

# Foundation Models for Wireless Communication and Sensing: Learning Universal Representations with LWMs

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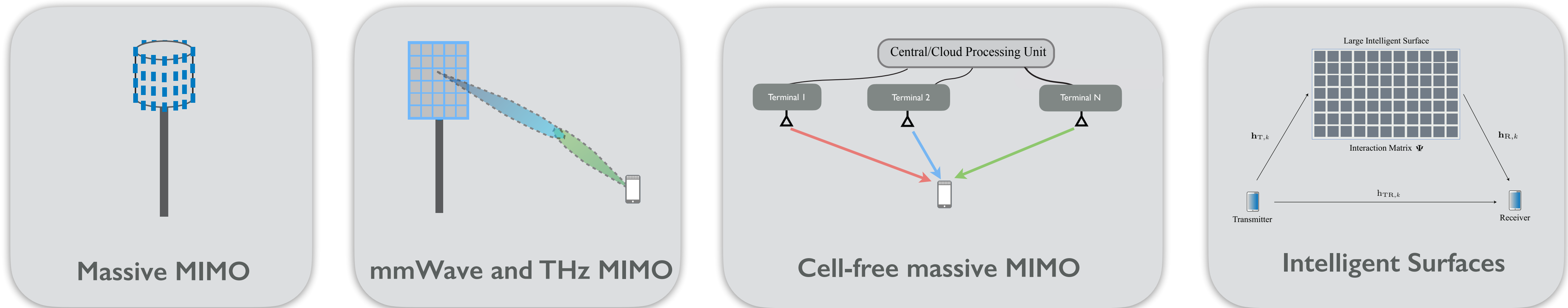
Joint work with my students:

**Sadjad Alikhani and Gouranga Charan**

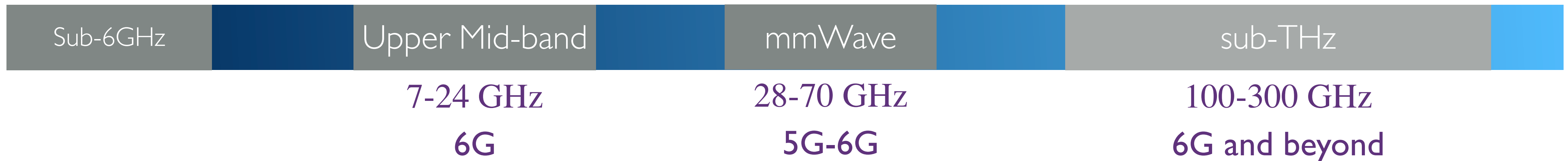
This work was supported in part by NSF (Grants No. 2048021 and 2426906) and  
by InterDigital, Meta, and Remcom

# Key trends in wireless communications and sensing

- ▶ The use of large antenna arrays (high spatial resolution)



- ▶ The increasing dependency on higher frequency bands (more bandwidth/range resolution)

