5G MEETS DEEP LEARNING, RAY TRACING, AND GPUS

Ahmed Alkhateeb, Assistant Professor, Arizona State University

Adriana Flores Miranda, NVIDIA

Nima PourNejatian, NVIDIA

AGENDA

Introduction

5G key aspects

MIMO limitations

Why Deep Learning overcomes limitations

Deep Learning in 5G applications

Auto-Precoder

Environment-aware joint channel estimation and precoding for mmWave MIMO

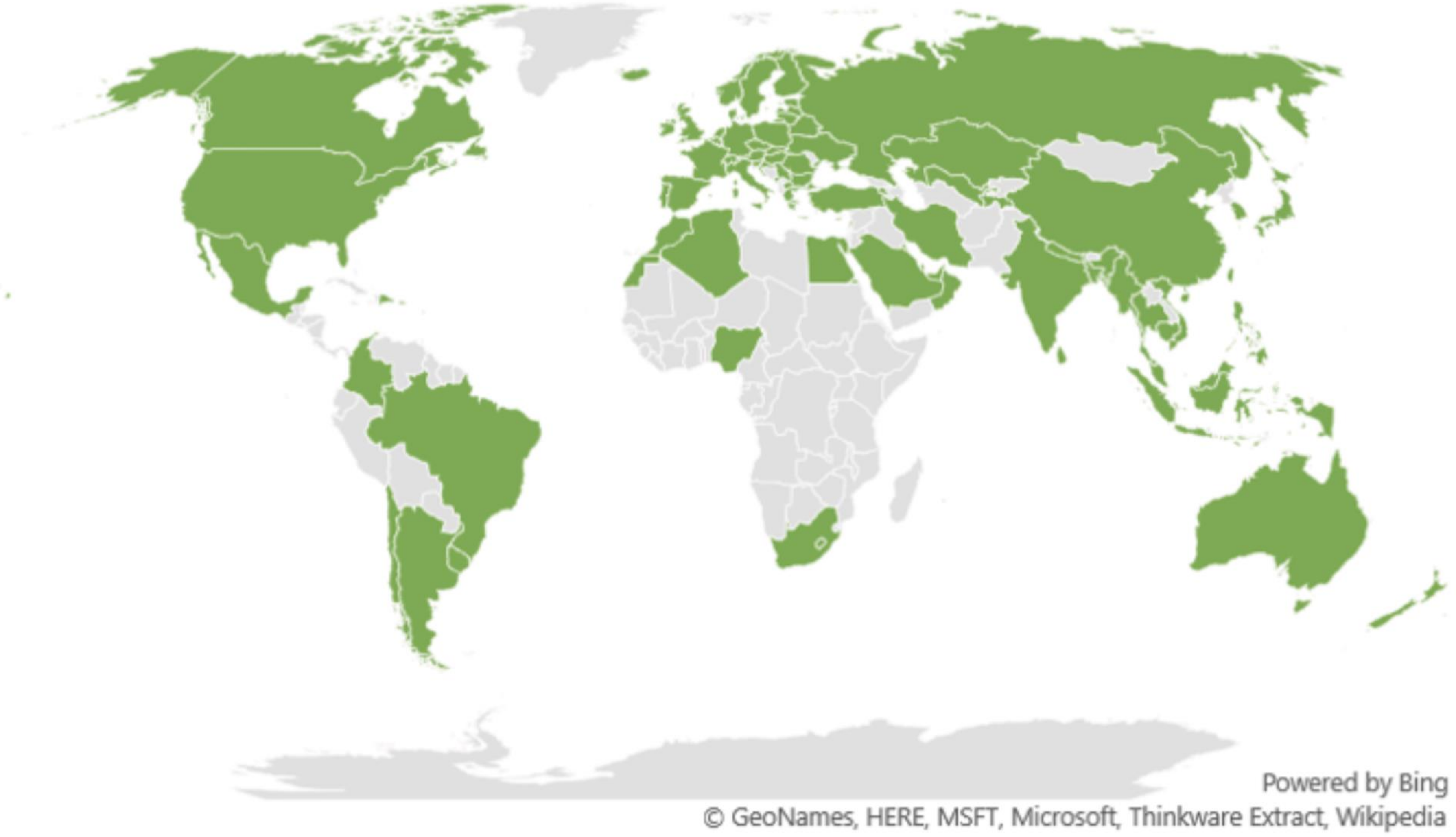
Demo and Results

An example based on accurate 3D ray-tracing simulations

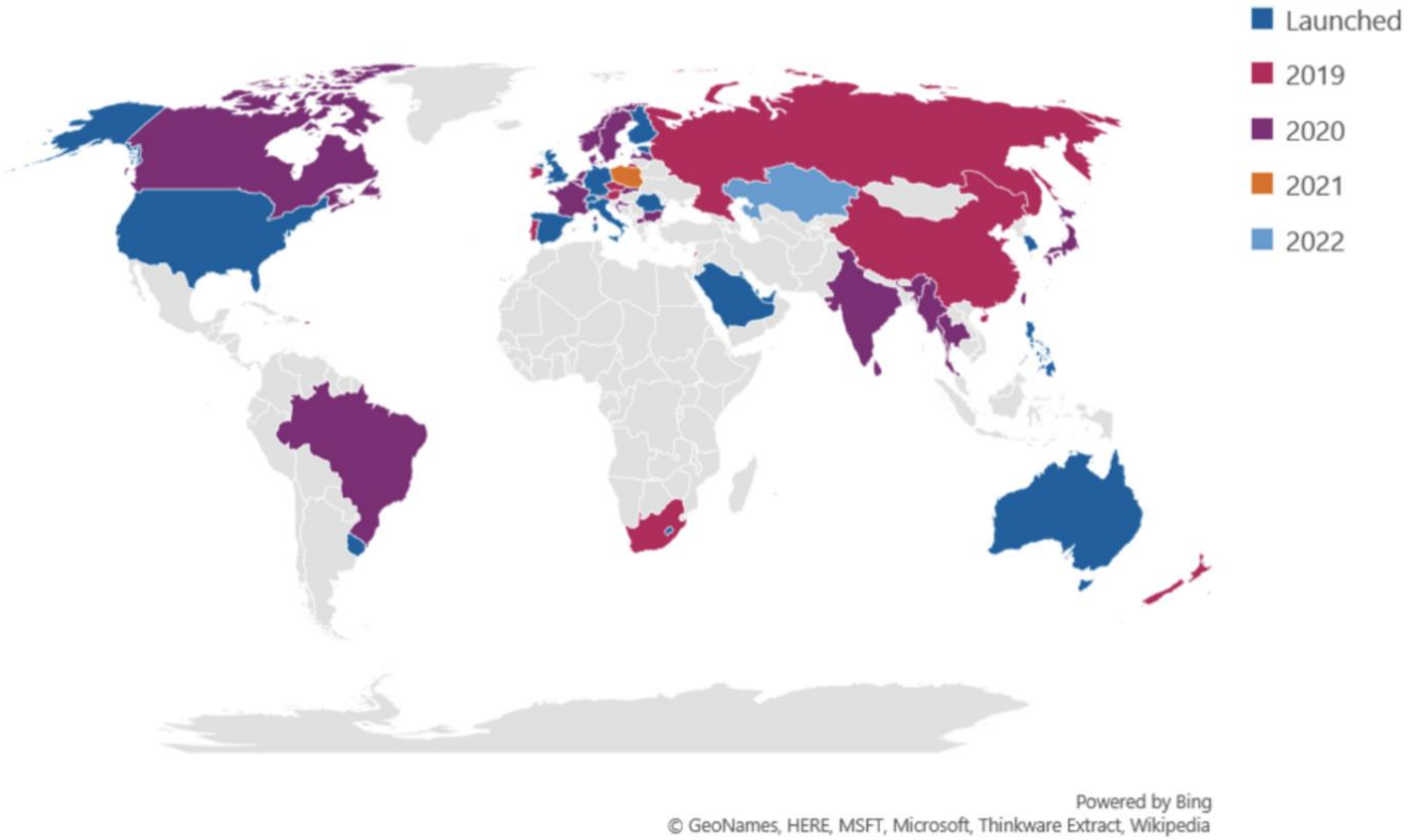
TREND: 4G IS MATURING WHILE 5G IS UNDER WAY

Global Wireless Telecommunications Carriers Industry

296 operators in 100 countries that have been investing in 5G



39 operators with 5G launches (either mobile or FWA, some with limited availability)



Source: GSA, August 2019

NVIDIA

5G OPPORTUNITY

7M+

Macro 4G Base Stations
to be upgraded to 5G

1M

IoT Devices / KM^2

100 Gbps

Bandwidth

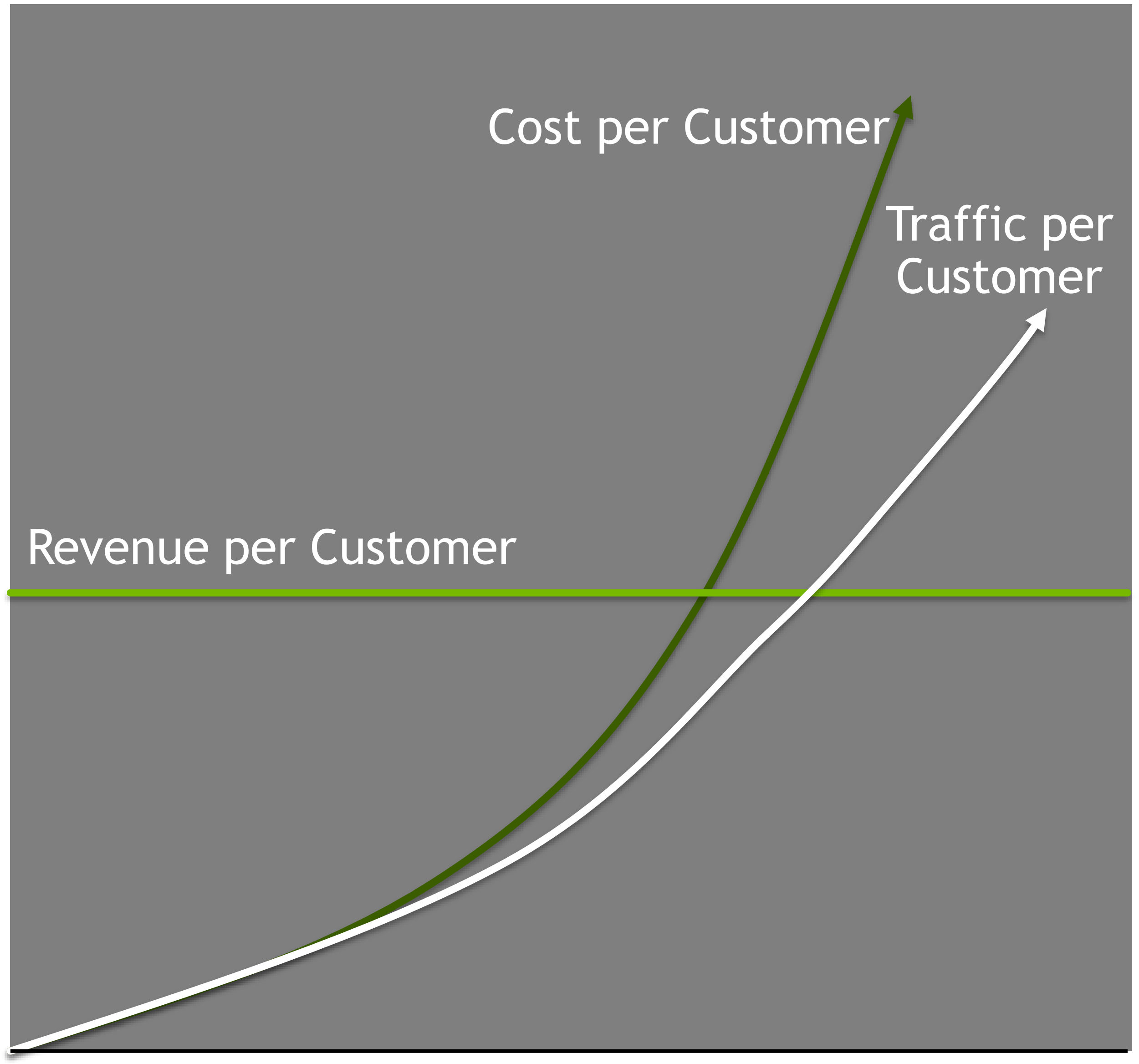
< 1ms

Latency
= AI at the Edge

TELCO'S CHALLENGES

5G mmWave, Massive MIMO, and AI

CHALLENGE



STRATEGIES

- ✓ 5G, mmWave, and Massive MIMO
- ✓ Artificial Intelligence
- ✓ Software Defined Networks
- ✓ Edge Computing

WHY MASSIVE MIMO AND 5G MMWAVE

Benefits And Requirement

User data rate per channel (bps) is limited by:

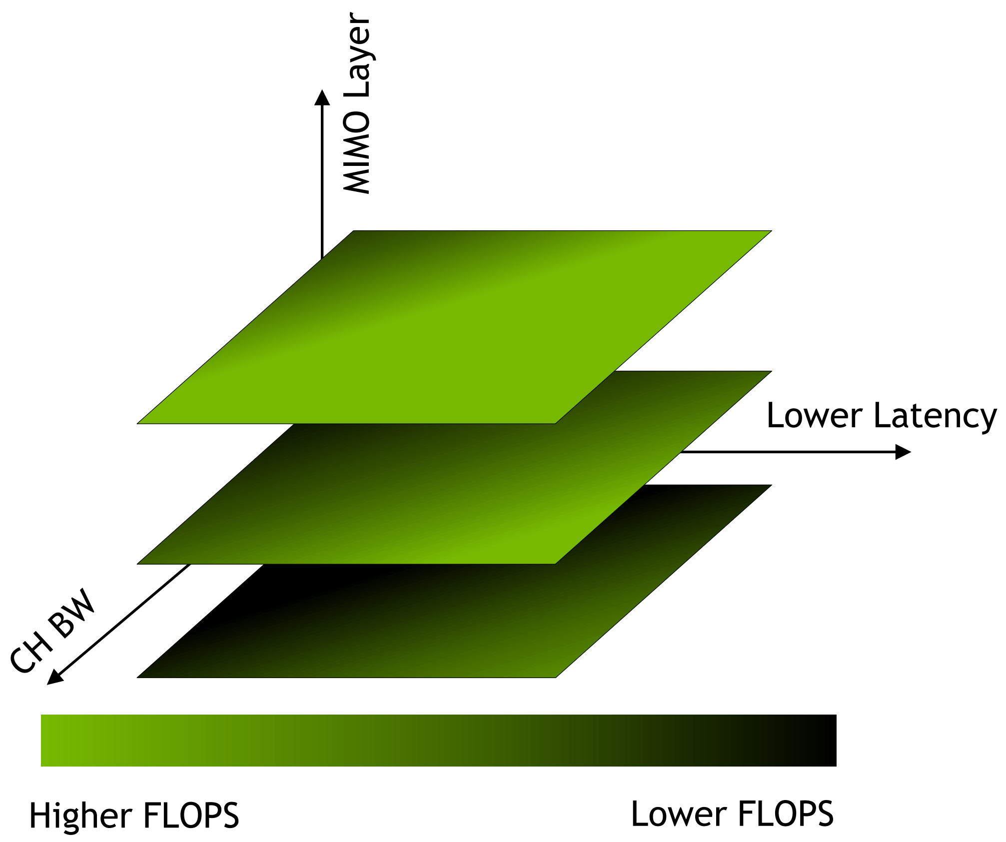
$$R \leq \frac{N_{MIMO}\, BW}{N_{users}} \log_2(1+SNIR)$$

How 5G enables 10Gbps+ data rates?

- Massive MIMO: Higher N_{MIMO}
- 5G mmWave:
  - Higher BW (from 20 MHz in 4G to 800 MHz in 5G mmWave)
  - Directional Beamforming:
    - Higher $SNIR$
    - Lower N_{users} sharing the beam resources

Key Objective

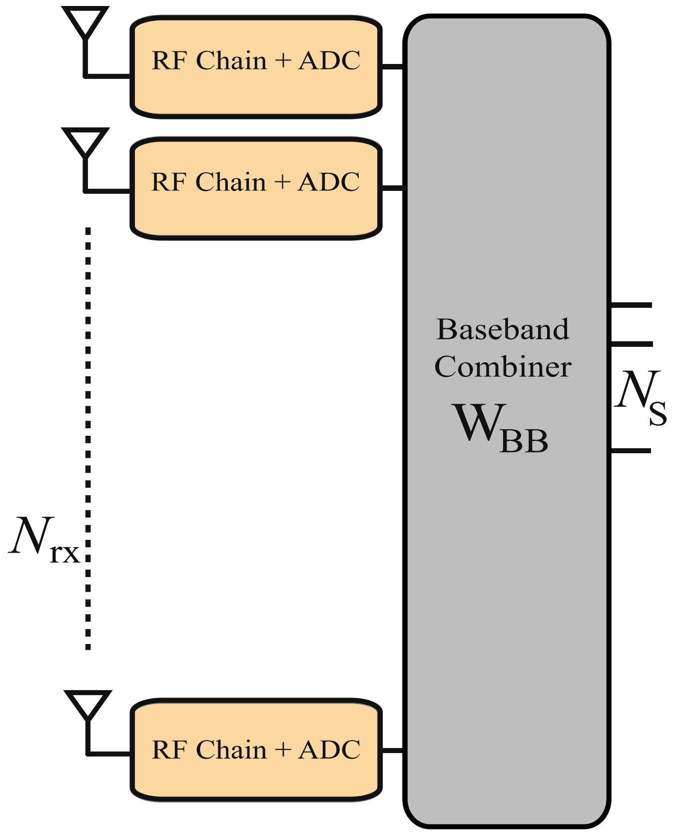
5G mmWave, Massive MIMO signal processing while meeting the low latency requirement



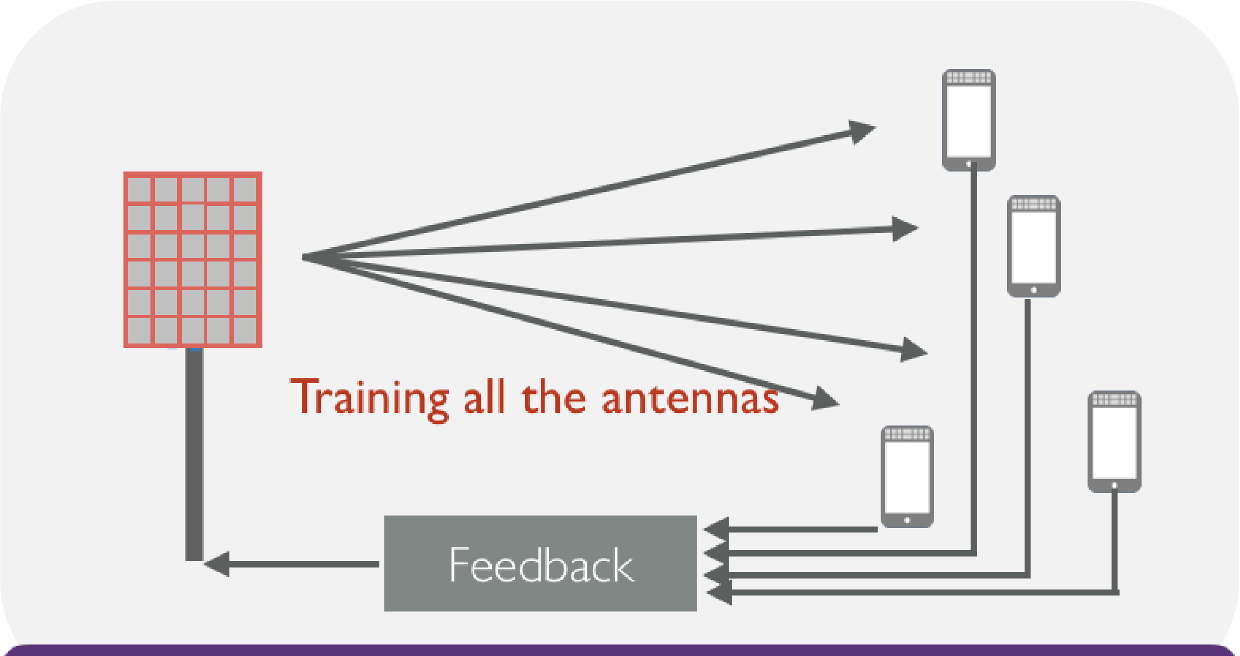
CHALLENGES WITH SCALING UP MIMO IN 5G AND BEYOND

Channel acquisition and hardware power consumption

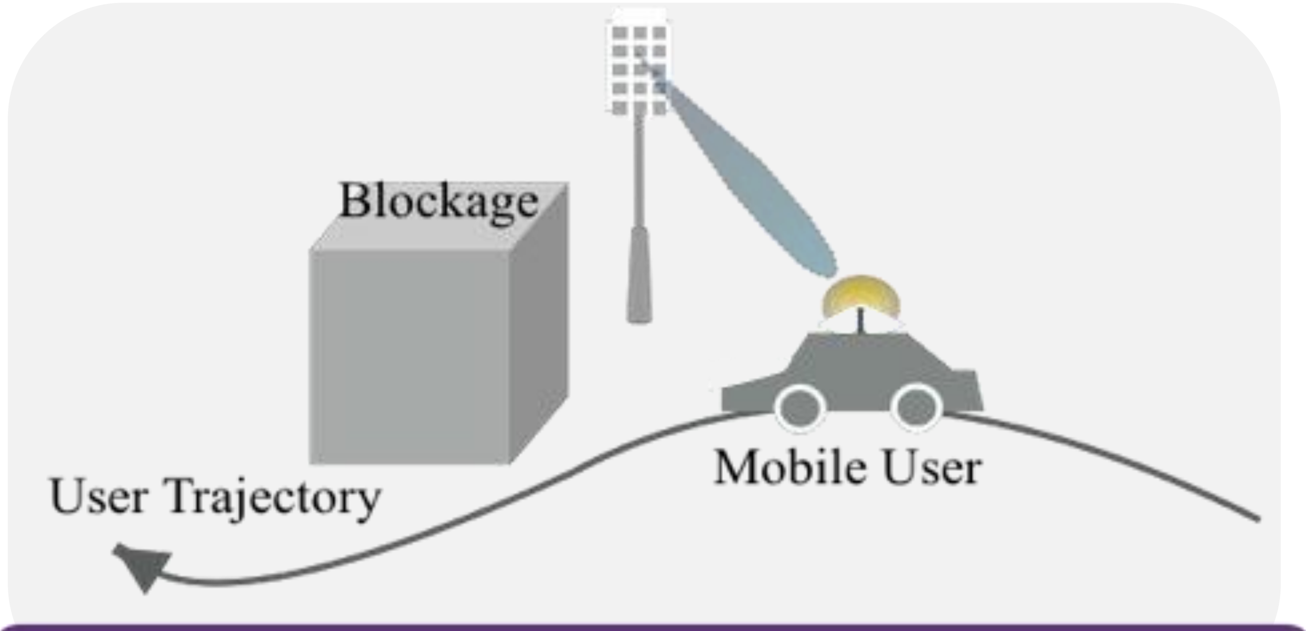
High beam training overhead in mmWave



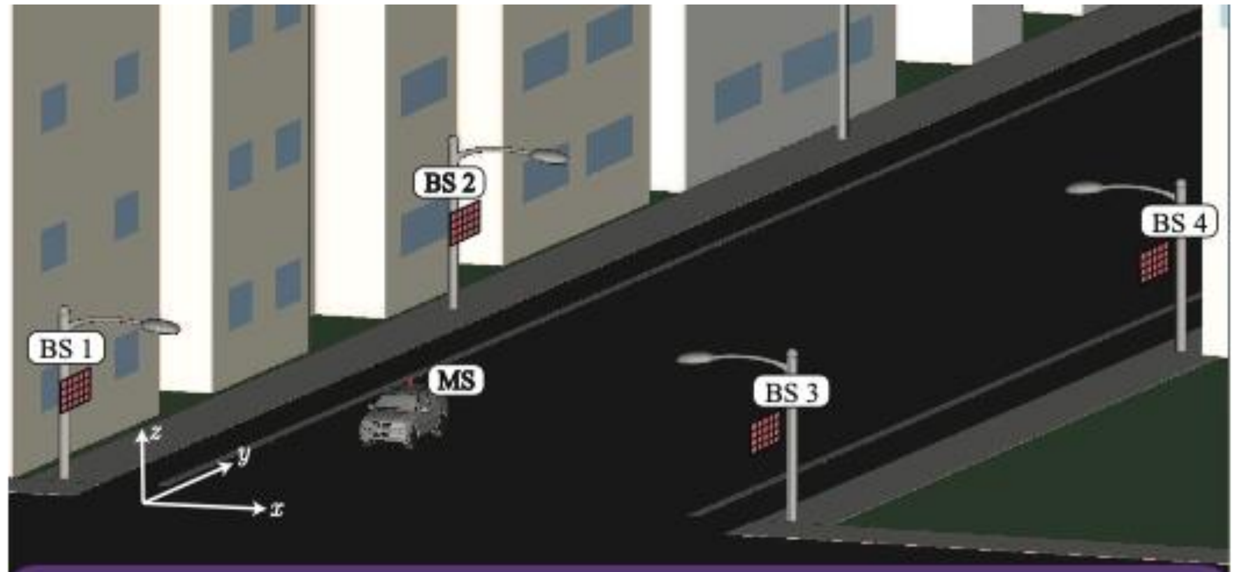
High cost and power consumption at fully-digital architectures



