Digital Twin Aided Compressive Sensing: Enabling Site-Specific MIMO Hybrid Precoding

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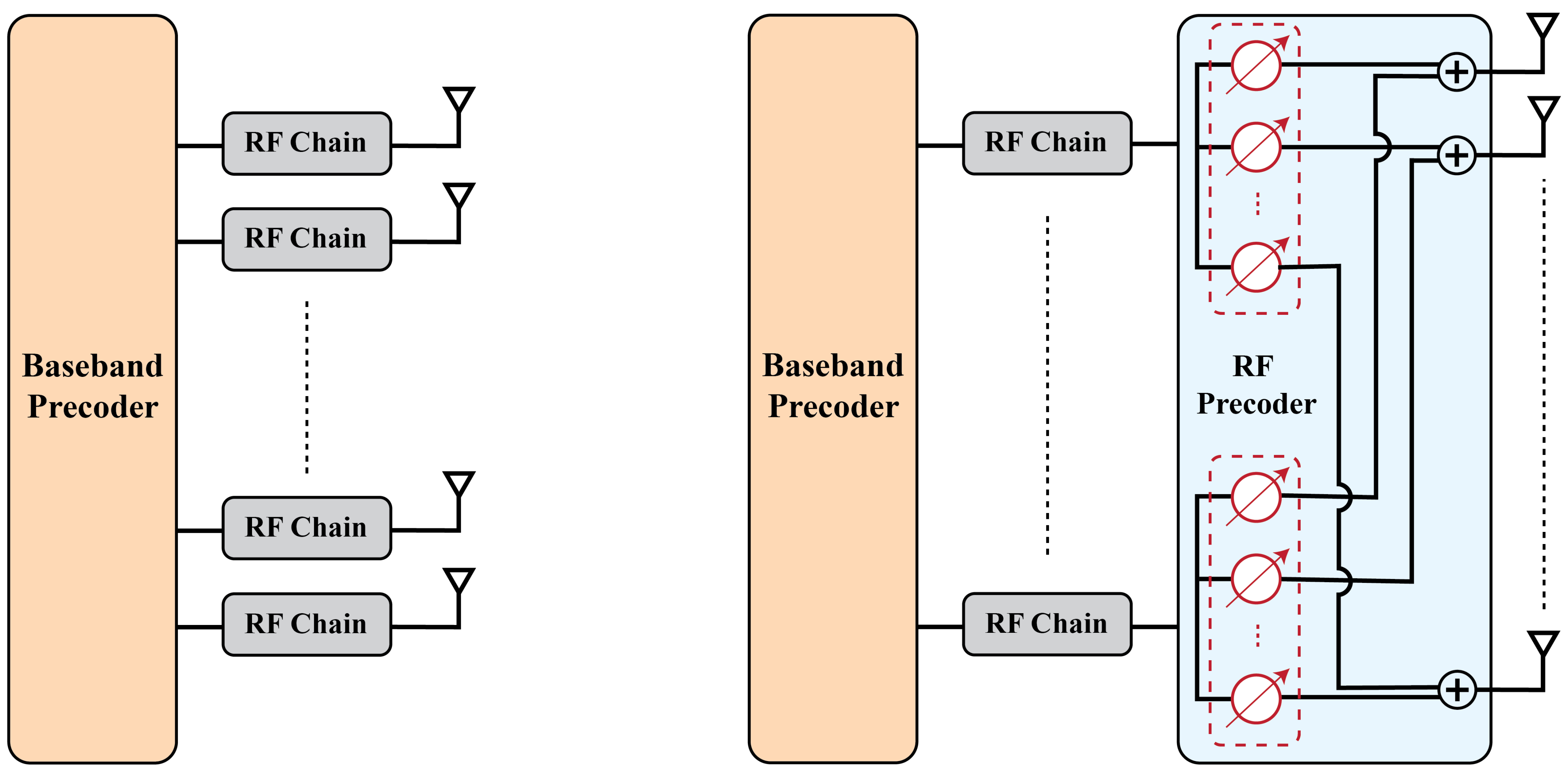
Motivation

- MIMO systems can employ large antenna arrays to improve spectral efficiency
  - Achieve high beamforming gain
  - Enable spatial multiplexing
- Traditional fully-digital array architecture
  - Hardware cost
  - Power consumption
- Hybrid analog/digital architecture
  - Fewer RF chains are deployed
  - Channel estimation becomes challenging

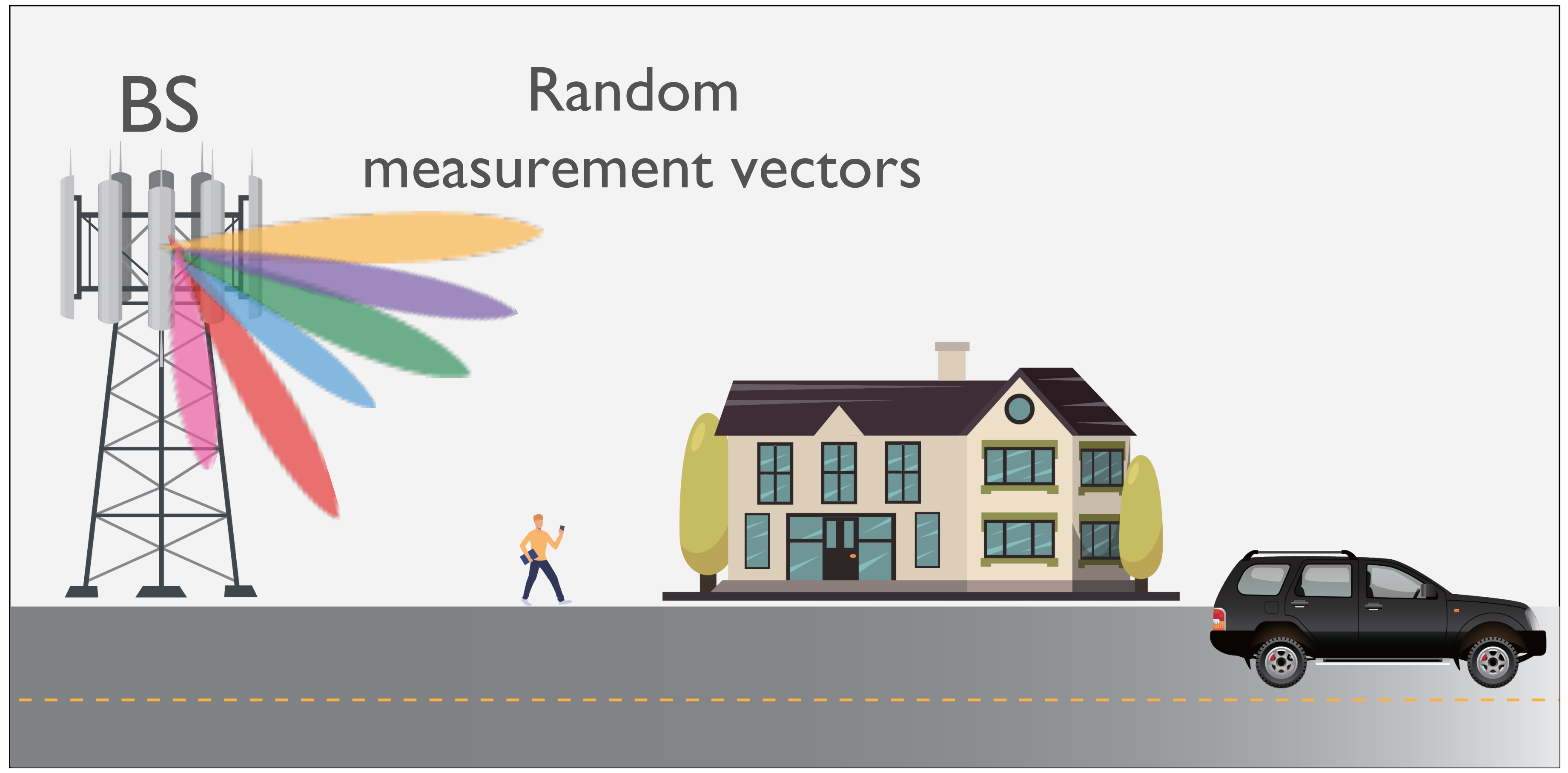


Hybrid architecture requires efficient channel estimation and precoder design methods

