

one6G Open Lecture 1 – 6G Network AI

Learning the Physical Layer in FDD Systems: Centralized Learning of Distributed Functions

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A note on UL–DL Distributional Invariance

Distributional Invariance of the Uplink & Downlink

Invariance of

- ✗ instantaneous UL & DL realizations (FDD systems \Rightarrow no reciprocity in general)
- ✓ UL & DL distributions

Distributional Invariance of the Uplink & Downlink:

“Sampling channel state information from the same propagation environment in different frequency bands, but still with similar radio propagation characteristics, represents approximately the same underlying probability distribution.”

Proof:

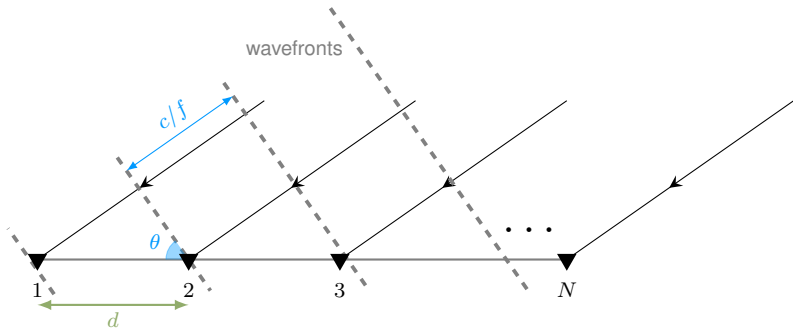
Not a rigorous proof, but there is some [evidence](#) by statistical hypothesis testing based on [two-sample tests](#), cf. [Utschick et al, IEEE T-WC, 2022](#).

An intuitive explanation (1)

Consider the simple case of a ULA with N antennas.
In this case the channel vector \mathbf{h} is such that:

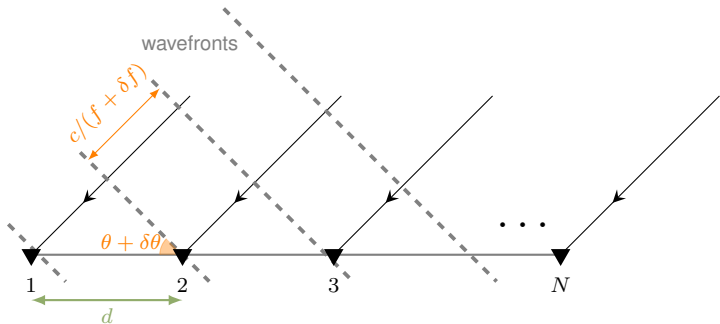
$$\mathbf{h} \propto [\alpha^0, \alpha^1, \alpha^2, \dots, \alpha^{N-1}]$$

with $\alpha = \exp\left(-j\frac{2\pi df}{c} \sin\theta\right)$

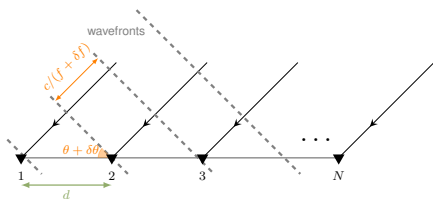
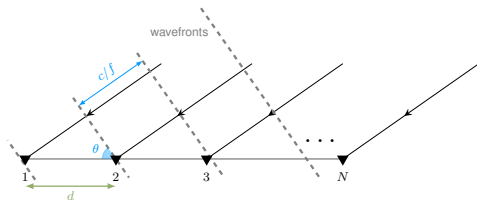


An intuitive explanation (2)

At the same time, for a different carrier frequency we have ...