High channel training in FDD massive MIMO



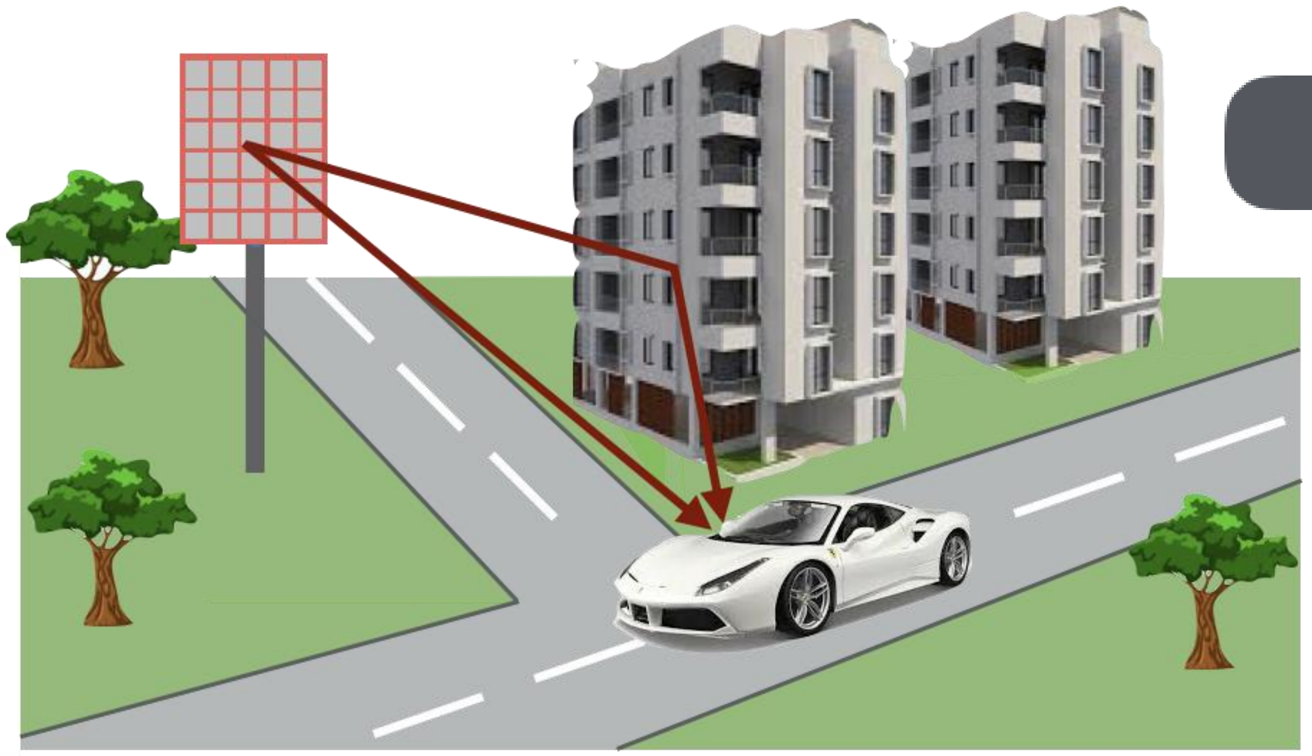
High sensitivity to blockages at mmWave



Sensitivity to user mobility at massive MIMO

DEEP LEARNING IN 5G

DL can overcome MIMO limitations



Channels are defined by the various elements of the environment

$$\mathbf{h} = f(\text{environment geometry, TX/RX locations,...})$$

Hard to characterize analytically

Environment geometry,
materials,
TX/RX locations, etc

→ **Deep Learning Model**
To learn f(inputs) → $\mathbf{h}$

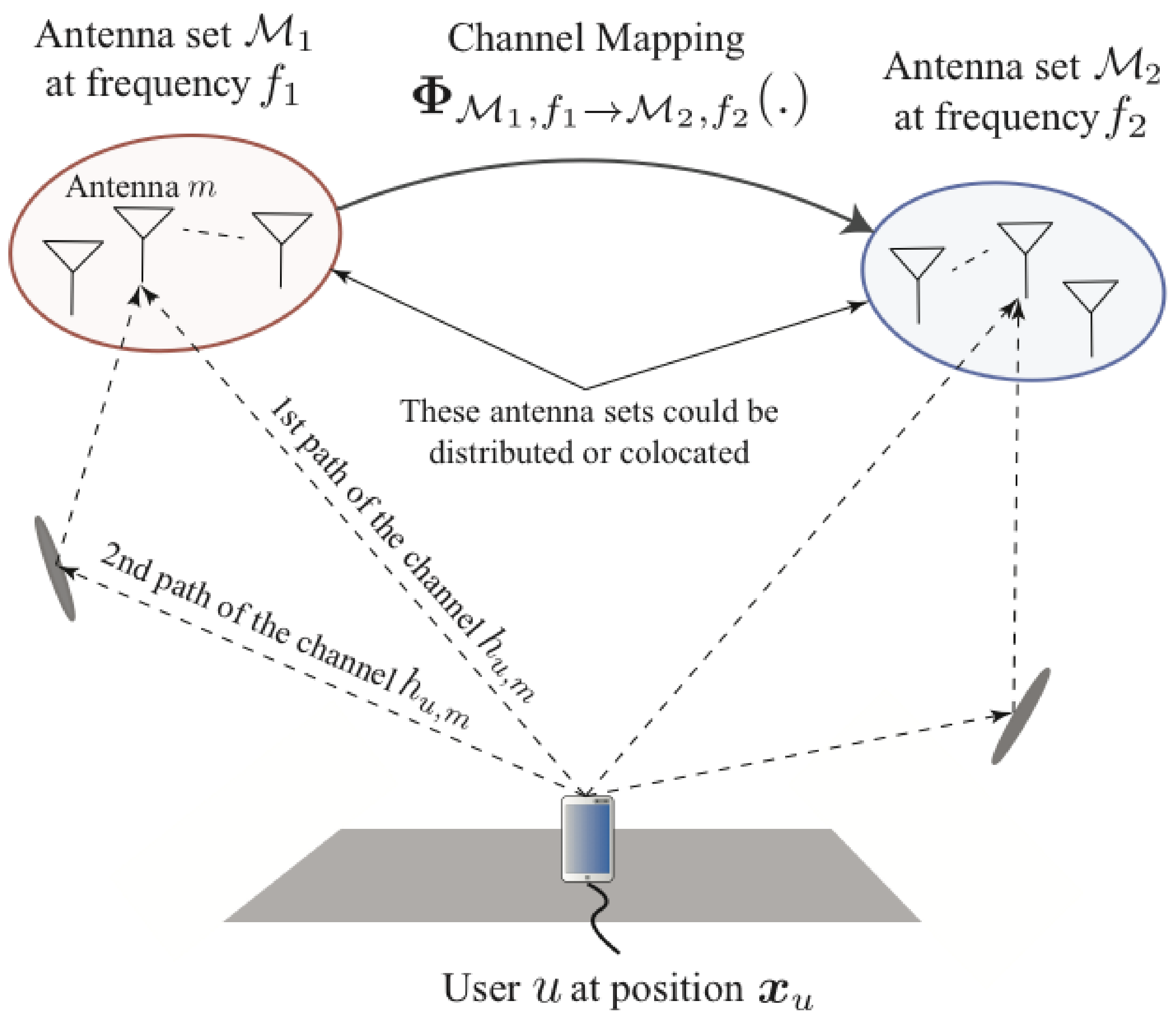
Channel
beamforming vector
channel covariance

We propose to leverage ML models to learn this mapping function

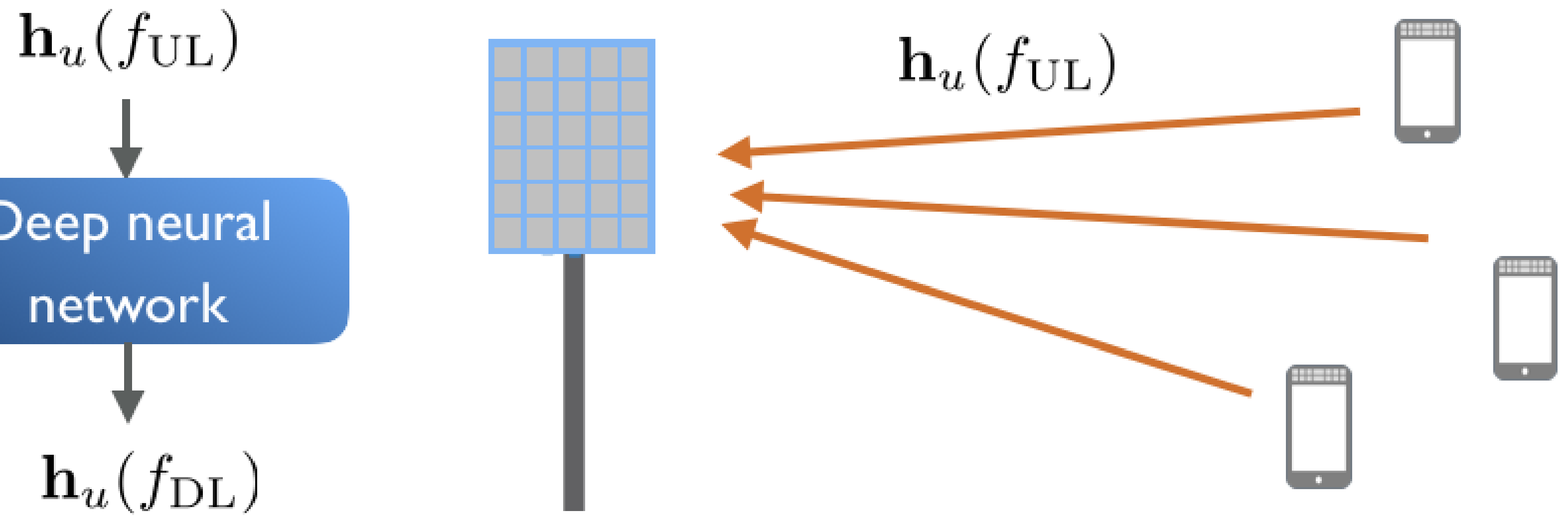
DEEP LEARNING APPLICATIONS IN 5G

Papers, datasets, and codes are available at www.DeepMIMO.net

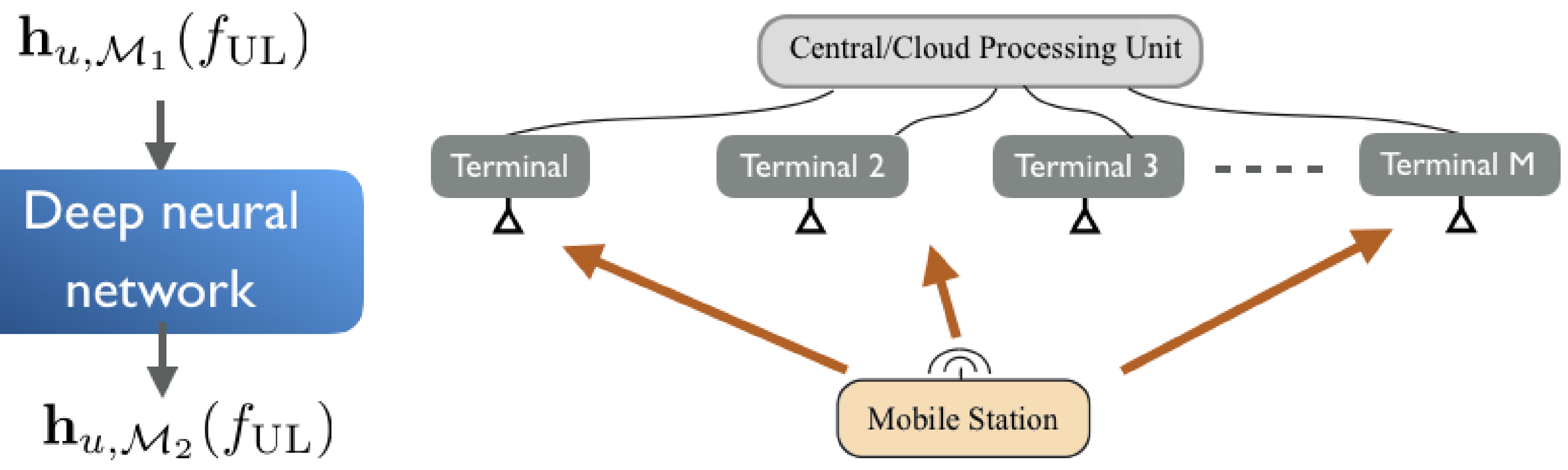
Deep learning enables reliable and highly-mobile massive MIMO applications



Channel mapping in space, frequency, and time



Enabling FDD massive MIMO systems



Enabling distributed (cell-free) massive MIMO systems

DEEP LEARNING APPLICATIONS IN 5G

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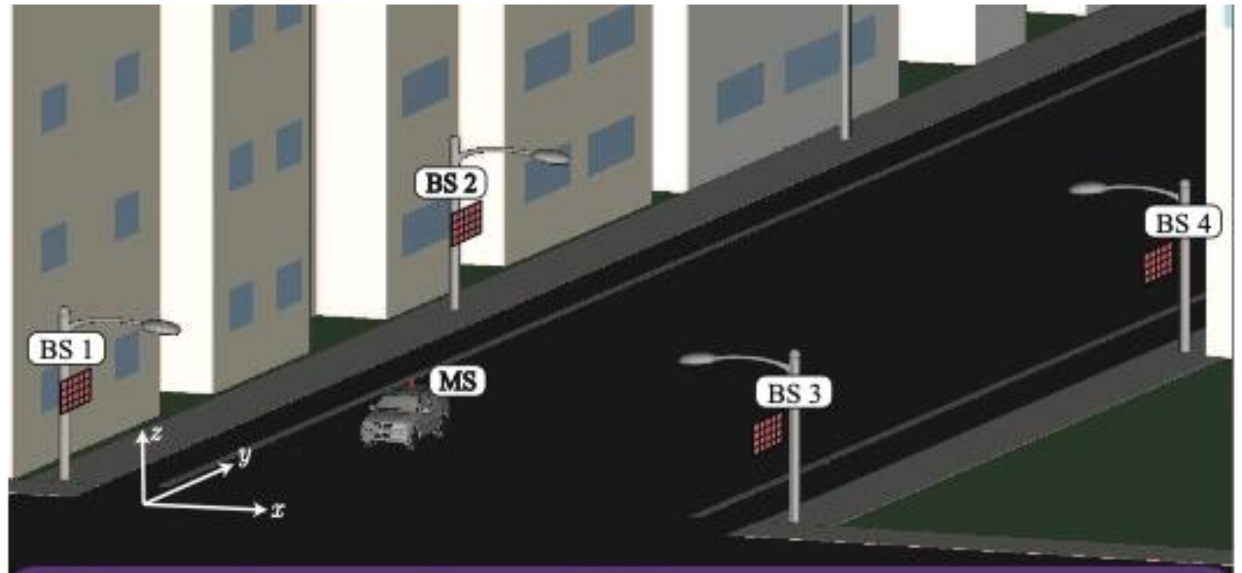
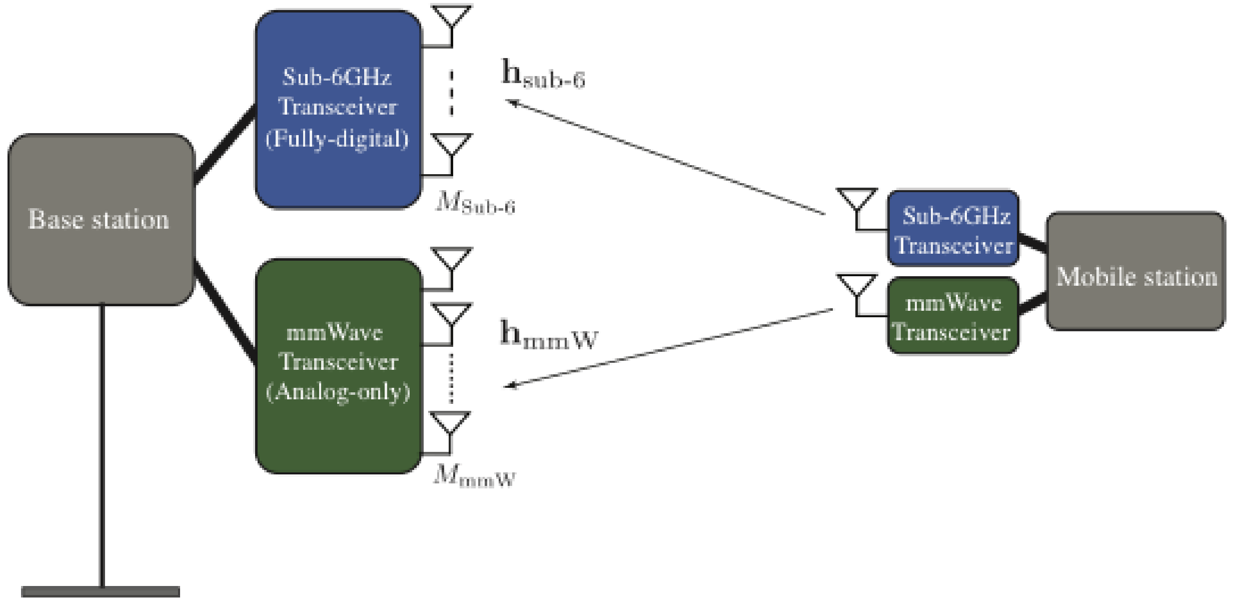
Deep learning enables reliable and highly-mobile mmWave applications