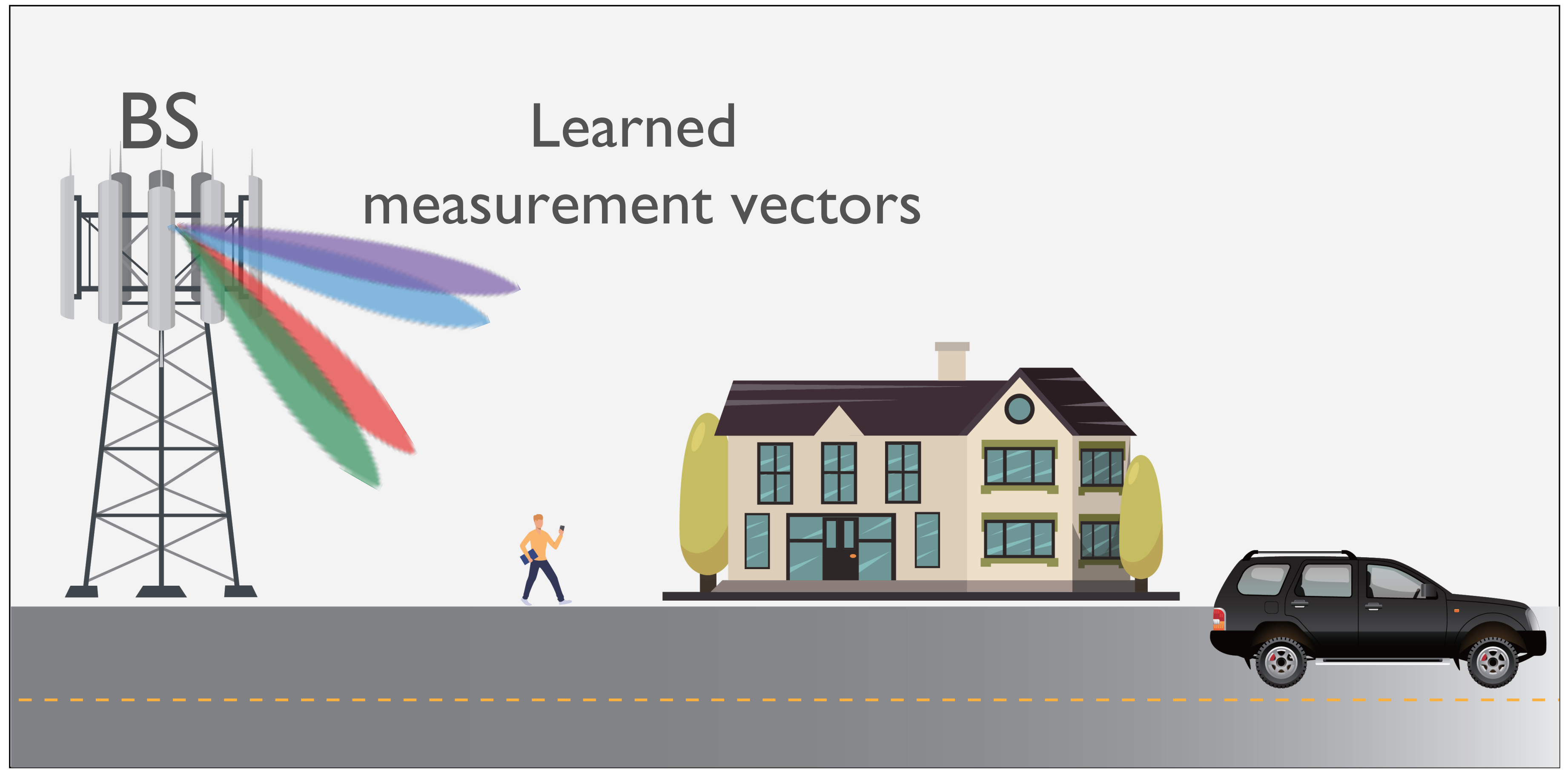
[Ayach'14] O. E. Ayach, S. Rajagopal, S. Abu-Surra, Z. Pi, and R. W. Heath, "Spatially Sparse Precoding in Millimeter Wave MIMO Systems," *IEEE Transactions on Wireless Communications*, vol. 13, no. 3, pp. 1499–1513, 2014.

Prior work

- Compressive sensing based methods [Alkhateeb'14]
  - Quantize the channel with an over-complete dictionary
  - Leverage random measurement for sparse recovery



- Machine learning (ML) based methods [Li'19]
  - Jointly learn channel sensing and hybrid precoding
  - Capture promising directions of the channel



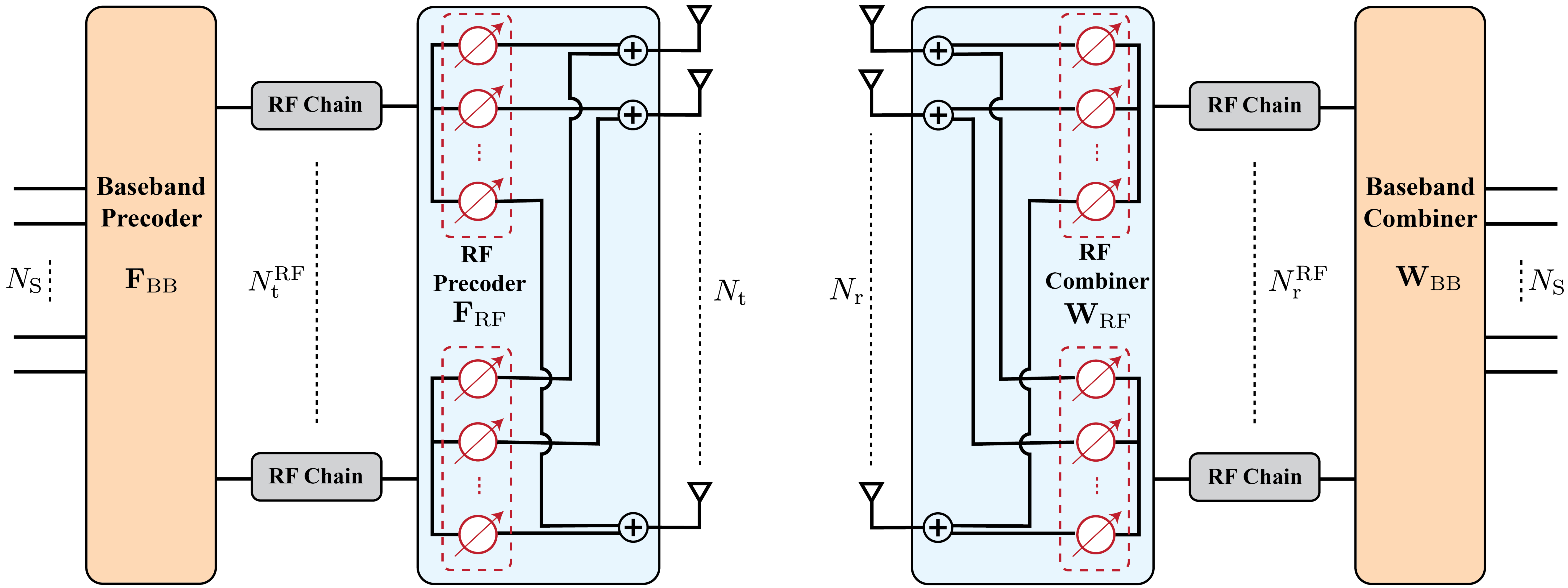
Data-driven methods require a large amount of training data

Site-specific digital twins can reduce data collection overhead

[Alkhateeb'14] A. Alkhateeb, O. El Ayach, G. Leus and R. W. Heath, "Channel Estimation and Hybrid Precoding for Millimeter Wave Cellular Systems," in *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 5, pp. 831-846, Oct. 2014.

[Li'19] X.Li and A.Alkhateeb, "Deep Learning for Direct Hybrid Precoding in Millimeter Wave Massive MIMO Systems," in *Proc. of 53rd Asilomar Conference on Signals, Systems, and Computers*, 2019, pp. 800–805.

System model



- Processed received signal

$$\mathbf{y} = \mathbf{W}^H \mathbf{H} \mathbf{F} \mathbf{s} + \mathbf{W}^H \mathbf{n}$$

Combiners: $\mathbf{W} = \mathbf{W}_{\mathrm{RF}} \mathbf{W}_{\mathrm{BB}}$

Precoders: $\mathbf{F} = \mathbf{F}_{\mathrm{RF}} \mathbf{F}_{\mathrm{BB}}$

- Geometric channel model

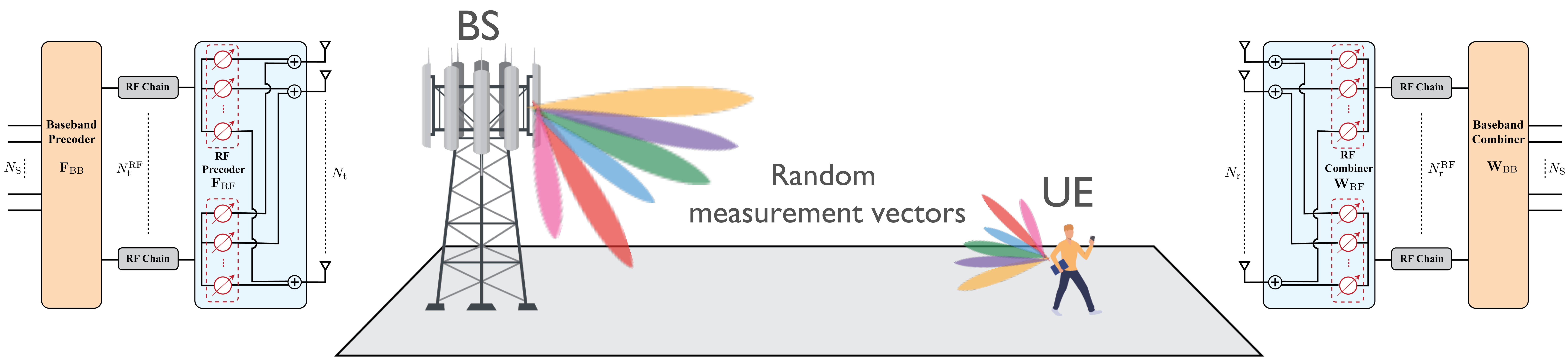
$$\mathbf{H} = \sum_{l=1}^{L} \alpha_l \mathbf{a}_{\mathrm{r}}(\theta_l) \mathbf{a}_{\mathrm{t}}^H(\phi_l)$$

- Spectral efficiency

$$R = \log_2 |\mathbf{I} + \mathbf{Q}^{-1} \mathbf{W}^H \mathbf{H} \mathbf{F} \mathbf{F}^H \mathbf{H}^H \mathbf{W}|$$

$$\mathbf{Q} = \frac{1}{\mathrm{SNR}} \mathbf{W}^H \mathbf{W}$$

Compressive sensing based channel estimation



- Sparse formulation of channel estimation

Dictionary matrix

Complex gains (sparse vector)

Channel measurements ←

$$\mathbf{y} = \sqrt{P}(\mathbf{P}^T \otimes \mathbf{Q}^H)\mathbf{A}_{\mathrm{D}}\mathbf{z} + \mathbf{n}_{\mathrm{Q}}$$

Design transmit/receive
measurement codebook

Classically, random measurement vectors are used to perform channel sensing

[Alkhateeb'14] A. Alkhateeb, O. El Ayach, G. Leus and R. W. Heath, "Channel Estimation and Hybrid Precoding for Millimeter Wave Cellular Systems," in *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 5, pp. 831-846, Oct. 2014.