An intuitive explanation (3)



Small changes δf in the carrier frequency can be compensated by small changes $\delta\theta$ of θ , therefore h is not changed if

$$f \sin \theta = (f + \delta f) \sin (\theta + \delta\theta)$$

Hypothesis Testing Based On Two-Sample Tests

Definition: Given a positive definite kernel $k(\cdot, \cdot) = \langle \varphi(\cdot), \varphi(\cdot) \rangle$ of a reproducing kernel Hilbert space (RKHS) \mathcal{H}_k with a feature map $\varphi(\cdot) \in \mathcal{H}_k$, the maximum mean discrepancy (MMD) between two probability distributions \mathbb{P} and \mathbb{Q} can be obtained by

$$\text{MMD}^2(\mathbb{P}, \mathbb{Q}, k) := \mathbb{E}[k(p, p') + k(q, q') - 2k(p, q)], \quad (9)$$

with random variables $(p, p') \sim \mathbb{P} \times \mathbb{P}$ and $(q, q') \sim \mathbb{Q} \times \mathbb{Q}$. It follows that $\text{MMD}(\mathbb{P}, \mathbb{Q}, k) = 0$ if and only if $\mathbb{P} = \mathbb{Q}$. Further assume that we have sample sets $\mathcal{P} \sim \mathbb{P}$ and $\mathcal{Q} \sim \mathbb{Q}$ of equal sample size n , an unbiased estimator of the squared MMD for measuring the discrepancy between \mathbb{P} and \mathbb{Q} can be obtained as

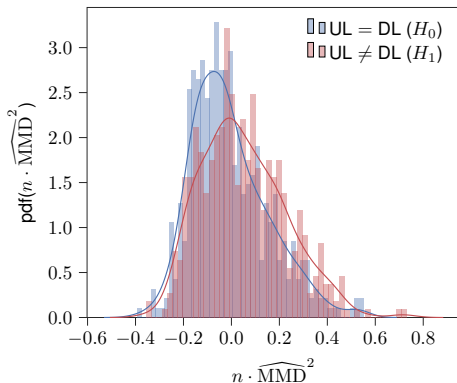
$$\overline{\text{MMD}} = \frac{1}{n(n-1)} \sum_{i \neq j} h_{ij}, \quad (10)$$

where $h_{ij} := k(p_i, p_j) + k(q_i, q_j) - 2k(p_i, q_j)$ with $p_i \in \mathcal{P}$ and $q_i \in \mathcal{Q}$ being the realizations of the random variables $p \sim \mathbb{P}$ and $q \sim \mathbb{Q}$. Following the usual kernel trick, we swap the choice of feature map $\varphi(\cdot)$ with the decision function $k(\cdot, \cdot)$. The most common choice for a kernel is the Gaussian kernel, i.e.,

$$k(p, q) = \exp\left(-\frac{\|p - q\|^2}{\sigma_{50}^2}\right),$$

where $p \in \mathcal{P}$ and $q \in \mathcal{Q}$ are two samples drawn from \mathbb{P} and \mathbb{Q} and σ_{50} corresponds to the 50-percentile (median) distance between elements in the aggregate sample, as suggested in [28].

Hypothesis Testing Based On Two-Sample Tests



V. Rizzello, N. Turan, M. Joham, and W. Utschick. Two-sample Tests for Validating the UL-DL Conjecture in FDD systems. In Proceedings of the 17th International Symposium on Wireless Communication Systems, Berlin, Germany, September 2021.

W. Utschick, V. Rizzello, M. Joham, Z. Ma and L. Piazzzi "Learning the CSI Recovery in FDD Systems", 2021, <https://arxiv.org/abs/2104.01322>.

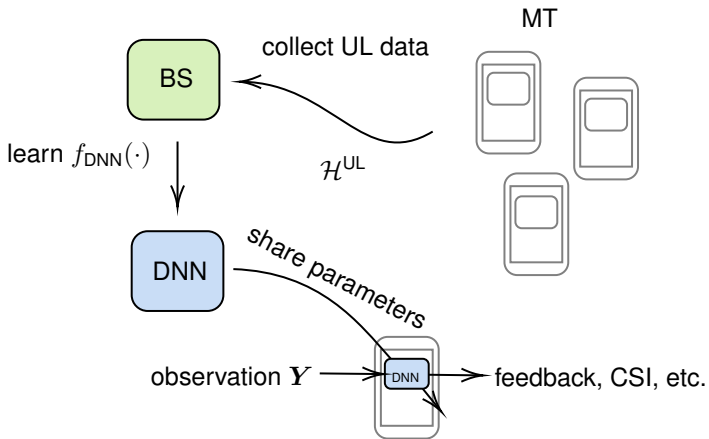
Why is this important?

