/ Model-based Deep Learning for Beam Prediction based on a Channel Chart /

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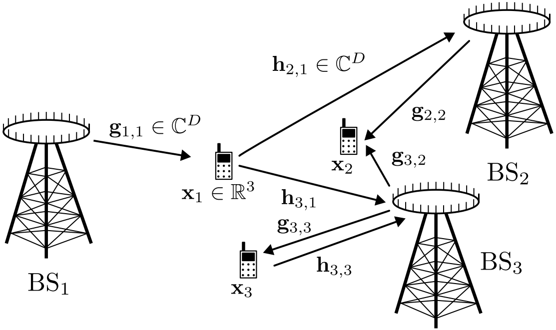
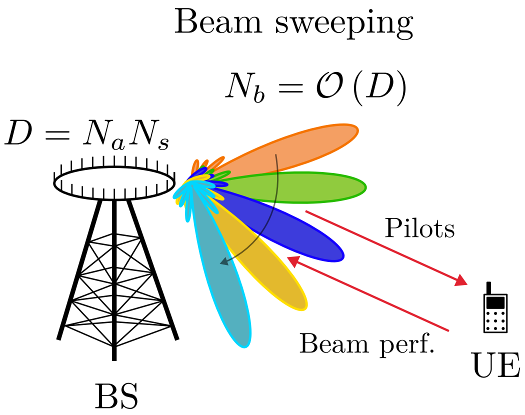
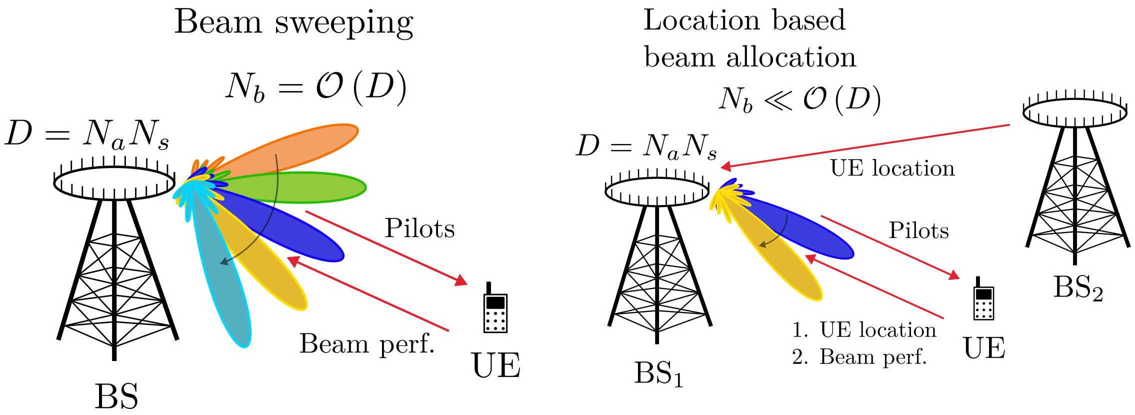
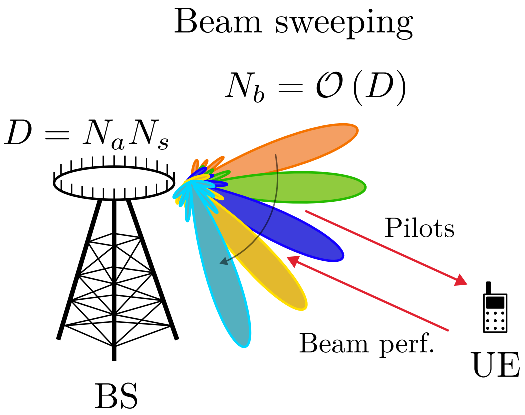
- In Cell Free Massive MIMO communication systems, with different uplink and downlink frequencies, how to attribute the best BS beam to a given UE ?