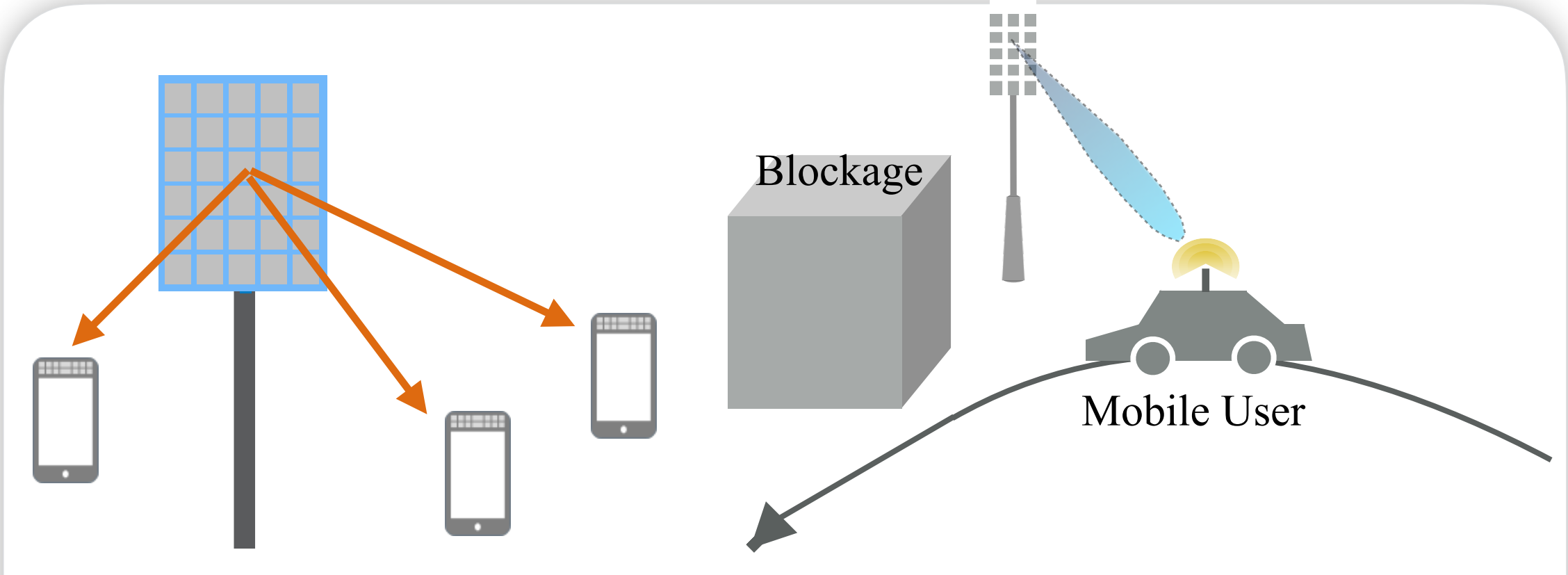
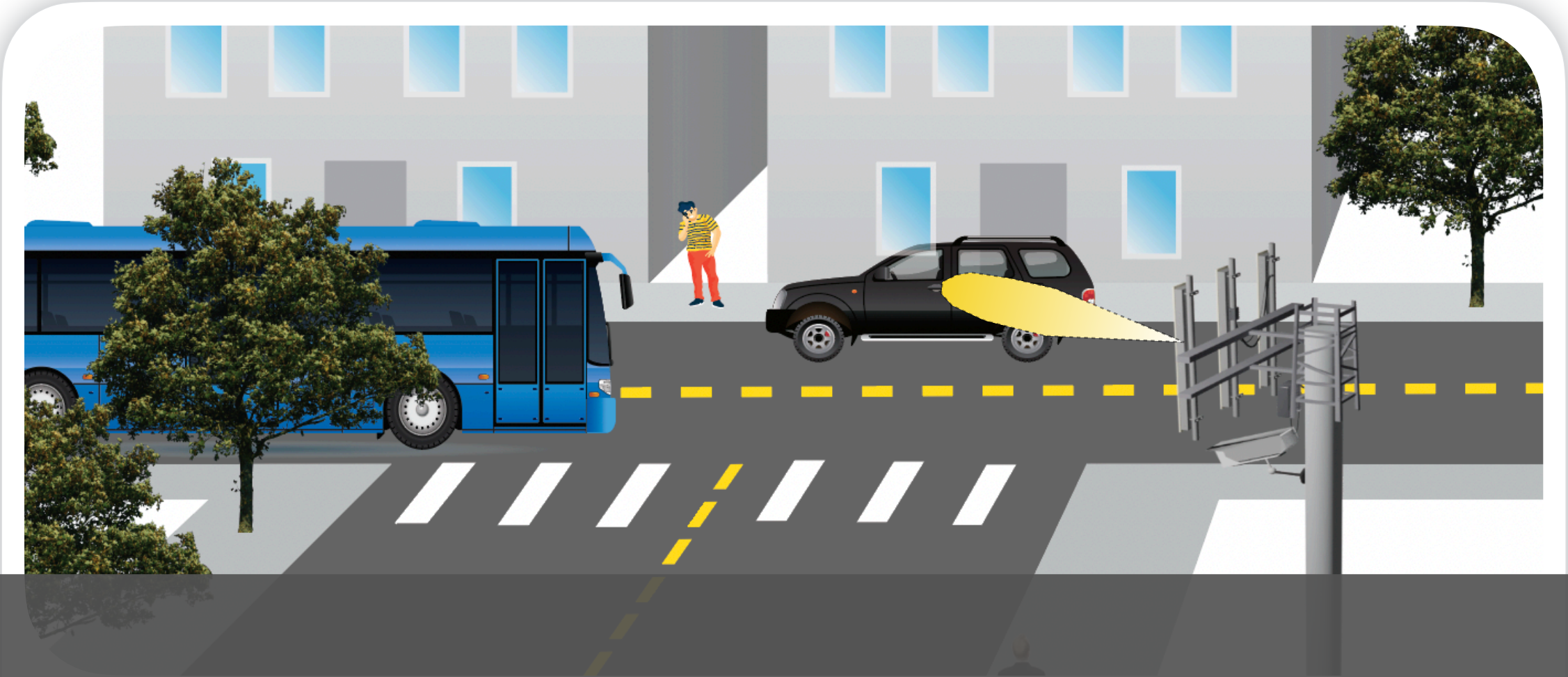