Because what really matters in machine learning is the **distribution** of data!

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ensembles

Novel Design Options for FDD PHY Layer Functions

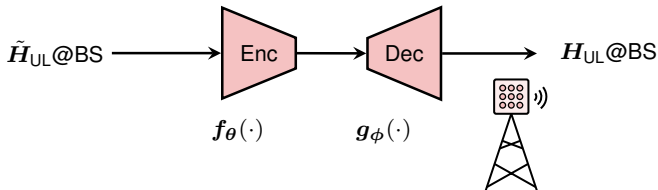
PHY Layer Functions Soley Based on UL-Data



Application:
Channel Compression & Reconstruction

Channel Compression & Reconstruction

1. Train an autoencoder **solely based on UL CSI**



- f_{θ} : encoder neural net

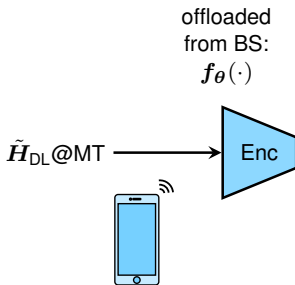
$$z_{UL} = f_{\theta}(\tilde{H}_{UL})$$

- g_{ϕ} : decoder neural net

$$H_{UL} \approx \hat{H}_{UL} = g_{\phi}(z_{UL}).$$

Channel Compression & Reconstruction

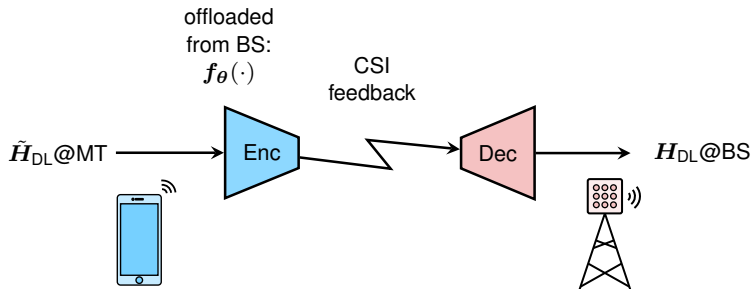
2. Offload the UL-trained encoder to each MTs in the cell
3. Compress the DL CSI at the MT



$$z_{DL} = f_{\theta}(\tilde{H}_{DL})$$

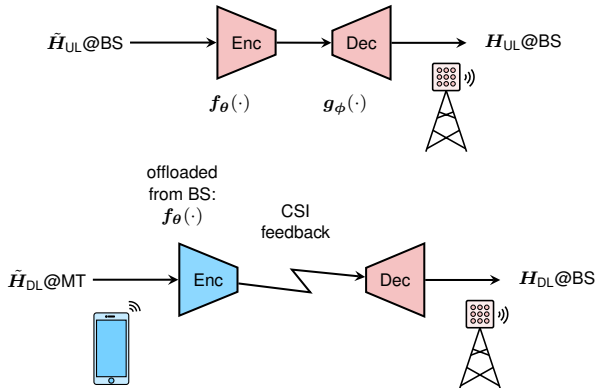
Channel Compression & Reconstruction

4. **Feed** the encoded DL CSI **back** to the BS
5. **Decode** the DL CSI at the BS with the UL-trained decoder




$$H_{DL} \approx \hat{H}_{DL} = g_{\phi}(z_{DL})$$

Channel Compression & Reconstruction



- not necessary to collect DL CSI data for training
- robust against Gaussian noise