Problem formulation

- Measurement codebook design

$$\mathbf{P}, \mathbf{Q} = f(\mathcal{D})$$

Collected channel data

Transmit/receive measurement codebooks

Task I:
Learn measurement codebooks

- Sparse formulation of channel estimation

$$\mathbf{y} = \sqrt{P}(\mathbf{P}^T \otimes \mathbf{Q}^H)\mathbf{A}_{\mathrm{D}}\mathbf{z} + \mathbf{n}_{\mathrm{Q}}$$

- Hybrid precoder/combiner design

$$\begin{aligned}
\max_{\{\mathbf{F}_{\mathrm{BB}}, \mathbf{F}_{\mathrm{RF}}, \mathbf{W}_{\mathrm{BB}}, \mathbf{W}_{\mathrm{RF}}\}} \quad & \log_2 \left|\mathbf{I} + \mathbf{Q}^{-1}\mathbf{W}^H \widehat{\mathbf{H}} \mathbf{F} \mathbf{F}^H \widehat{\mathbf{H}}^H \mathbf{W}\right|, \\
\text{s.t.} \quad & \mathbf{F} = \mathbf{F}_{\mathrm{RF}}\mathbf{F}_{\mathrm{BB}}, \\
& \mathbf{W} = \mathbf{W}_{\mathrm{RF}}\mathbf{W}_{\mathrm{BB}}, \\
& \mathbf{F}_{\mathrm{RF}} \in \boldsymbol{\mathcal{F}}, \quad \forall n_{\mathrm{t}}, \\
& \mathbf{W}_{\mathrm{RF}} \in \boldsymbol{\mathcal{W}}, \quad \forall n_{\mathrm{r}}, \\
& \|\mathbf{F}_{\mathrm{RF}}\mathbf{F}_{\mathrm{BB}}\|_F^2 = N_{\mathrm{S}}.
\end{aligned}$$

Pre-defined codebook

Transmit power constraint

RF precoder/combiner contain orthogonal vectors

Task II:
Predict RF beams

$$\begin{aligned}
\max_{\{\mathbf{F}_{\mathrm{RF}}, \mathbf{W}_{\mathrm{RF}}\}} \quad & \log_2 \left|\mathbf{I} + \mathrm{SNR}\, \mathbf{W}_{\mathrm{RF}}^H \widehat{\mathbf{H}} \mathbf{F}_{\mathrm{RF}} \right. \\
& \left. \times \left(\mathbf{F}_{\mathrm{RF}}^H \mathbf{F}_{\mathrm{RF}}\right)^{-\frac{1}{2}} \mathbf{F}_{\mathrm{RF}}^H \widehat{\mathbf{H}}^H \mathbf{W}_{\mathrm{RF}}\right|, \\
\text{s.t.} \quad & \mathbf{F}_{\mathrm{RF}} \in \boldsymbol{\mathcal{F}}, \quad \forall n_{\mathrm{t}}, \\
& \mathbf{W}_{\mathrm{RF}} \in \boldsymbol{\mathcal{W}}, \quad \forall n_{\mathrm{r}},
\end{aligned}$$

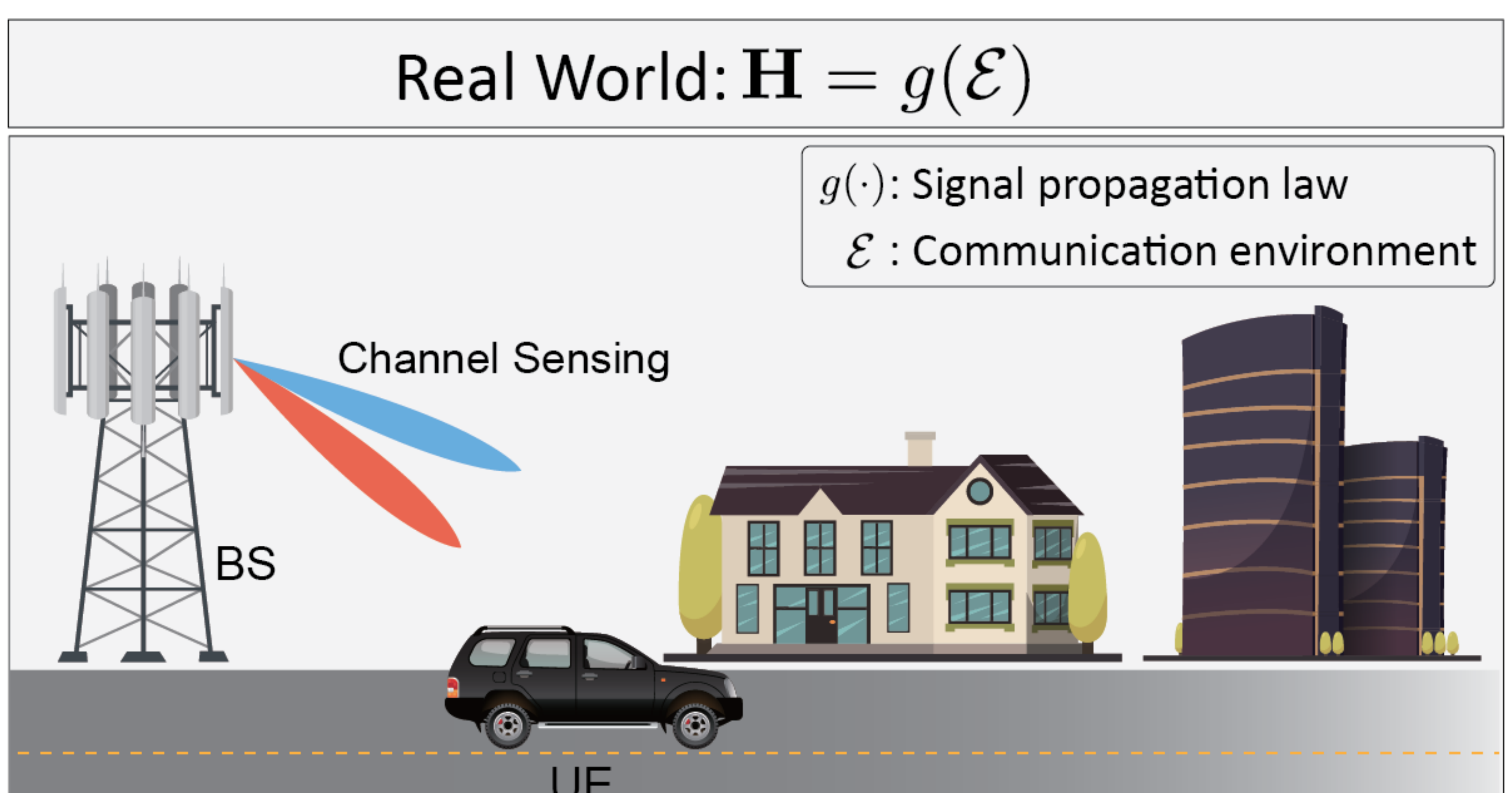
These problems can be jointly solved with ML and site-specific digital twins

