CSI COMPRESSION USING CHANNEL CHARTING

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SUM-RATE MAXIMIZATION IN FDD MMIMO SYSTEMS

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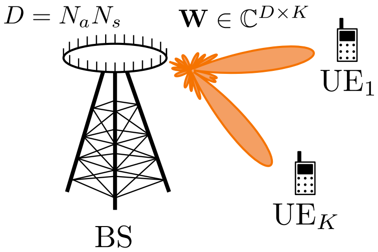

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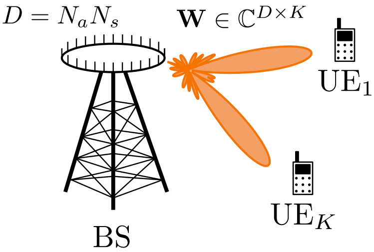

$$\max_{\mathbf{W} \in \mathbb{C}^{D \times K}} \sum_{k=1}^{K} \log_2 \left(1 + \frac{\left|\mathbf{h}_k^{\mathsf{H}} \mathbf{w}_k\right|^2}{\sigma_k^2 + \sum_{j \neq k} \left|\mathbf{h}_k^{\mathsf{H}} \mathbf{w}_j\right|^2} \right) \quad \text{s.t.} \quad \mathcal{C}_p : \forall k \in [\![1, K]\!], \|\mathbf{w}_k\|_2 = \frac{1}{\sqrt{K}} \tag{1}$$

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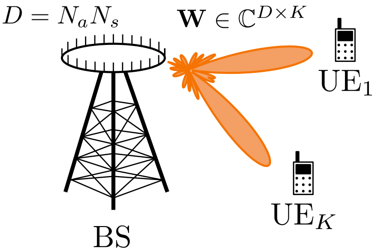

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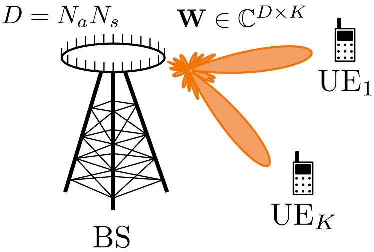

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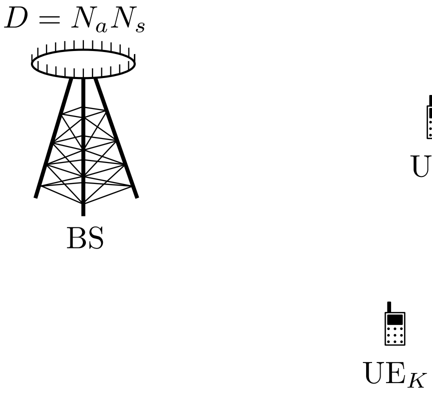

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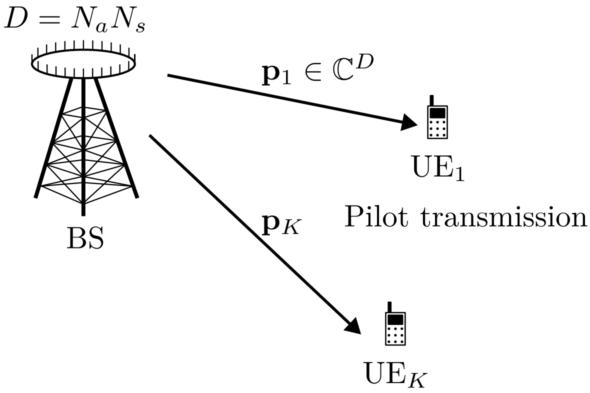

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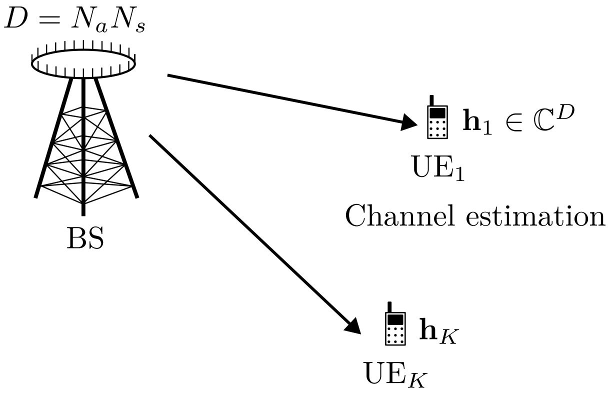