Channel Compression & Reconstruction

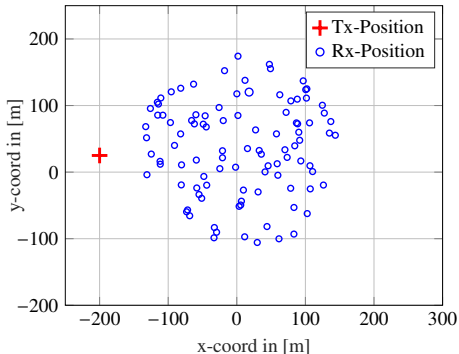


Layer type	Output shape	#Parameters θ
Input	$64 \times 160 \times 2$	0
Conv2D, strides=2	$32 \times 80 \times 8$	152
Batch normalization	$32 \times 80 \times 8$	32
ReLU	$32 \times 80 \times 8$	0
Conv2D, strides=2	$16 \times 40 \times 16$	1168
Batch normalization	$16 \times 40 \times 16$	64
ReLU	$16 \times 40 \times 16$	0
Conv2D, strides=2	$8 \times 20 \times 32$	4640
Batch normalization	$8 \times 20 \times 32$	128
ReLU	$8 \times 20 \times 32$	0
Conv2D, strides=2	$4 \times 10 \times 64$	18496
Batch normalization	$4 \times 10 \times 64$	256
ReLU	$4 \times 10 \times 64$	0
Conv2D, strides=2	$2 \times 5 \times 128$	73856
Batch normalization	$2 \times 5 \times 128$	512
ReLU	$2 \times 5 \times 128$	0
Flatten	1280	0
Fully-connected	256	327936
Tanh	256	0

- autoencoder is based on convolutional layers instead of fully connected layers
⇒ architecture can be easily scaled to high dimensional CSI

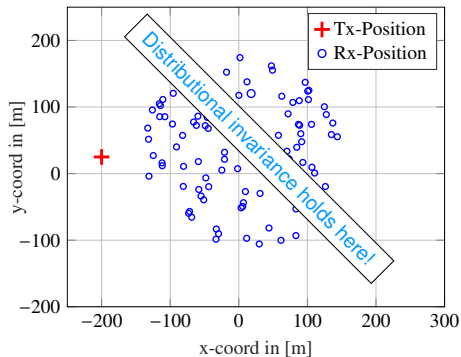
Channel Compression & Reconstruction

- QuaDRiGa channel simulator
- Urban Microcell NLoS
- 58 paths
- training samples = 48 K
- validation/test samples = 2×6 K
- number of antennas = 64
- number of carriers = 160
- center frequency = 2.5 GHz
- frequency gap = 120 and 480 MHz



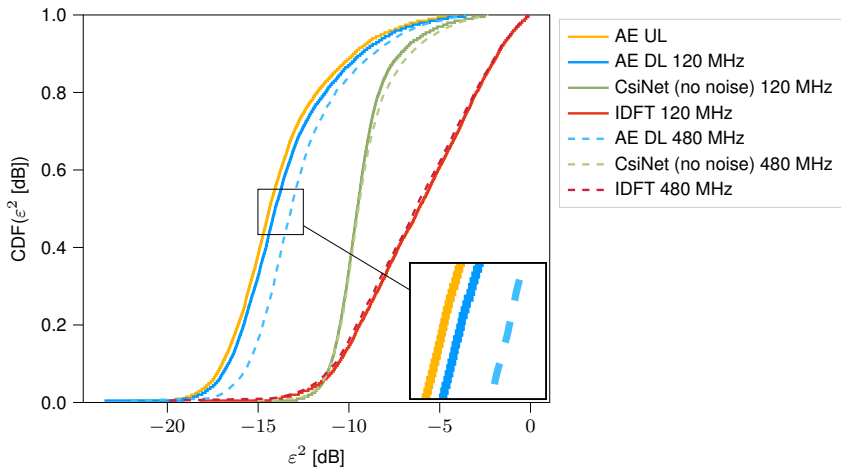
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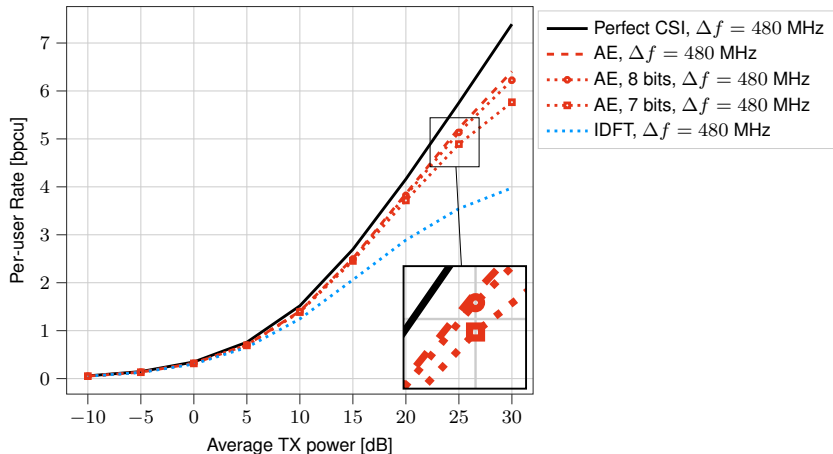


Channel Compression & Reconstruction

NMSE of different methods for SNR=10 dB.