Beam sweeping
$N_b = \mathcal{O}(D)$
$D = N_a N_s$
Pilots
Beam perf.
UE
BS


Beam sweeping
$N_b = \mathcal{O}(D)$
$D = N_a N_s$
Pilots
Beam perf.
UE
BS
Location based
beam allocation
$N_b \ll \mathcal{O}(D)$
$D = N_a N_s$
UE location
Pilots
1. UE location
2. Beam perf.
UE
BS_1
BS_2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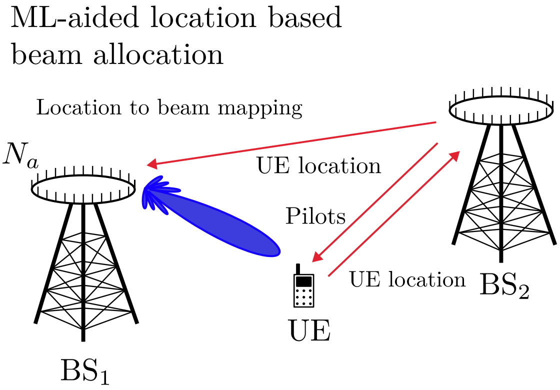
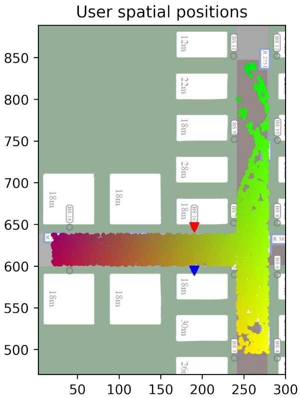
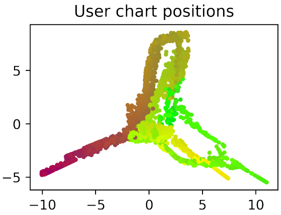
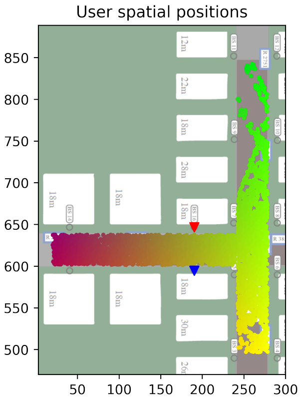
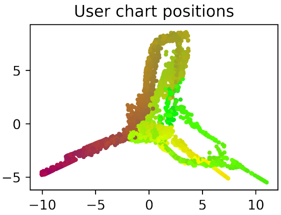

ML-aided location based beam allocation
Location to beam mapping
N_a
UE location
Pilots
UE location
BS_2
UE
BS_1

What happens if the location becomes a chart location ?