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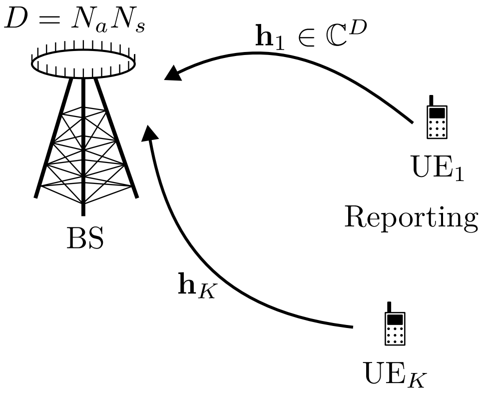

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Huge complexity reduction

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Is it possible to decode a beamforming matrix from the compressed CSI?

CONTRIBUTIONS

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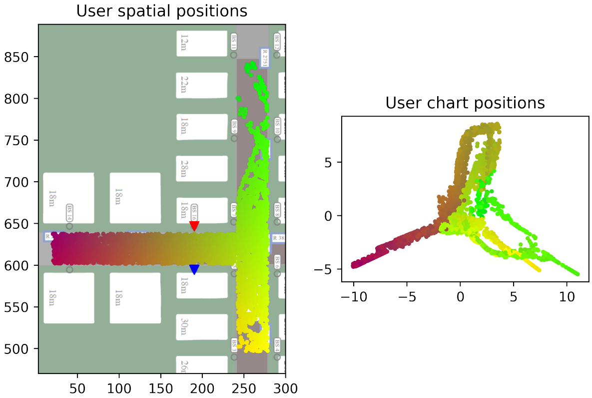
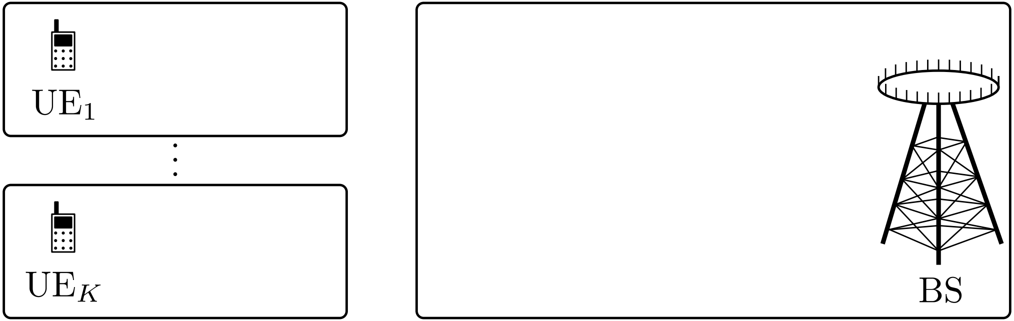


PROPOSED APPROACH



- System model

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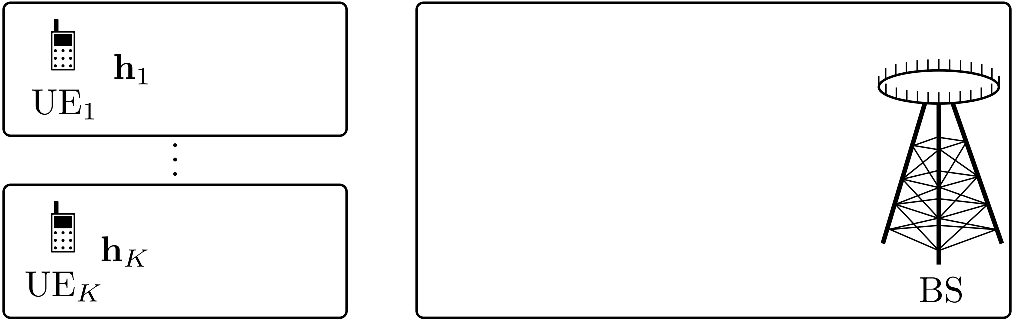