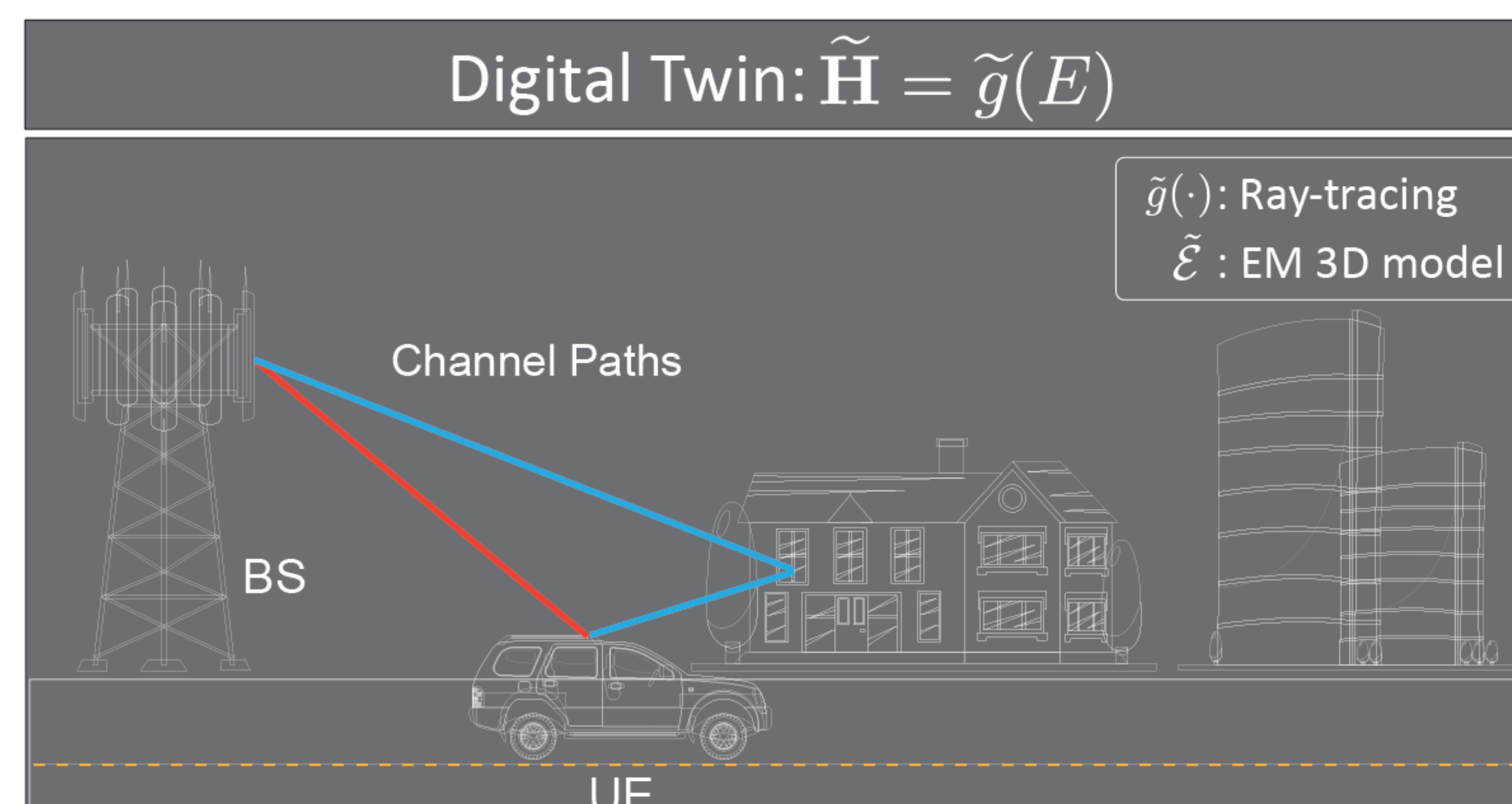
[Alkhateeb'16] A. Alkhateeb and R. W. Heath, "Frequency Selective Hybrid Precoding for Limited Feedback Millimeter Wave Systems," *IEEE Transactions on Communications*, vol. 64, no. 5, pp. 1801–1818, 2016.

Proposed solution: Digital twin construction

- The real-world channel is determined by
  - **Communication environment**: Positions, orientations, dynamics, shapes, and EM materials of the objects
  - **Signal propagation law**
  - **Hardware characteristics** (assumed to be known)

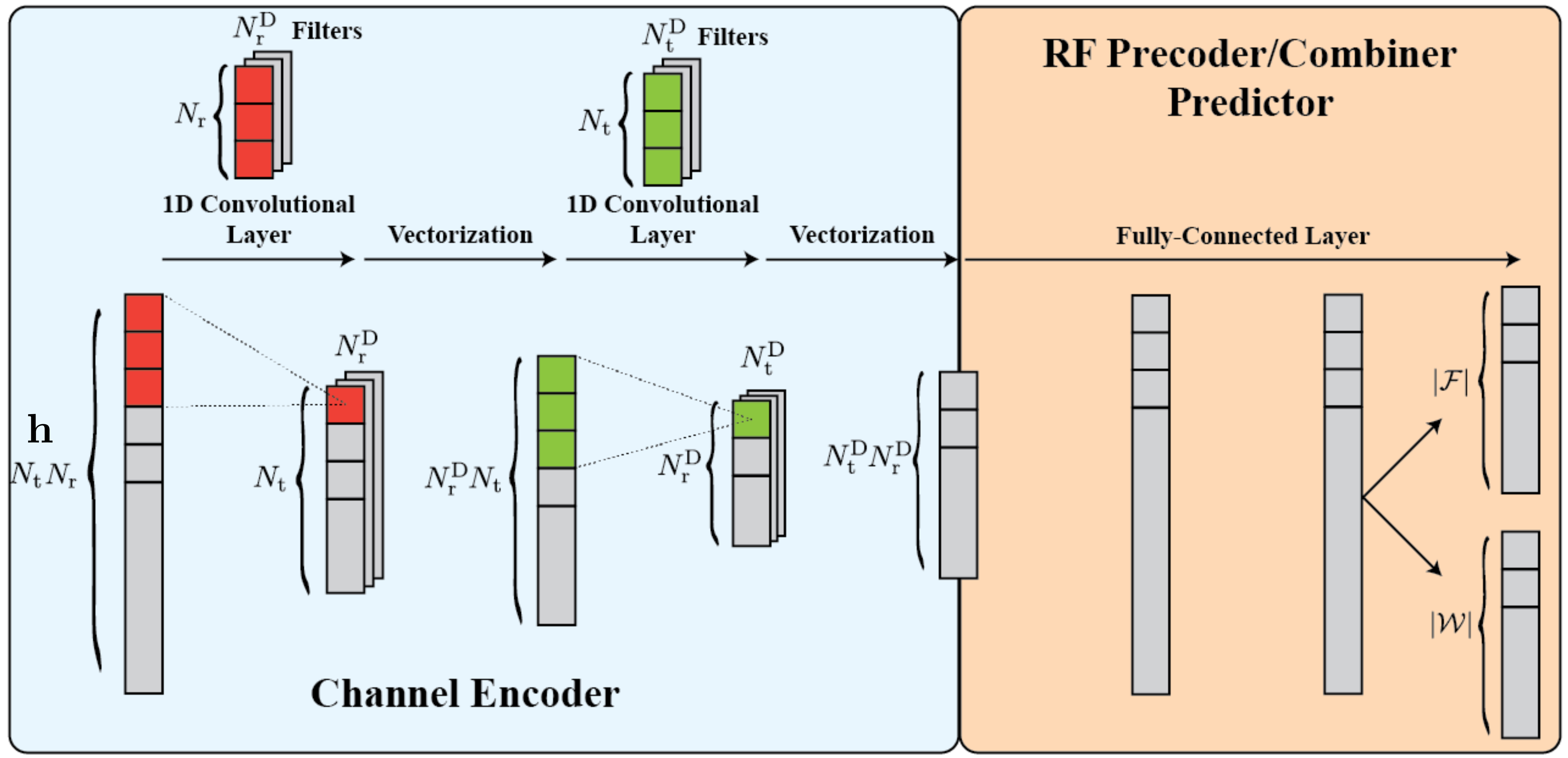
- Digital twins
  - Approximate the communication environment using **electromagnetic (EM) 3D model**
  - Approximate the signal propagation law using **ray tracing**





[Alkhateeb'23] A. Alkhateeb, S. Jiang, and G. Charan, "Real-Time Digital Twins: Vision and Research Directions for 6G and Beyond," *IEEE Communications Magazine*, vol. 61, no. 11, pp. 128–134, 2023.

Proposed solution: Deep learning based compressive sensing



- Channel encoder

$$\mathbf{z} = f_{\text{enc}}(\mathbf{h})$$

Mimic channel measurements

$$\mathbf{z} = \sqrt{P}\text{vec}(\mathbf{Q}^H\mathbf{H}\mathbf{P}) + \text{vec}(\mathbf{Q}^H\mathbf{N})$$

Trainable parameters ($\mathbf{Q}$, $\mathbf{P}$)

- RF precoder/combiner predictor

$$\widehat{\mathbf{p}} = f_{\text{pred,t}}(\mathbf{z}) \qquad \widehat{\mathbf{q}} = f_{\text{pred,r}}(\mathbf{z})$$

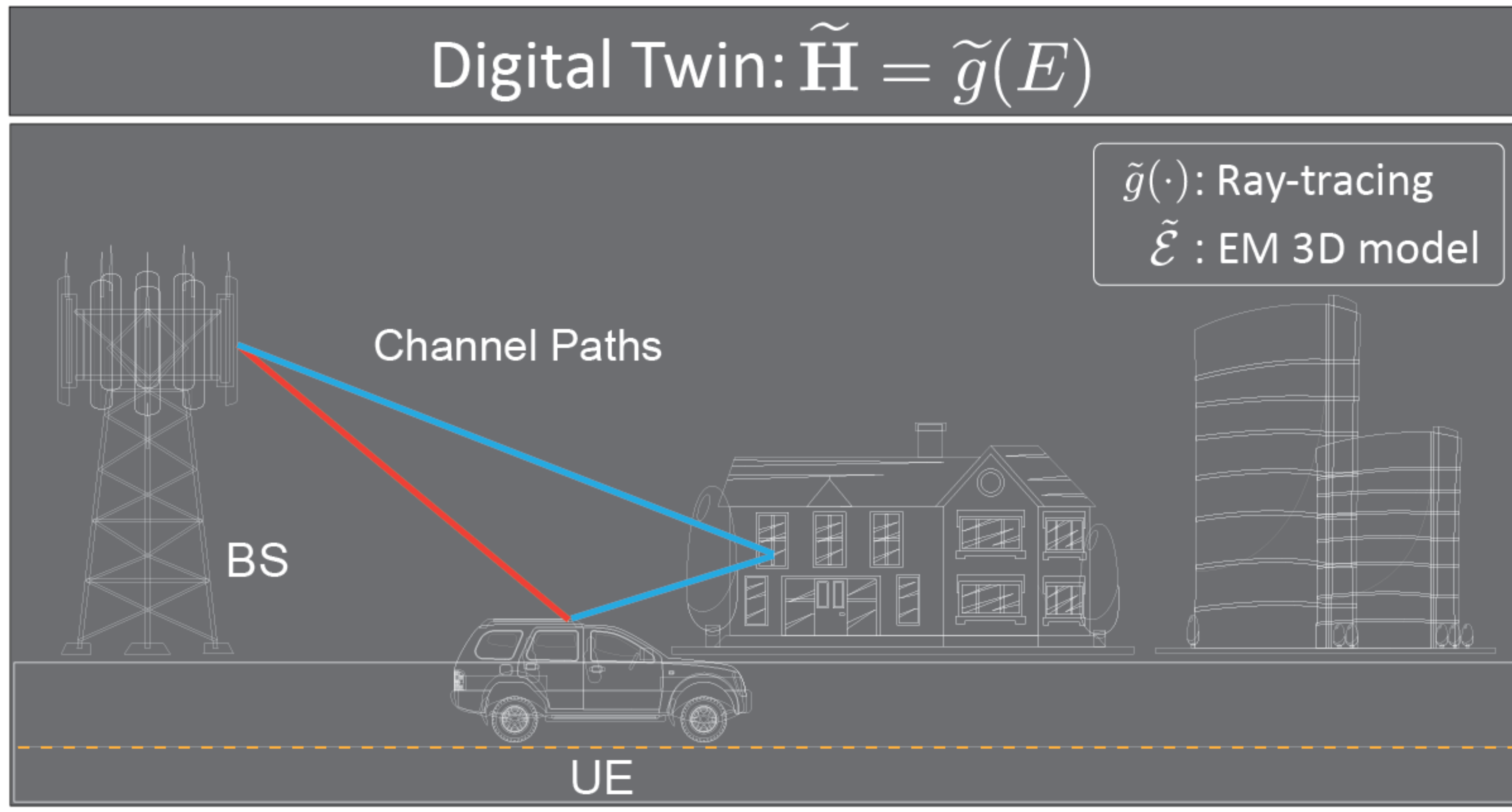
Probability distributions of the codebook indices