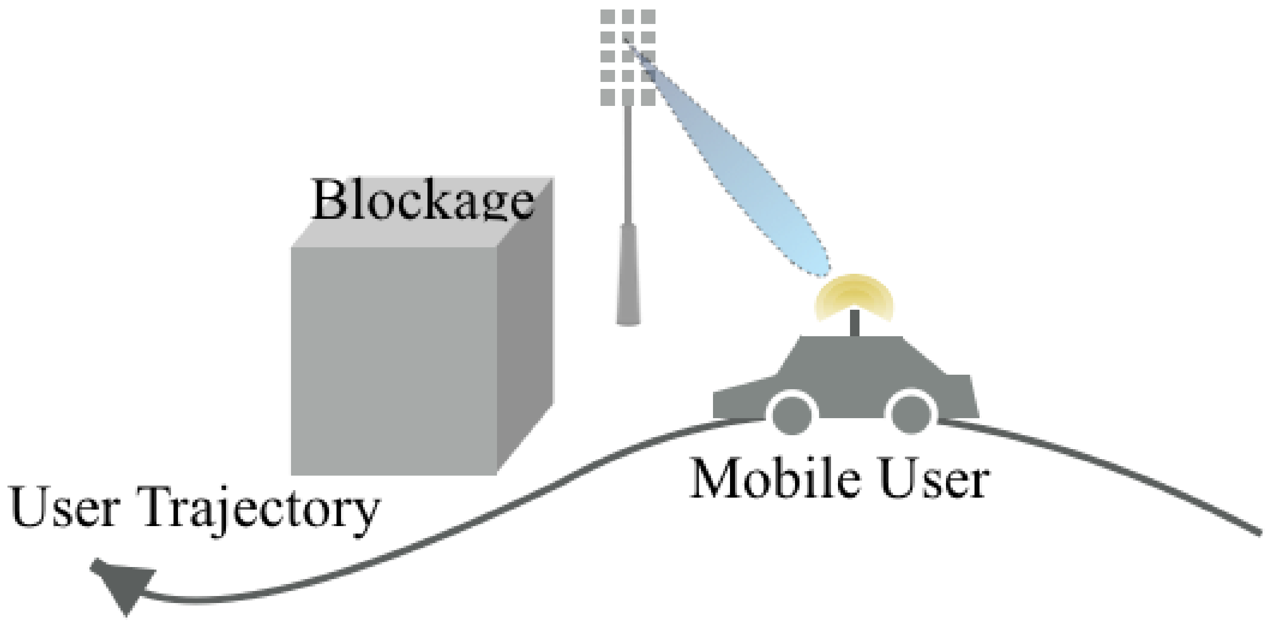
mmWave beam prediction



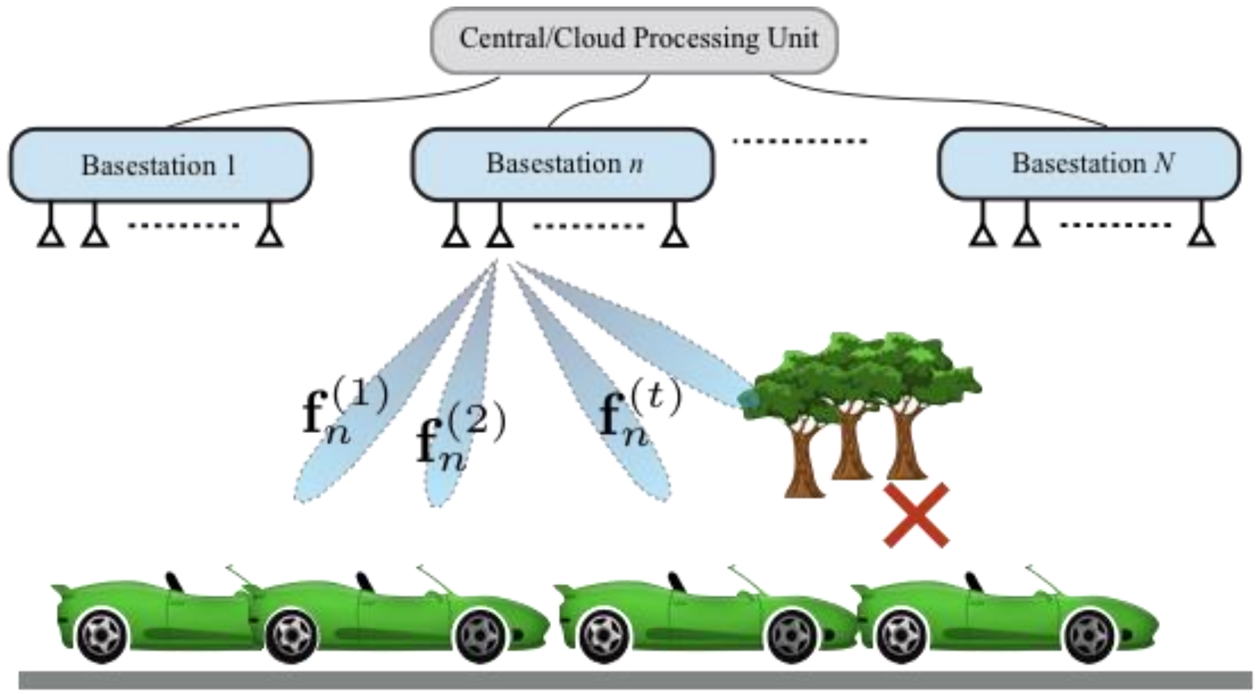
Coordinated mmWave transmission



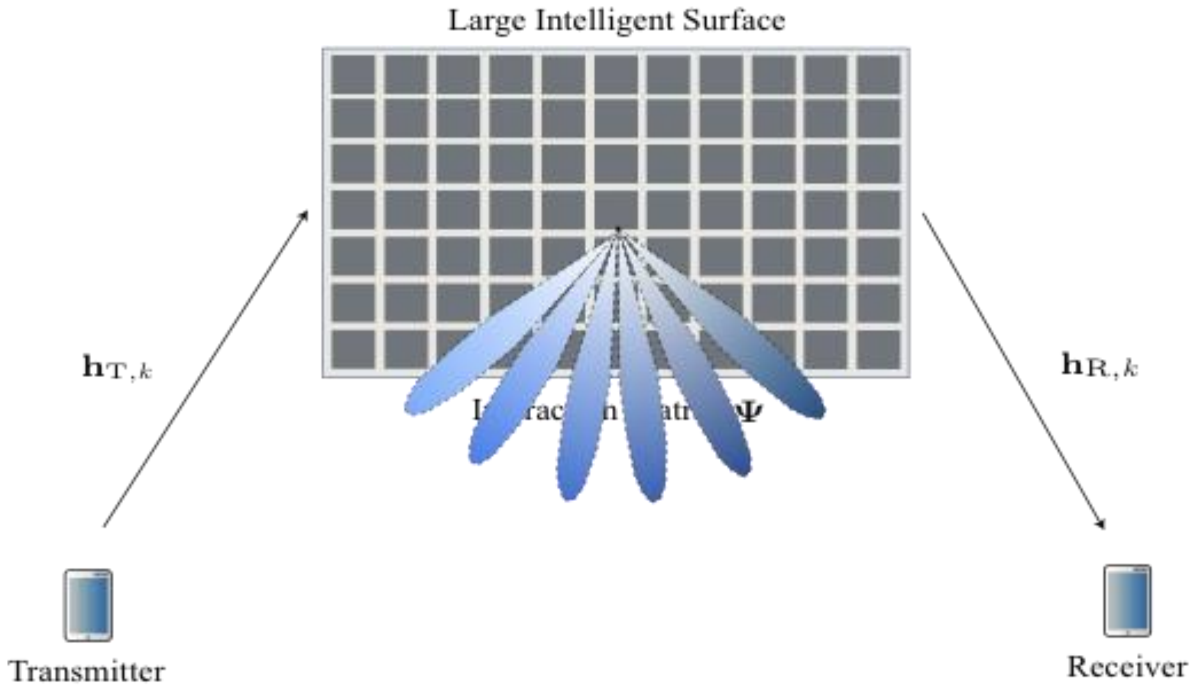
Using sub-6GHz channels



mmWave blockage prediction



Proactive hand-off at mmWave



Enabling large-intelligent surfaces

DEEP LEARNING APPLICATIONS IN 5G

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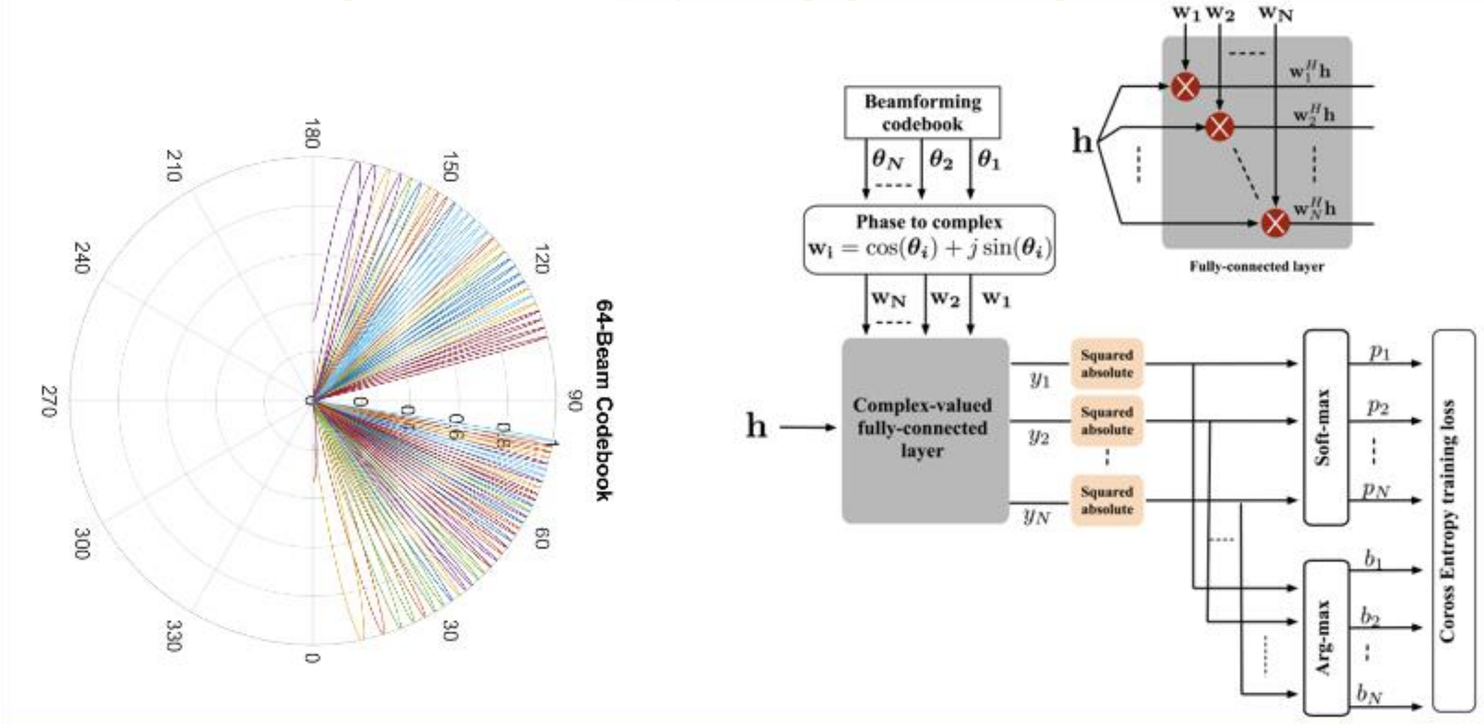
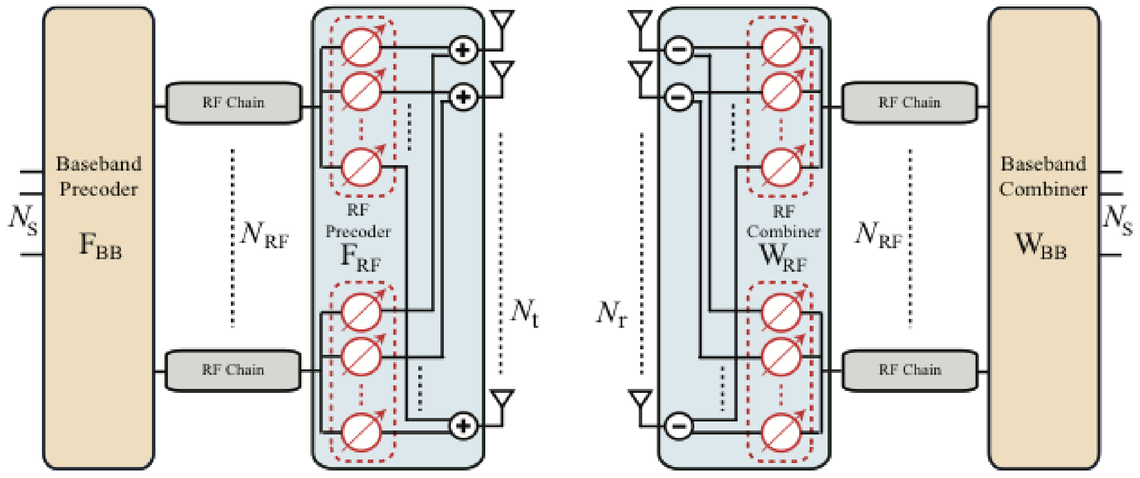
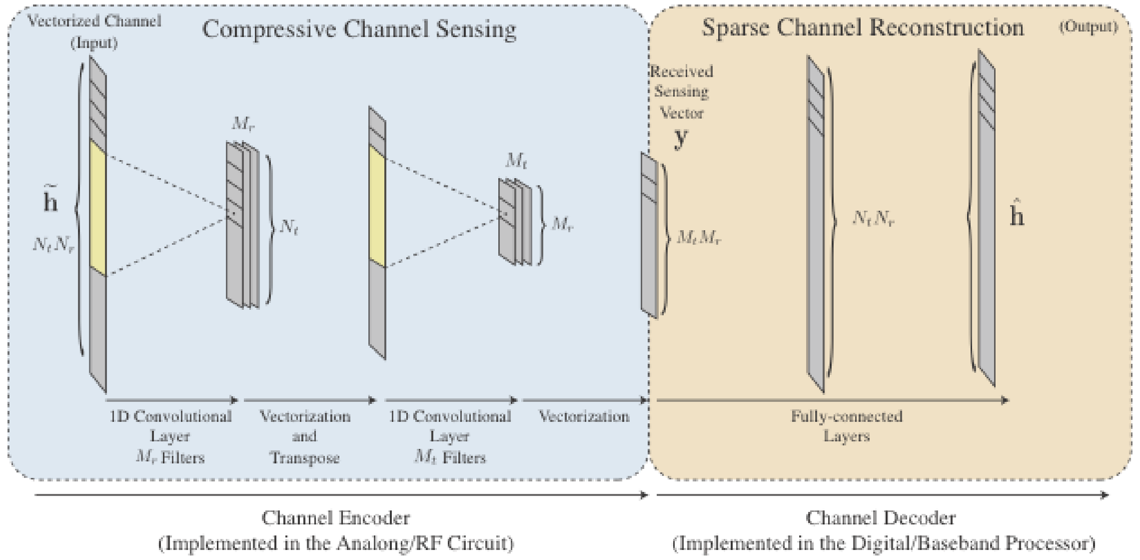
Deep learning supports practical large-scale MIMO transceivers

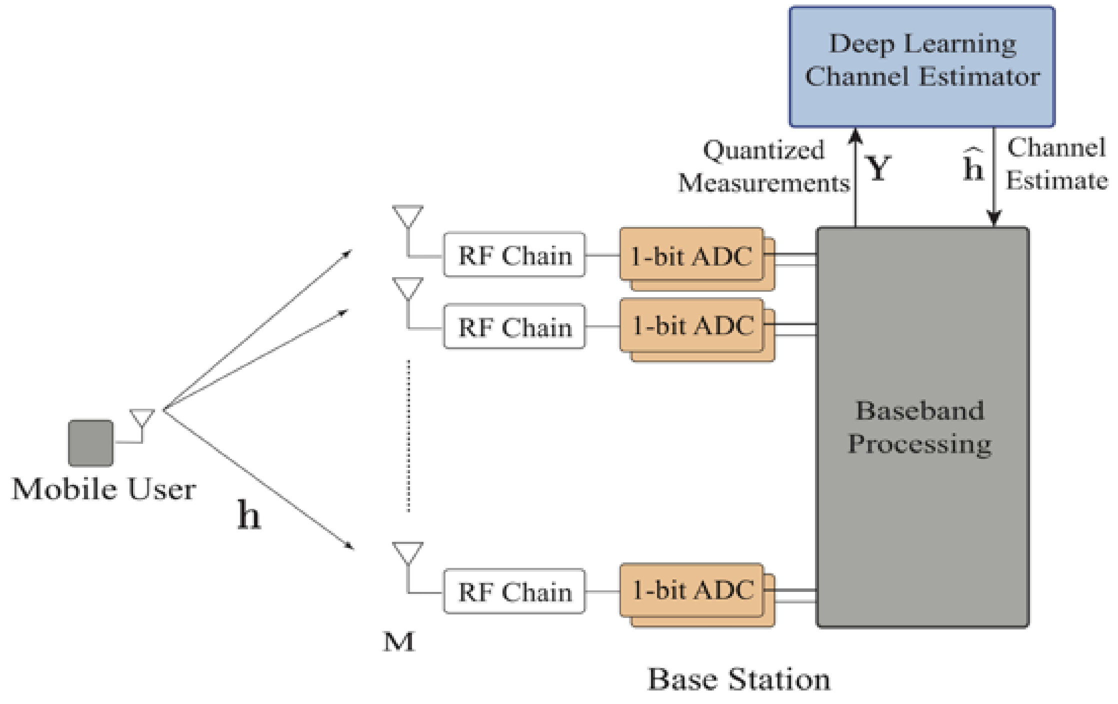


Environment and hardware-aware codebook learning





Deep learning for hybrid beam prediction and channel estimation

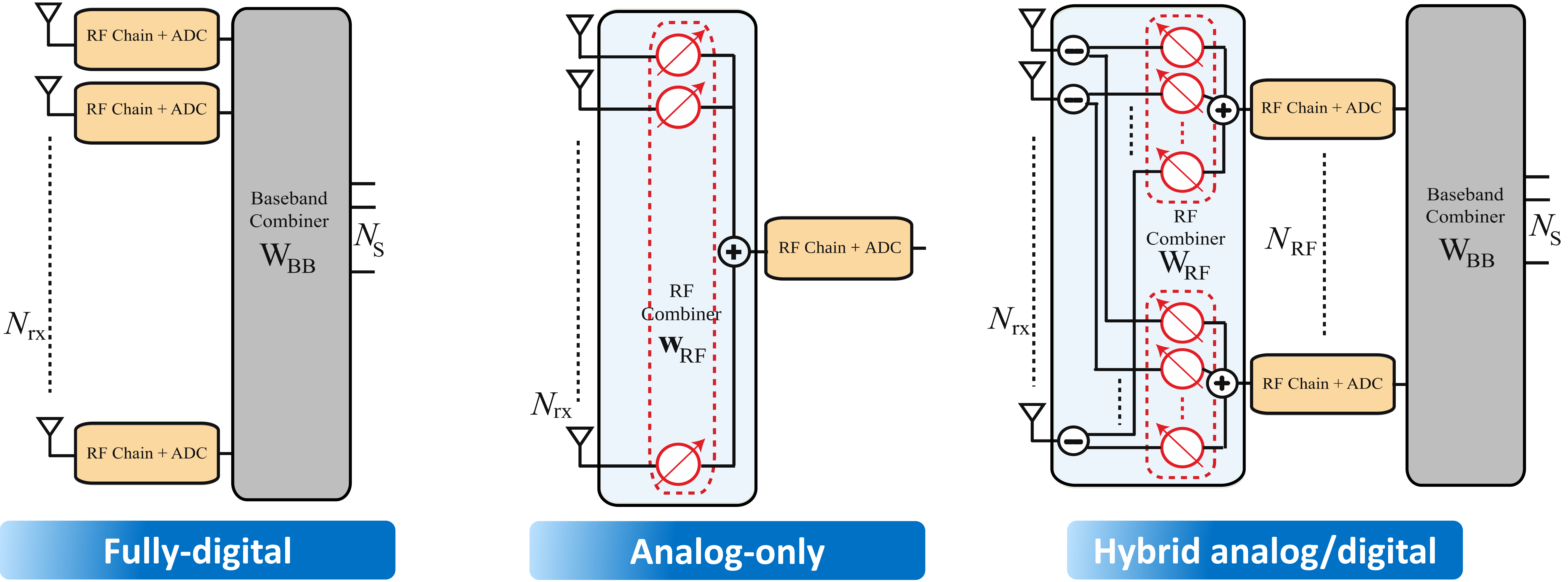


Enabling MIMO systems with low-resolution ADCs

AUTO-PRECODER

BACKGROUND AND MOTIVATION

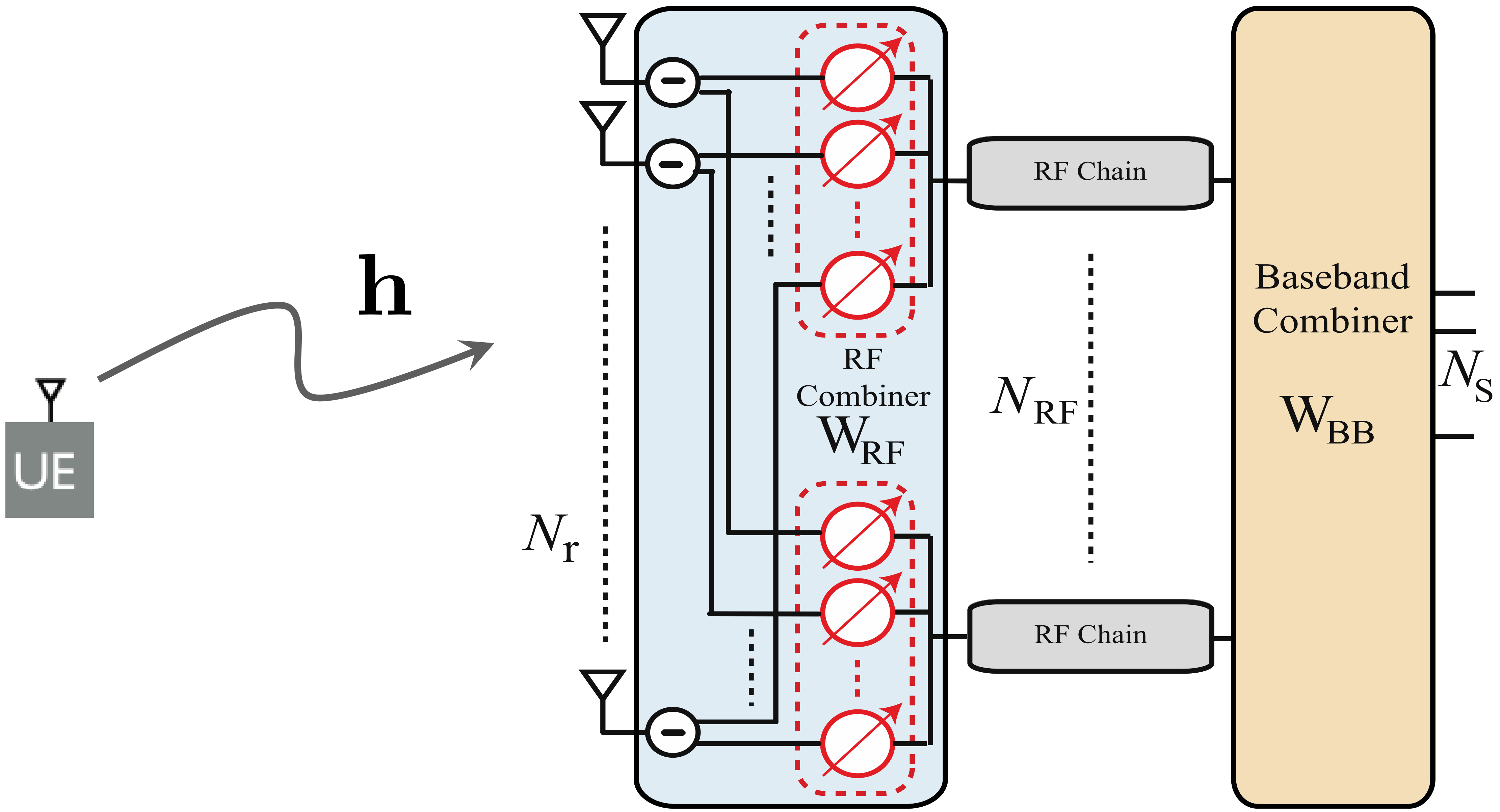
Why hybrid analog-digital architectures?



Hybrid analog/digital architectures achieve high data rates with reasonable complexity

BACKGROUND AND MOTIVATION

Channel estimation is challenging!



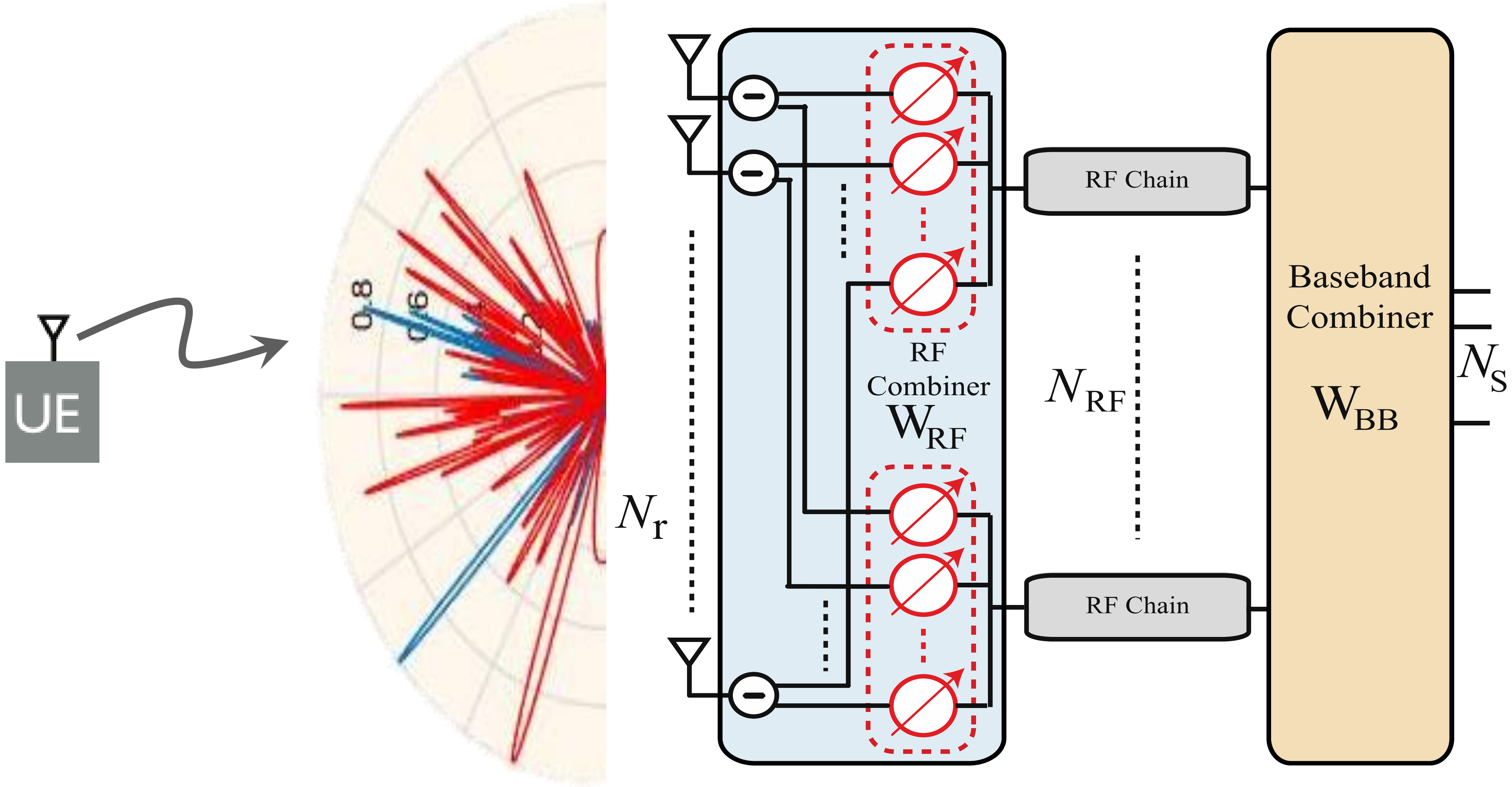
Channel is seen through the RF lens

Analog circuits add strict constraints

Leveraging hybrid architectures requires developing efficient channel estimation solutions

BACKGROUND AND MOTIVATION

Classical channel estimation approaches for hybrid architectures



Classical Compressive Sensing Approach

Sensing the channel with random beam patterns

Sparse channel reconstruction using approaches such as OMP

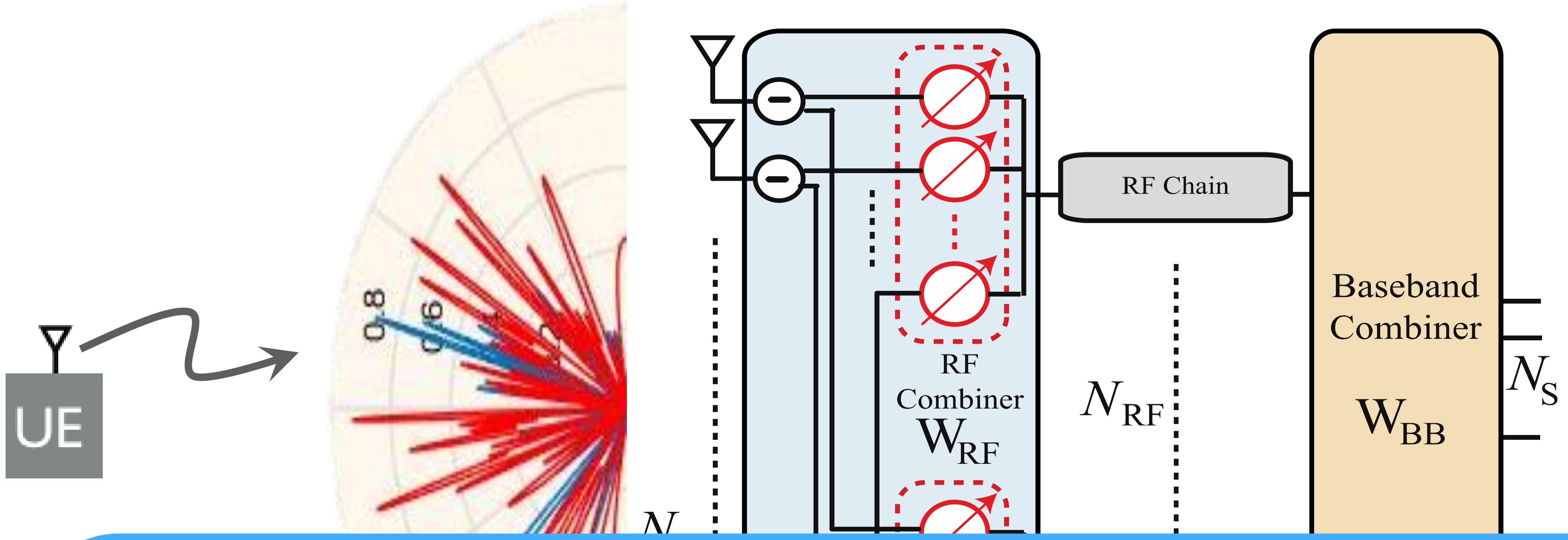
Limitations

Random beams sense directions that may never be used

Prior channel observations are not leveraged

BACKGROUND AND MOTIVATION

Classical channel estimation approaches for hybrid architectures



Classical Compressive Sensing Approach

Sensing the channel with random beam patterns

How can deep learning help?

