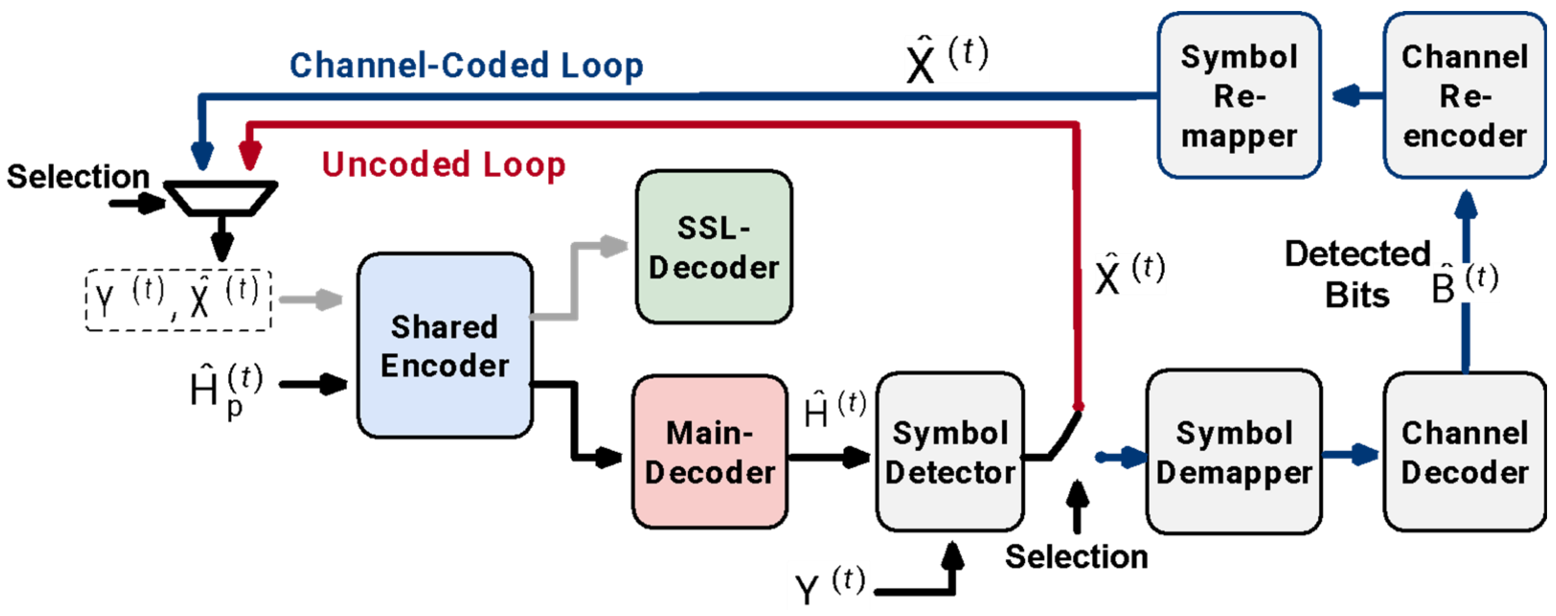
Challenge 3: How to Design an Efficient Training Strategy

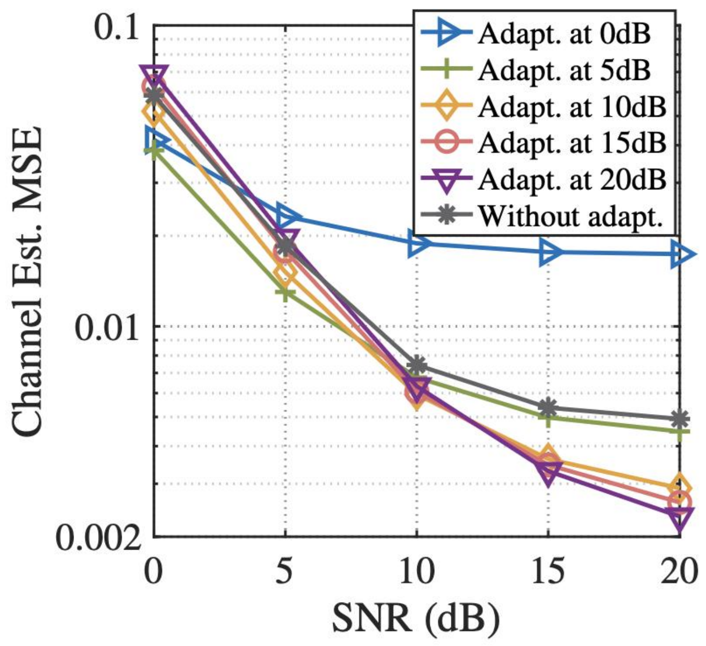
Two-Phase Training Strategy



Synergy between the main and SSL tasks

Online Symbol-Recovery Mechanism





Worse channel condition ⟹ Larger symbol-error rate

Key insights: *set* ***an SNR threshold for adaptation (5 dB)*** *to reduce impact of erroneous symbols*

Performance Evaluation: Setup

Standard 3GPP channel datasets with diverse mobilities		Ray-Traced (RT) channel datasets using real-world scenes	
Offline Env.	**Online Env.**	**Offline Env.**	**Online Env.**
Urban macro	Urban micro	San Francisco	Florence & other 5 cities

Conventional Baselines

- **LS**
- **Ideal** approximate-LMMSE (i.e., **ALMMSE**)
- **Ideal** LMMSE (i.e**., LMMSE**)