Lead to higher data rates and better sensing capabilities

But ... lead to other challenges!



# Challenges

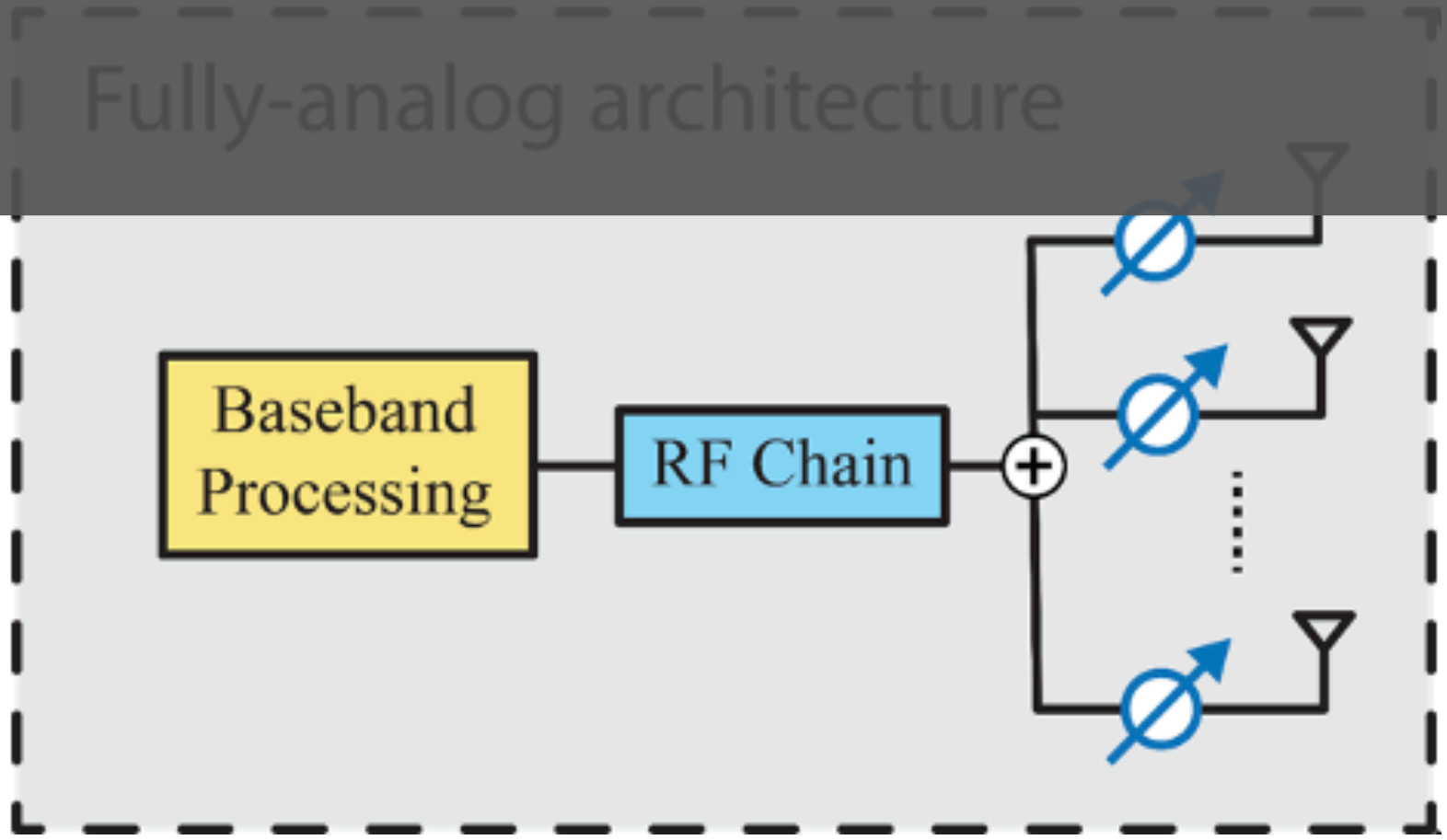


Difficult to support mobility

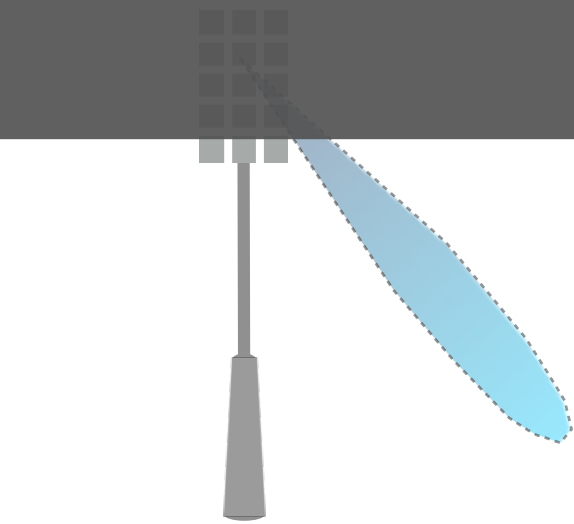
Difficult to ensure robustness/reliability