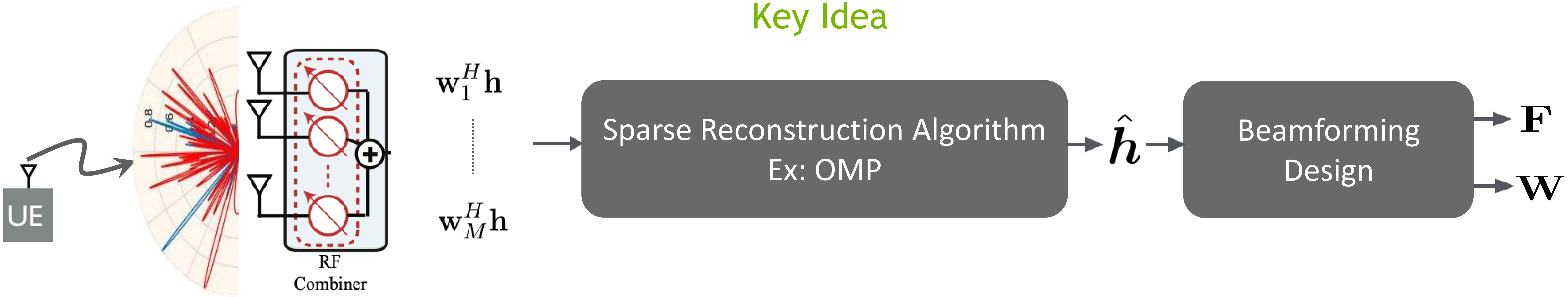
Limitations

Random beams sense directions that may never be used

Prior channel observations are not leveraged

AUTO PRECODER

Key Idea



mmWave channel estimation .. followed by hybrid precoding design

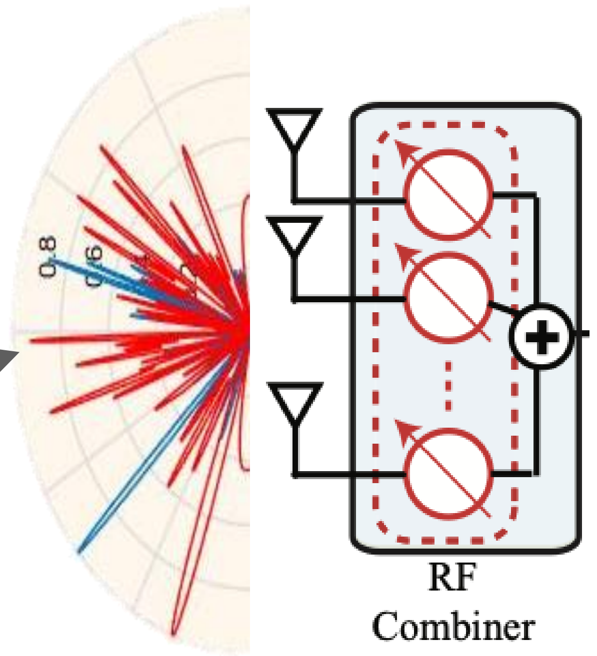
Neural network weights realize measurement beams focusing on important directions

Channel reconstruction leverages prior observation

AUTO PRECODER

Key Idea

UE



$\mathbf{w}_1^H \mathbf{h}$

$\mathbf{w}_M^H \mathbf{h}$

Sparse Reconstruction Algorithm
Ex: OMP

$\hat{h}$

Beamforming Design

$\mathbf{F}$

$\mathbf{W}$

mmWave channel estimation .. followed by hybrid precoding design

UE

h

Single-layer Perceptron

Neural network weights

$\mathbf{w}_1^H \mathbf{h}$

$\mathbf{w}_M^H \mathbf{h}$

"Precoder"
Neural Network

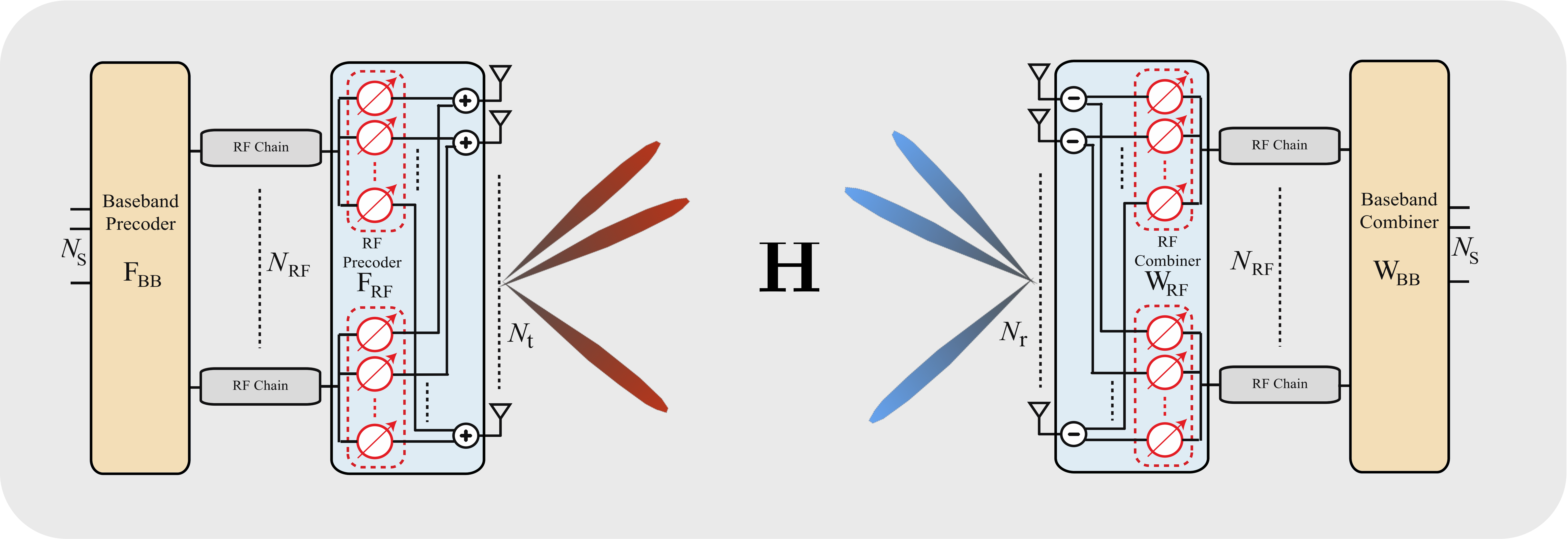
$\mathbf{F}$

$\mathbf{W}$

Proposed "Auto-precoder": Optimizes measurements and leverages prior observations

AUTO PRECODER

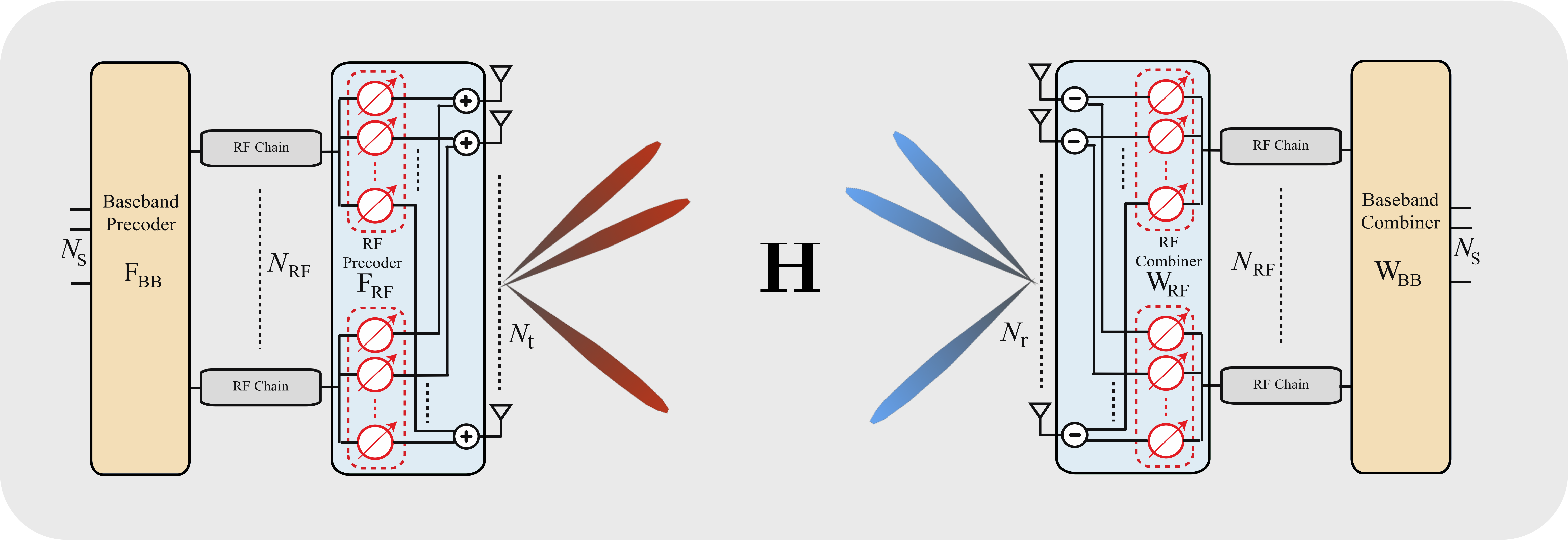
Joint channel sensing and precoder prediction



$$\mathbf{y} = \mathbf{Q}^H \mathbf{H} \mathbf{P} + \mathbf{Q}^H \mathbf{N}$$

AUTO PRECODER

Joint channel sensing and precoder prediction



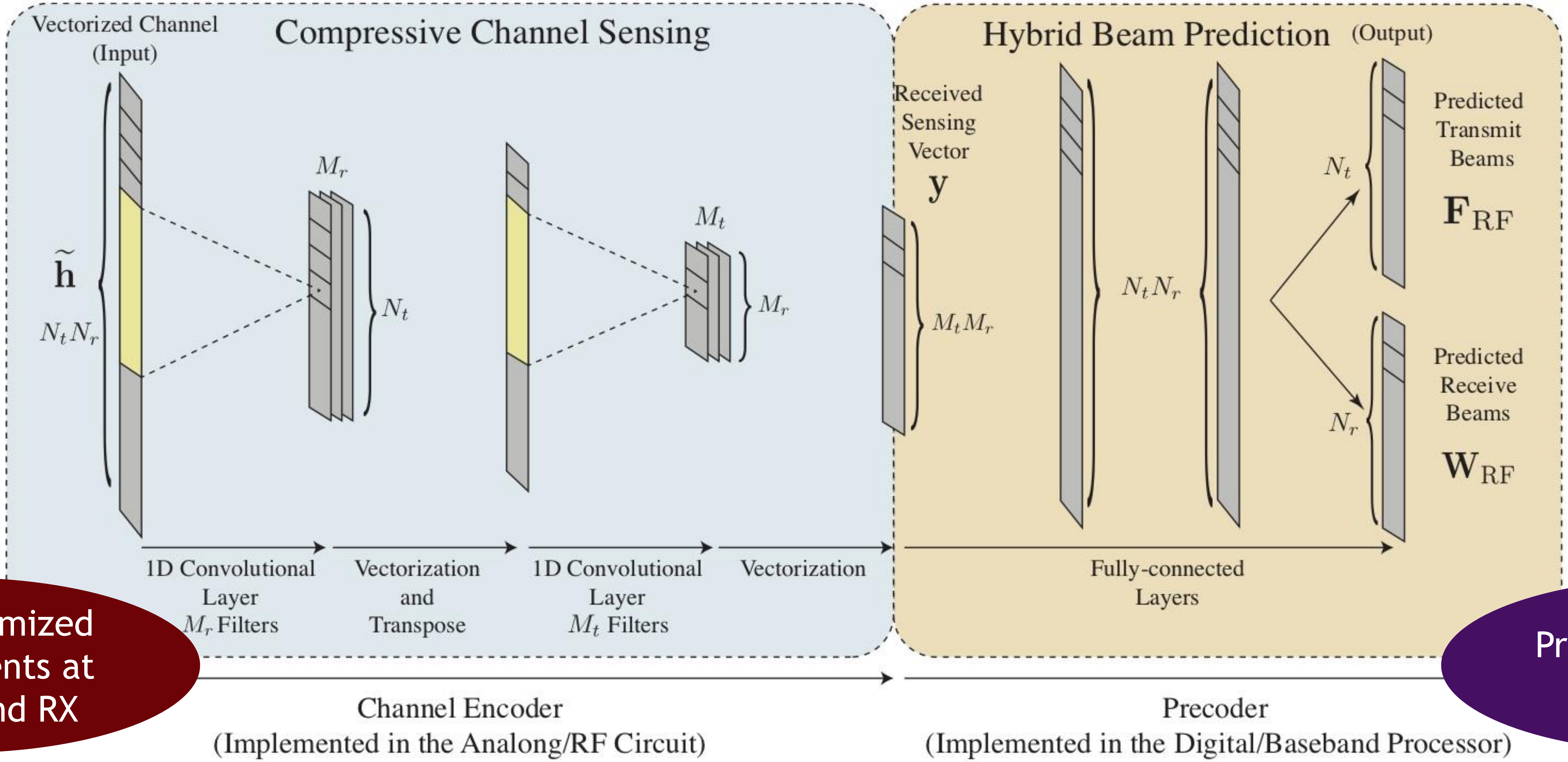
$\mathbf{H}$ — "channel sensing" Neural Network → $\mathbf{y}$ — "Beam Prediction" Neural Network → $\mathbf{F}$, $\mathbf{W}$

$$\mathbf{y} = \mathbf{Q}^H \mathbf{H} \mathbf{P} + \mathbf{Q}^H \mathbf{N}$$

Papers, datasets, and codes are available at www.DeepMIMO.net

HYBRID BEAM PREDICTION

Joint channel sensing and hybrid beam prediction



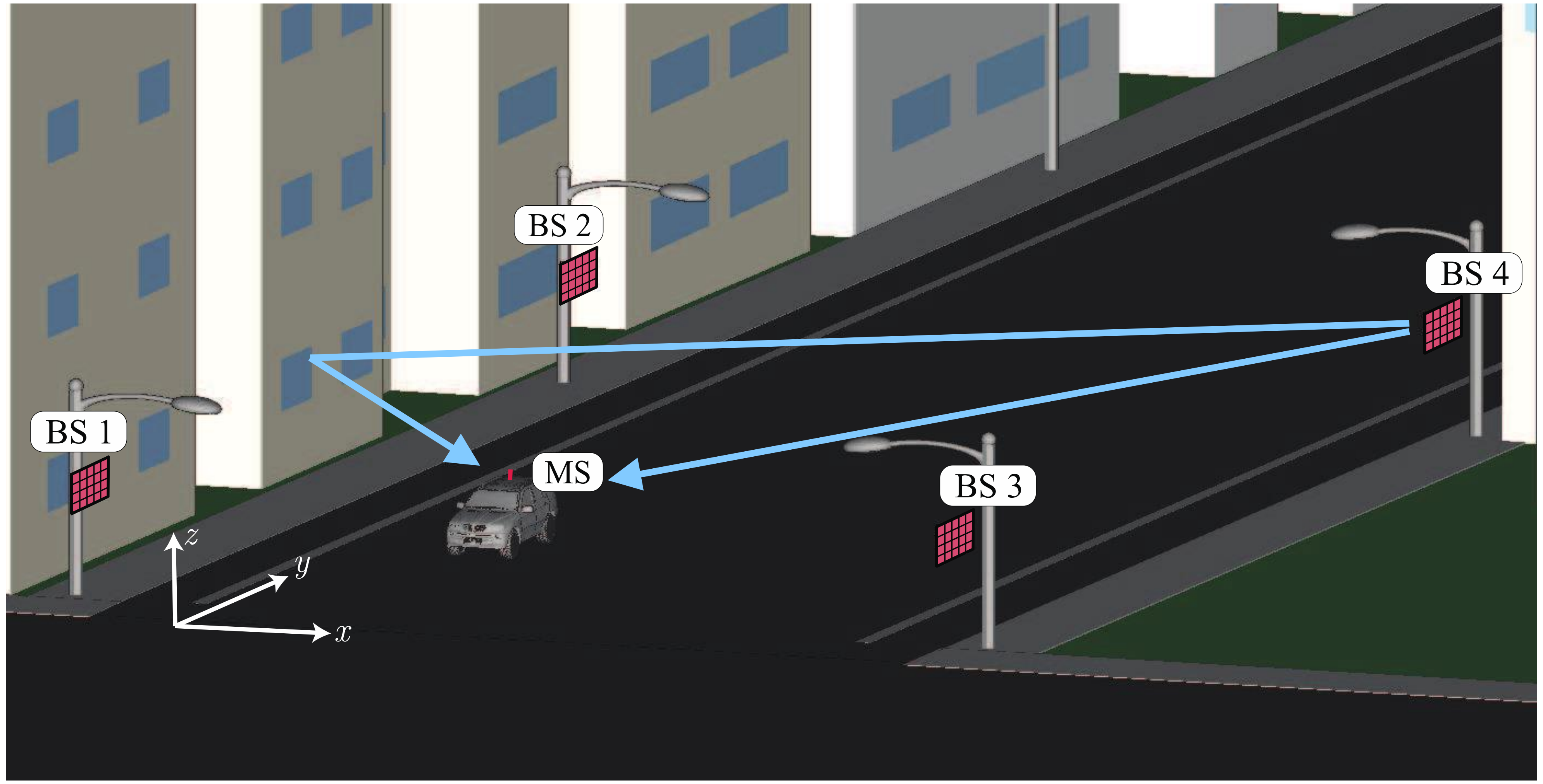
Learns optimized measurements at both TX and RX

Predicts TX and RX hybrid beams

X. Li, and A. Alkhateeb "Deep Learning for Direct Hybrid Precoding in Millimeter Wave Massive MIMO Systems" Asilomar 2019 (arXiv: https://arxiv.org/abs/1905.13212)

REAL WORLD DEPLOYMENT

THE NEED FOR RAY-TRACING

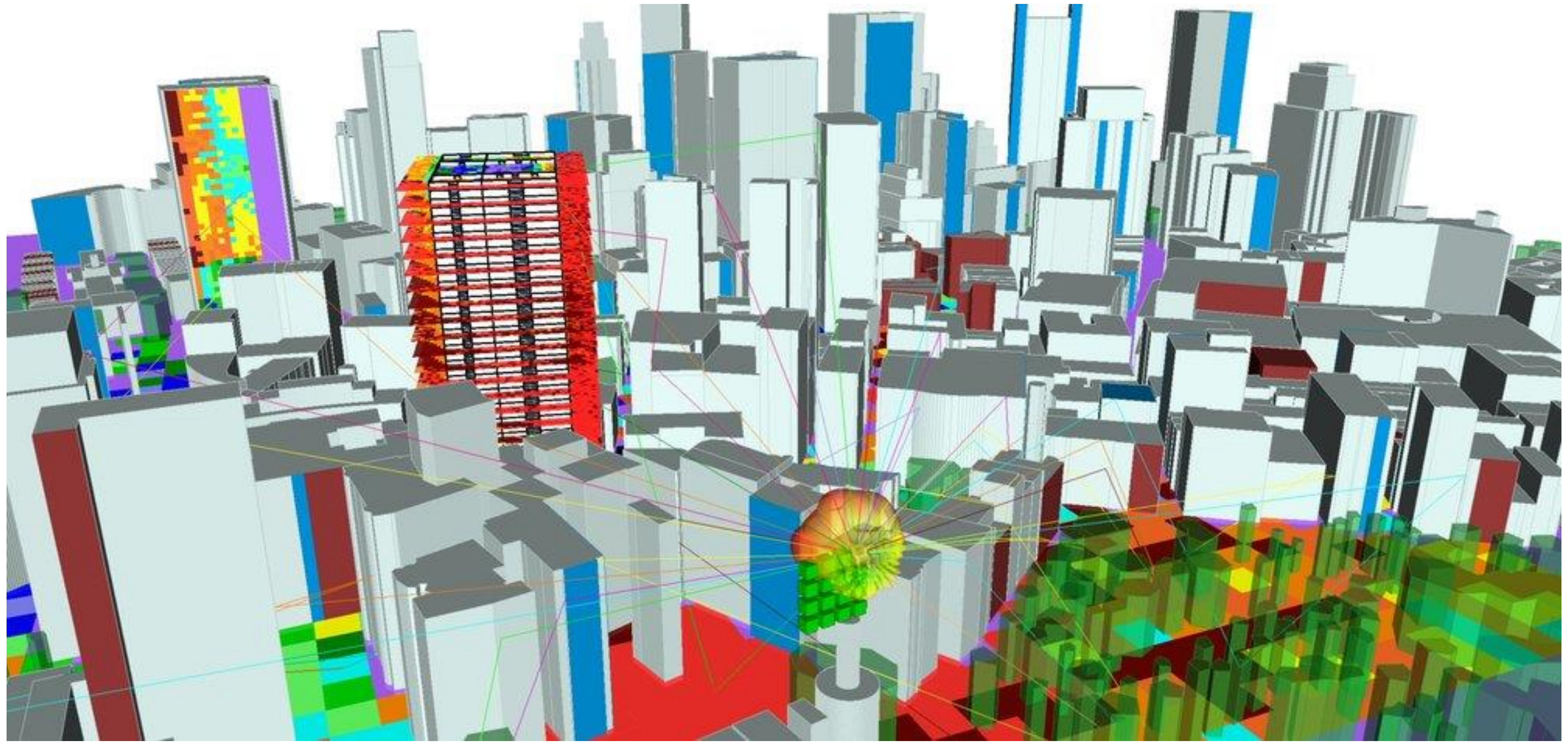


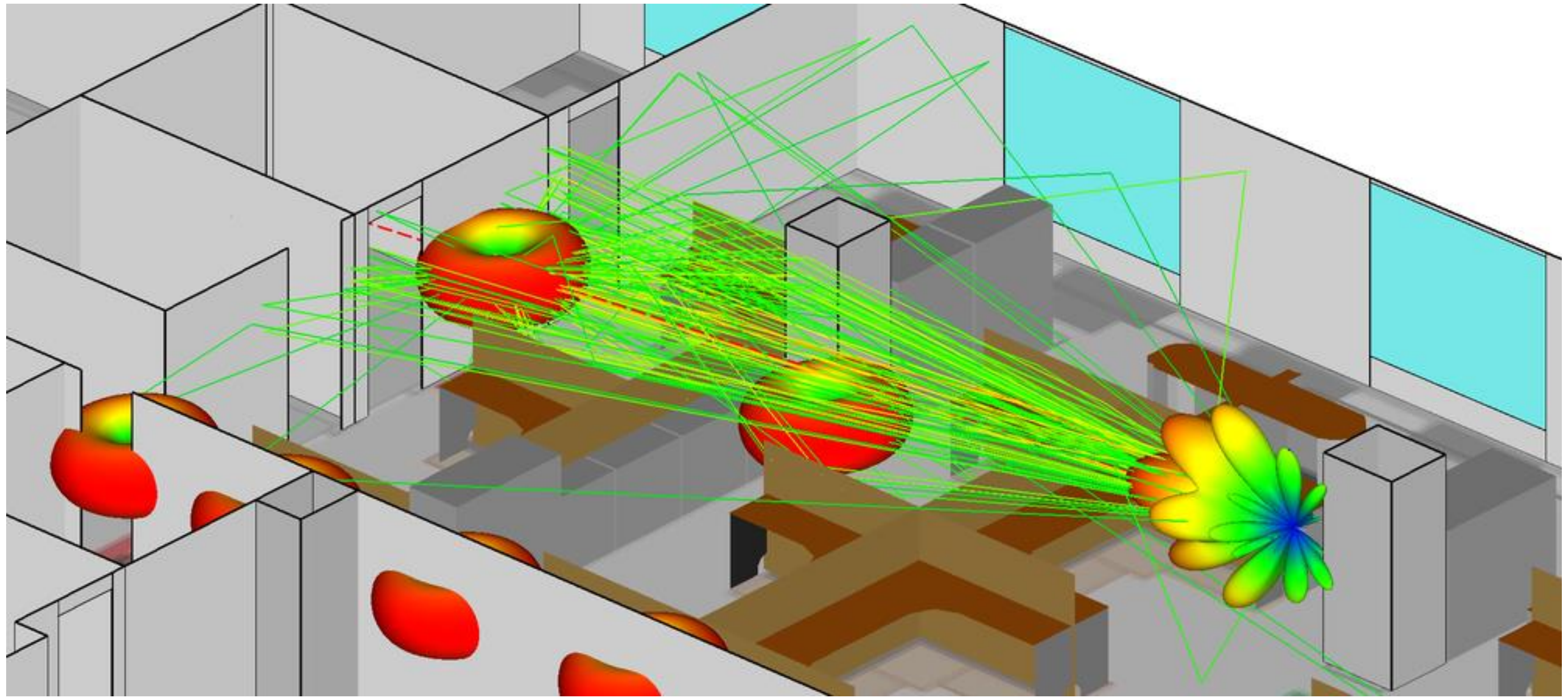
Studying the performance of the proposed deep learning approaches needs channel datasets

Generated channels should capture the dependency on the environment

Accurate 3D ray-tracing simulators could be the solution

REMCOM WIRELESS INSITE: AN ACCURATE RAY-TRACING TOOL





Accurate 3D ray-tracing

Advanced propagation models

MIMO capabilities

Ray-tracing results have been validated with measurements at both sub-6GHz and mmWave

DEEPMIMO: A DEEP-LEARNING DATASET FOR MIMO SYSTEMS

https://www.deepmimo.net/

Captures the dependence on environment, locations, etc.

Generic/parametrized for system & channels

Enables accurate definition and simple reproduction

A ray-tracing scenario ‘R’ → Channel parameters → DeepMIMO dataset generation code → The DeepMIMO dataset of scenario ‘R’ and paramerers $\mathcal{S}$

DeepMIMO dataset parameters $\mathcal{S}$

Active BSs
Active users
Number of BS Antennas
Antenna spacing
Number of OFDM subcarriers
OFDM sampling factor
OFDM limit
Number of paths

Channel matrices between every TX and RX

In addition to other features such as TX/RX locations

The DeepMIMO dataset enables a wide range of machine learning tasks

1-DATA COLLECTION: MMWAVE PRECODING PREDICTION

Data Collection and Evaluation Using Accurate 3D Ray Tracing

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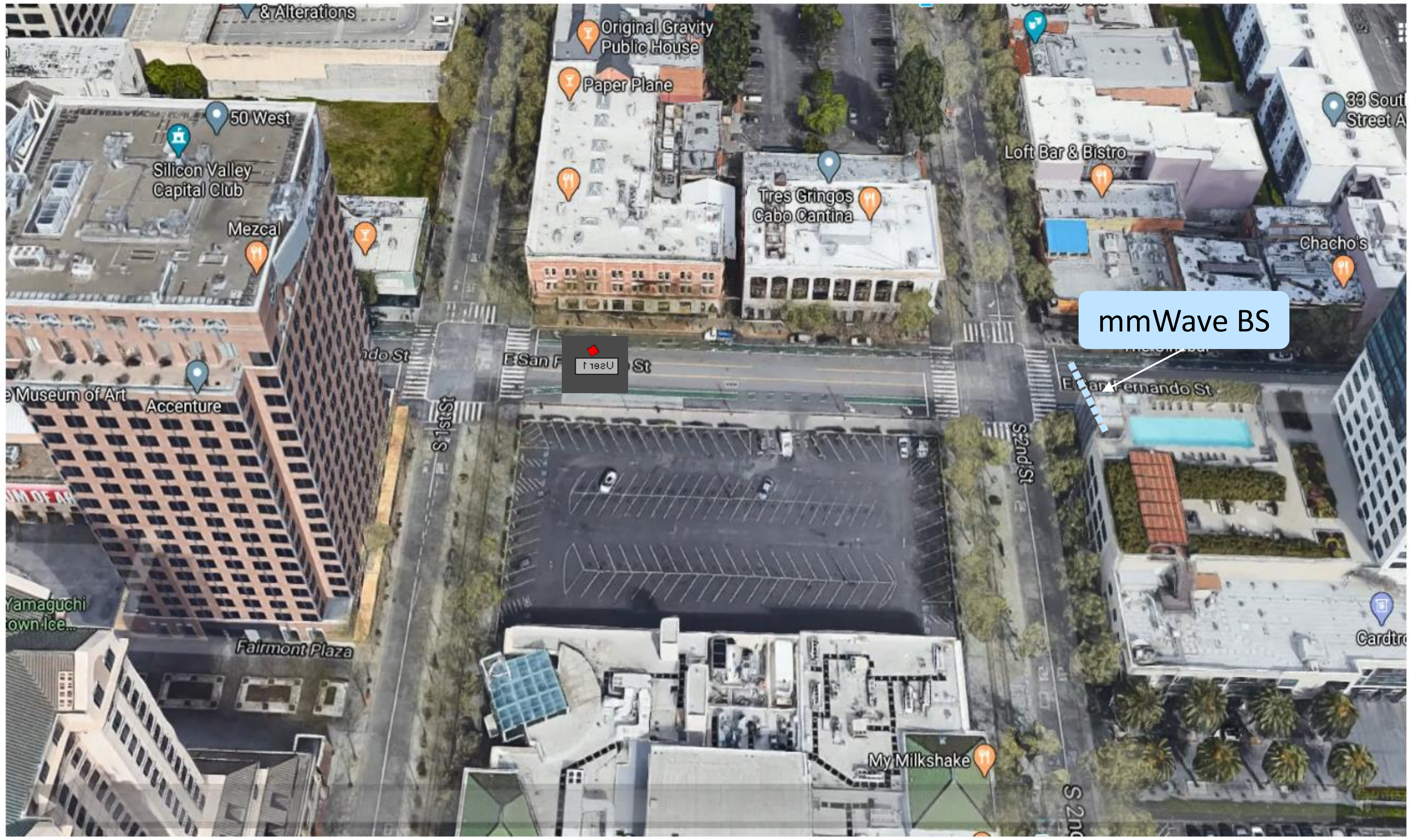
Data Collection and Evaluation Using Accurate 3D Ray Tracing