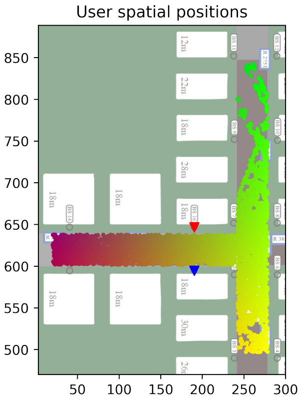

User spatial positions
850
800
750
700
650
600
550
500
50
100
150
200
250
300

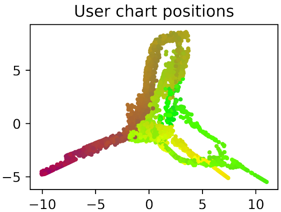

User chart positions
5
0
−5
−10
−5
0
5
10





- Locations: GNSS





- Locations: GNSS
- Chart/Pseudo-locations: dim. reduction of the channel

Contributions

- **New neural architecture for the pseudo-location to beam mapping**

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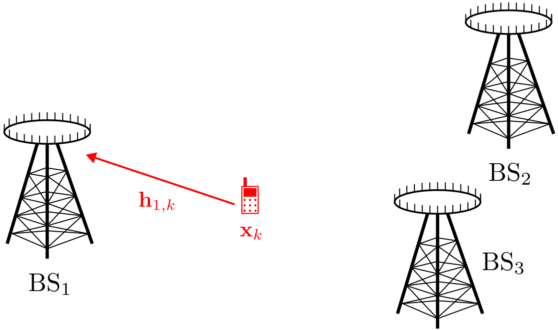
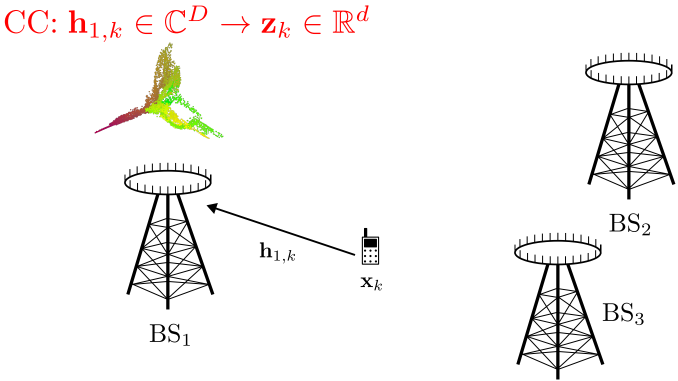
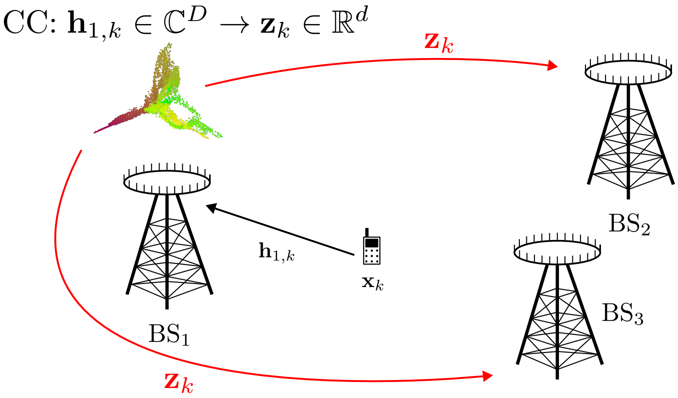
- **Assessment of codebook performance versus precoder learning in cell-free systems**



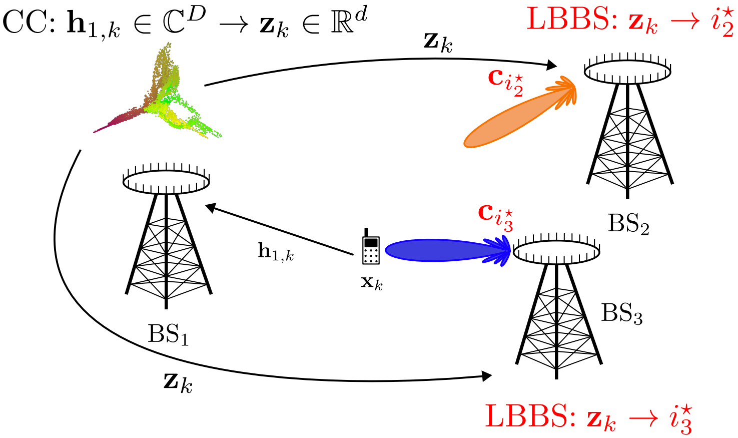
- Inference: get uplink channels at BS1



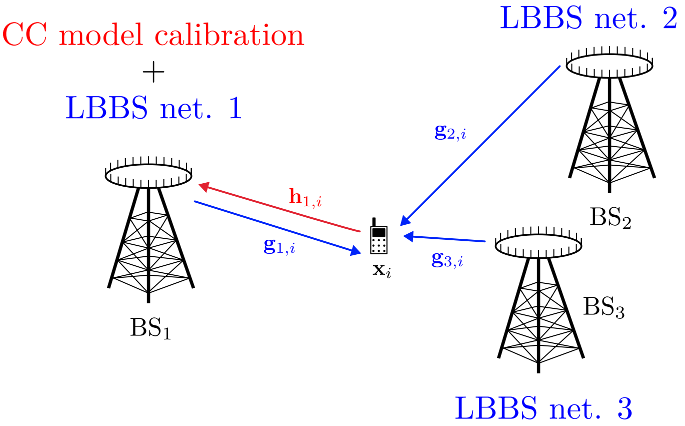
- Inference: channel charting



- Inference: send pseudo-locations to other BSs

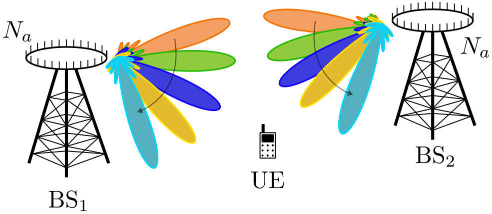


- Inference: beam selection from pseudo-locations



- Training: CC only at BS1, LBBS networks at all BSs

- Classical approach:



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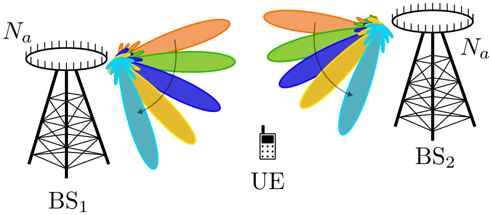

  - All BSs perform beam sweeping: $\mathcal{O}(BD)$

< Beam allocation complexity >

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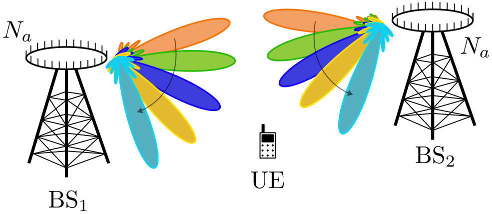

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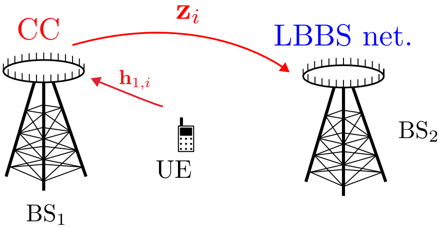

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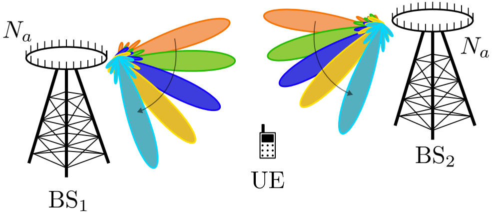

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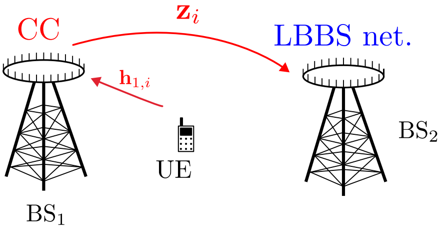

  - One BS performs channel estimation and channel charting

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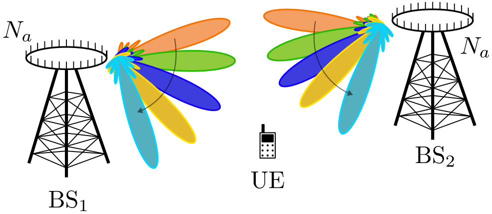

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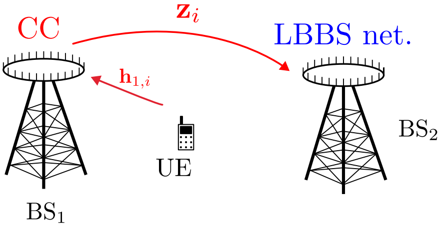

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  - Then it sends the pseudo-loc. to other BSs

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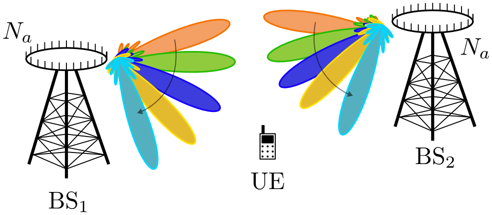

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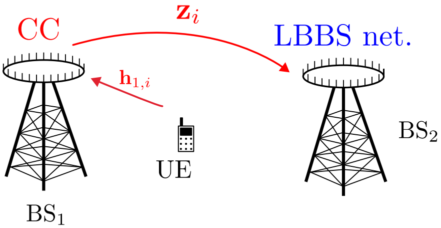