## How Can Machine Learning Help?

Fully-analog architecture



Limited observability in baseband



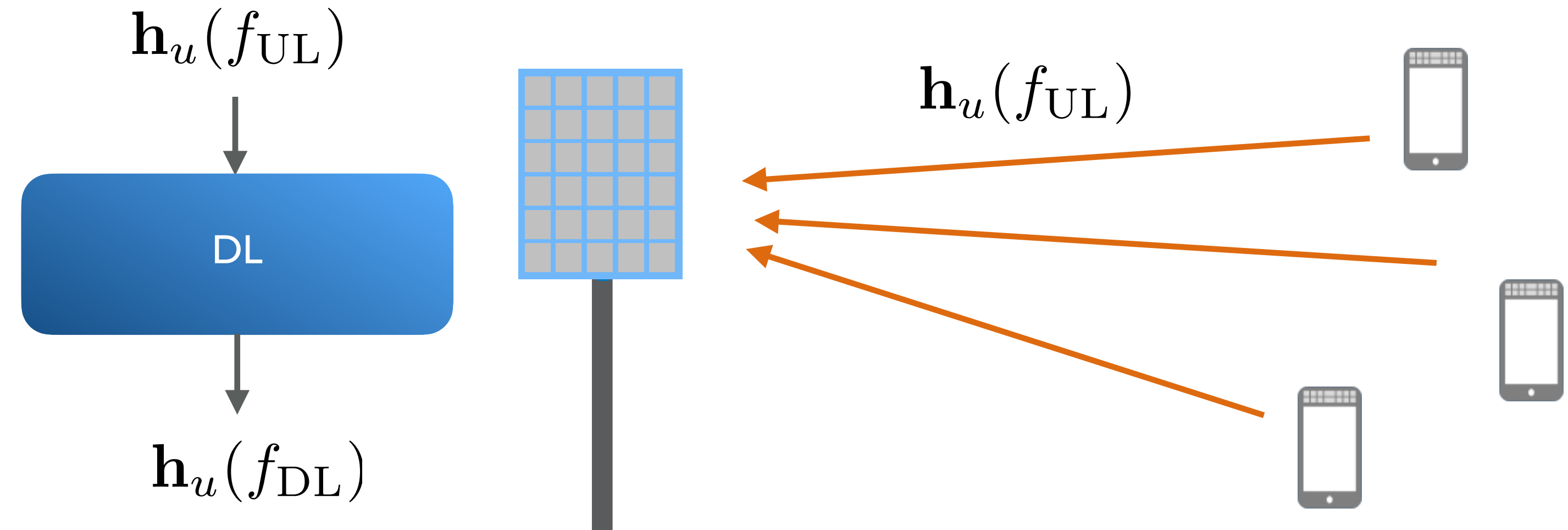
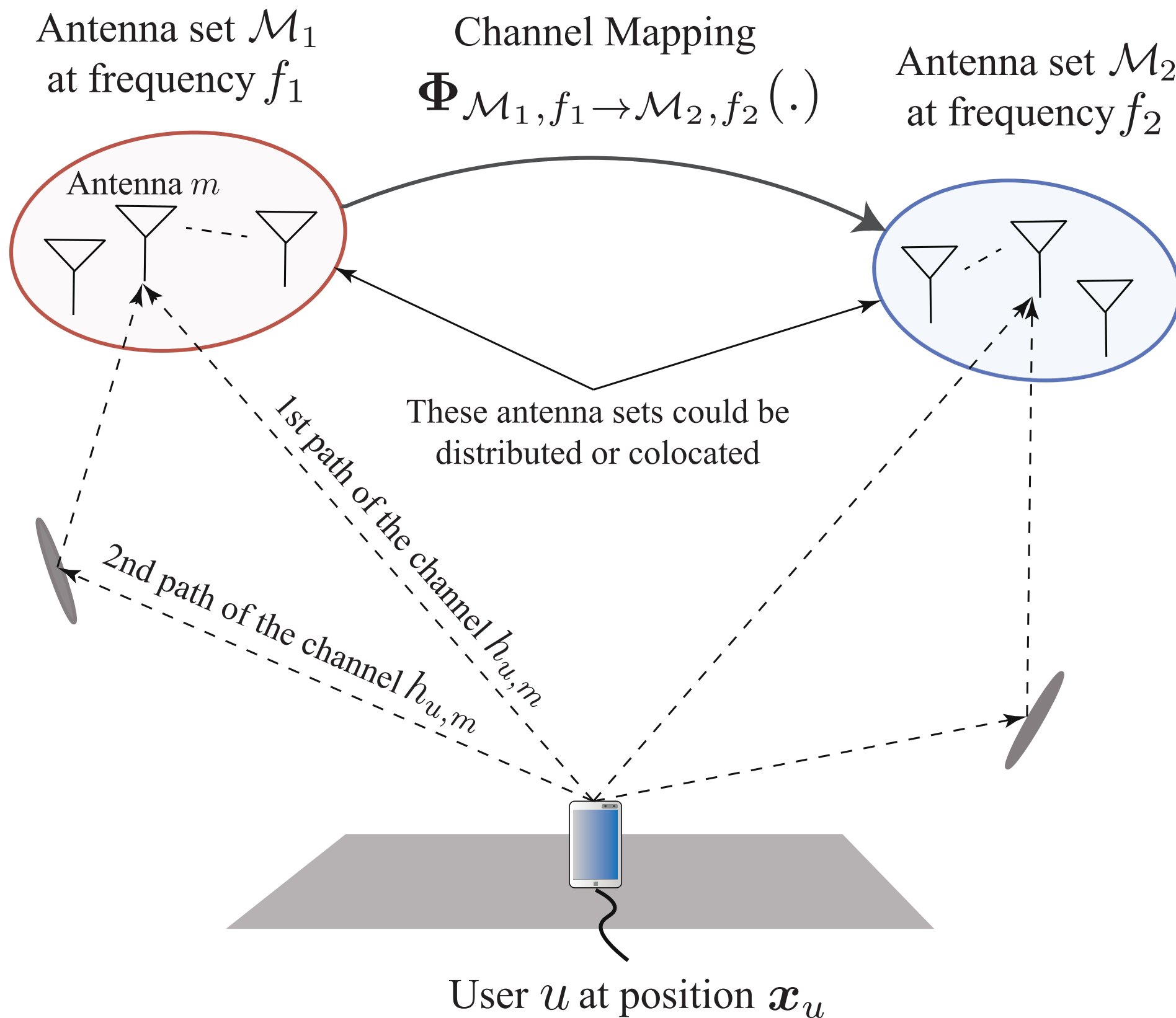
Deployment and maintenance cost