Top View

1-DATA COLLECTION: MMWAVE PRECODING PREDICTION

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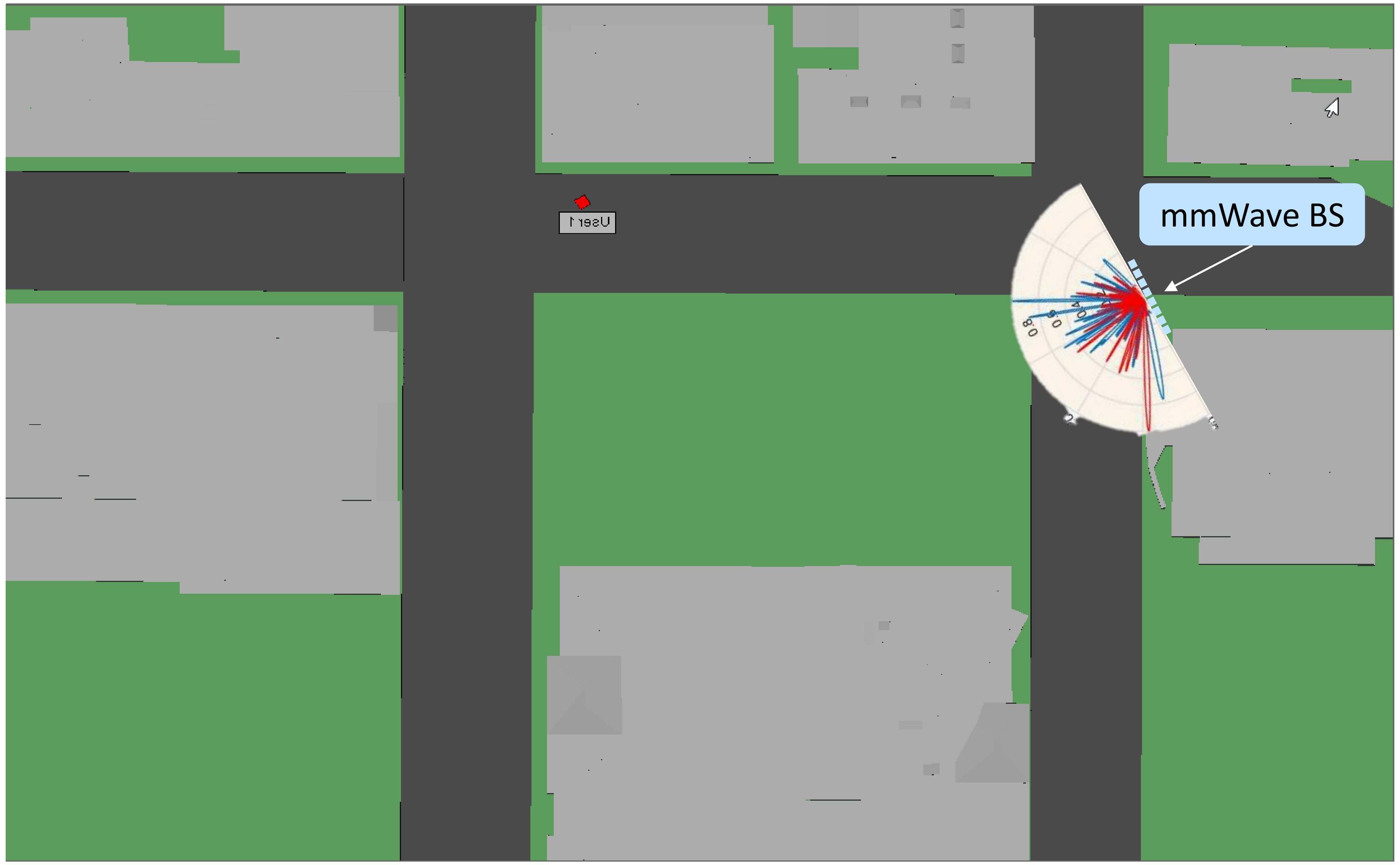

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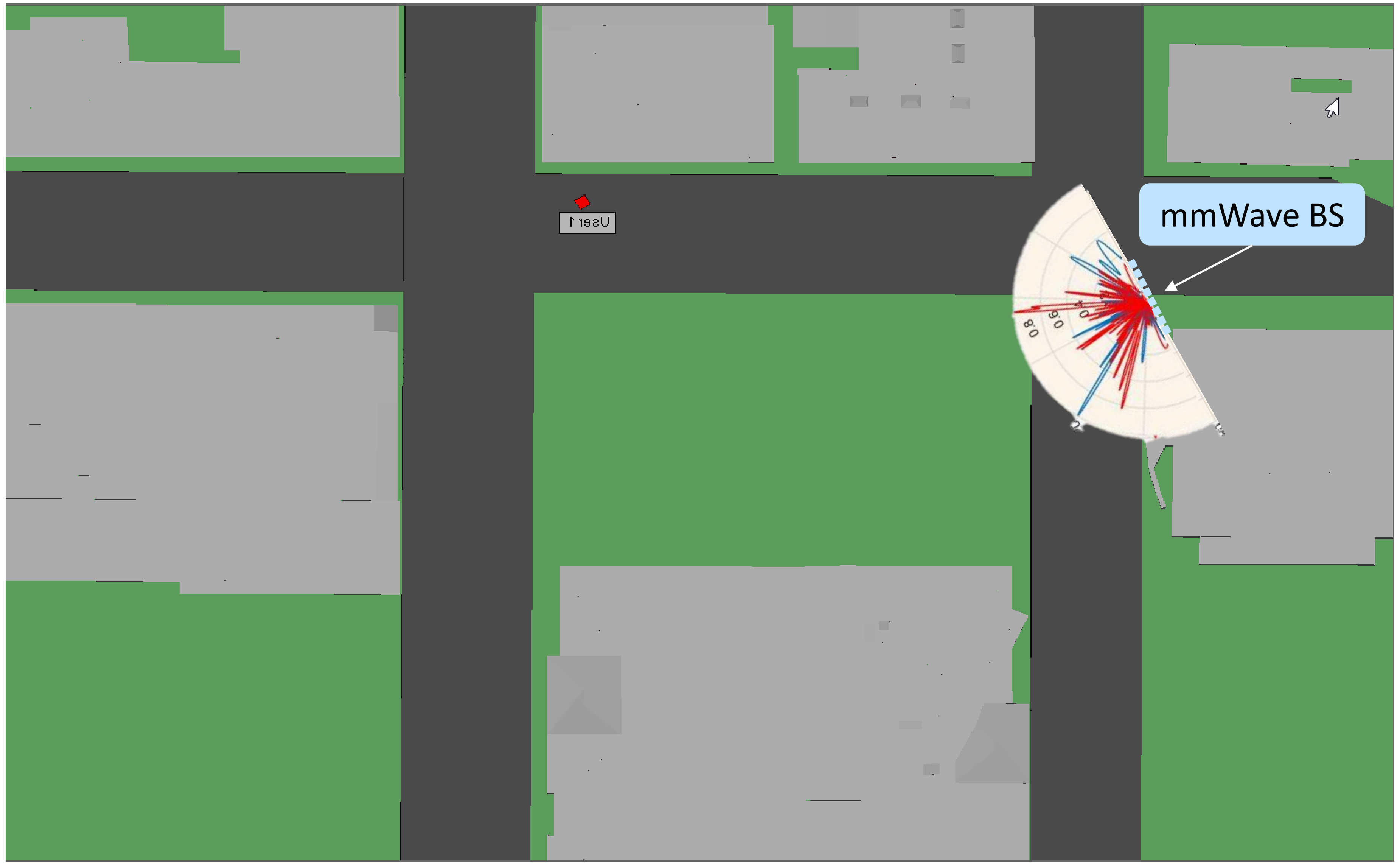

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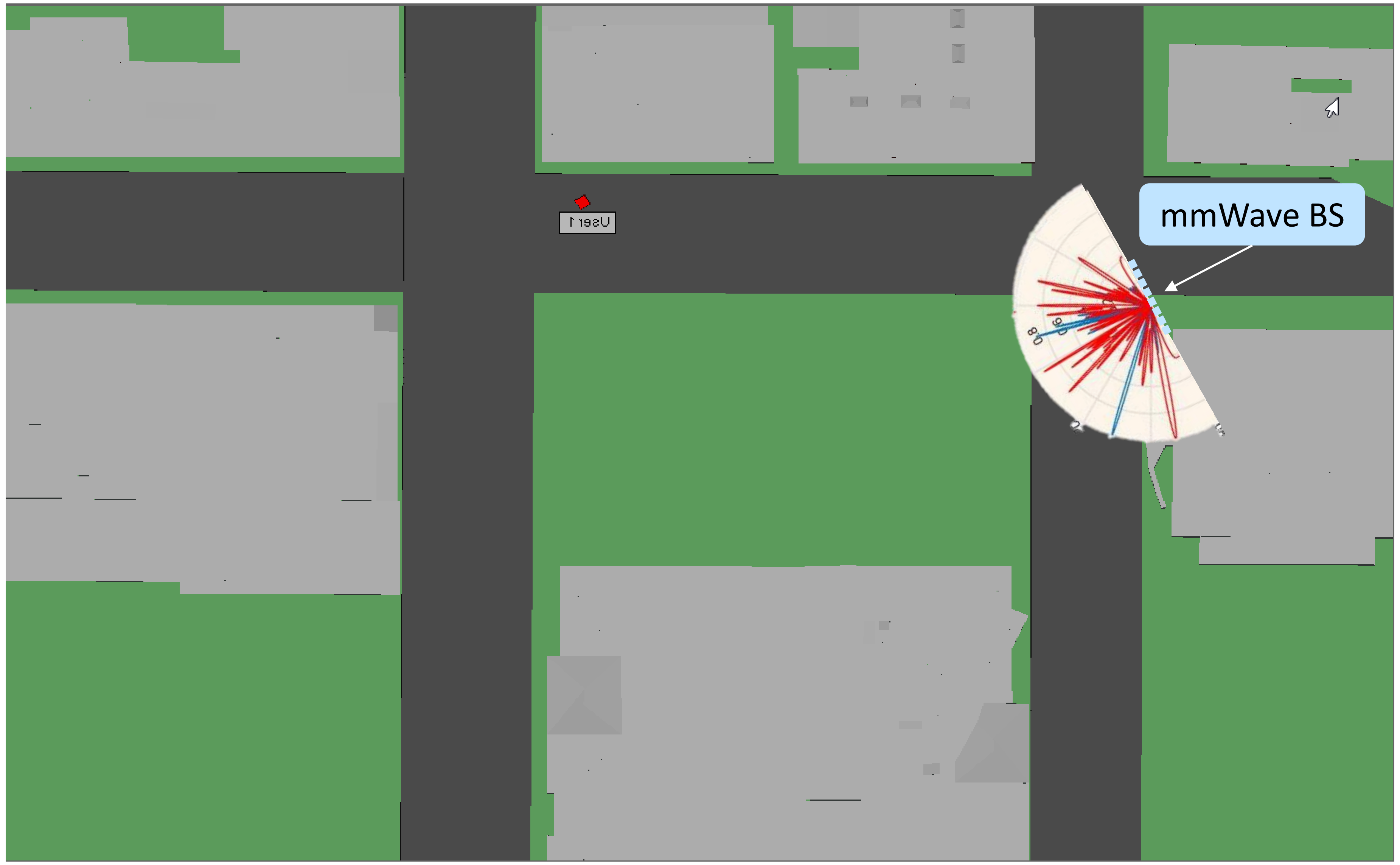

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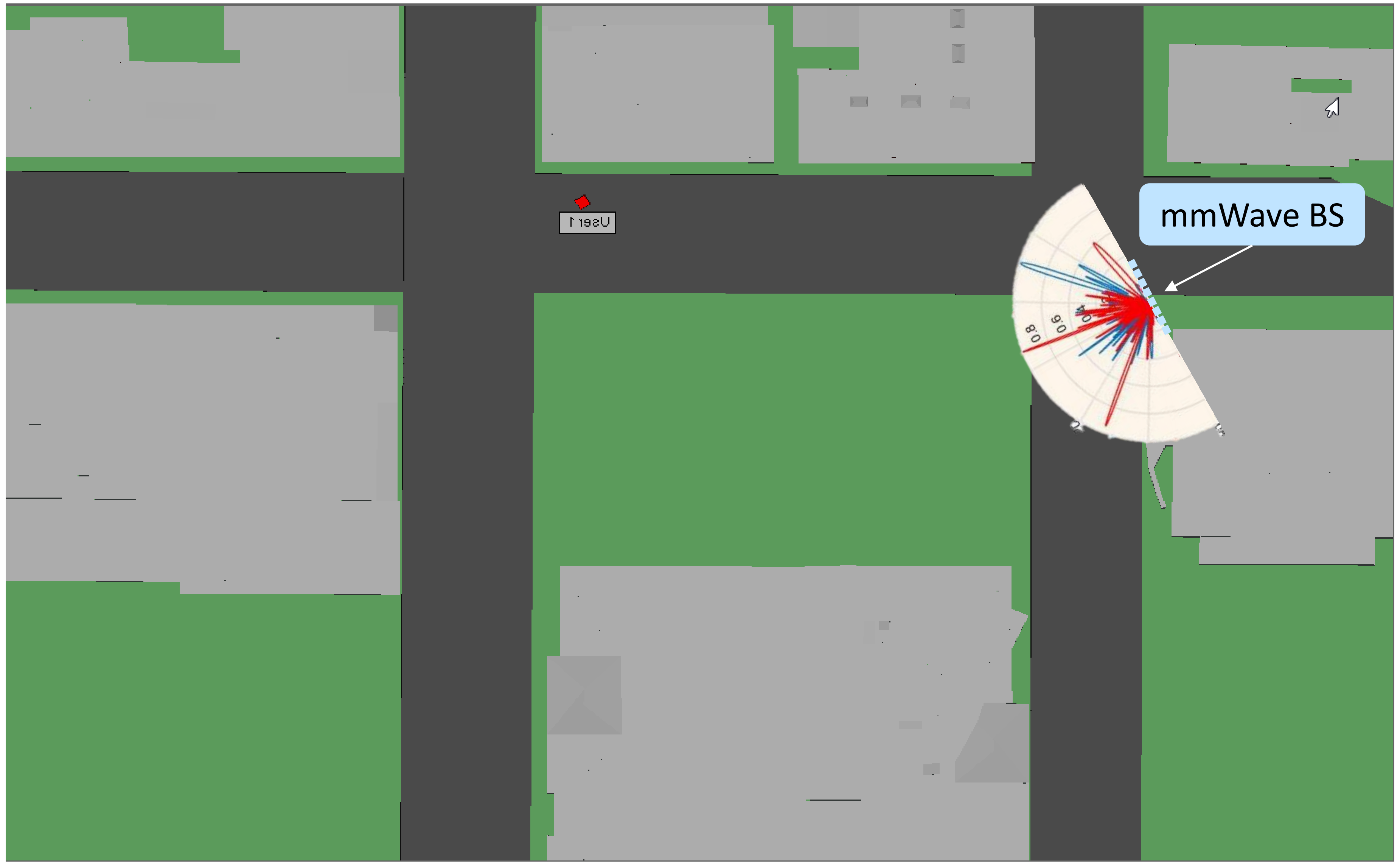

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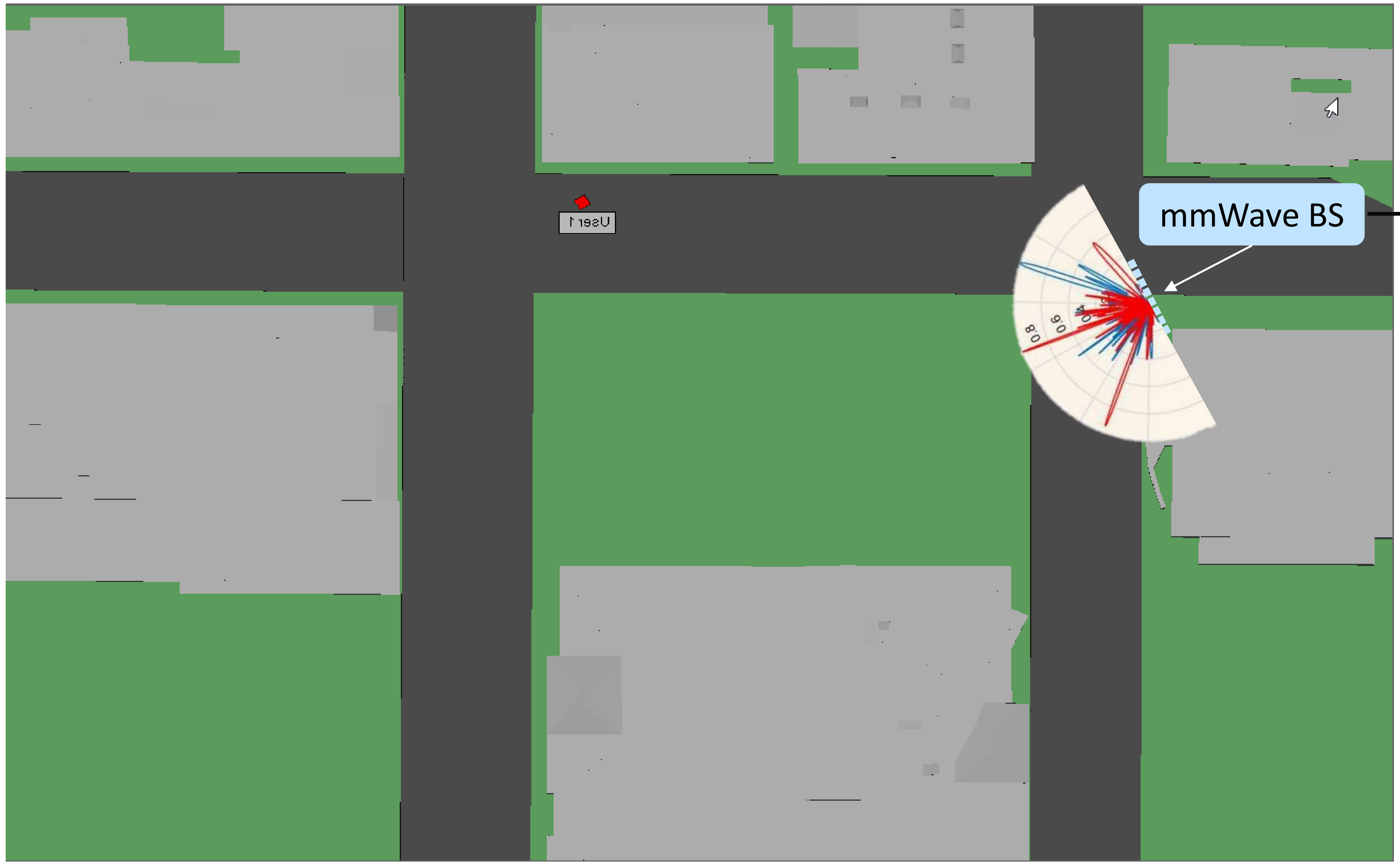


Top View

Channel Estimation (compressive sensng /reconsruction) → $\hat{\mathbf{H}}$ → Hybrid Precoding Design → $\mathbf{F}$, $\mathbf{W}$

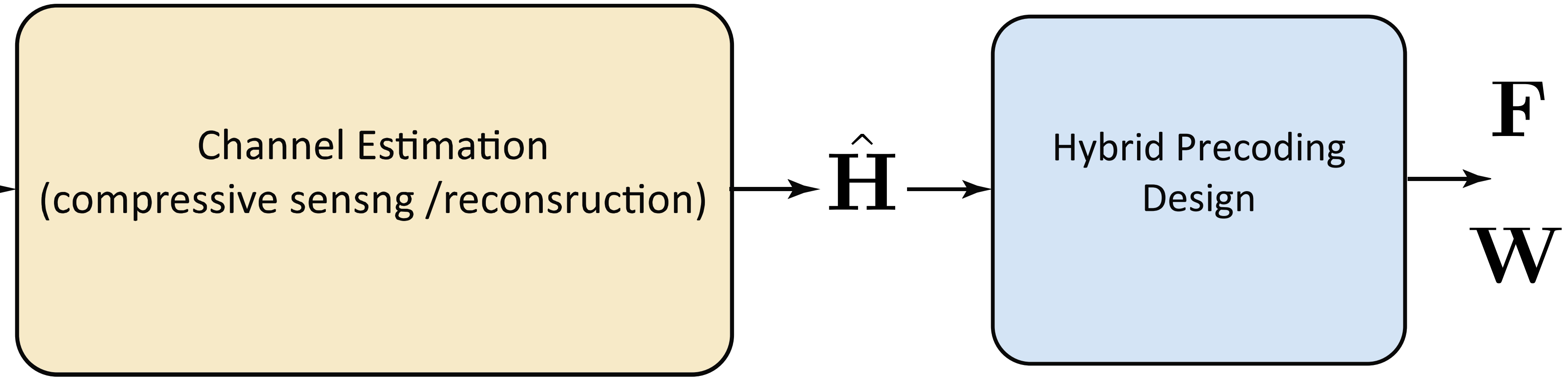
Dataset Construction

Estimated Channel	BS Beams	Mobile User Beams
$\hat{\mathbf{H}}$	$\mathbf{F}$	$\mathbf{W}$

1-DATA COLLECTION: MMWAVE PRECODING PREDICTION

Data Collection and Evaluation Using Accurate 3D Ray Tracing

Top View



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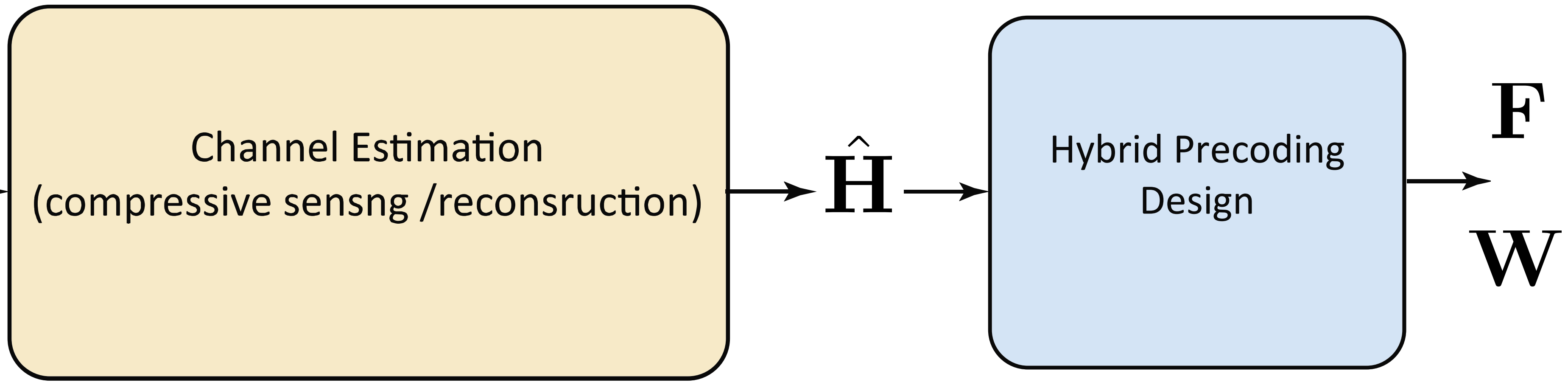

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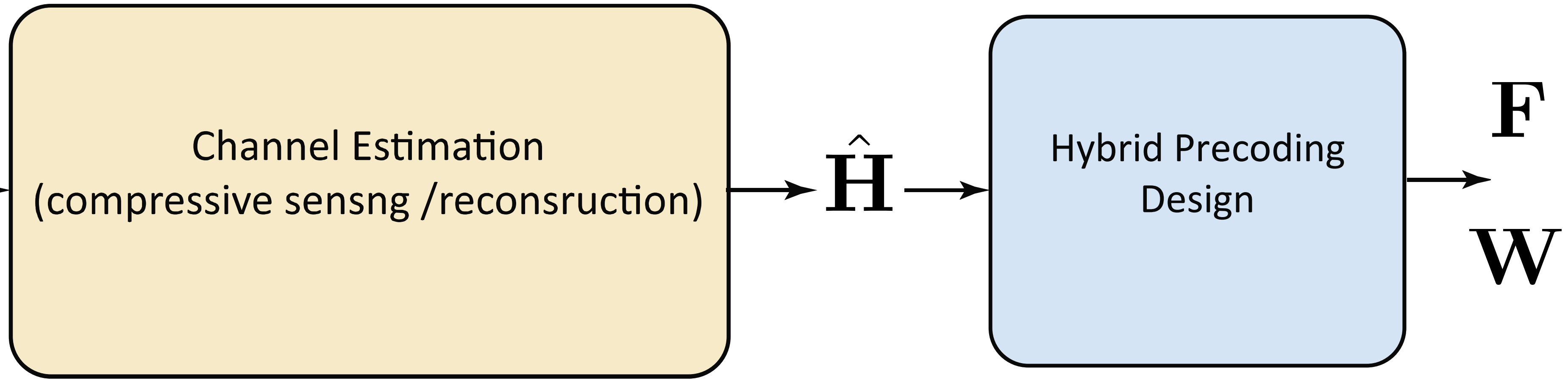