- Objective function

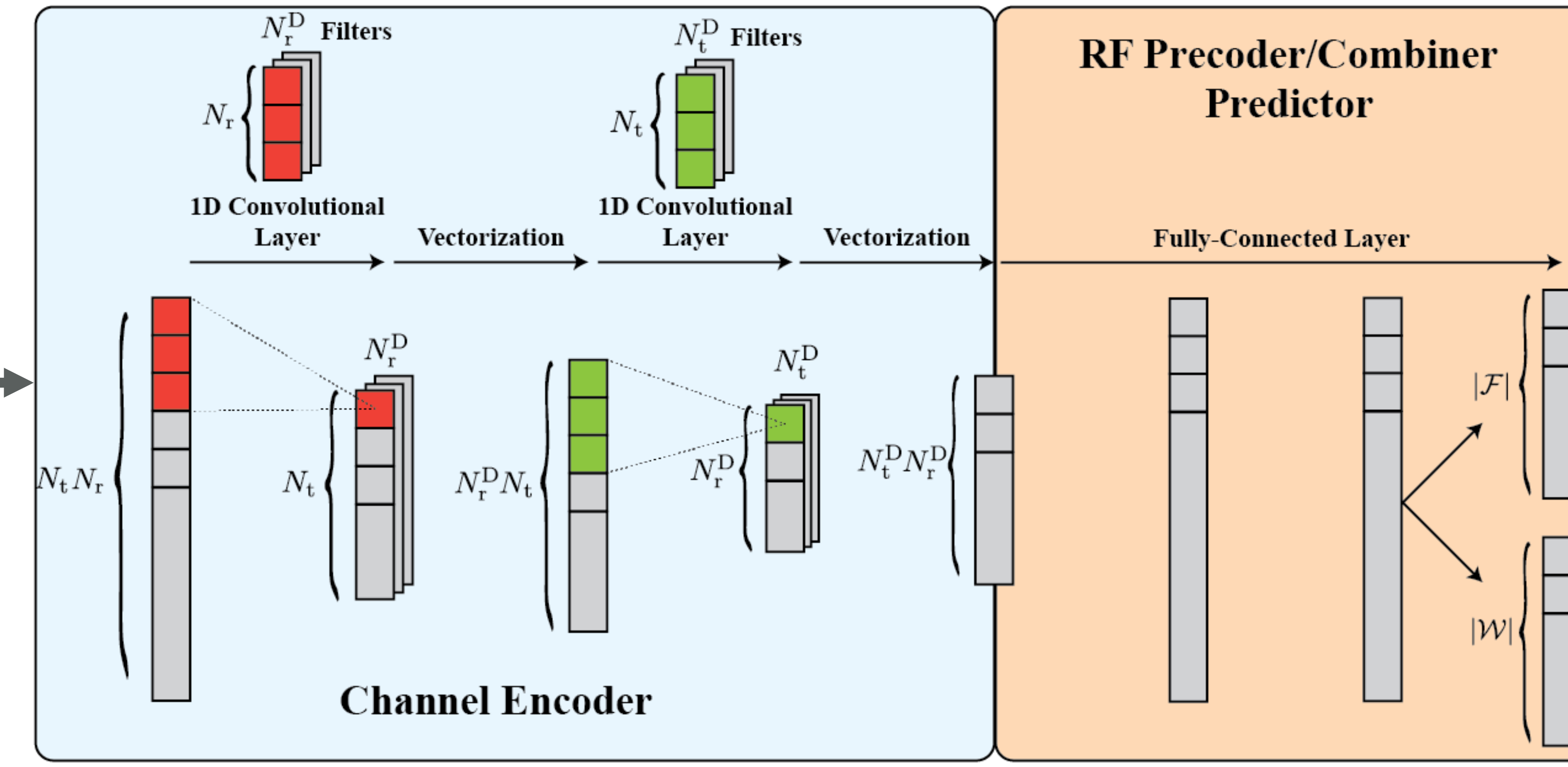
$$\text{CE}(\mathbf{p}, \mathbf{q}, \widehat{\mathbf{p}}, \widehat{\mathbf{q}}) = -\left(\sum_{i=1}^{|\mathcal{F}|} p_i^\star \log \widehat{p}_i + \sum_{j=1}^{|\mathcal{W}|} q_j^\star \log \widehat{q}_j\right)$$

[Li'19] X.Li and A.Alkhateeb, "Deep Learning for Direct Hybrid Precoding in Millimeter Wave Massive MIMO Systems," in *Proc. of 53rd Asilomar Conference on Signals, Systems, and Computers*, 2019, pp. 800–805.

Proposed solution: Digital twin aided compressive sensing



Generate synthetic channel data



- **Objective**

Performance evaluated on real data

$$\min_{\substack{\widetilde{f}_{\mathrm{enc}}(;\widetilde{\Theta}_{\mathrm{enc}}) \\ \widetilde{f}_{\mathrm{pred,t}}(;\widetilde{\Theta}_{\mathrm{pred,t}}) \\ \widetilde{f}_{\mathrm{pred,r}}(;\widetilde{\Theta}_{\mathrm{pred,t}})}} \left| \underbrace{\mathcal{L}\left(\widetilde{\Theta}_{\mathrm{enc}}, \widetilde{\Theta}_{\mathrm{pred,t}}, \widetilde{\Theta}_{\mathrm{pred,r}}, \mathcal{H}\right)}_{\text{Model trained on DT data}} - \underbrace{\mathcal{L}\left(\Theta^{\star}_{\mathrm{enc}}, \Theta^{\star}_{\mathrm{pred,t}}, \Theta^{\star}_{\mathrm{pred,r}}, \mathcal{H}\right)}_{\text{Model trained on real data}} \right|$$