Channel Compression & Reconstruction



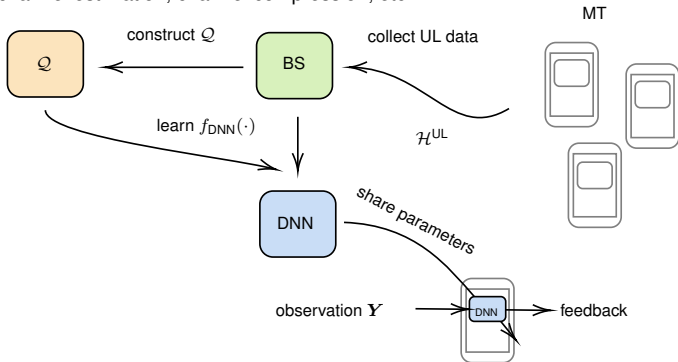
- achievable per-user rate in a multiuser scenario (8 user)
- zero-forcing precoding based on recovered DL CSI
- the [hyperbolic tangent](#) as activation function in the latent space makes easy to quantize the CSI

Application:

Codebook Construction & Feedback
Generation

Codebook Construction & Feedback Generation

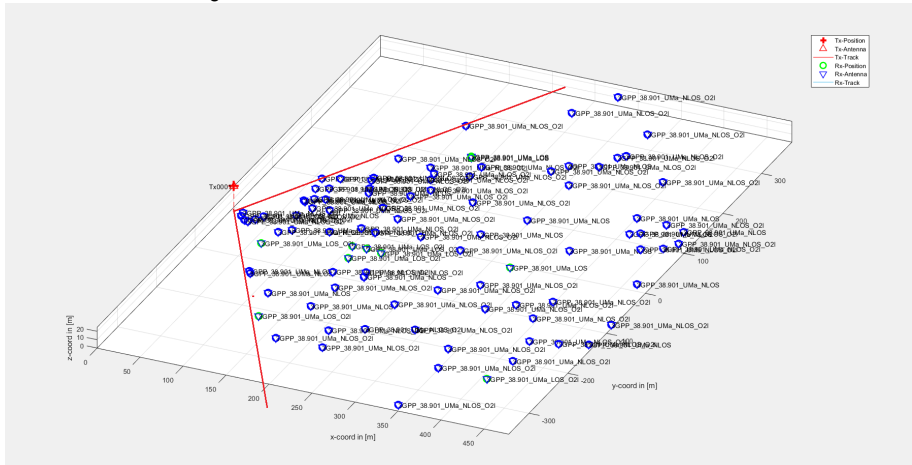
Proposed concept: Training based **solely on uplink (UL) data at the base station (@BS)** and subsequent **offloading of trained deep neural networks** to the mobile terminals (MTs) for feedback generation, channel estimation, channel compression, etc.



- kind of distributed implementation of **AI-aided physical layer** functions
- offloading deep functionalities **anywhere and anytime** in the networks for increasing performance