- Downlink channel estimation

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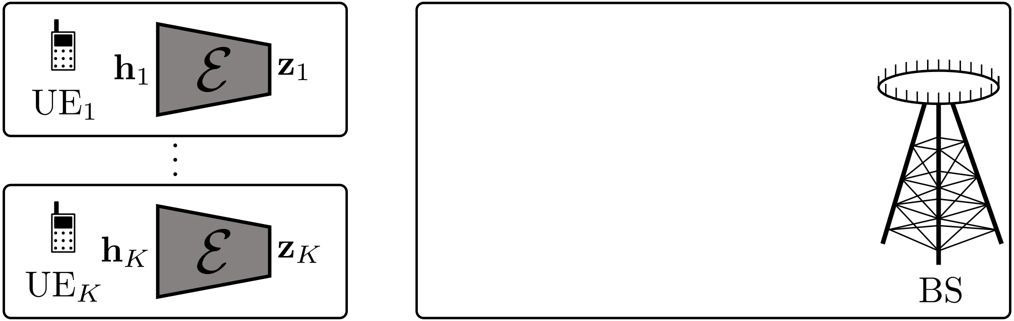

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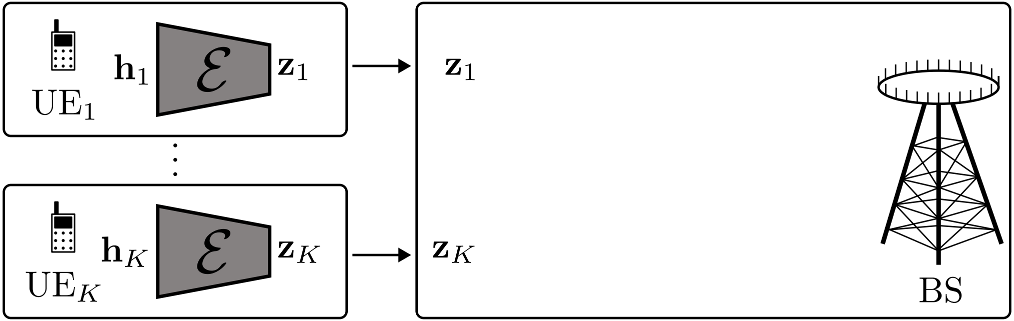

- Encoded channel transmission

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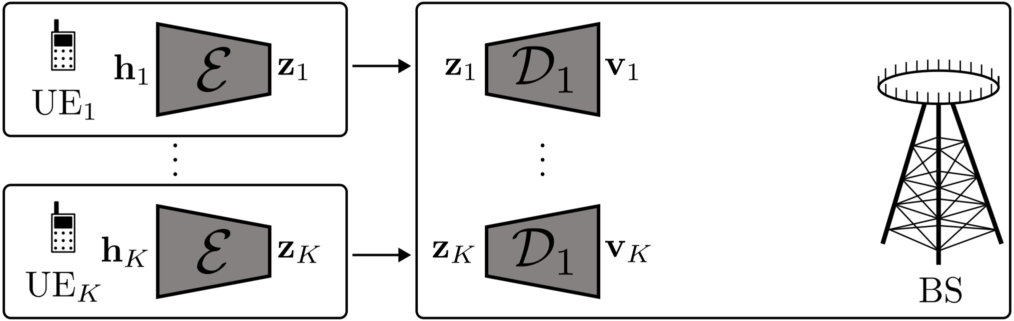

- Individual decoding: mono-UE processing

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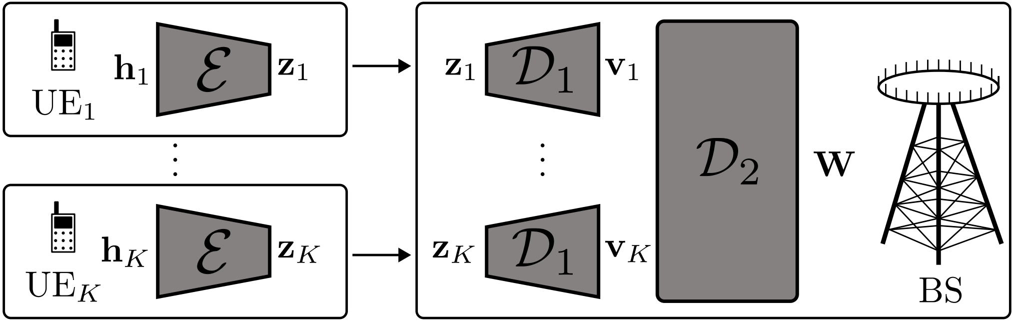