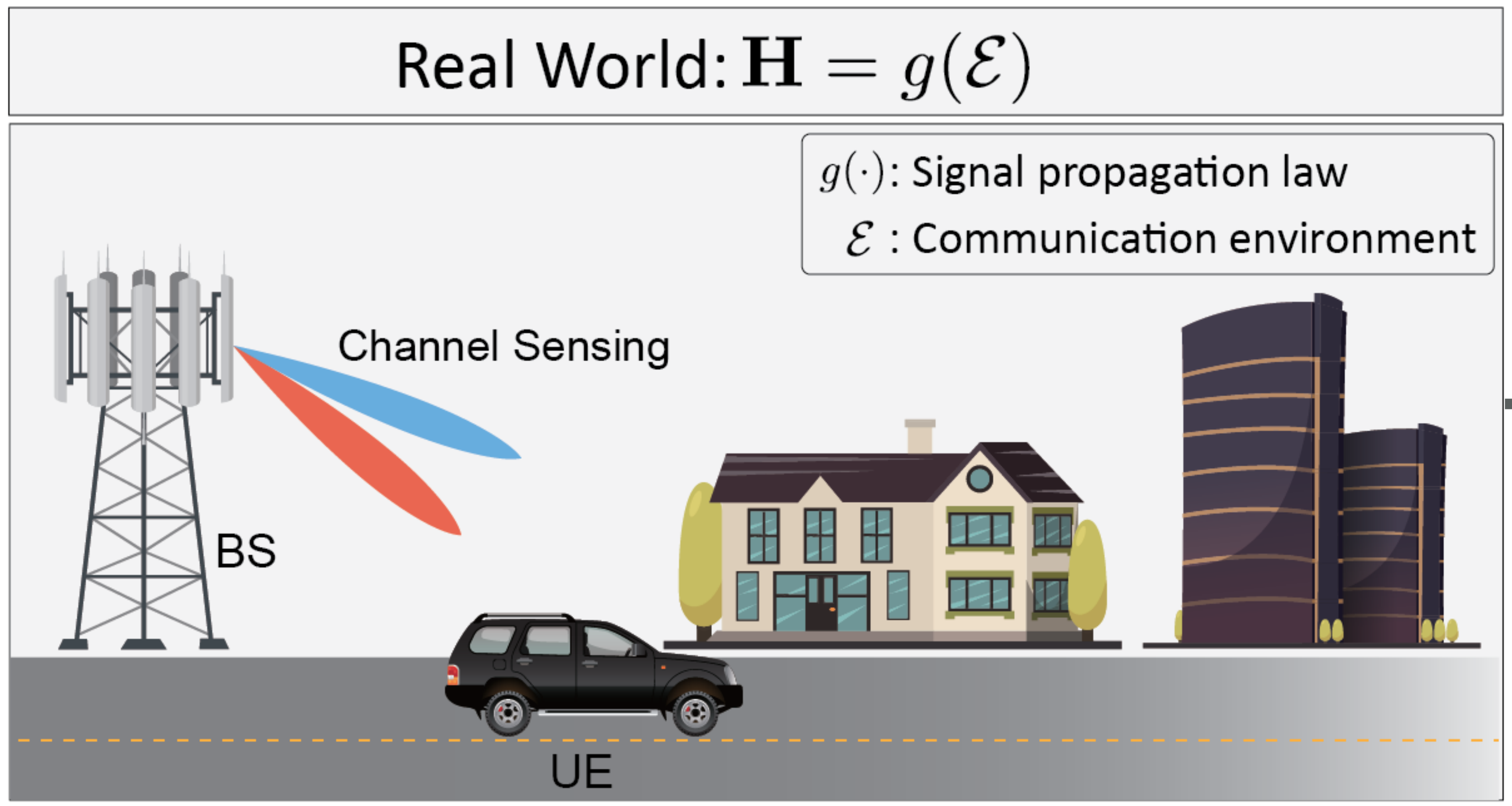
- **Direct generalization**

$$\left|\mathcal{L}\left(\widetilde{\Theta}_{\mathrm{enc}}, \widetilde{\Theta}_{\mathrm{pred,t}}, \widetilde{\Theta}_{\mathrm{pred,r}}, \mathcal{H}\right) - \mathcal{L}\left(\Theta^{\star}_{\mathrm{enc}}, \Theta^{\star}_{\mathrm{pred,t}}, \Theta^{\star}_{\mathrm{pred,r}}, \mathcal{H}\right)\right|$$
$$\leq \mathcal{L}\left(\widetilde{\Theta}_{\mathrm{enc}}, \widetilde{\Theta}_{\mathrm{pred,t}}, \widetilde{\Theta}_{\mathrm{pred,r}}, \widetilde{\mathcal{H}}\right) + \mathrm{disc}\left(\mathcal{H}, \widetilde{\mathcal{H}}\right) + \epsilon,$$

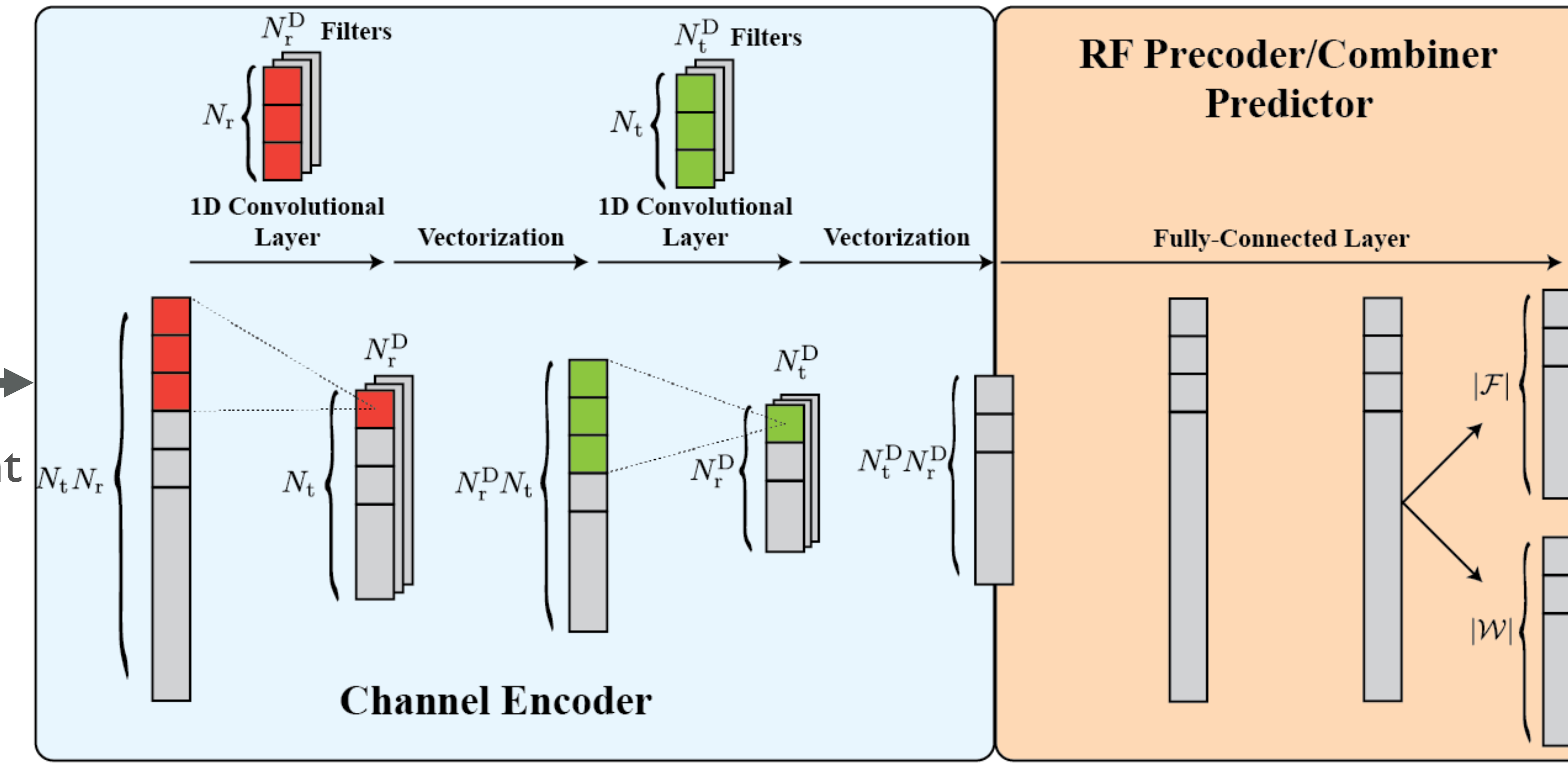
Discrepancy between two distributions

[Mansour'09] Y. Mansour, M. Mohri, and A. Rostamizadeh, "Domain Adaptation: Learning Bounds and Algorithms," *arXiv preprint arXiv:0902.3430*, 2009.

Proposed solution: Model refinement with real-world data



Collect a small amount of real-world data



- Building a digital twin that perfectly mimics the real-world environment is challenging
- The model trained on DT data can be fine-tuned with a small amount of real-world data
- Rehearsal fine-tuning strategy: Training with both previously learned and new data samples

How many real-world data samples do we need for fine-tuning?

[Robins'95] A. Robins, "Catastrophic Forgetting, Rehearsal and Pseudorehearsal," *Connection Science*, vol. 7, no. 2, pp. 123–146, 1995.