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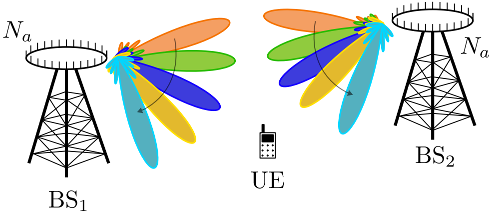

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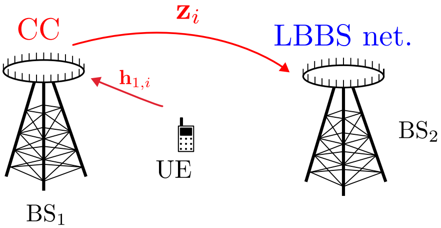

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Huge complexity reduction

- Manifold learning methods such as `ISOMAP` are computationally intensive in out-of-sample scenarios

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[2] Le Magoarou, "Efficient Channel Charting via Phase-Insensitive Distance Computation".

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$$\{\mathbf{h}_{1,n}\}_{n=1}^{N} \xrightarrow{\texttt{ISOMAP}} \{\mathbf{z}_{1,n}\}_{n=1}^{N}$$

$$\left(\mathbf{D} \triangleq (\mathbf{h}_{1,1} \cdots \mathbf{h}_{1,N}) \in \mathbb{C}^{N_a \times N}\right) \qquad \left(\mathbf{Z} \triangleq (\mathbf{z}_{1,1} \cdots \mathbf{z}_{1,N}) \in \mathbb{C}^{d \times N}\right)$$

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Out-of-sample channel: $\mathbf{h}_{1,j}$

$$\mathbf{h}_{1,j} \rightarrow \boxed{\mathbf{D}^{\mathrm{H}}} \rightarrow \boxed{|\cdot|} \rightarrow \boxed{\mathrm{HT}_K} \rightarrow \boxed{\frac{\cdot}{\|\cdot\|_1}} \rightarrow \boxed{\mathbf{Z}} \rightarrow \mathbf{z}_{1,j}$$

- $\mathbf{z}_{1,j}$ can be seen as a convex combination of the pseudo-locations associated to the K most correlated channels with $\mathbf{h}_{1,j}$.

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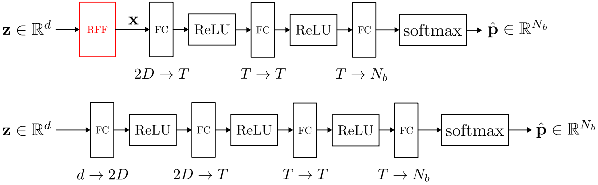
RFF

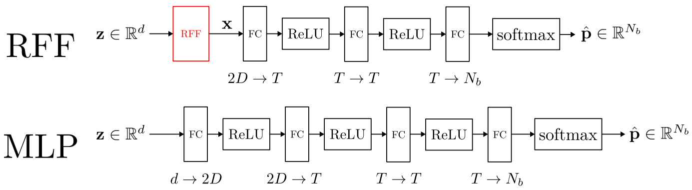
MLP



Training loss: multi-class cross entropy

$$\mathcal{L} = -\sum_{u=1}^{\mathcal{B}} \mathbf{p}_u^{\mathrm{T}} \log_2 \left(\hat{\mathbf{p}}_u\right)$$

$$\mathbf{p}_u \in \mathbb{R}^{N_b},\ \left(\mathbf{p}_u\right)_j = 1 \Leftrightarrow i^\star = j \text{ for UE } u.$$