- Parallel decoding: multi-UE processing

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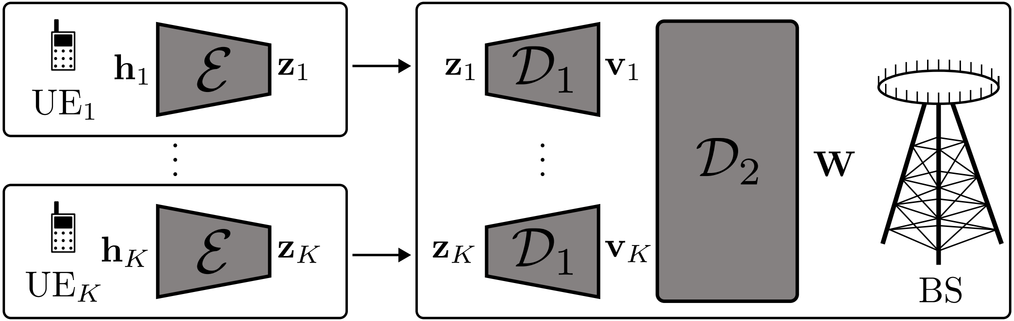

- Loss function: $\mathbf{v} = (\mathcal{D}_1 \circ \mathcal{E})(\mathbf{h})$

$$\mathcal{L} = 1 - \frac{1}{|\mathcal{B}|} \sum_{\mathbf{h} \in \mathcal{B}} \frac{\left|\mathbf{v}^{\mathsf{H}} \mathbf{h}\right|^2}{\|\mathbf{h}\|_2^2}, \qquad (3)$$

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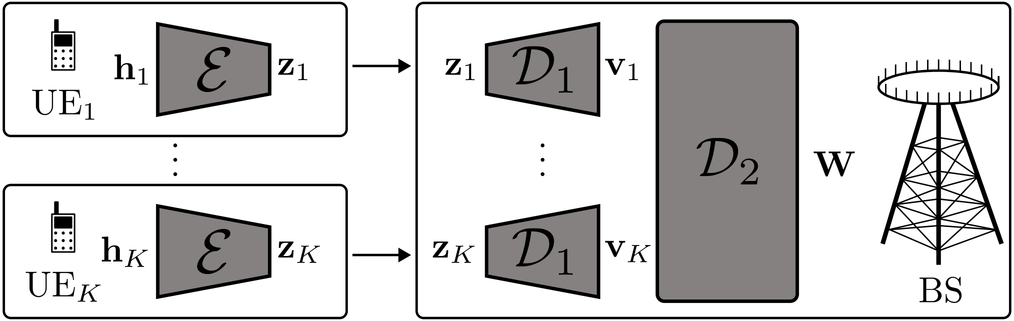

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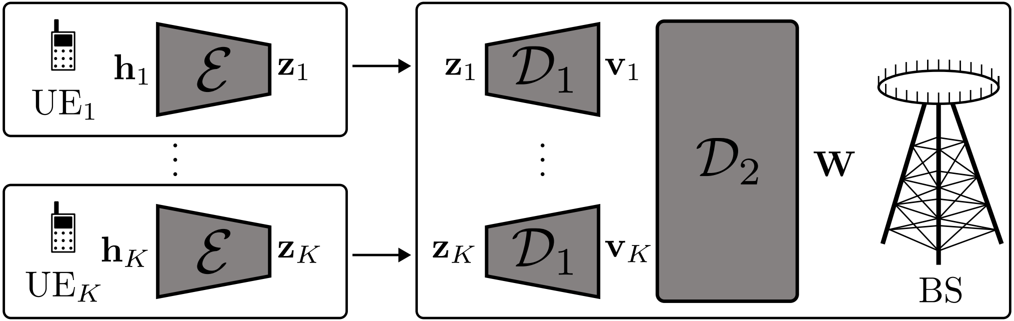