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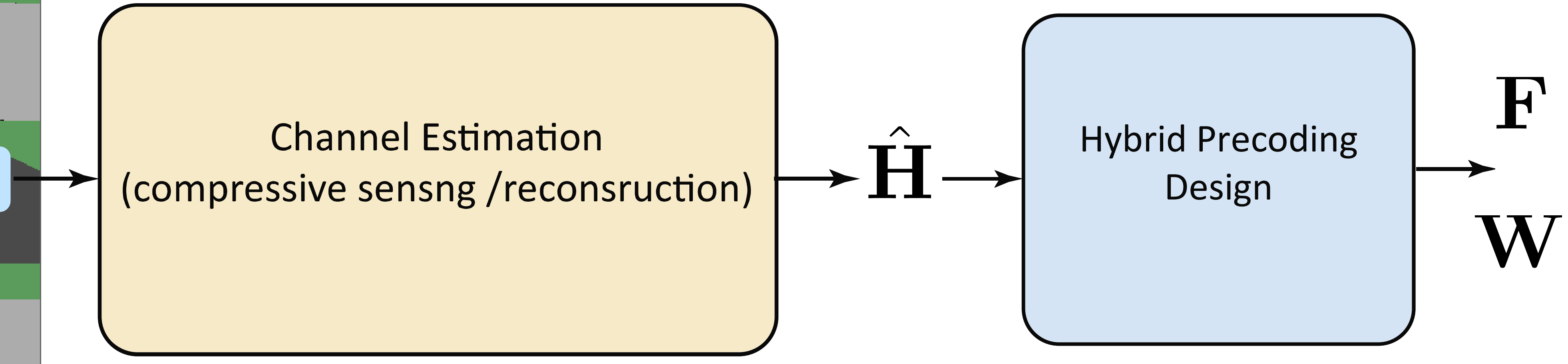
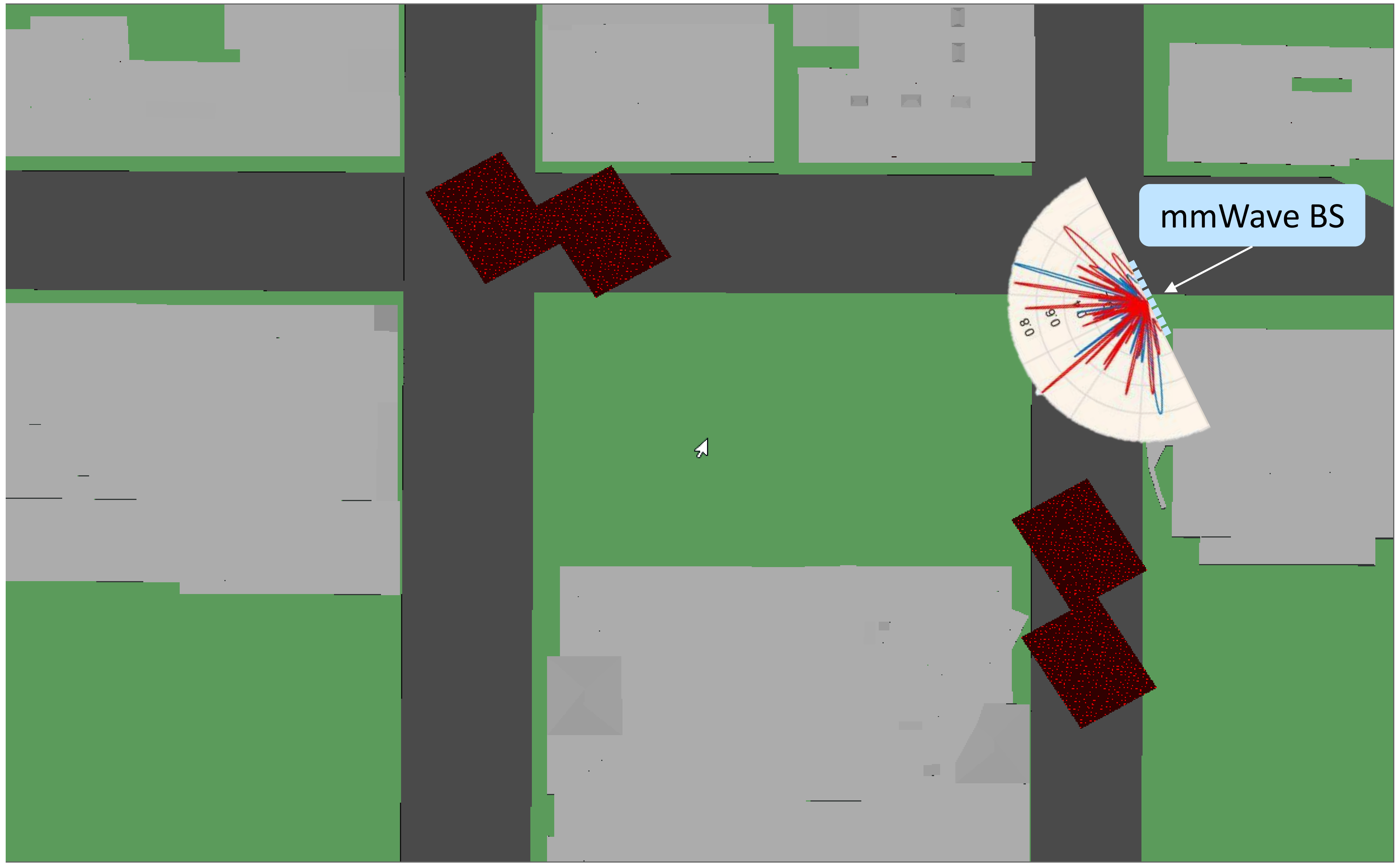


Dataset Construction

Estimated Channel	BS Beams	Mobile User Beams
$\hat{\mathbf{H}}$	$\mathbf{F}$	$\mathbf{W}$

2. TRAINING: MMWAVE PRECODING PREDICTION

Training the Auto-Precoder Neural Network Model



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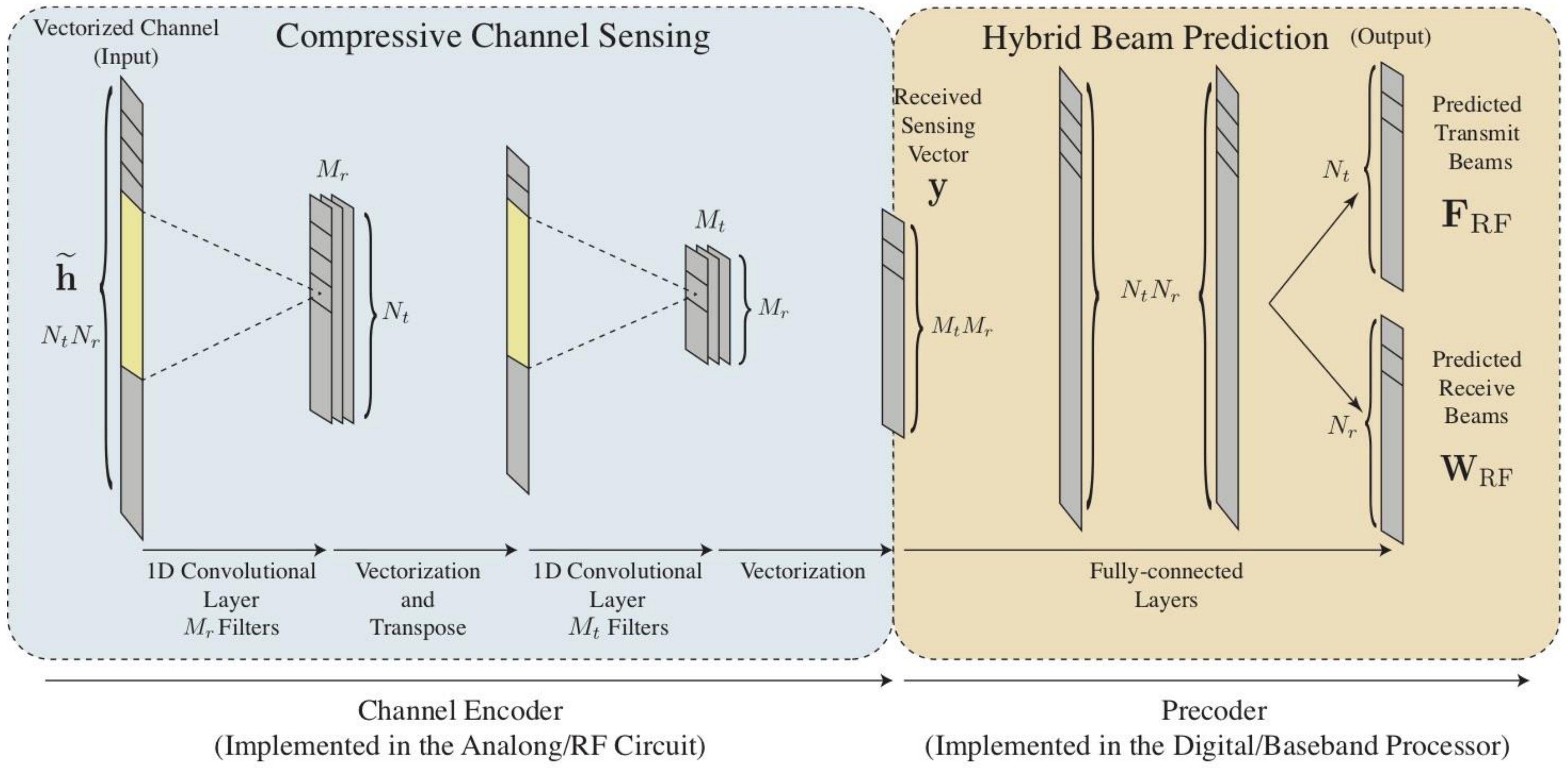
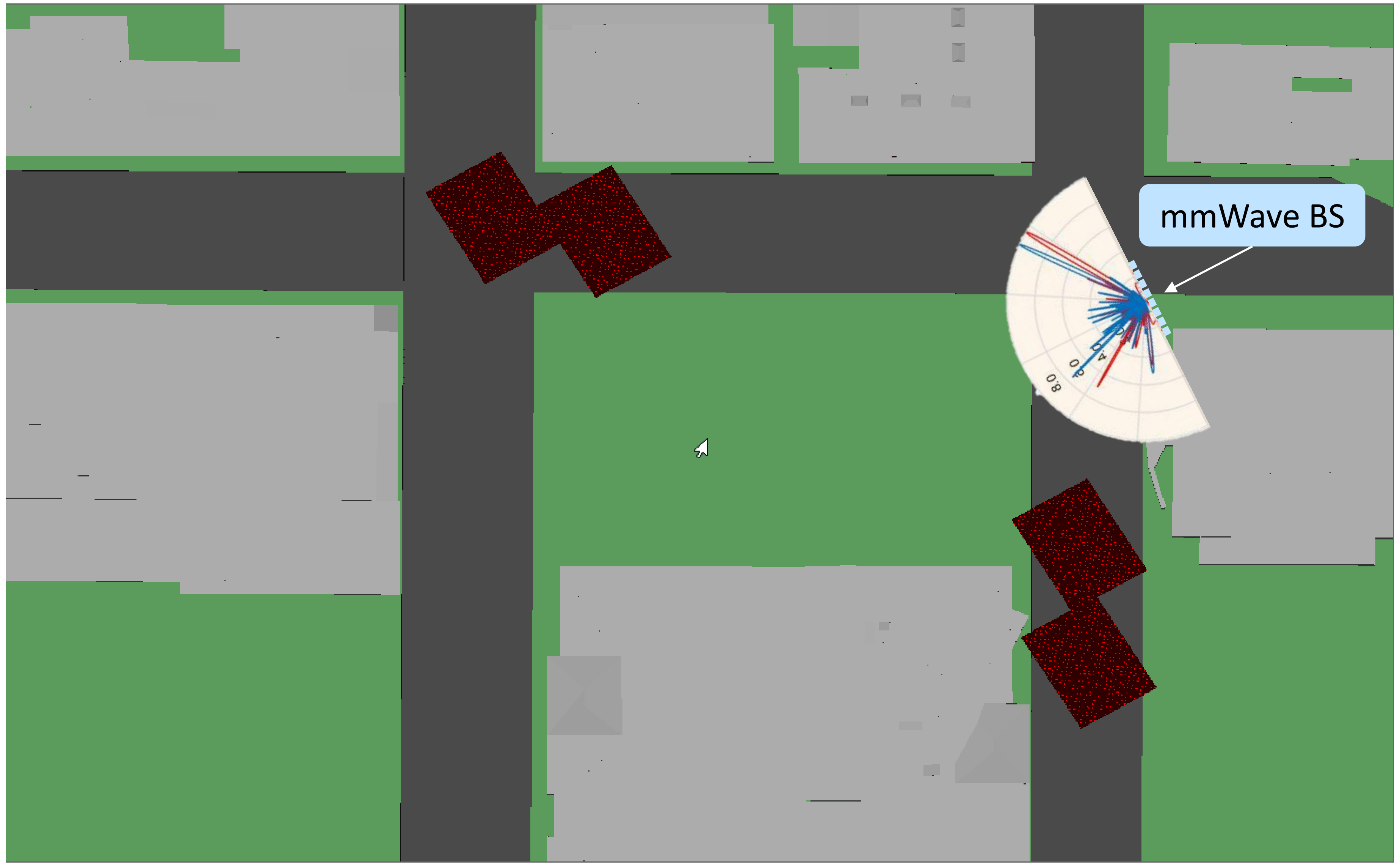


The collected dataset is used to train the NN end-to-end

2. TRAINING: MMWAVE PRECODING PREDICTION

Training the Auto-Precoder Neural Network Model



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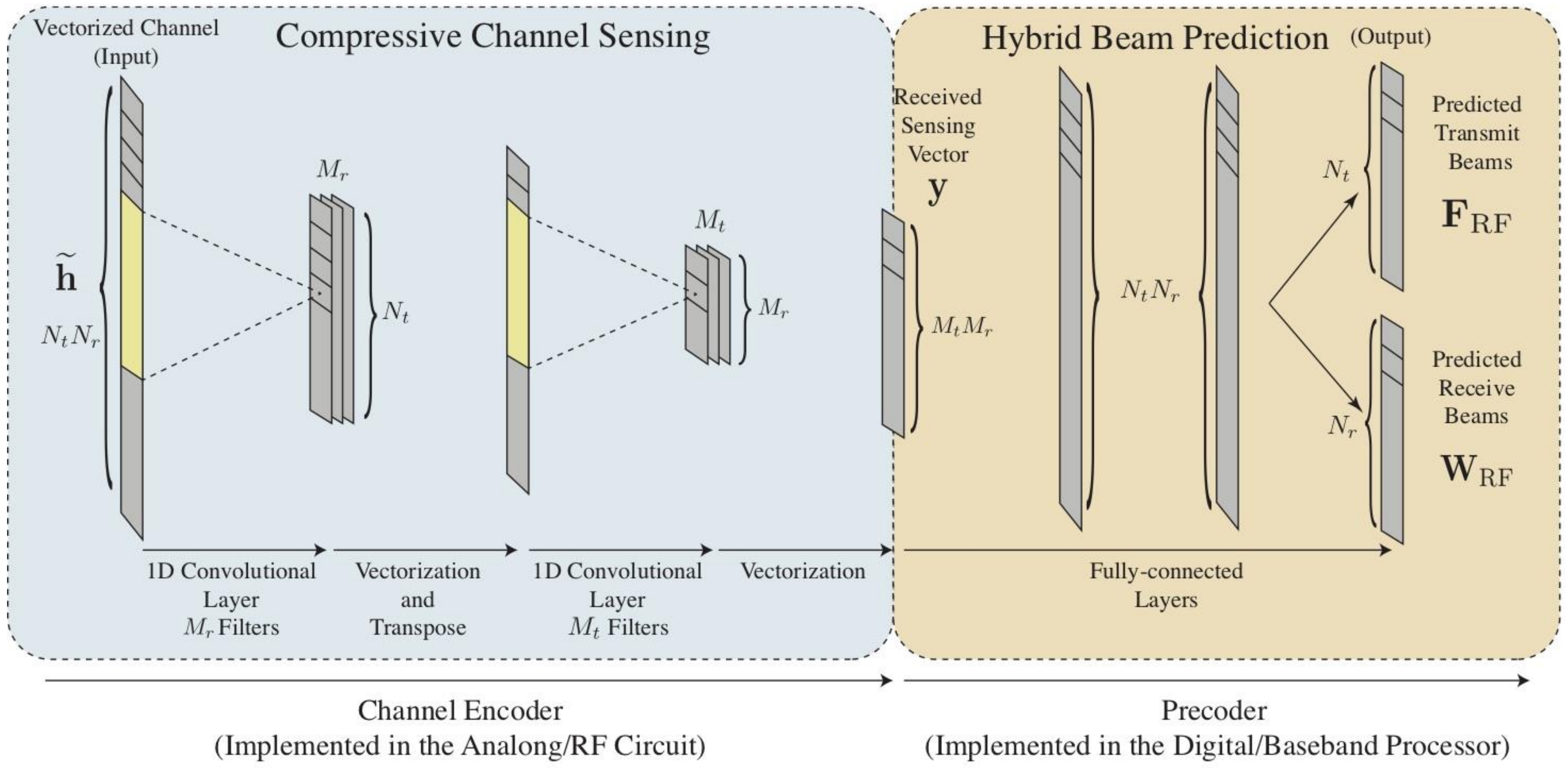

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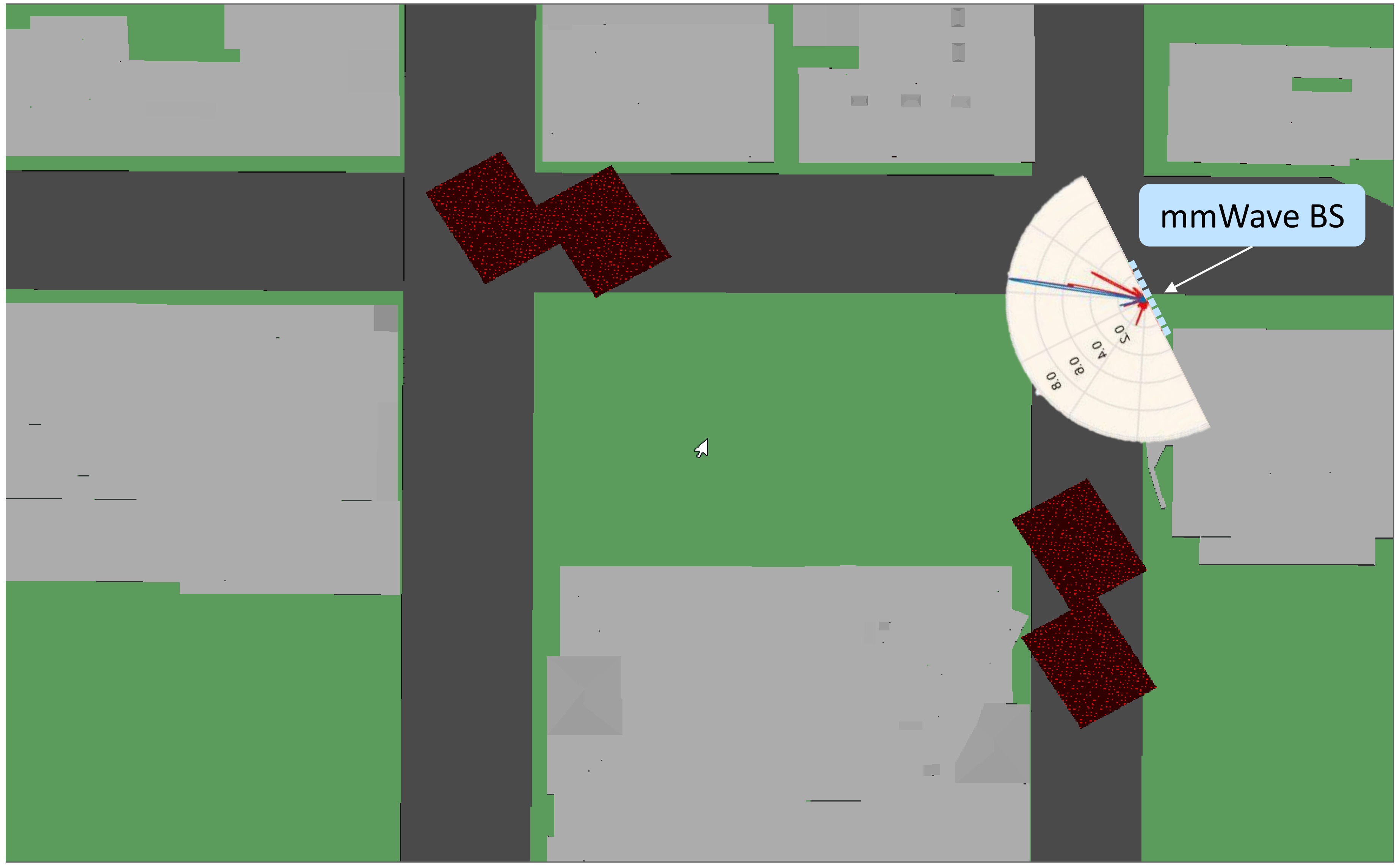

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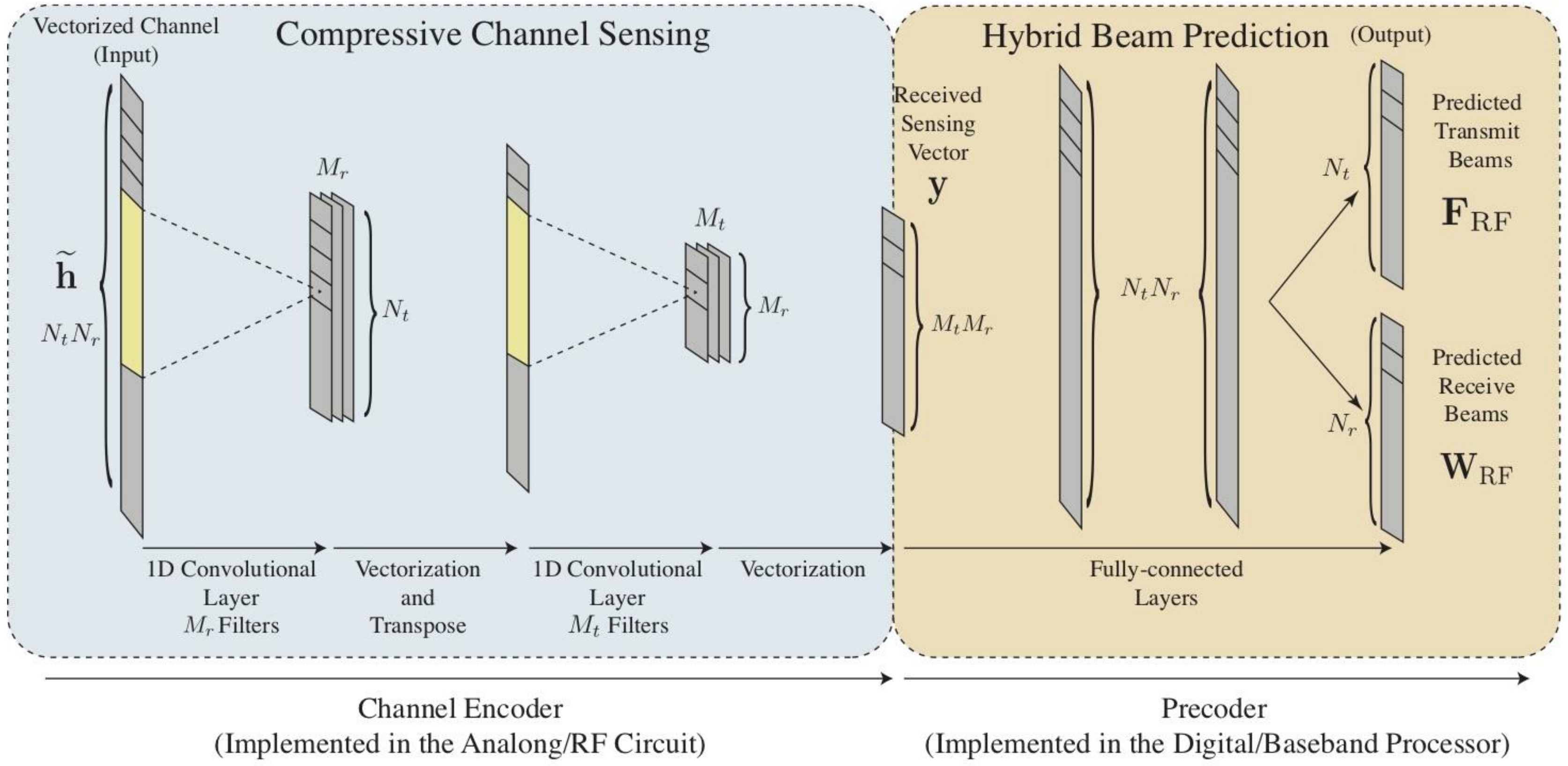