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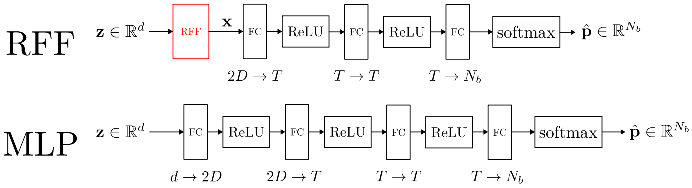
- $\mathbf{x} = \begin{bmatrix} \cos(2\pi \mathbf{B}\mathbf{z}) \\ \sin(2\pi \mathbf{B}\mathbf{z}) \end{bmatrix}, \mathbf{B} \in \mathbb{R}^{F \times d}$
- $\mathbf{B} \sim \mathcal{N}\left(\mathbf{0}_F, \sigma^2 \mathbf{Id}_F\right)$
- $d = 5,\ F = 200,\ T = 64,\ N_b = 256$



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- $\mathbf{B} \sim \mathcal{N}\left(\mathbf{0}_F, \sigma^2\mathbf{Id}_F\right)$
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- Baseline: 1-NN $\to$ the best beam for a given test pseudo-loc. is the optimal beam of the closest train pseudo-loc.

- Two different scenes:
  - Urban canyon with *DeepMIMO*[3]
  - Paris, Étoile neighborhood with *Sionna*[4]

[3] Alkhateeb, “DeepMIMO: A Generic Deep Learning Dataset for Millimeter Wave and Massive MIMO Applications”.
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- Radio parameters:
  - 2 BSs: UPA $8\text{x}8 \Rightarrow N_a = 64$
  - 2D-DFT codebook: $N_b = 4N_a$
  - UEs: mono-antenna
  - Uplink: 3.5GHz
  - Downlink: 28GHz
  - Multicarrier: 16 subcarriers over 20MHz bandwidth

[3] Alkhateeb, “DeepMIMO: A Generic Deep Learning Dataset for Millimeter Wave and Massive MIMO Applications”.
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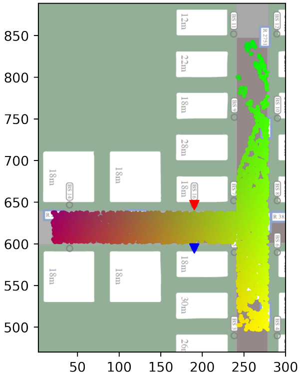
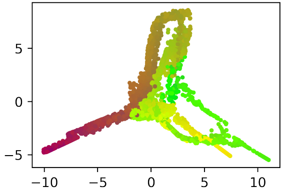
User spatial positions

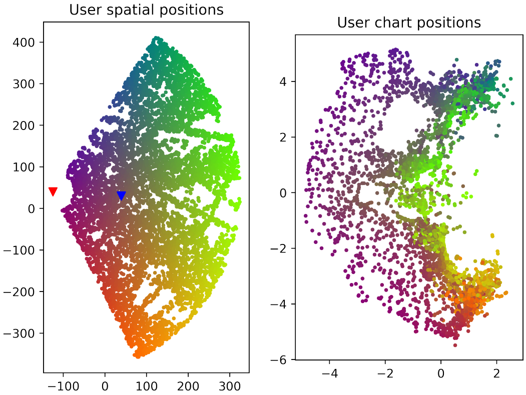


User chart positions



- Neighbours: 5% of dataset size

TW	CT	KS
0.973	0.929	0.471



- Neighbours: 5% of dataset size

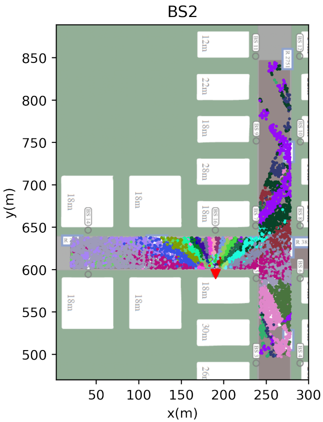
TW	CT	KS
0.960	0.952	0.292

- Chart shape can be explained[5]

[5] Yassine et al., *Optimizing Multicarrier Multiantenna Systems for LoS Channel Charting*.

< Best beam spatial distribution: BS2 >

- DeepMIMO



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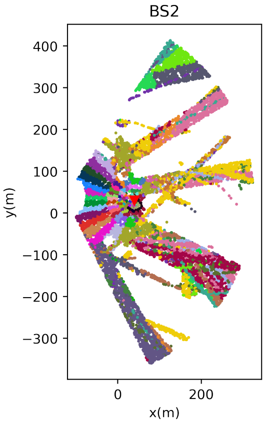

- Pseudo-locs.