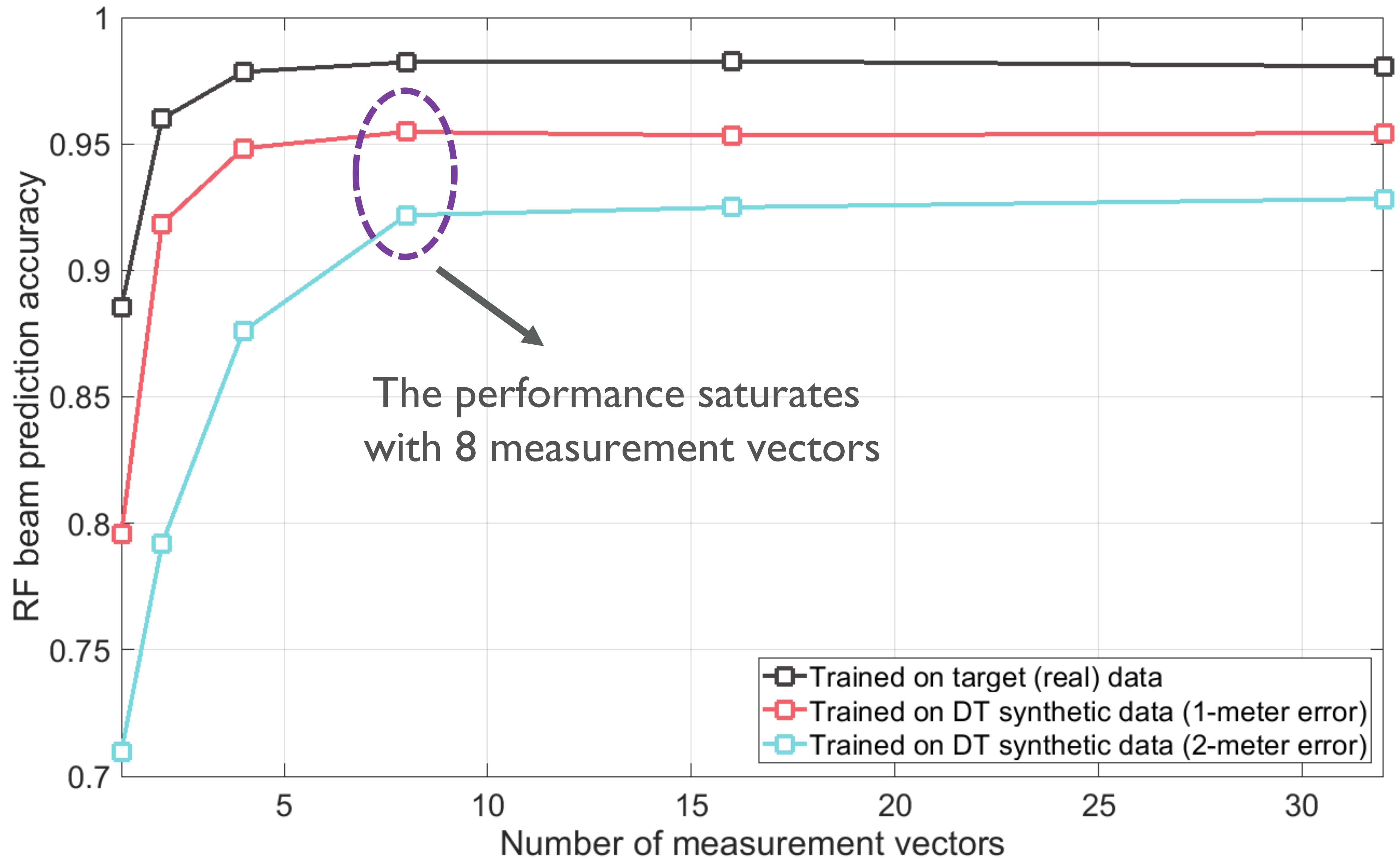
Simulation setup

- Target (real-world) scenario
  - Built based on downtown Boston
  - BS with 32-antenna ULA
  - Single-antenna user
- Digital twin scenario
  - Neglect foliage model
  - Has building position errors
- Dataset generation
  - Wireless Insite ray-tracing simulator
  - DeepMIMO channel generator
- Deep learning architecture
  - Channel encoder: 1D complex-valued CNN
  - RF precoder predictor: Fully-connected layers

Next, we evaluate the model trained on DT data

[Alkhateeb'19] A. Alkhateeb, "DeepMIMO: A Generic Deep Learning Dataset for Millimeter Wave and Massive MIMO Applications," in *Proc. of Inf. Theory and Appl. Workshop*, 2019, pp. 1–8.

Simulation results: Prediction accuracy vs. number of measurement vectors

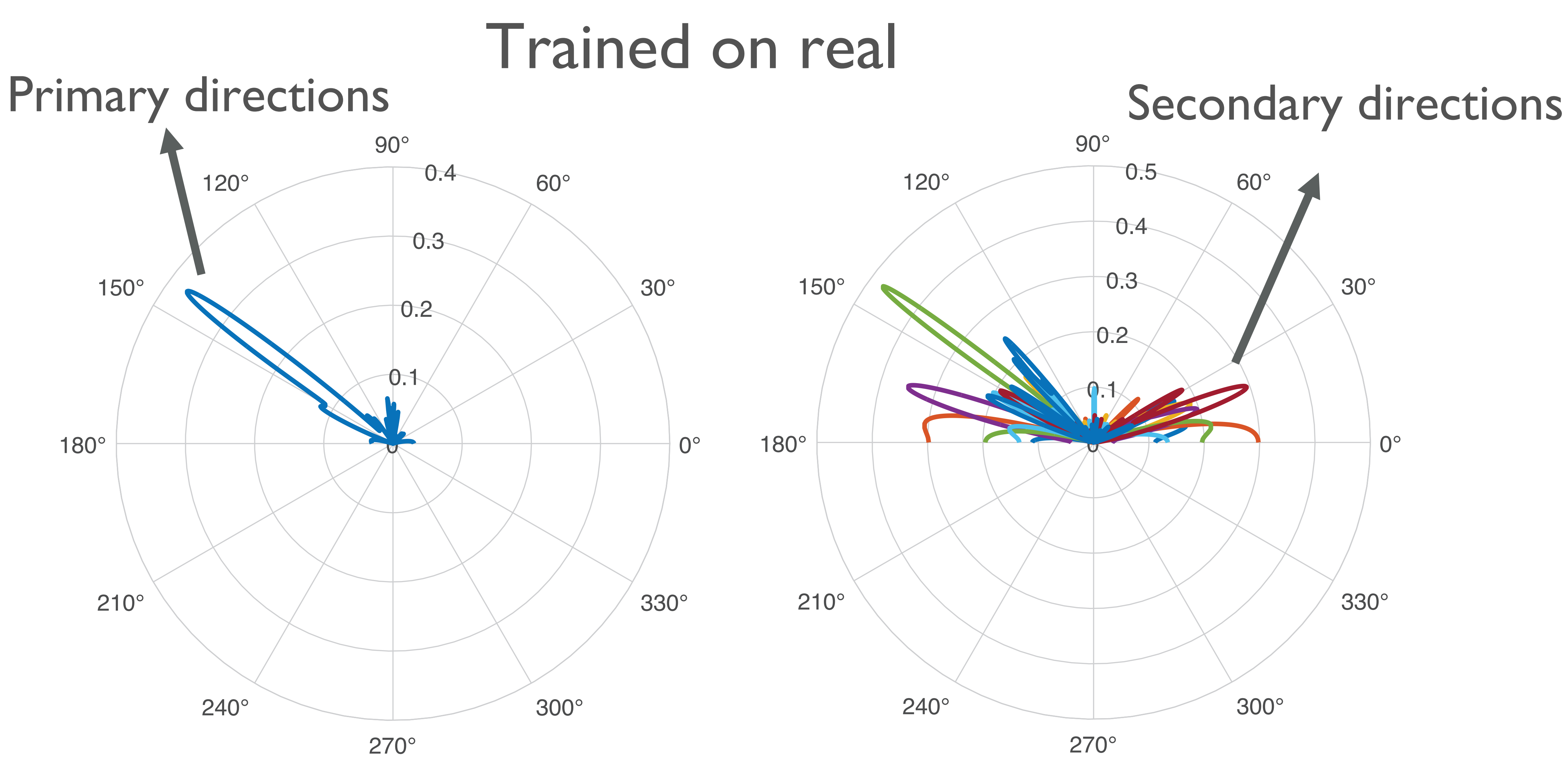


- The number of data samples is 10240 for both target and DT scenarios
- With the modeling error of 1 meter in building positions, the model can achieve 95% accuracy
- 8 measurement vectors are sufficient to capture promising directions