Beamforming-driven power consumption

Higher cost and power consumption

# Example: Learning complex mapping



UL/DL channel prediction

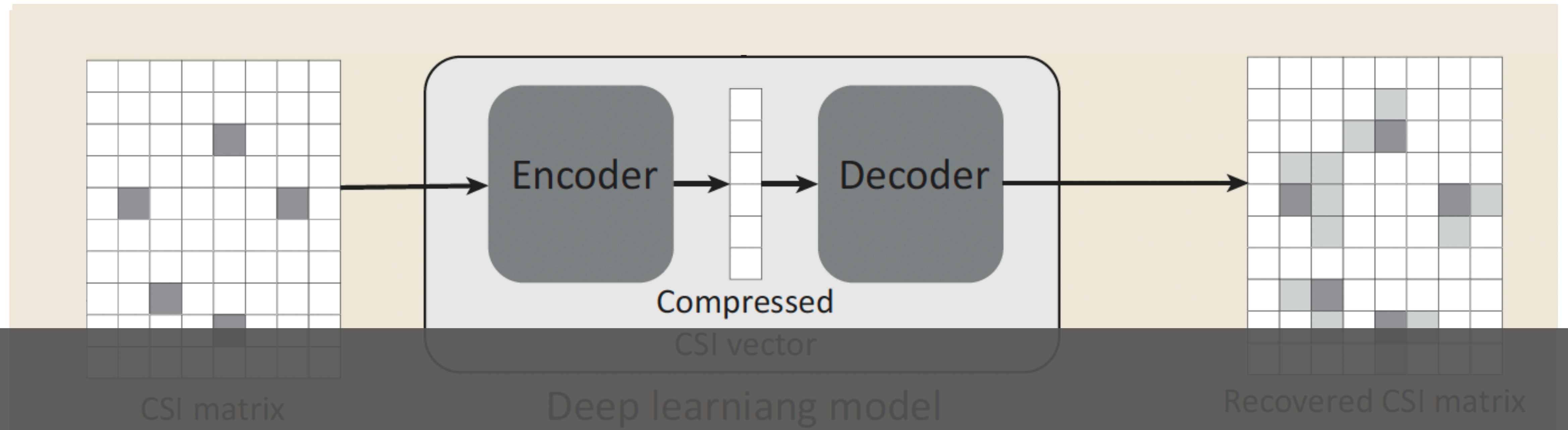
Channel tracking

Spatial/temporal beam prediction

Activity recognition

Presence detection

# Example: Representation learning



**But realizing these ML gains in practice has challenges**



# Challenges with complex communication/sensing ML tasks

**Need large labelled datasets**

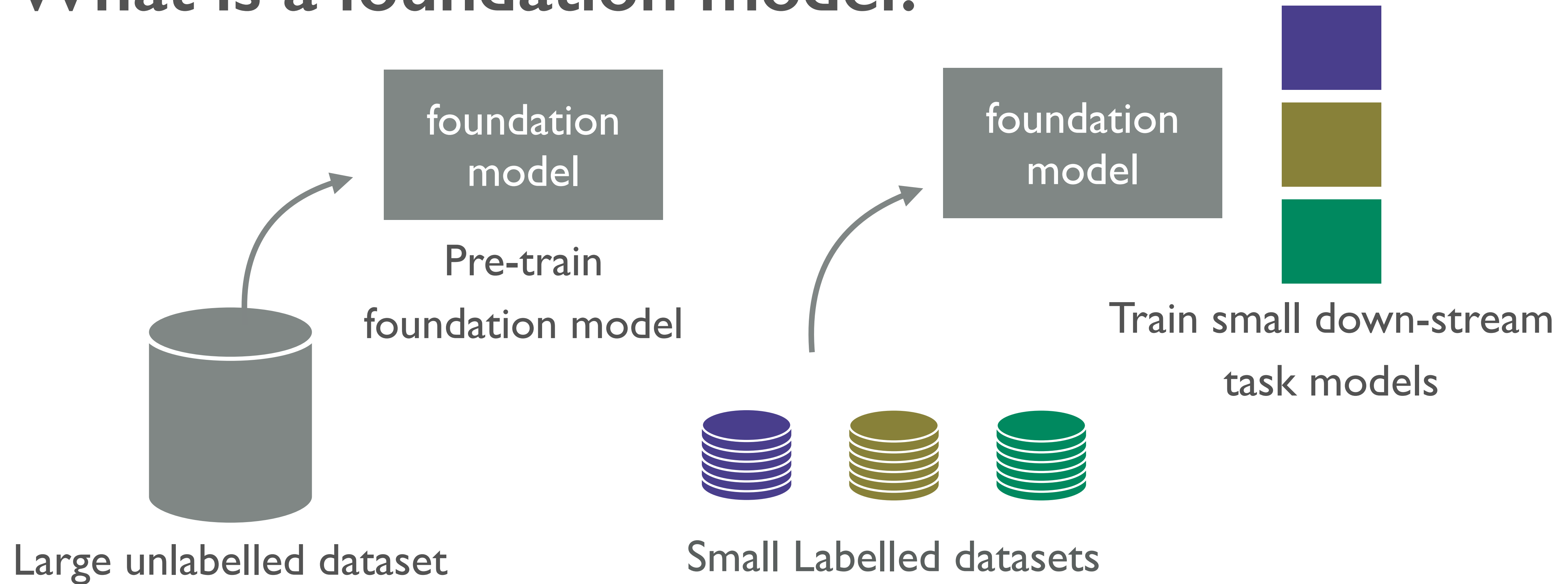
**Complex and non-trivial model architecture design**