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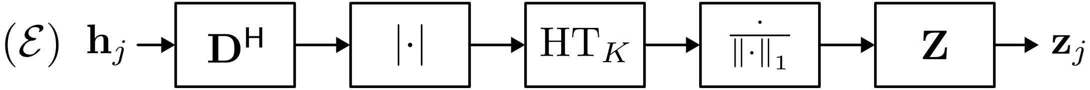
- $\mathcal{L}$ is minimized when $\mathbf{v} \rightarrow \mathbf{h}\mathrm{e}^{\mathrm{j}\phi} / \|\mathbf{h}\|_2$
- After denormalization, $\mathbf{v}$ is an imperfect channel estimate, that can be used in linear precoders

ENCODER ARCHITECTURE

- Architecture presented in[1,2,3]



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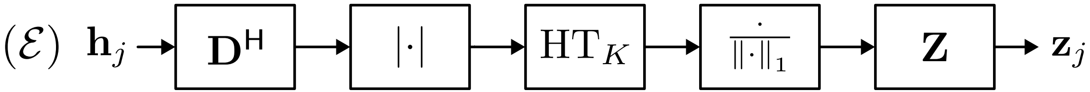

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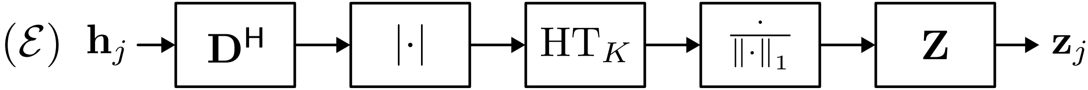

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- $\mathbf{z}_j$ can be seen as a wisely chosen convex combination of calibration chart locations

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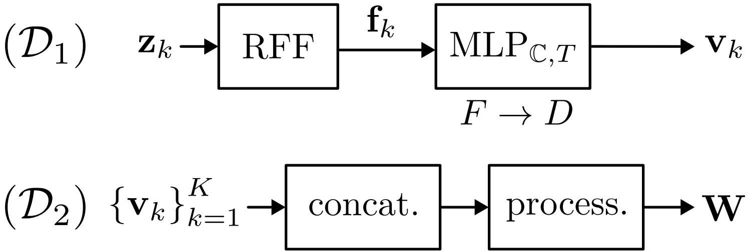

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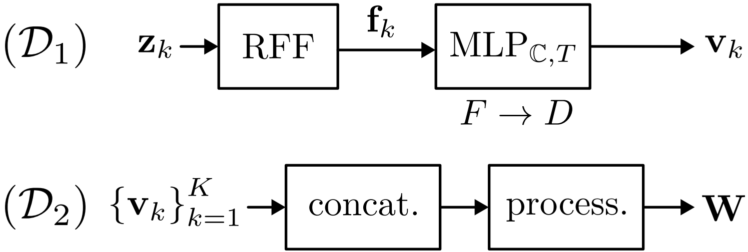

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- $\mathbf{f}_k = \begin{bmatrix} \cos(2\pi \mathbf{F}\mathbf{z}_k) \\ \sin(2\pi \mathbf{F}\mathbf{z}_k) \end{bmatrix}, \mathbf{F} \sim \mathcal{N}\left(\mathbf{0}_F, \sigma_F^2 \mathrm{Id}_F\right)$

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where $\operatorname{sim}\left(\mathbf{h}_i, \mathbf{h}_j\right)$ is a similarity metric:

$$\operatorname{sim}\left(\mathbf{h}_i, \mathbf{h}_j\right) = \frac{\left|\mathcal{E}\left(\mathbf{h}_i\right)^{\mathsf{H}} \mathcal{E}\left(\mathbf{h}_j\right)\right|}{\left\|\mathcal{E}\left(\mathbf{h}_i\right)\right\|_2 \left\|\mathcal{E}\left(\mathbf{h}_j\right)\right\|_2}. \tag{5}$$