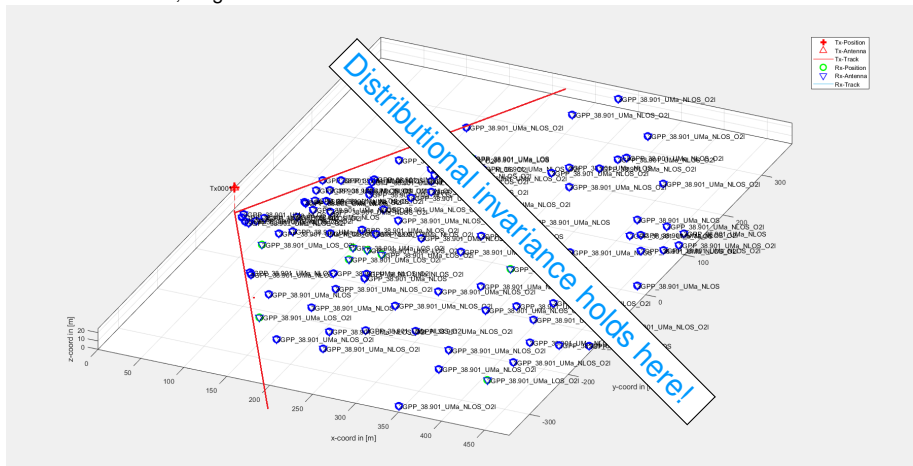
Urban Macrocell Scenario

3GPP 38.901 UMa, single carrier scenario:



Urban Macrocell Scenario

3GPP 38.901 UMa, single carrier scenario:

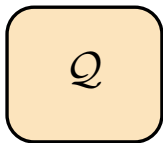


Urban Macrocell Scenario

3GPP 38.901 UMa, single carrier scenario:

- QuaDRiGa channel simulator
- MIMO channels: (BS antennas, MT antennas) = (16,4) or (32,16),
- non-line-of-sight (NLOS), line-of-sight (LOS) and outdoor-to-indoor (O2I)
- UL carrier frequency= 2.53 GHz,
- DL carrier frequency= 2.73 GHz,
- BS-UPLA with “3GPP-3D” antennas,
- MT-UPLA with “omni- directional” antennas,
- BS placed at a height of 25 m with a sector of 120° ,
- minimum distance of the MT location to the BS is 35 m,
- maximum distance to the BS is 500 m.
- 10^4 training, 2.5×10^3 validation and $\sim 5 \times 10^3$ test samples.

Codebook Construction



Codebook Construction

- unsupervised codebook design
- using the k-means algorithm based on the achievable data rate metric
- solely based on UL channel state information (CSI)

1. Divide the training set \mathcal{H} into K clusters $\mathcal{V}_k^{(i)}$:

$$\mathcal{V}_k^{(i)} = \{\mathbf{H} \in \mathcal{H} \mid r(\mathbf{H}, \mathbf{Q}_k^{(i)}) \geq r(\mathbf{H}, \mathbf{Q}_j^{(i)}), k \neq j\}.$$

2. Find new covariance matrices or update the so called “cluster centers”:

$$\mathbf{Q}_k^{(i+1)} = \underset{\mathbf{Q} \succeq \mathbf{0}}{\operatorname{argmax}} \frac{1}{|\mathcal{V}_k^{(i)}|} \sum_{\mathbf{H} \in \mathcal{V}_k^{(i)}} r(\mathbf{H}, \mathbf{Q})$$

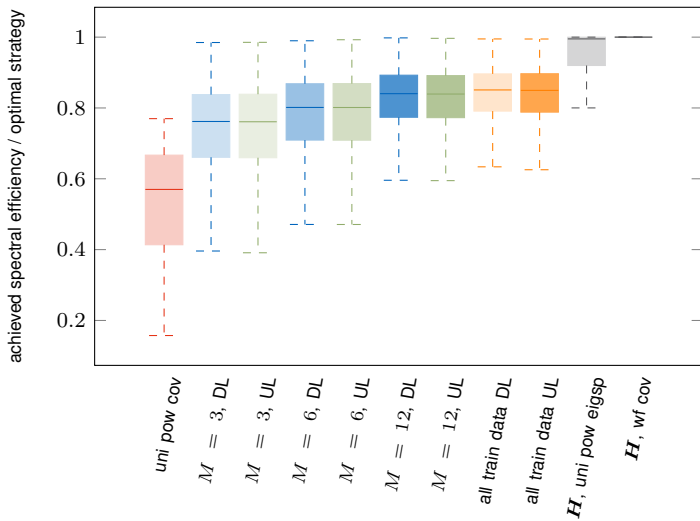
$$\text{subject to } \operatorname{trace}(\mathbf{Q}) \leq \rho \text{ and } \operatorname{rank} \mathbf{Q} \leq N_{\text{rx}}.$$