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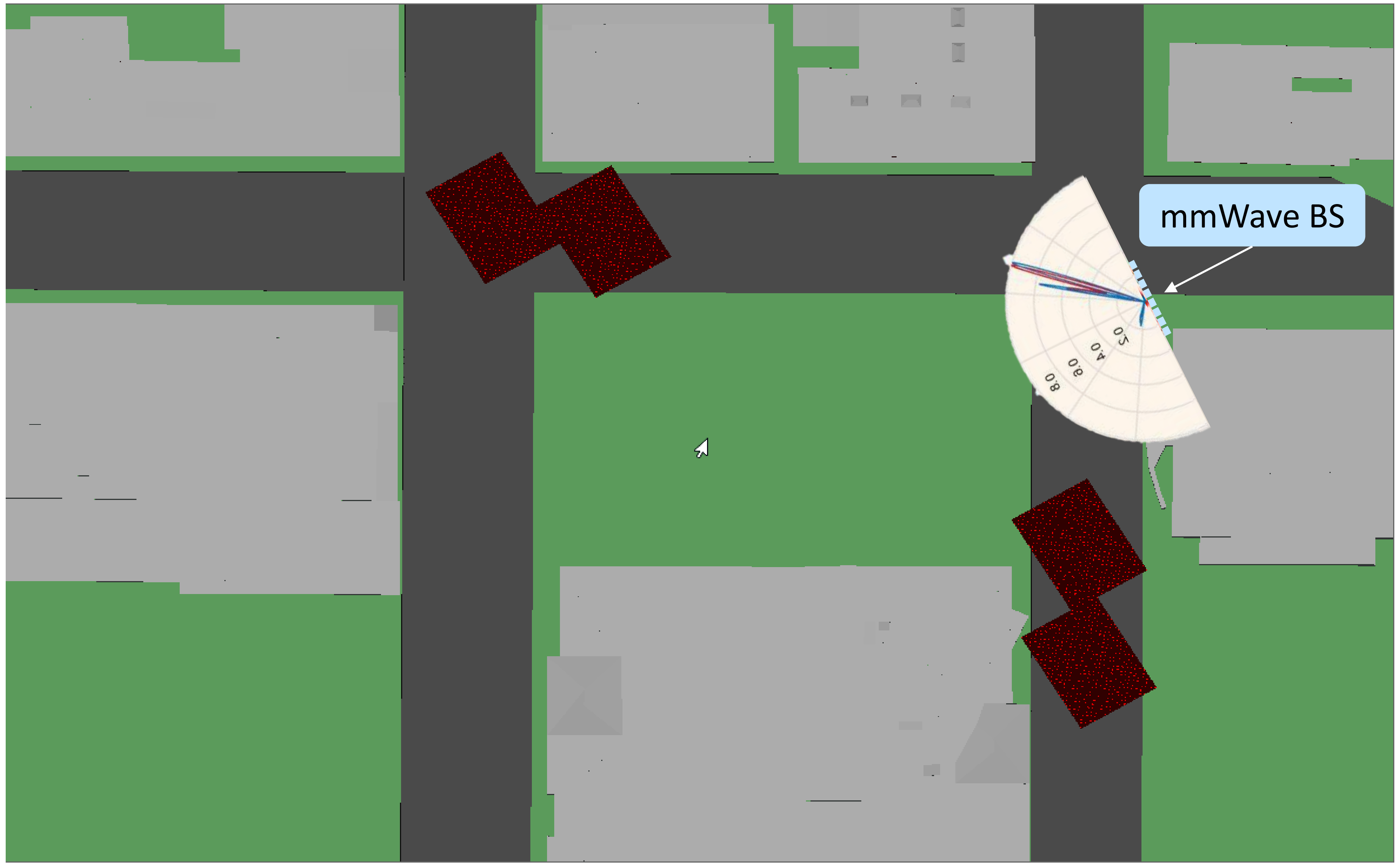
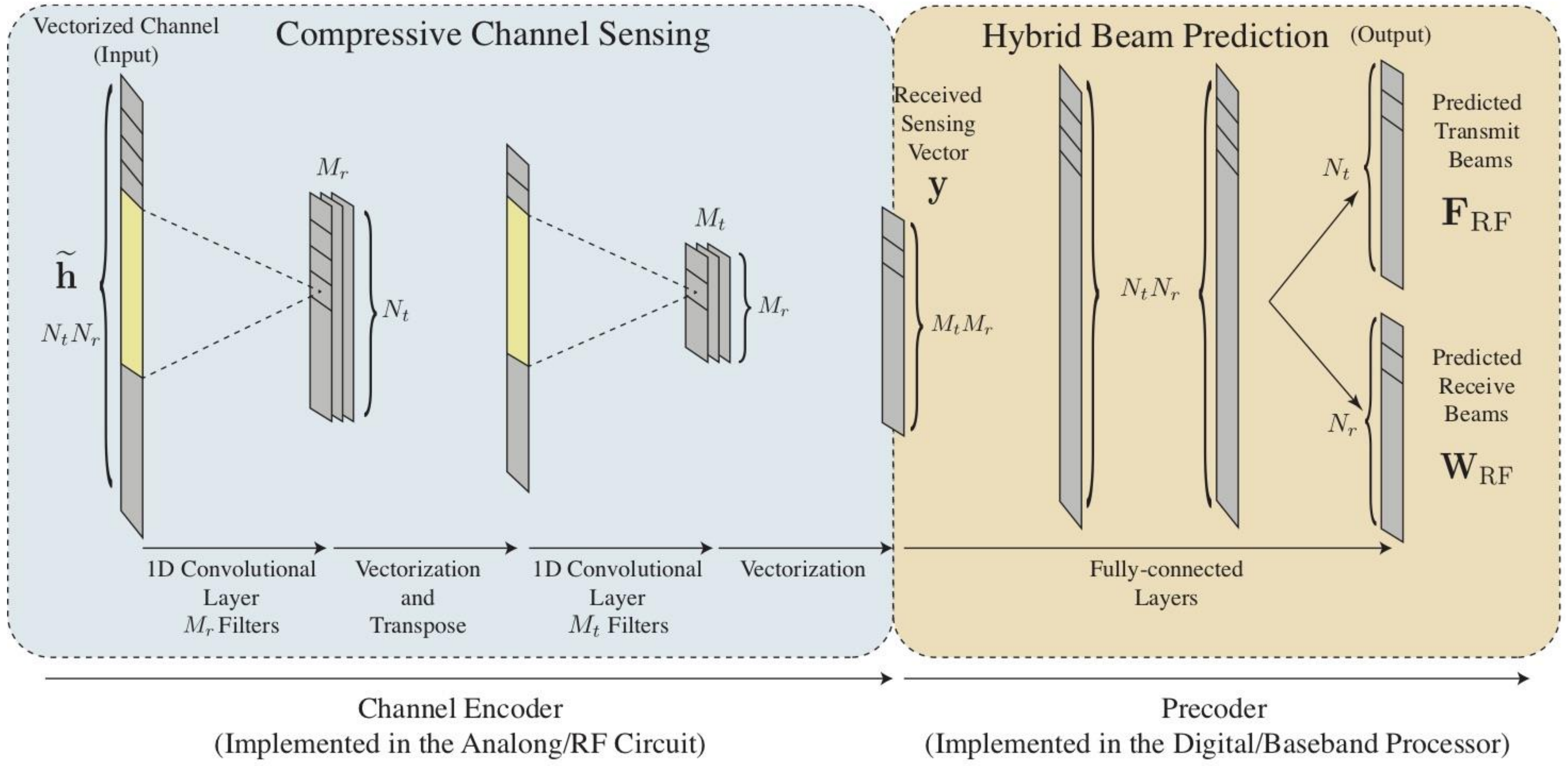


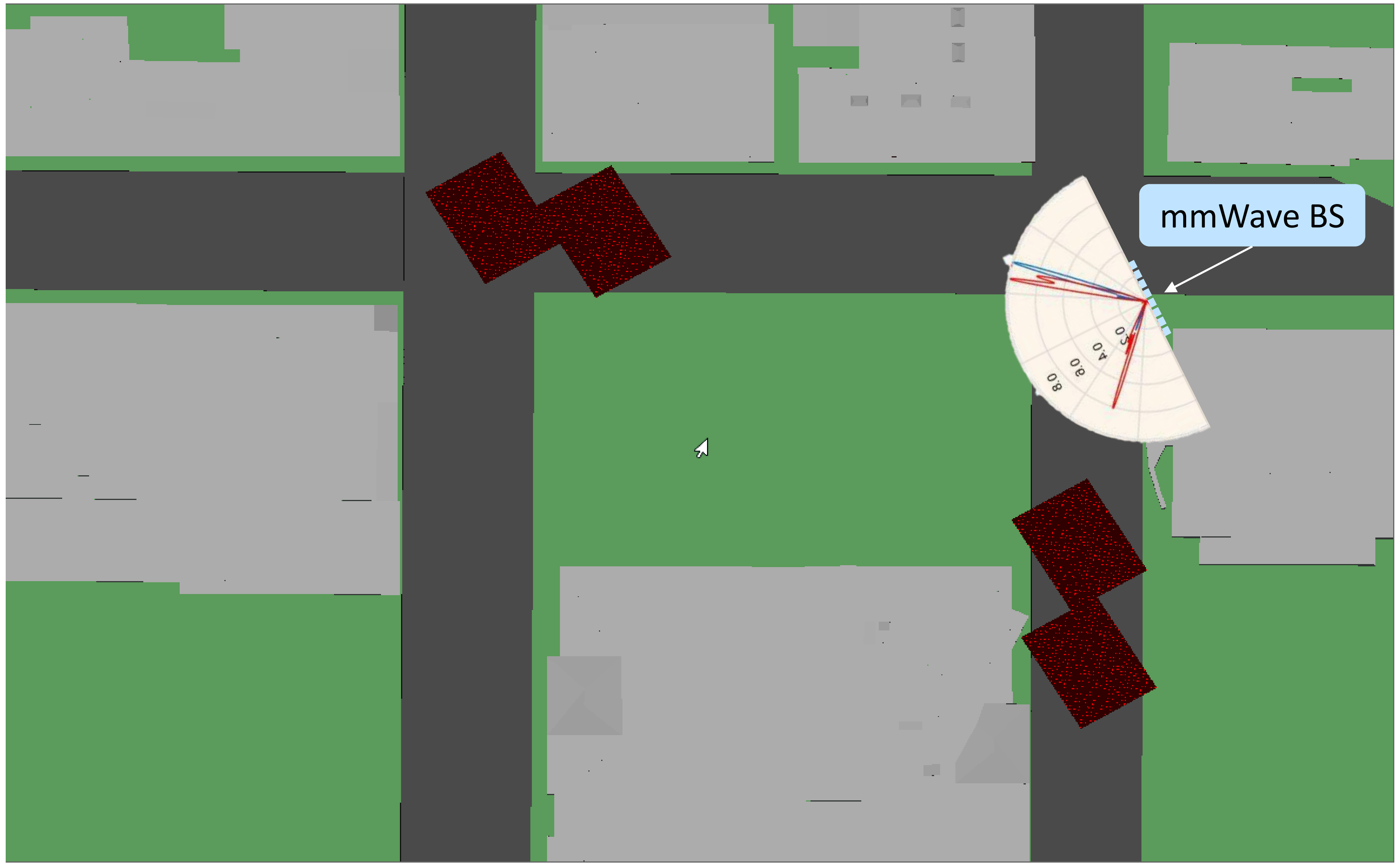
Top View



The collected dataset is used to train the NN end-to-end

2. TRAINING: MMWAVE PRECODING PREDICTION

Training the Auto-Precoder Neural Network Model



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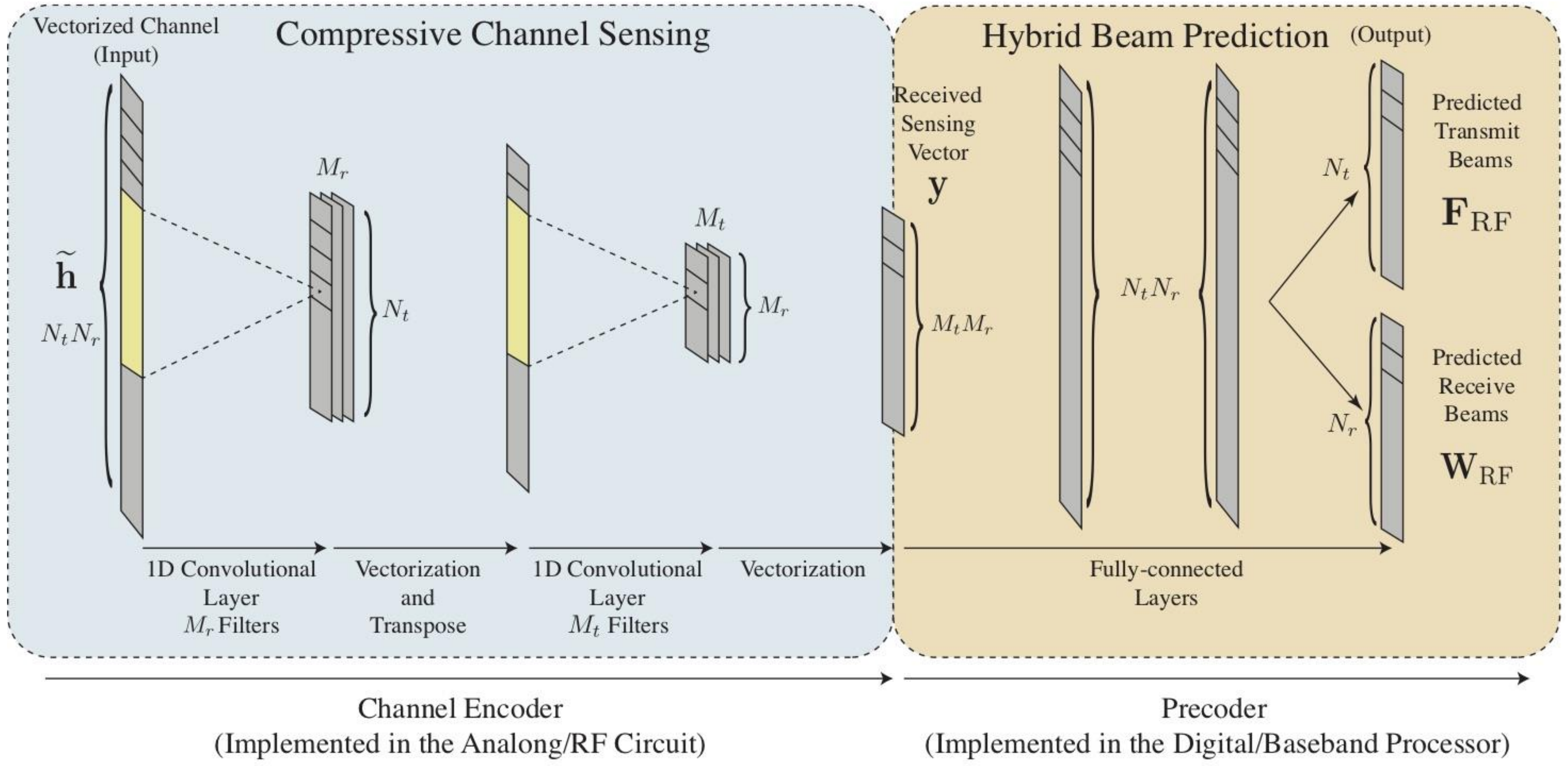

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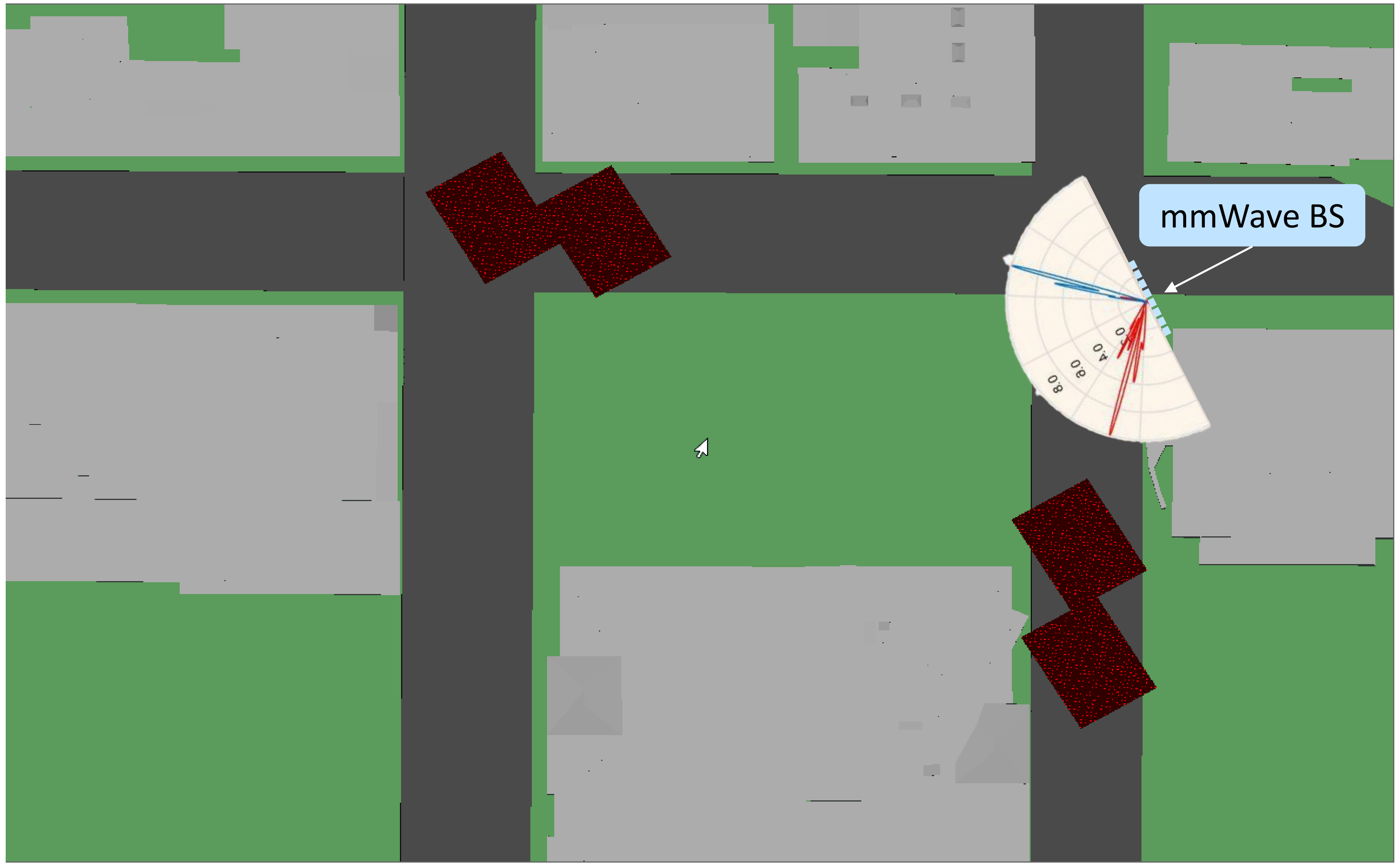

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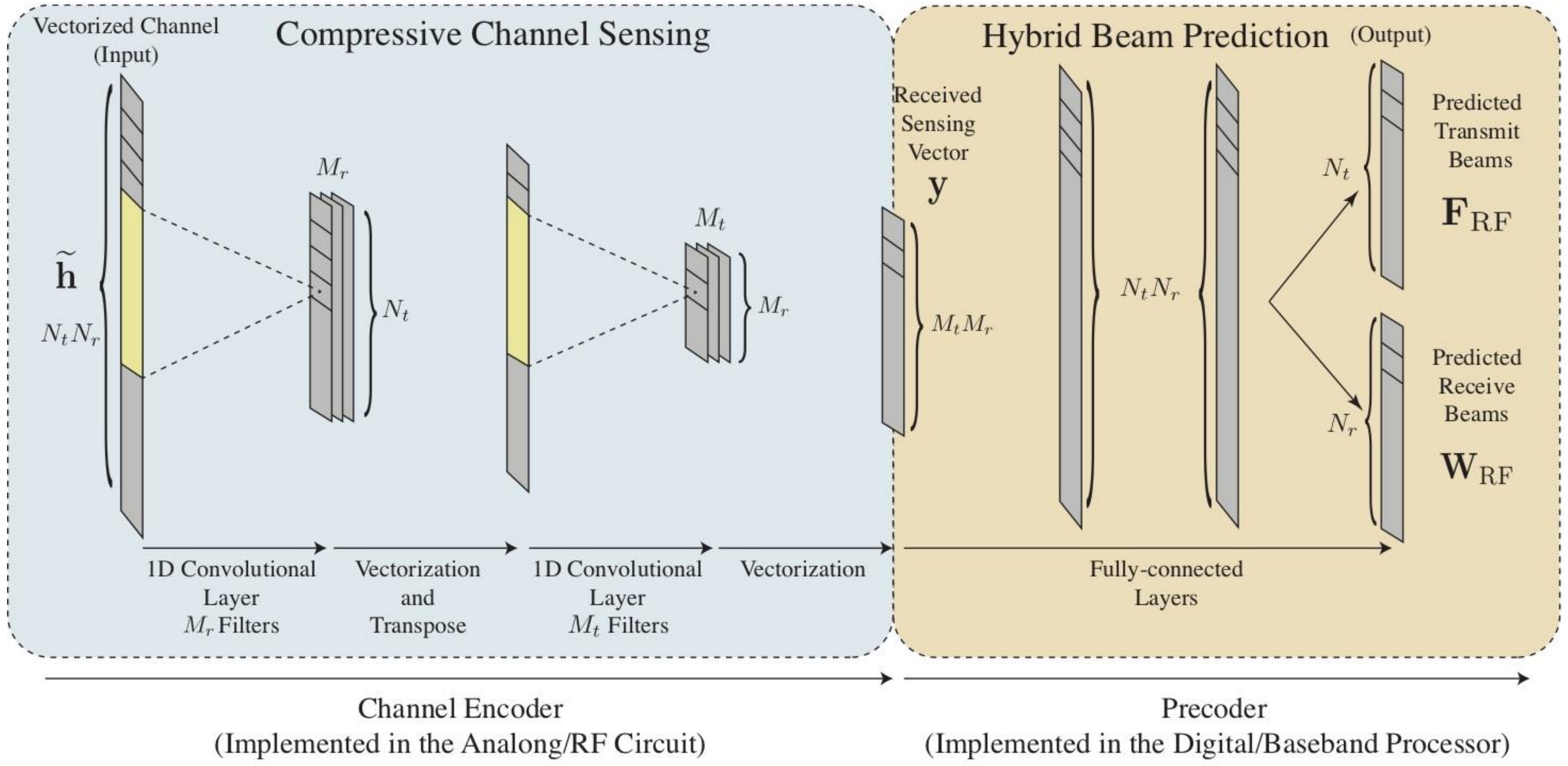

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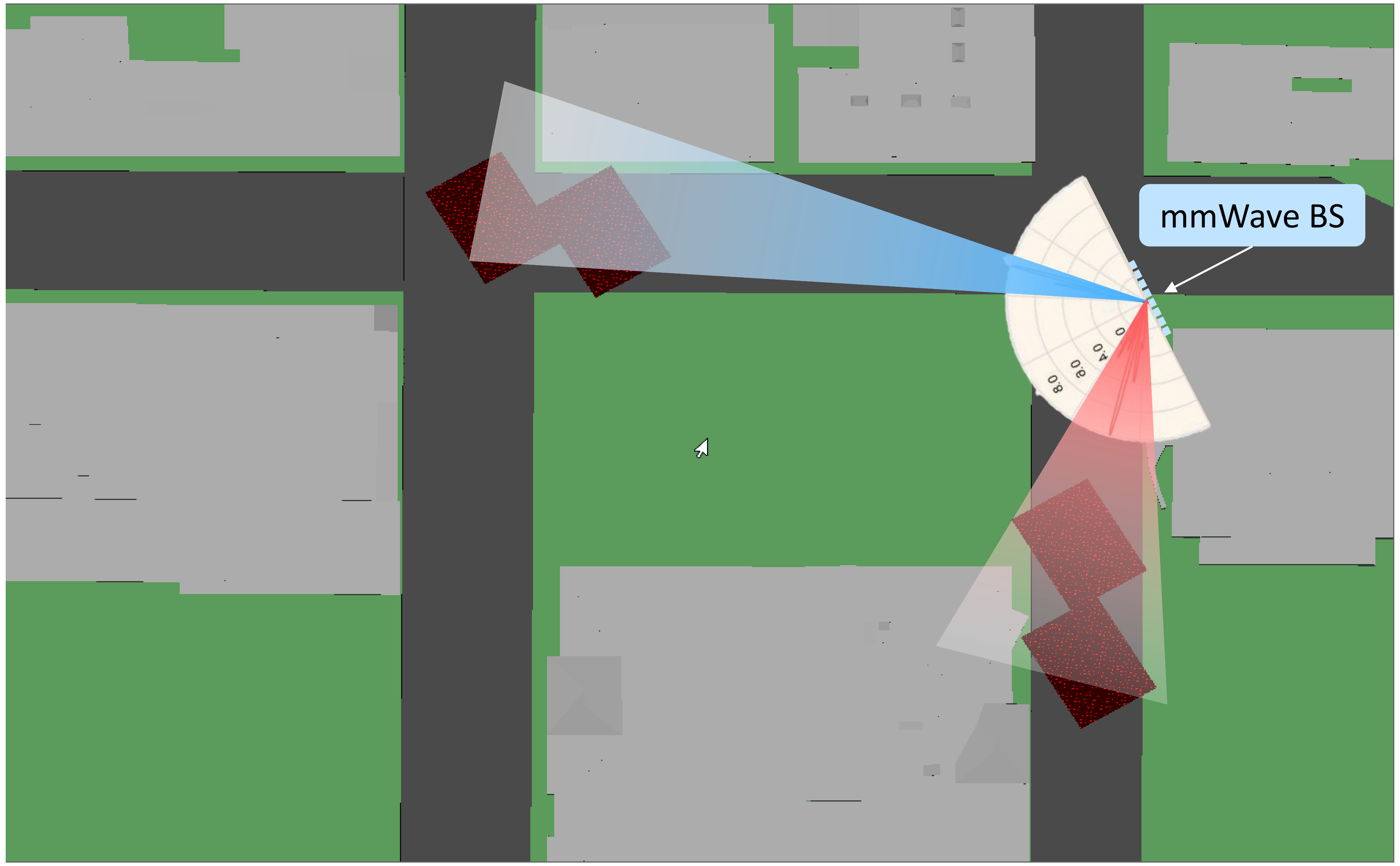