The model trained on DT data performs well on target data

The modeling errors cause a degradation in performance

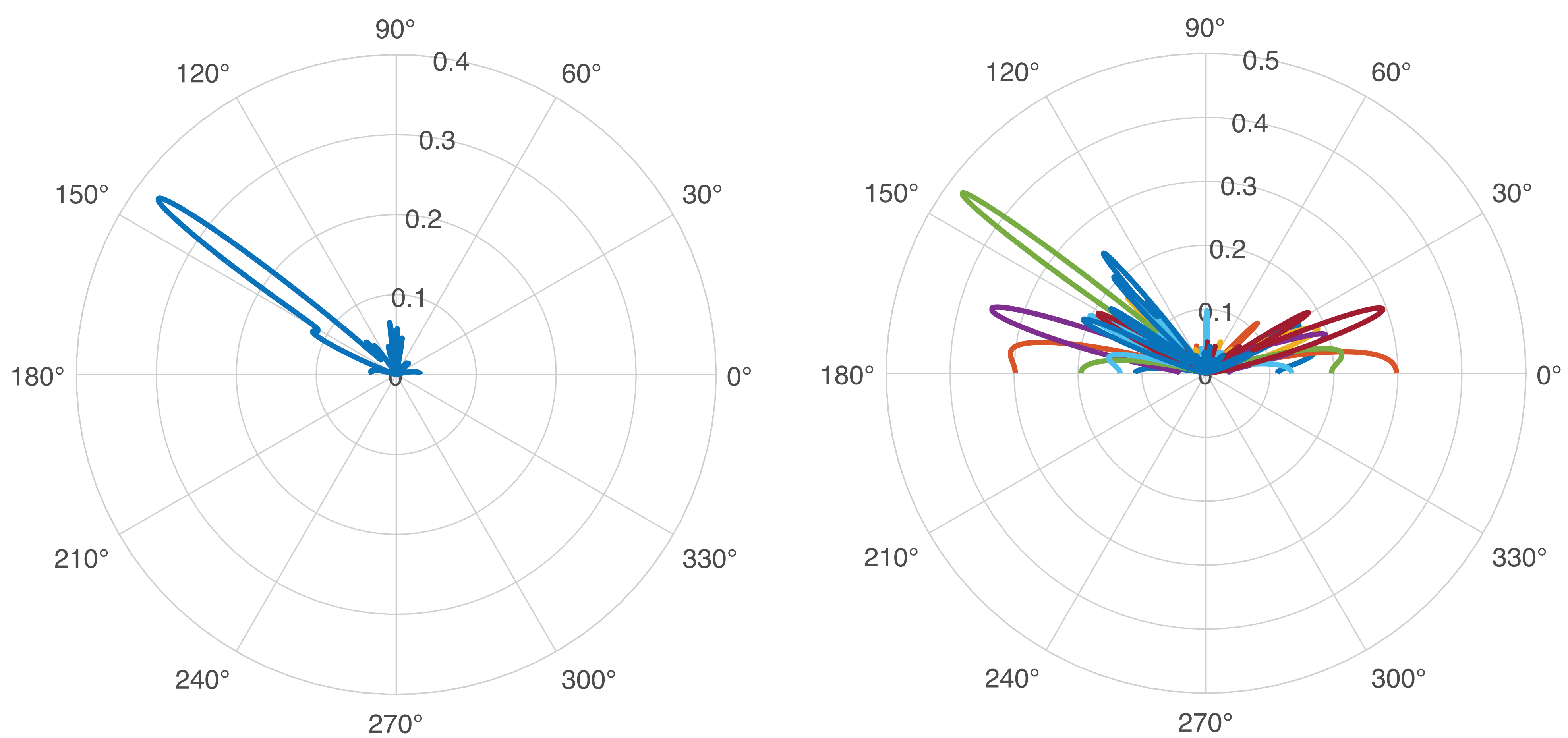
Simulation results: Beamforming pattern



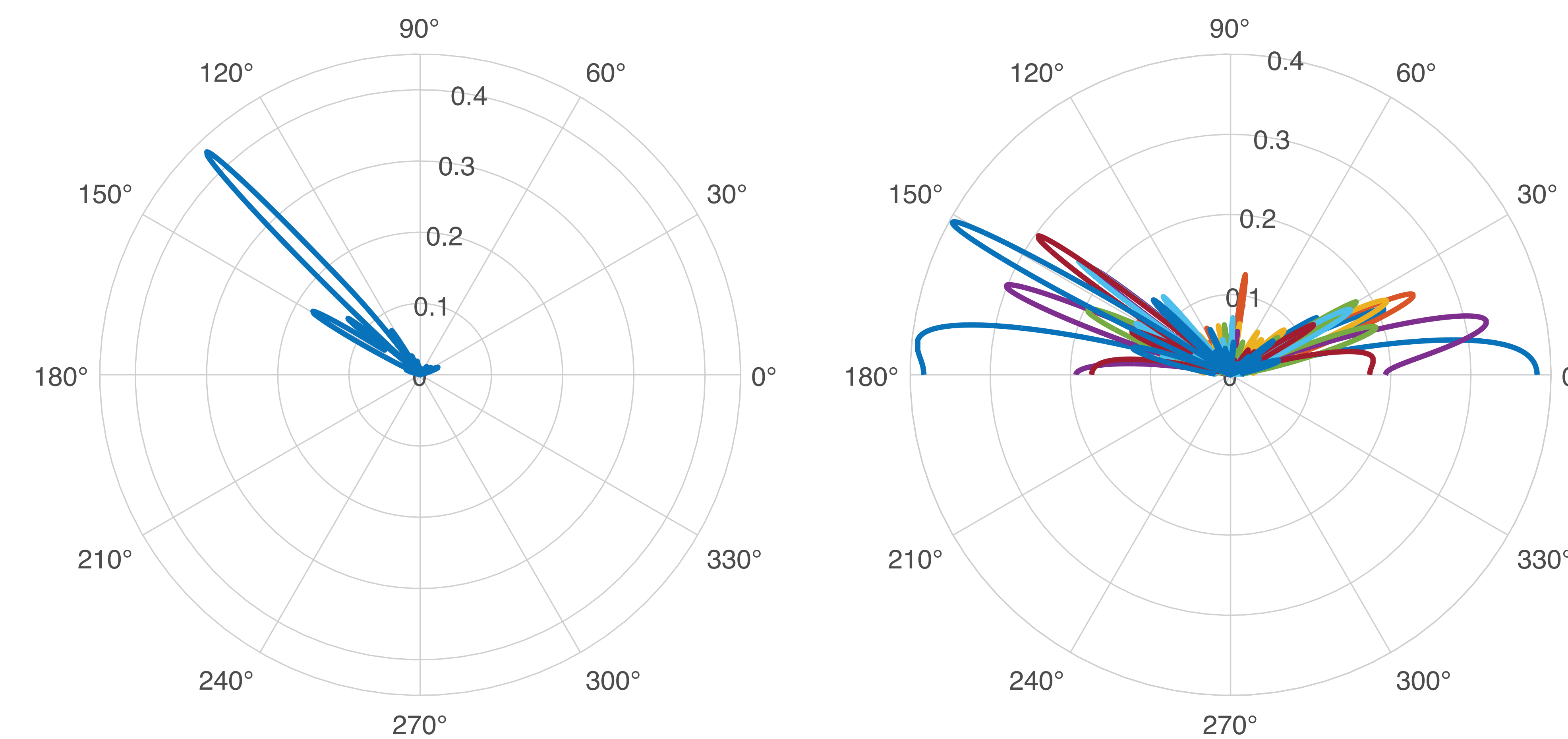
- The number of measurement vectors is set to {1, 8}
- The learned measurement vectors focus the power on the directions ranging from 120° and 180°

Simulation results: Beamforming pattern

Trained on real



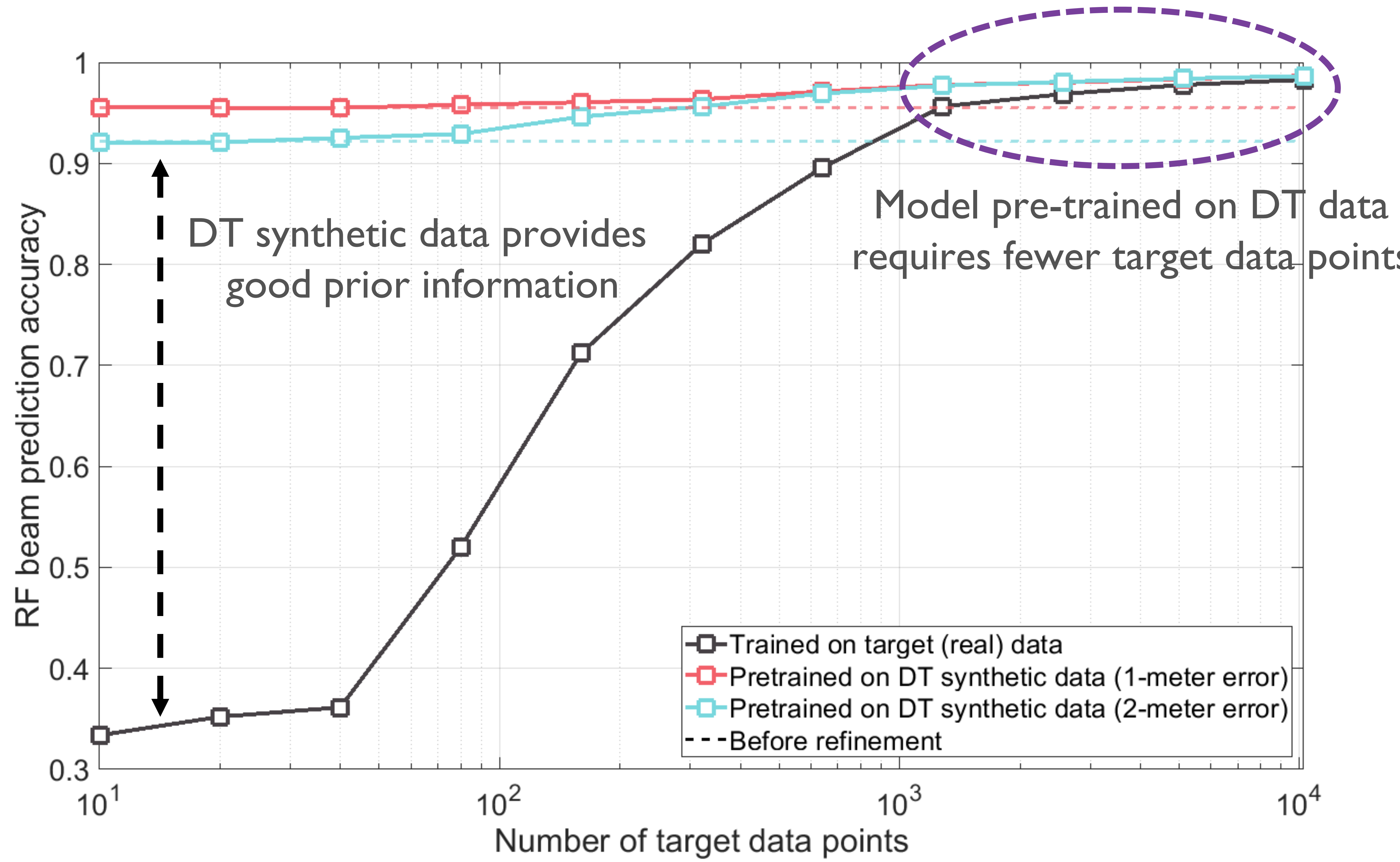
Trained on DT



- The number of measurement vectors is set to {1, 8}
- The learned measurement vectors focus the power on the directions ranging from 120° and 180°
- The model can learn the promising spatial directions from the DT synthetic data

The learned measurement vectors adapt to geometry and user distribution

Simulation results: Model refinement



- The number of antenna is set to 8
- The models are pre-trained on 10240 synthetic data points, and fine-tuned on target data
- Less number of real-world data points are needed to achieve the same performance

Digital twins can reduce the data collection overhead

Conclusion and future work

- We propose leveraging site-specific DT to aid MIMO systems with hybrid architectures
  - Generating DT synthetic data for training channel encoder and RF precoder predictor
  - Refining the model trained on DT synthetic data with a small amount of target data
- The results highlight the efficacy of the proposed solution
  - The model trained on DT data performs well on target data
  - The learned measurement vectors adapt to environment geometry and user distribution
  - Model refinement can further improve the performance with smaller data collection overhead
- Future work
  - Considering the scenario with multiple-antenna users
  - Evaluating the performance of DT on data collected in the physical world

The code and dataset files of this paper is available at www.wi-lab.net

Q&A

Thank you!