DeepMIMO	RFF	MLP	1-NN
Top 1 acc. (%)	**66.07**	56.06	61.40
Top 2 acc. (%)	**84.87**	76.97	81.31
Top 3 acc. (%)	**90.66**	85.09	88.77
Sionna	RFF	MLP	1-NN
Top 1 acc. (%)	66.07	54.07	**69.73**
Top 2 acc. (%)	75.13	65.00	**79.47**
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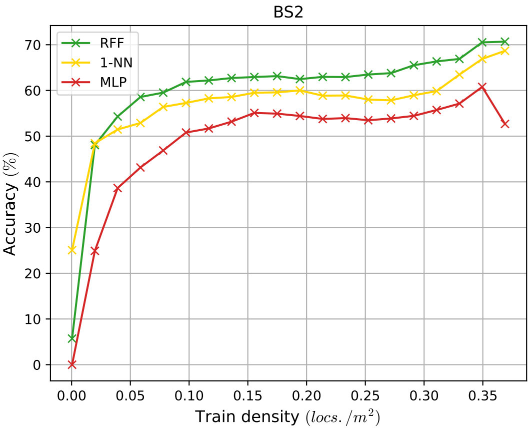
- True locs.

DeepMIMO	RFF	MLP	1-NN
Top 1 acc. (%)	**74.53**	34.15	71.08
Top 2 acc. (%)	**91.21**	46.61	88.32
Top 3 acc. (%)	**95.77**	54.39	94.33
Sionna	RFF	MLP	1-NN
Top 1 acc. (%)	**82.53**	42.40	82.07
Top 2 acc. (%)	**88.40**	49.93	88.27
Top 3 acc. (%)	**89.87**	53.80	**89.87**

- DeepMIMO



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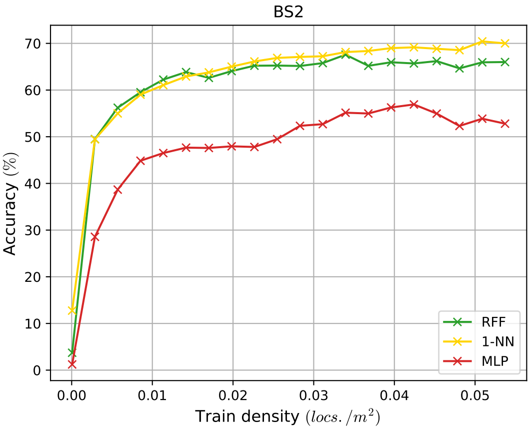

- Mean execution time for inference (1.5M pseudo-locs.)

	RFF	MLP	1-NN (ball-tree)	1-NN (brute force)
Execution time (ns)	602.6	$\mathbf{145.8}$	4928.2	10913.9

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- GPU implementation of RFF/MLP: very fast inference times

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- When considering online learning, parametric methods (i.e. RFF/MLP) would outperform non-parametric methods (i.e. 1-NN) in terms of inference complexity

- From a pseudo-location learn a precoder $\mathbf{w} \in \mathbb{C}^{N_a}$
  - Pseudo-location based beamforming

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- Training loss: correlation-based (between precoder and downlink channel)

$$\mathcal{L} = 1 - \frac{1}{\mathcal{B}} \sum_{u=1}^{\mathcal{B}} \frac{\left| \mathbf{w}_u^{\mathsf{H}} \mathbf{g}_u \right|^2}{\left\| \mathbf{g}_u \right\|_2^2} \tag{1}$$