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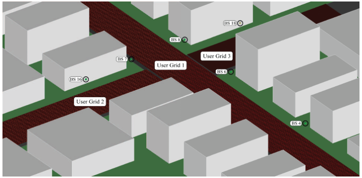

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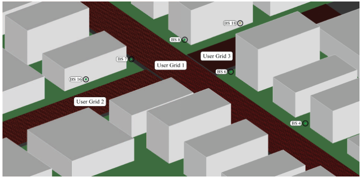

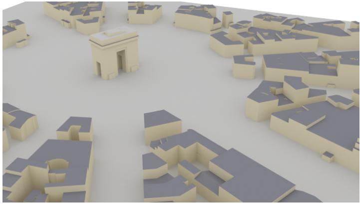

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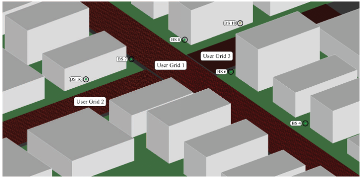

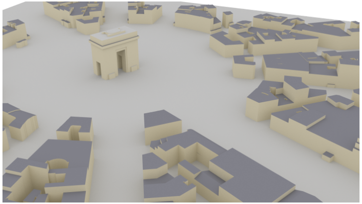

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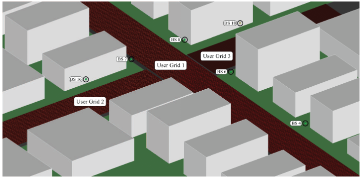

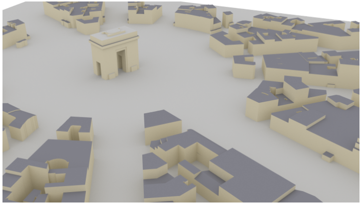

EXPERIMENTS: DATASETS AND METRICS

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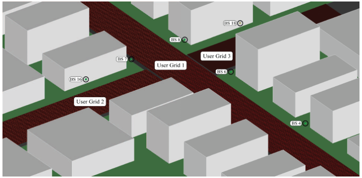

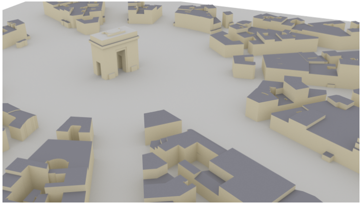

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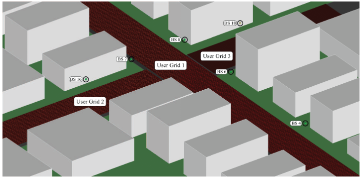

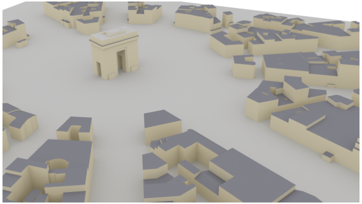

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$$\rho_k = \frac{\left|\mathbf{v}_k^{\mathsf{H}}\mathbf{h}_k\right|^2}{\|\mathbf{v}_k\|_2^2\,\|\mathbf{h}_k\|_2^2}, \tag{6}$$

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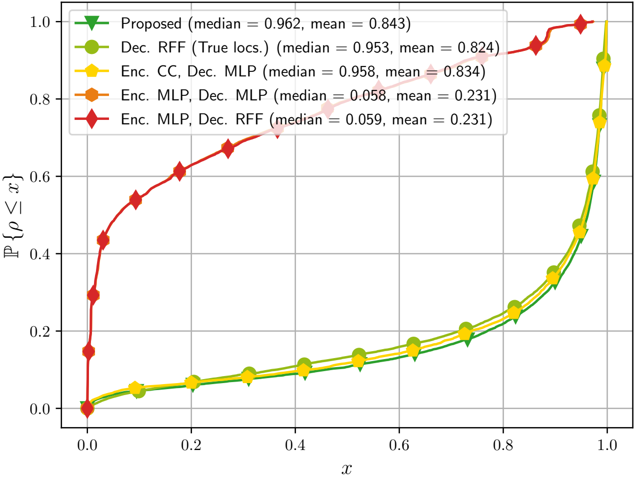
    $\mathbf{v}_k = (\mathcal{D}_1 \circ \mathcal{E})(\mathbf{h}_k)$.
  - Multi-UE scenario, ergodic sum-rate:

$$\mathring{\mathcal{R}} = \frac{1}{B}\sum_{b=1}^{B}\sum_{k}\log_2\left(1 + \frac{\left|\mathbf{h}_{k,b}^{\mathsf{H}}\mathbf{w}_{k,b}\right|^2}{\sigma_{k,b}^2 + \sum_{j\neq k}\left|\mathbf{h}_{k,b}^{\mathsf{H}}\mathbf{w}_{j,b}\right|^2}\right), \tag{7}$$

    UE set partition into B groups of K UEs. $\mathbf{W}_b = \mathcal{D}_2 \circ \left(\{\mathbf{v}_{k,b}\}_{k=1}^{K}\right)$

EXPERIMENTS: PERFORMANCE WRT. BASELINES



EXPERIMENTS: ENC. LEARNING AND SUBSAMPLING IMPACT

	Network	a
	Params.	$101\mathrm{k}$
`Sionna`	Median ρ	0.88
	Mean ρ	0.79
`DeepMIMO`	Median ρ	0.91
	Mean ρ	0.73

- a. No encoder learning, no subsampling

EXPERIMENTS: ENC. LEARNING AND SUBSAMPLING IMPACT

	Network	a	b
	Params.	101k	10.3M
`Sionna`	Median ρ	0.88	**0.94**
	Mean ρ	0.79	0.86
`DeepMIMO`	Median ρ	0.91	0.96
	Mean ρ	0.73	0.85

- a. No encoder learning, no subsampling
- b. Encoder learning, no subsampling

EXPERIMENTS: ENC. LEARNING AND SUBSAMPLING IMPACT

	Network	a	b	c
	Params.	101k	10.3M	306k
Sionna	Median ρ	0.88	**0.94**	**0.94**
	Mean ρ	0.79	0.86	**0.88**
DeepMIMO	Median ρ	0.91	0.96	**0.97**
	Mean ρ	0.73	0.85	**0.87**

- a. No encoder learning, no subsampling
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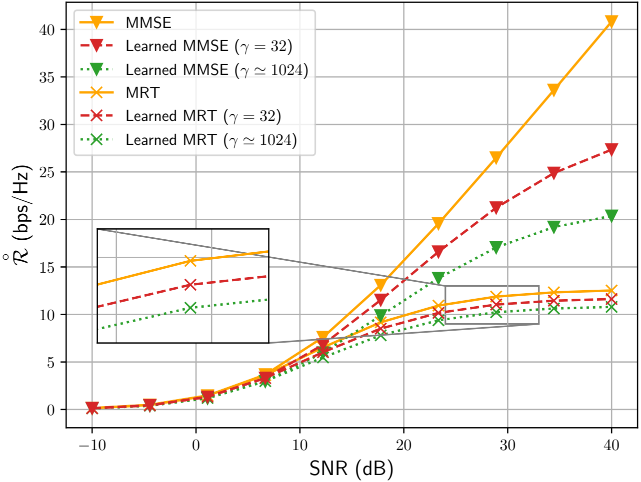
- c. Encoder learning, subsampling ($\tilde{N} = 100$)

EXPERIMENTS: ENC. LEARNING AND SUBSAMPLING IMPACT

	Network	a	b	c	d
	Params.	101k	10.3M	306k	121k
Sionna	Median ρ	0.88	**0.94**	**0.94**	**0.94**
	Mean ρ	0.79	0.86	**0.88**	**0.88**
DeepMIMO	Median ρ	0.91	0.96	**0.97**	0.96
	Mean ρ	0.73	0.85	**0.87**	0.84

- a. No encoder learning, no subsampling
- b. Encoder learning, no subsampling
- c. Encoder learning, subsampling ($\tilde{N} = 100$)
- d. Encoder learning, subsampling ($\tilde{N} = 10$)

EXPERIMENTS: MULTI-UE PERFORMANCE



CONCLUSION

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- Future work:
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  - SR-optimization through UE grouping policy learning

Thanks!