**Significant training hyper parameter optimization**

# Foundation Models



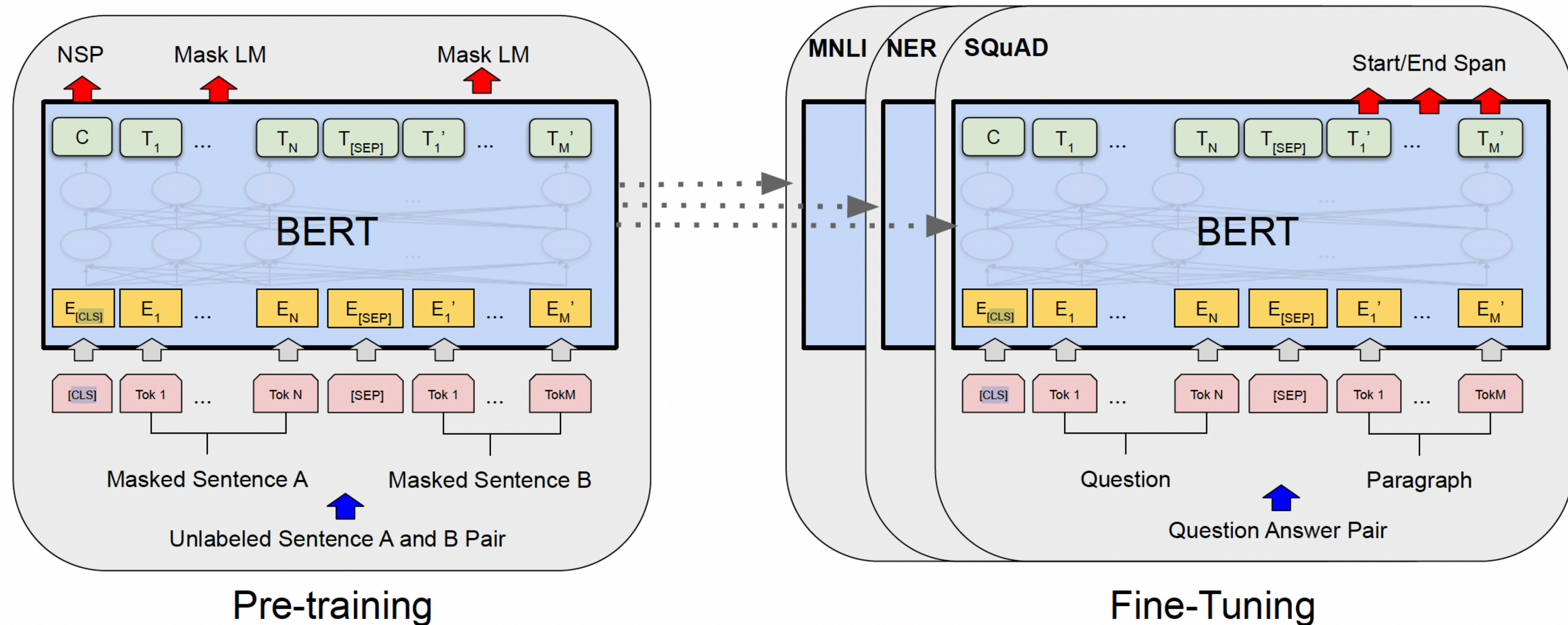
# What is a foundation model?