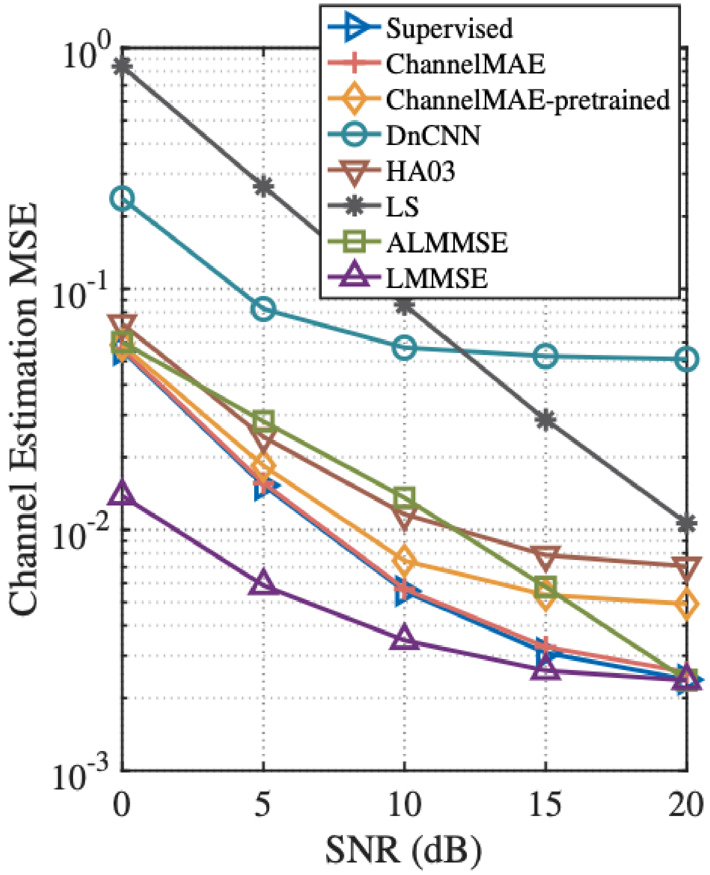
Model	Total params(M)	Online-trainable params(M)
HA03	**0.147**	0.147
ChannelMAE	0.206	**0.126**
DnCNN	0.228	0.227
HA02	0.272	N/A
ChannelNet	0.686	N/A

DL-based Baselines

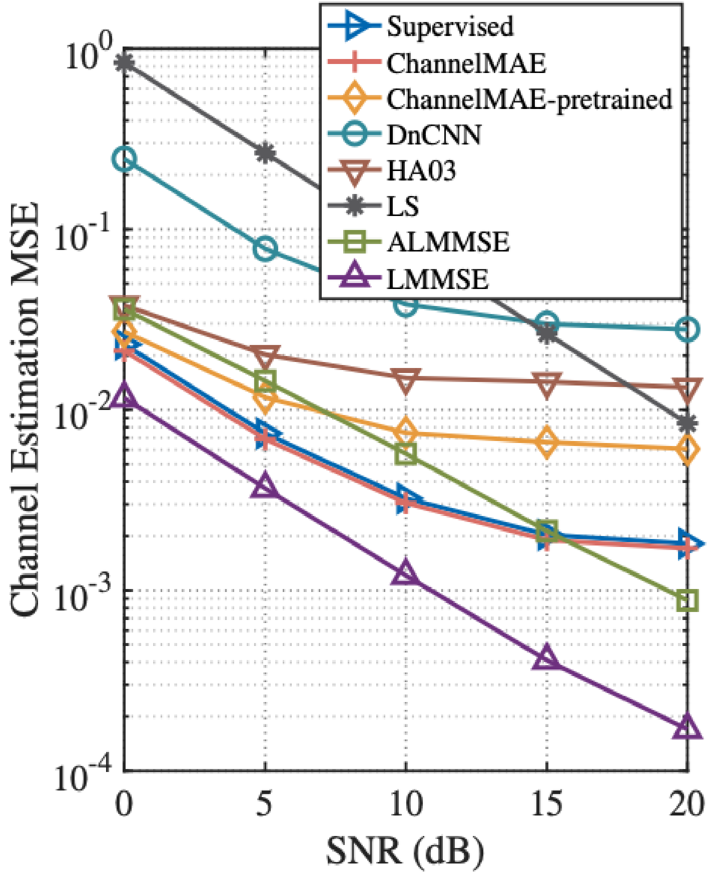
- CNN-based benchmark **ChannelNet**
- SOTA transformer-based **HA02**
- Online denoiser **DnCNN**
- Online SOTA **HA03**
- **Supervised ChannelMAE**

Other setup: SIMO-OFDM, 3.5GHz, standard-aligned DMRS pattern etc.

Performance Evaluation: Online Adaptation



(a) Online 3GPP channel



(b) Online RT channel

ChannelMAE

- Outperform the **pretrained** one by **up to 71.8%**
- Outperform the **SOTA baseline** of neural estimators by **up to 87.1%**
- Reach **close to the supervised scheme** using ground-truth channels

Please see more details in our paper

Key Takeaways

- ChannelMAE is the **first** approach that realizes test-time adaptation of neural channel estimators **without ground-truth channel coefficients, prior channel statistics, or additional pilot overhead**

- The proposed **two-task framework (where an SSL task is introduced)** shows great promise for label-free adaptation across a broad range of wireless applications

- ChannelMAE reduces estimation error **by up to 71.8% and 87.1%** compared with the pretrained model and the baseline respectively

Scan ME (Paper & full code)

Thank you!