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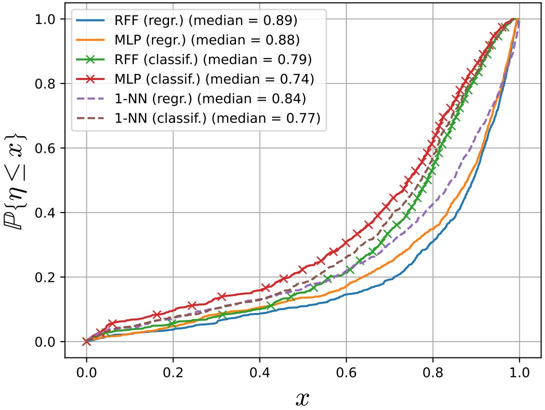
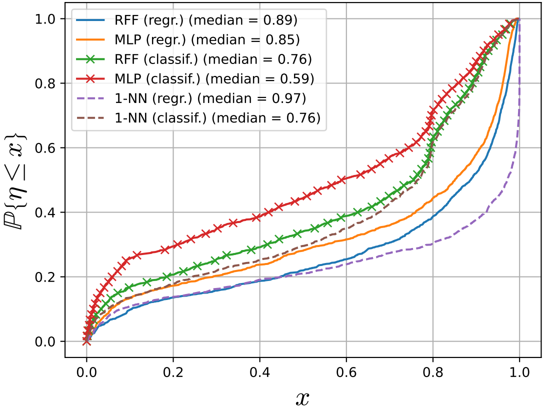
- Evaluation metric: normalized correlation between precoder and downlink channel:

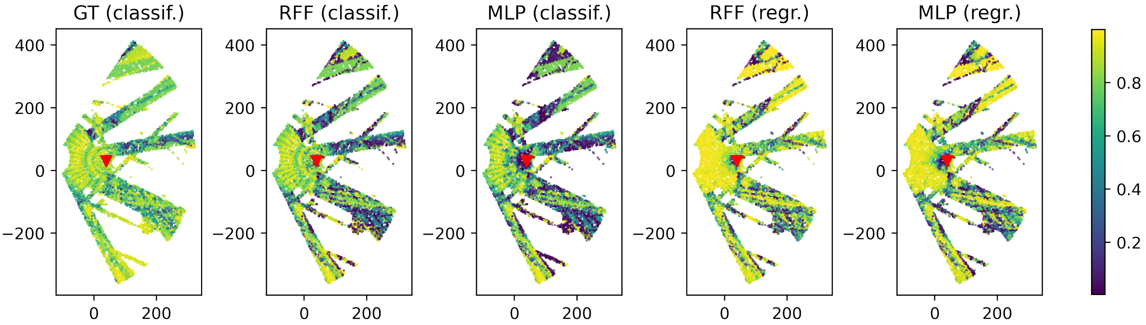
$$\eta = \frac{\left|\mathbf{w}^{\mathsf{H}} \mathbf{g}\right|^2}{\|\mathbf{g}\|_2^2} \tag{2}$$

- DeepMIMO



- Sionna




GT (classif.)
RFF (classif.)
MLP (classif.)
RFF (regr.)
MLP (regr.)
400
200
0
−200
0
200
0.8
0.6
0.4
0.2

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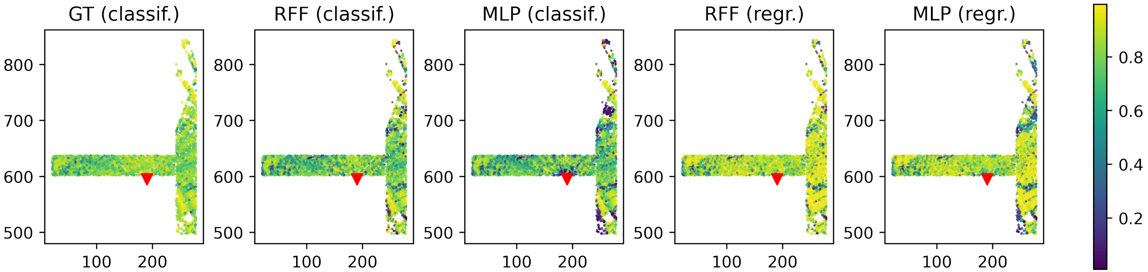
    - Would using an auto-encoders cause a performance drop ?
  - End-to-end training for channel charting and neural network.

Thank you!
Questions?



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Thanks