Applying a projected gradient algorithm on the candidate set of precoding covariances:

$$\mathbf{g}_Q = \frac{1}{\sigma_n^2 \ln(2)} \sum_{\mathbf{H} \in \mathcal{V}_k^{(i)}} \mathbf{H}^H \left(\mathbf{I} + \frac{1}{\sigma_n^2} \mathbf{H} \mathbf{Q} \mathbf{H}^H \right)^{-1} \mathbf{H},$$

$$\mathbf{Q} \leftarrow \mathbf{Q} + \alpha \mathbf{g}_Q.$$

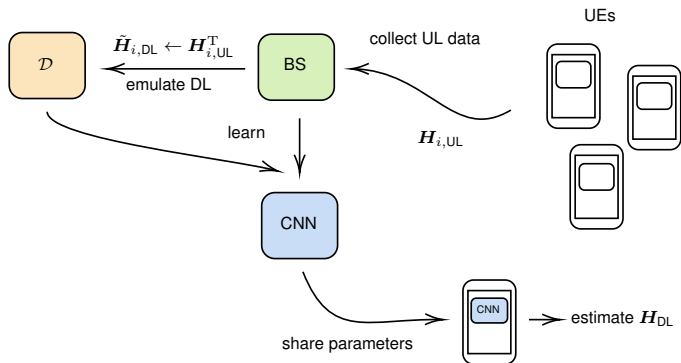
Codebook Construction



$N_{tx} = 16, N_{rx} = 4$, with different codebook sizes (2^M)

Application:
Channel Estimation

Channel Estimation



Downlink observations @MT:

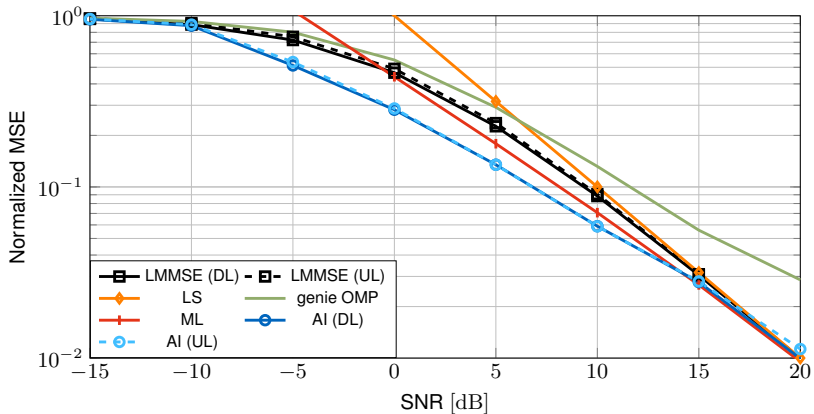
$$Y_{i,DL} = H_{i,DL} X + Z_i$$

Emulated downlink system @BS:

$$\tilde{Y}_{i,DL} = H_{i,UL}^T X + Z_i$$

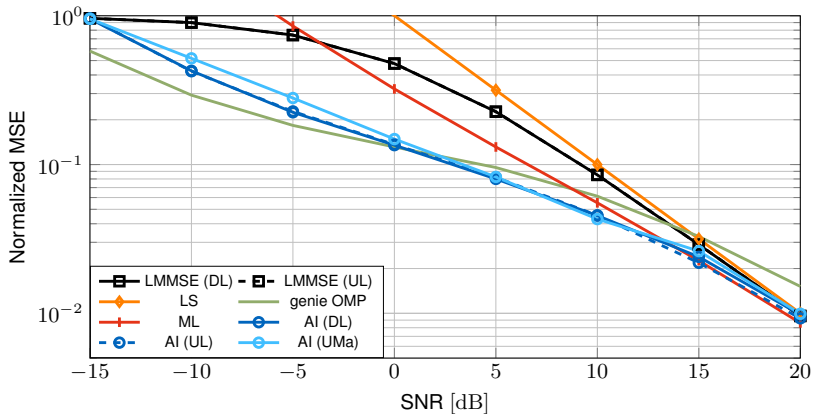
Channel Estimation

$N_{BS} = 64$, $N_{MS} = 4$, $N_P = 64$, mixed NLOS/LOS scenario, 20K training samples



Channel Estimation

$N_{BS} = 64$, $N_{MS} = 4$, $N_P = 64$, mainly LOS scenario, 20K training samples



Thank You!