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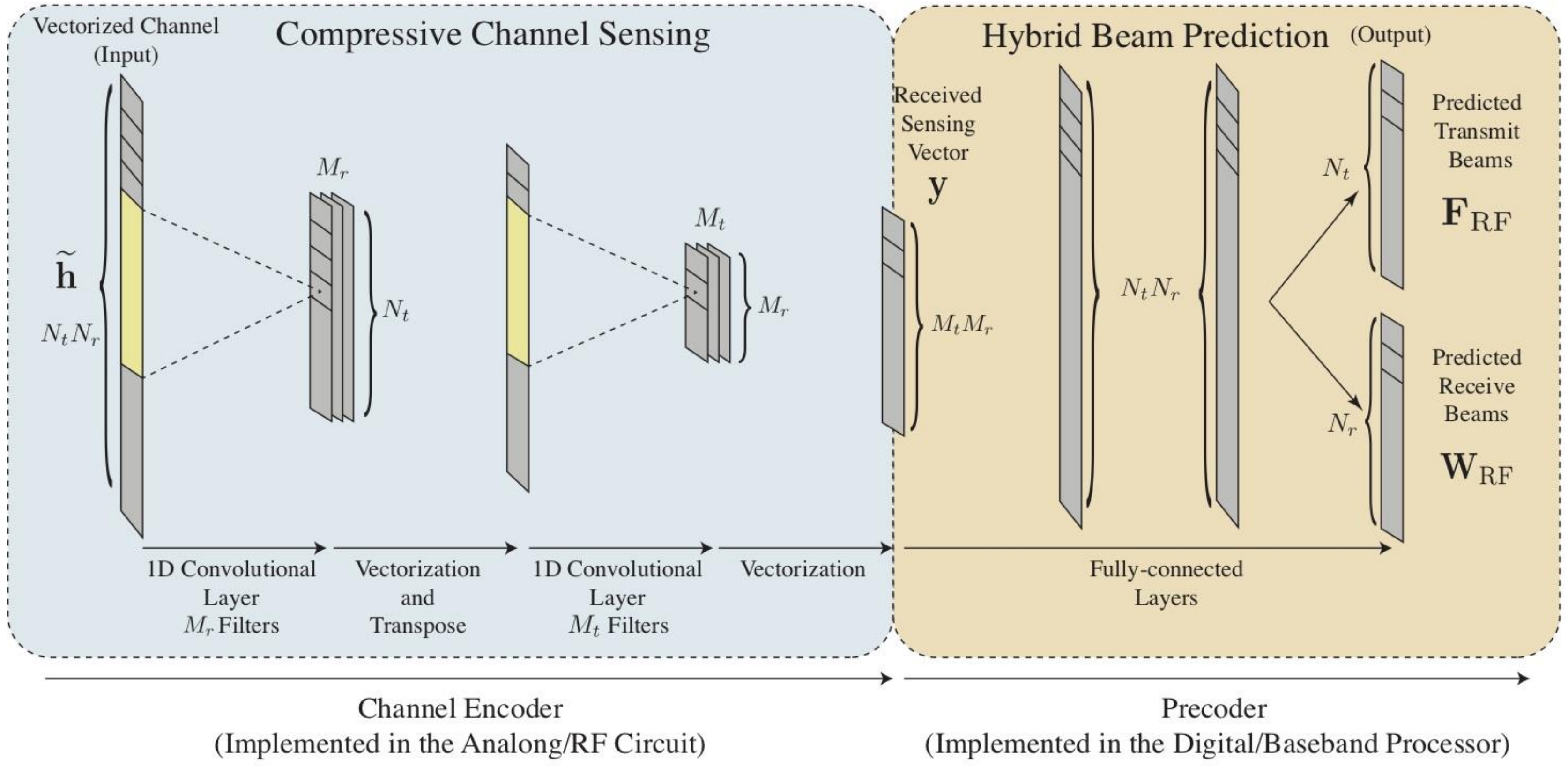

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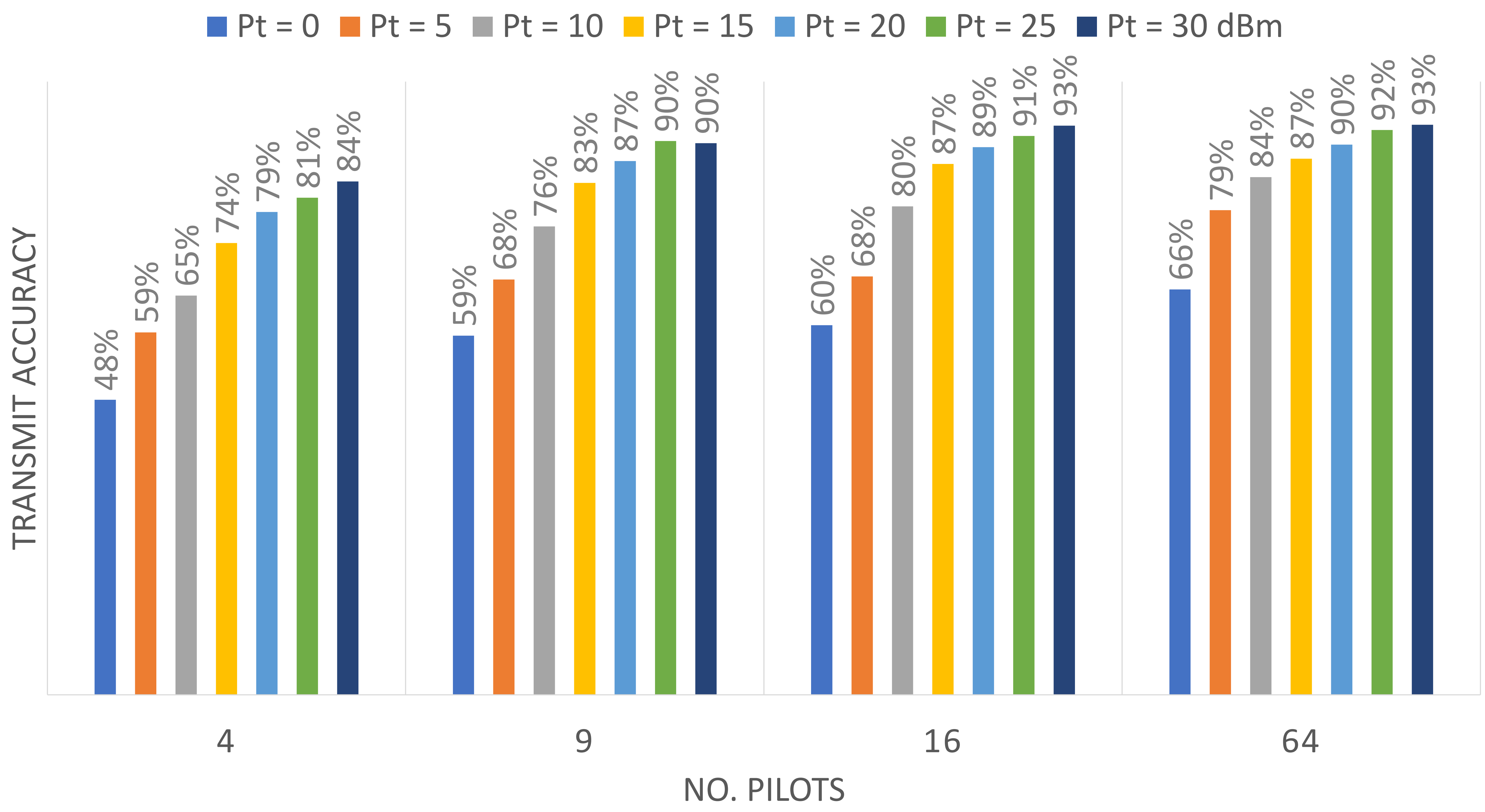
RESULTS

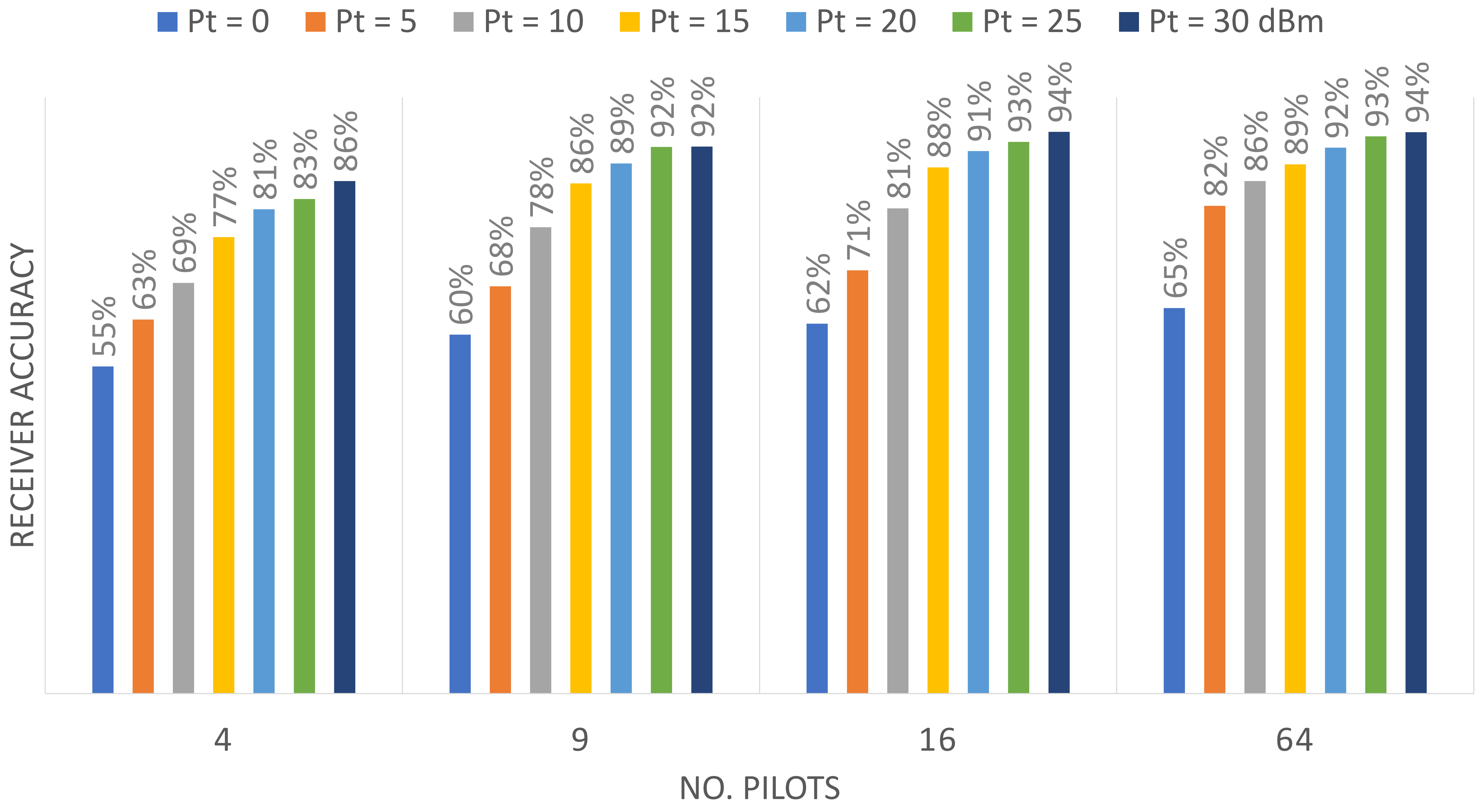
TRANSMIT BEAM ACCURACY

90%+ Accuracy in Beam Perdition with A Few Pilots



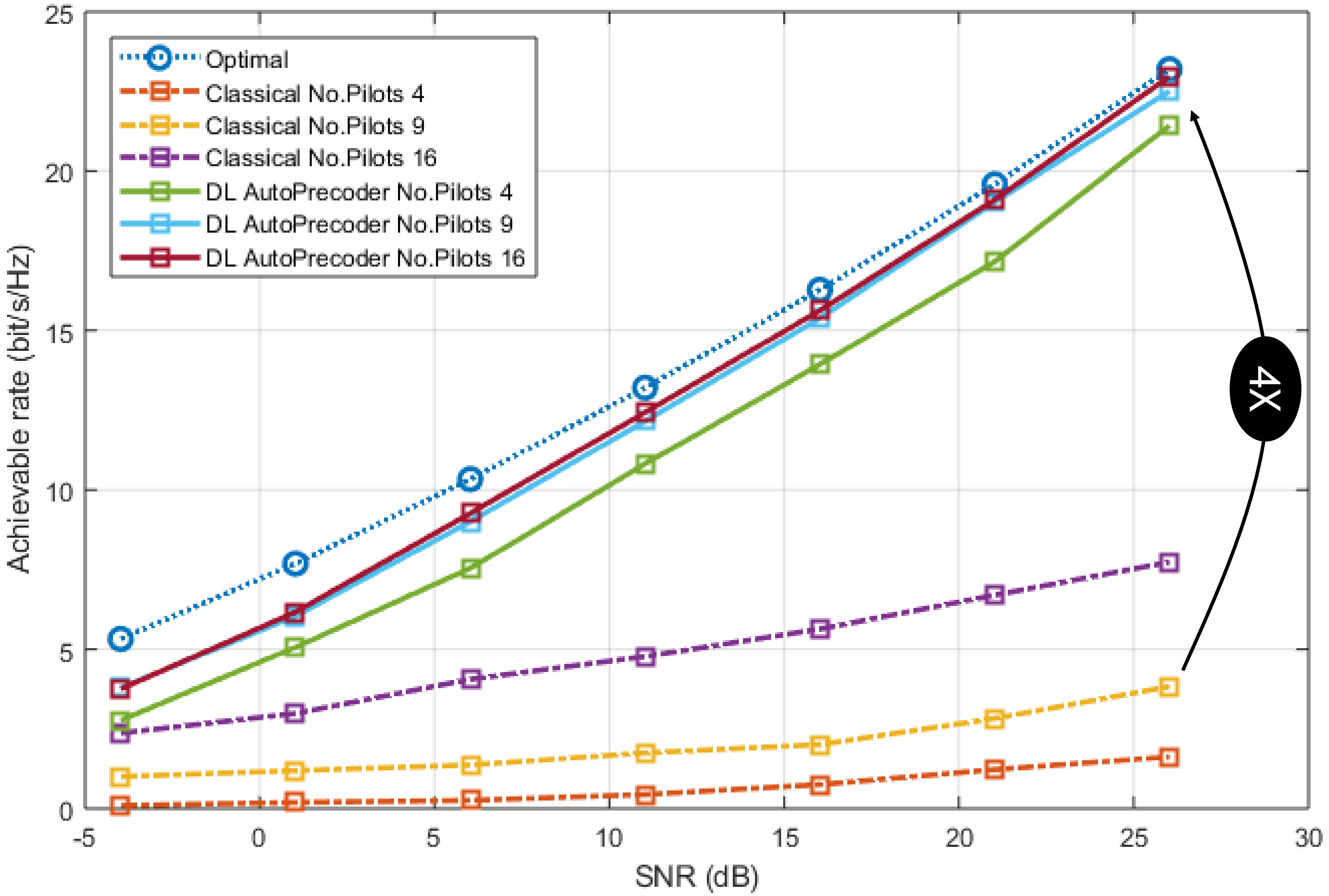
RECEIVER BEAM ACCURACY

90%+ Accuracy in Beam Perdition with A Few Pilots



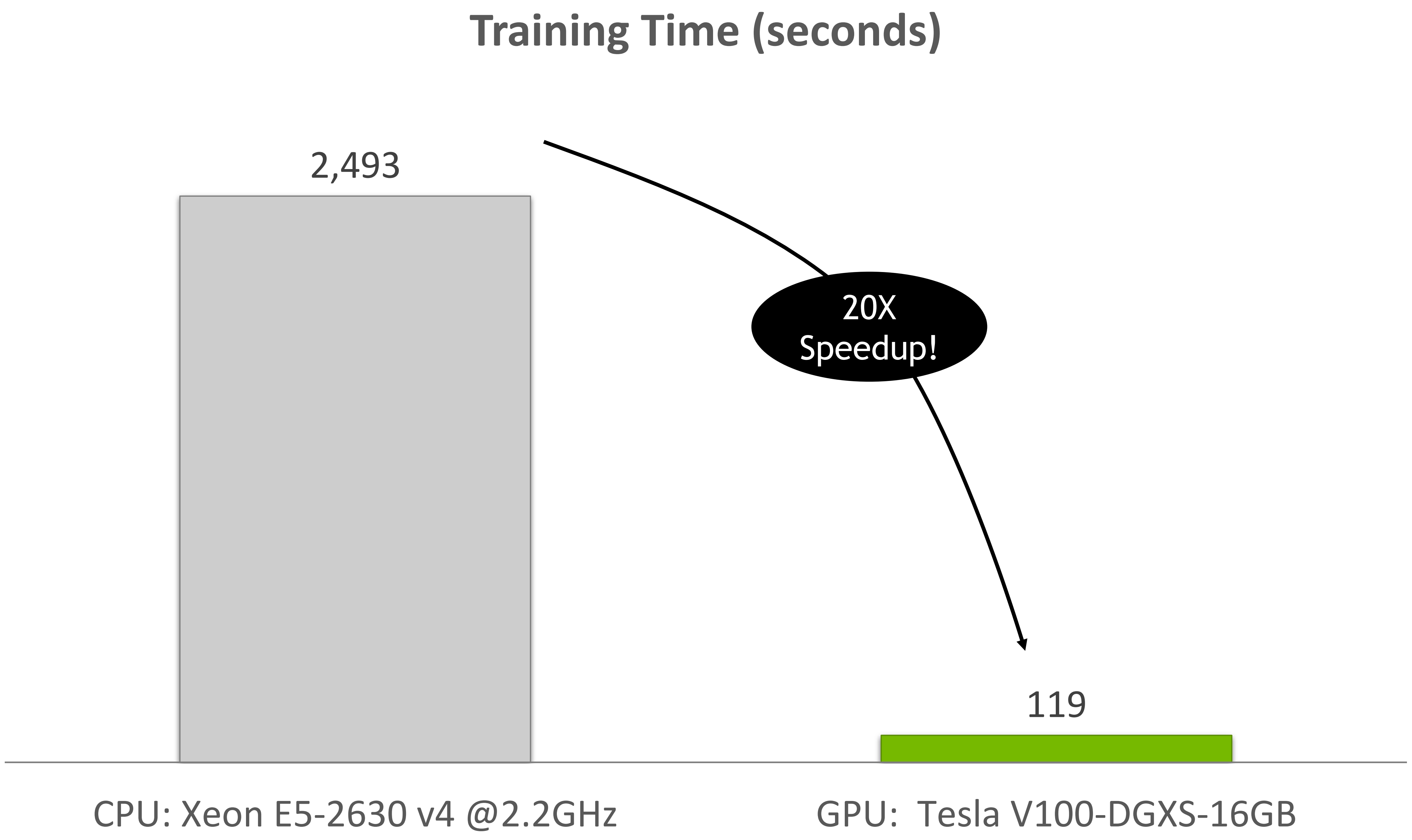
ACHIEVABLE DATA RATES

Performance: With a few measurements, 4X higher data rate



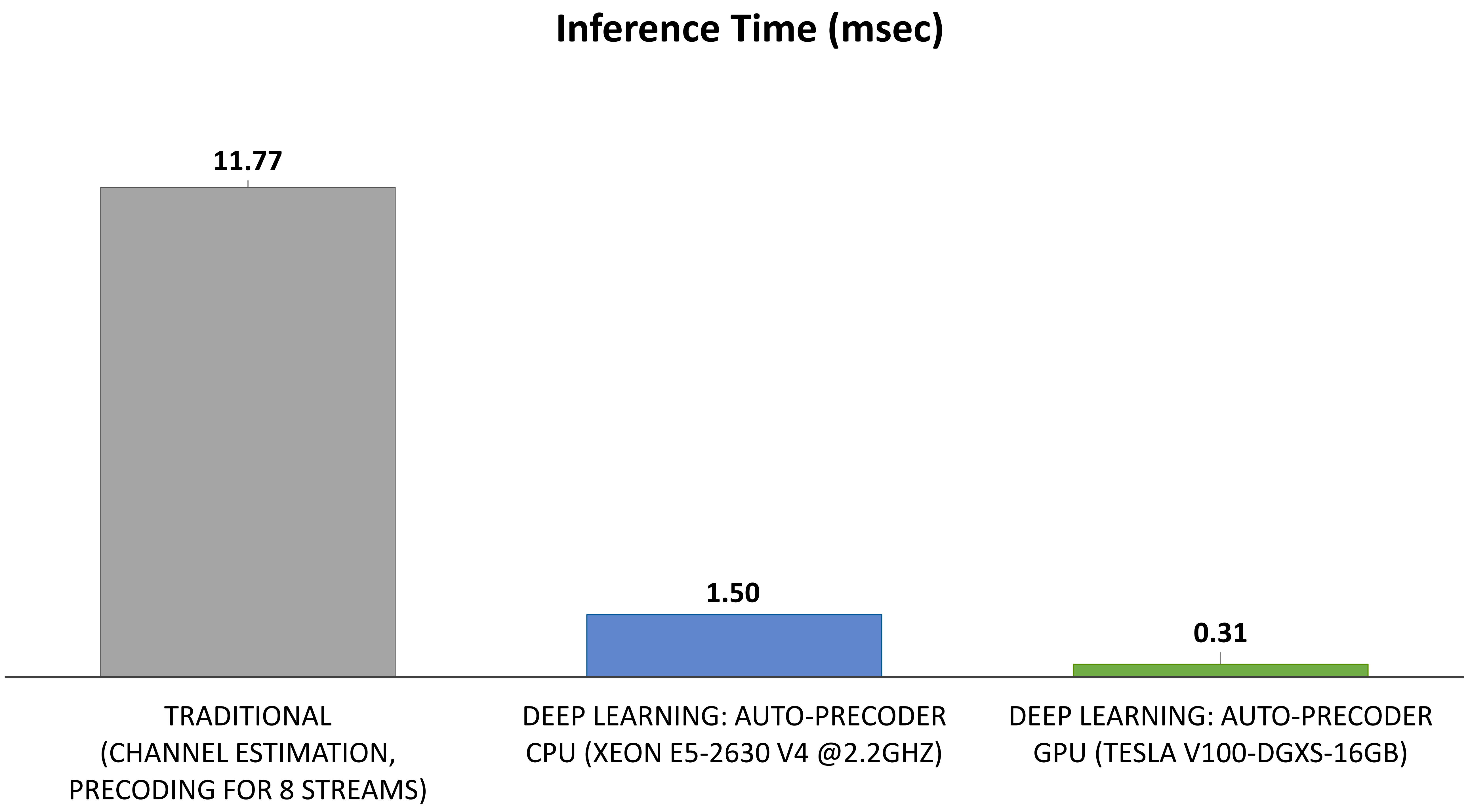
TRAINING TIME

Parameters: Batch Size of 64 and 15 Epoch Counts



INFERENCE TIME

Per each UE



TAKEAWAYS

5G Meets Deep Learning, Ray Tracing, and GPUs

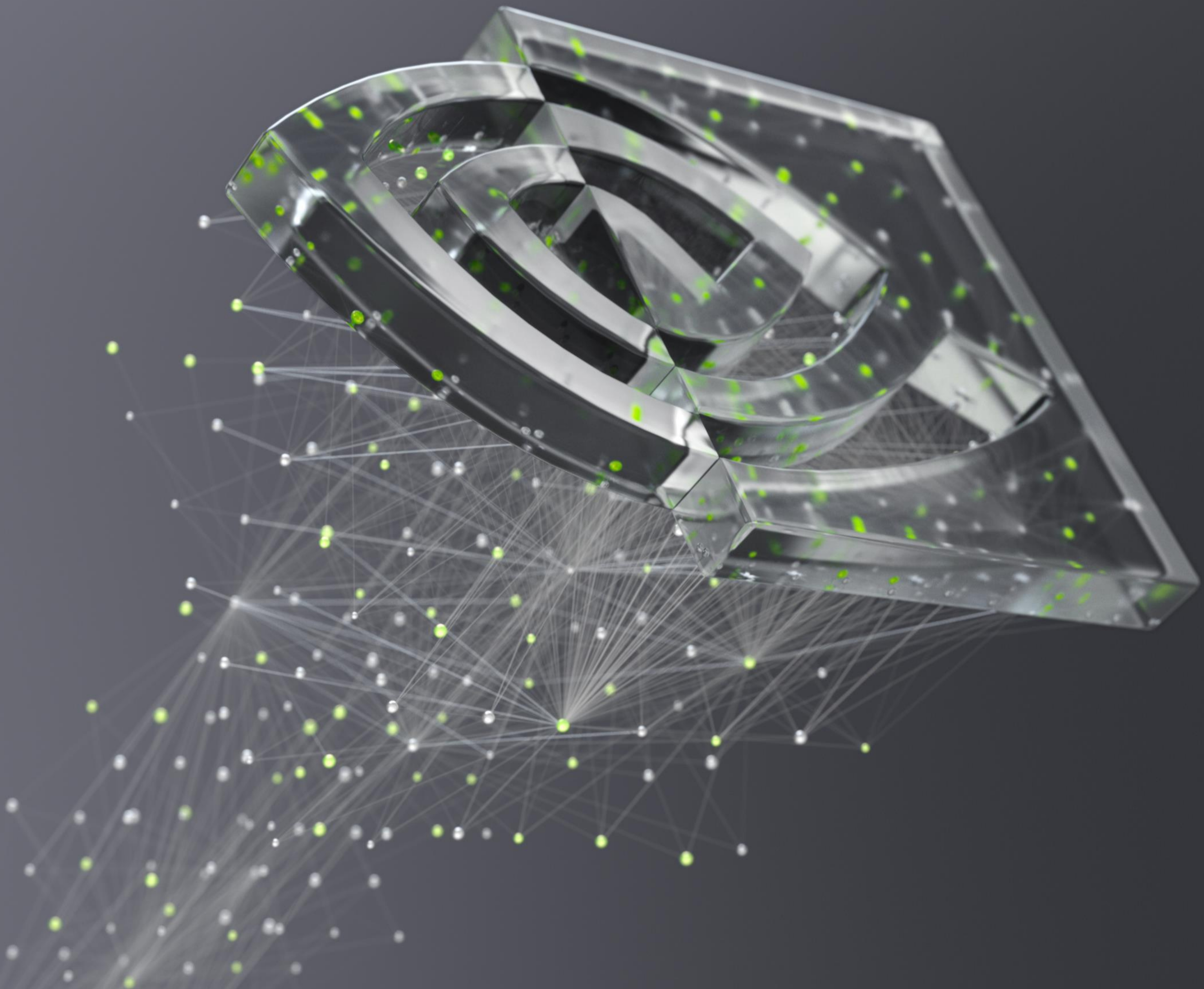
- 5G mmwave massive MIMO is promising but have limitations
- Channel acquisition overhead is a key challenge
- Deep Learning has the potential of predicting these channel and beams and thus removing the overhead
- Ray tracing is needed to construct realistic and accurate dataset
- Our proposed solution – prior channel observations to optimize the sensing beams to focus where the users are and predict the beams effectively without channel estimation
- The proposed hybrid beam prediction outperforms traditional methods with few measurements
- This is done in less time than traditional methods thanks to accelerated inference on GPUs.

QUESTIONS

How to contact us

- Ahmed Alkhateeb: alkhateeb@asu.edu
- Adriana Flores: adrianaf@nvidia.com
- Nima Pour Nejatian: npour@nvidia.com

Papers, datasets, and codes are available at www.DeepMIMO.net



NVIDIA