Links to Recent Work

- Channel Estimation, Prediction, and Extrapolation:
Learning The CSI Recovery in FDD Systems (IEEE T-WC 2022)
(<https://arxiv.org/abs/2104.01322>)
Centralized Learning of the Distributed Downlink Channel Estimators in FDD Systems using Uplink Data (WSA 2021)
(<https://arxiv.org/abs/2105.10746>)
- Codebook Design and Feedback Generation in Multiuser MIMO Systems:
Learning The CSI Denoising and Feedback Without Supervision (SPAWC 2021)
(<https://arxiv.org/abs/2104.05002>)
Unsupervised Learning of Adaptive Codebooks for Deep Feedback Encoding in FDD Systems (Asilomar 2021)
(<https://arxiv.org/abs/2105.09125>)

Appendix

Quantitative Analysis: More About Two-Sample Tests

MMD definition

The two-sample tests are based on the maximum mean discrepancy metric. The **maximum mean discrepancy** is the distance between **feature means**:

$$\text{MMD}^2(\mathbb{P}, \mathbb{Q}, k) := \mathbb{E}[k(p, p') + k(q, q') - 2k(p, q)], \quad (1)$$

where:

- $k(\cdot, \cdot) = \langle \varphi(\cdot), \varphi(\cdot) \rangle$: positive definite kernel of a reproducing kernel Hilbert space (RKHS) \mathcal{H}_k with a feature map $\varphi(\cdot) \in \mathcal{H}_k$
- $(p, p') \sim \mathbb{P} \times \mathbb{P}$
- $(q, q') \sim \mathbb{Q} \times \mathbb{Q}$

Hence, $\text{MMD}(\mathbb{P}, \mathbb{Q}, k) = 0$ if and only if $\mathbb{P} = \mathbb{Q}$.

Kernels descriptions

- “1-percentile”: $\sigma = 1$ -percentile of the distance between points in the aggregate sample

$$k(a, b) = \exp\left(-\frac{\|a - b\|^2}{\sigma_1^2}\right)$$

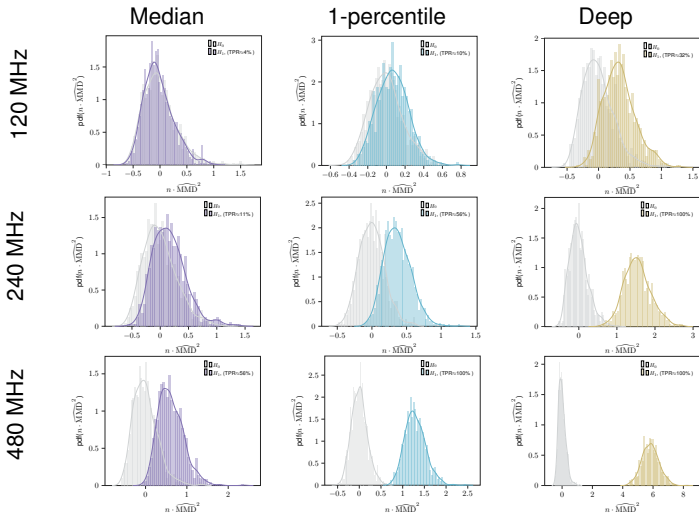
- “median”: $\sigma = 50$ -percentile of the distance between points in the aggregate sample

$$k(a, b) = \exp\left(-\frac{\|a - b\|^2}{\sigma_{50}^2}\right)$$

- “deep”: $\sigma = 50$ -percentile of the distance between points in the aggregate sample of the latent space of an autoencoder

$$k(a, b) = \exp\left(-\frac{\|\mathbf{f}_\theta(a) - \mathbf{f}_\theta(b)\|^2}{\sigma_{50, \text{latent}}^2}\right)$$

Different frequency gaps in a UMi LOS scenario



The larger the frequency gaps, larger is the discrepancy between the UL & DL distributions.

Over different UMi NLOS ($\Delta f = 120$ MHz)