# BERT in natural language processing

2018 by Google

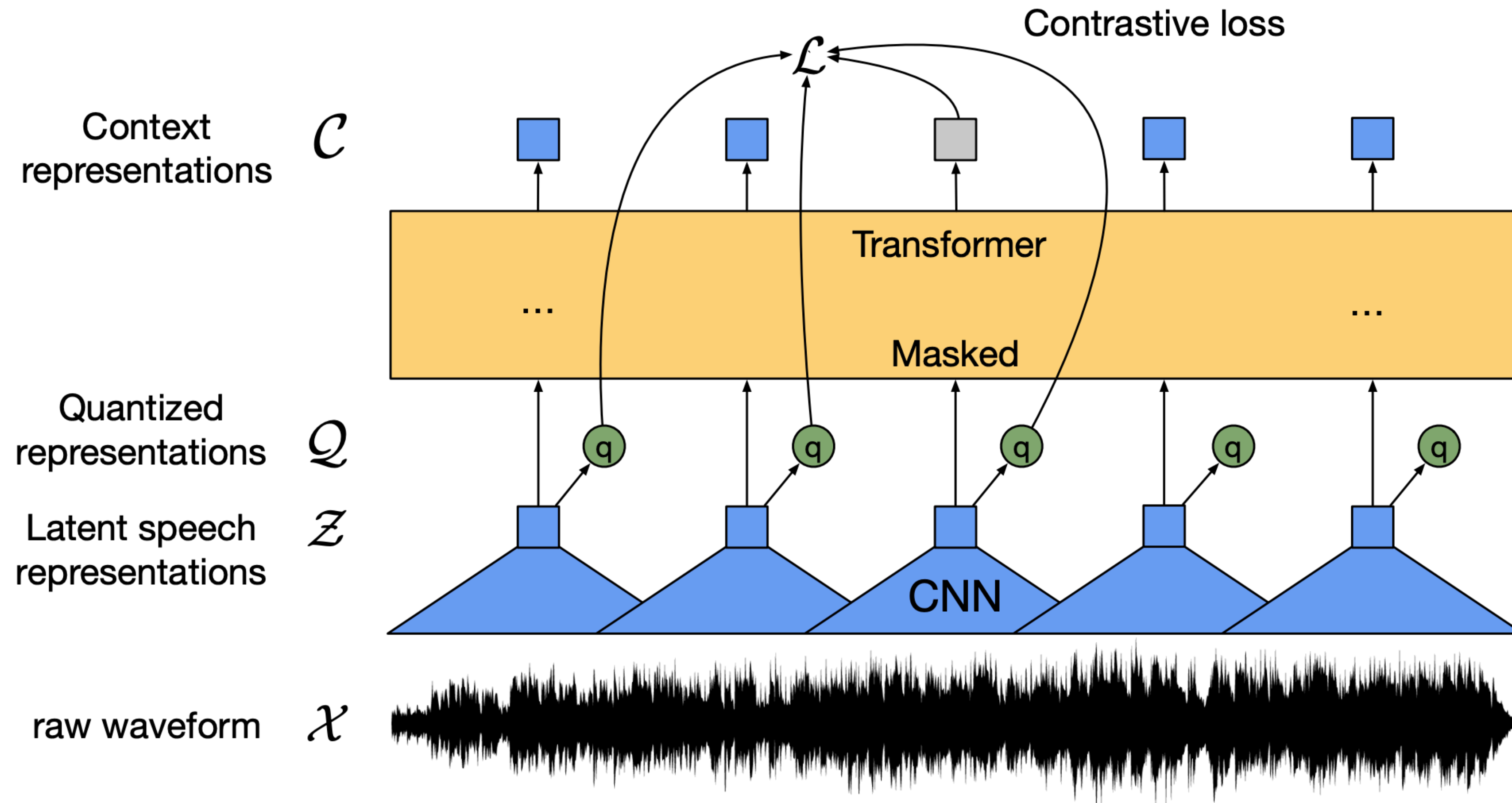


- ▶ Pre-trained on a massive dataset (including Wikipedia and BookCorpus)
- ▶ Can be fine-tuned for many tasks such as question answering and text classification



# wav2vec in speech processing

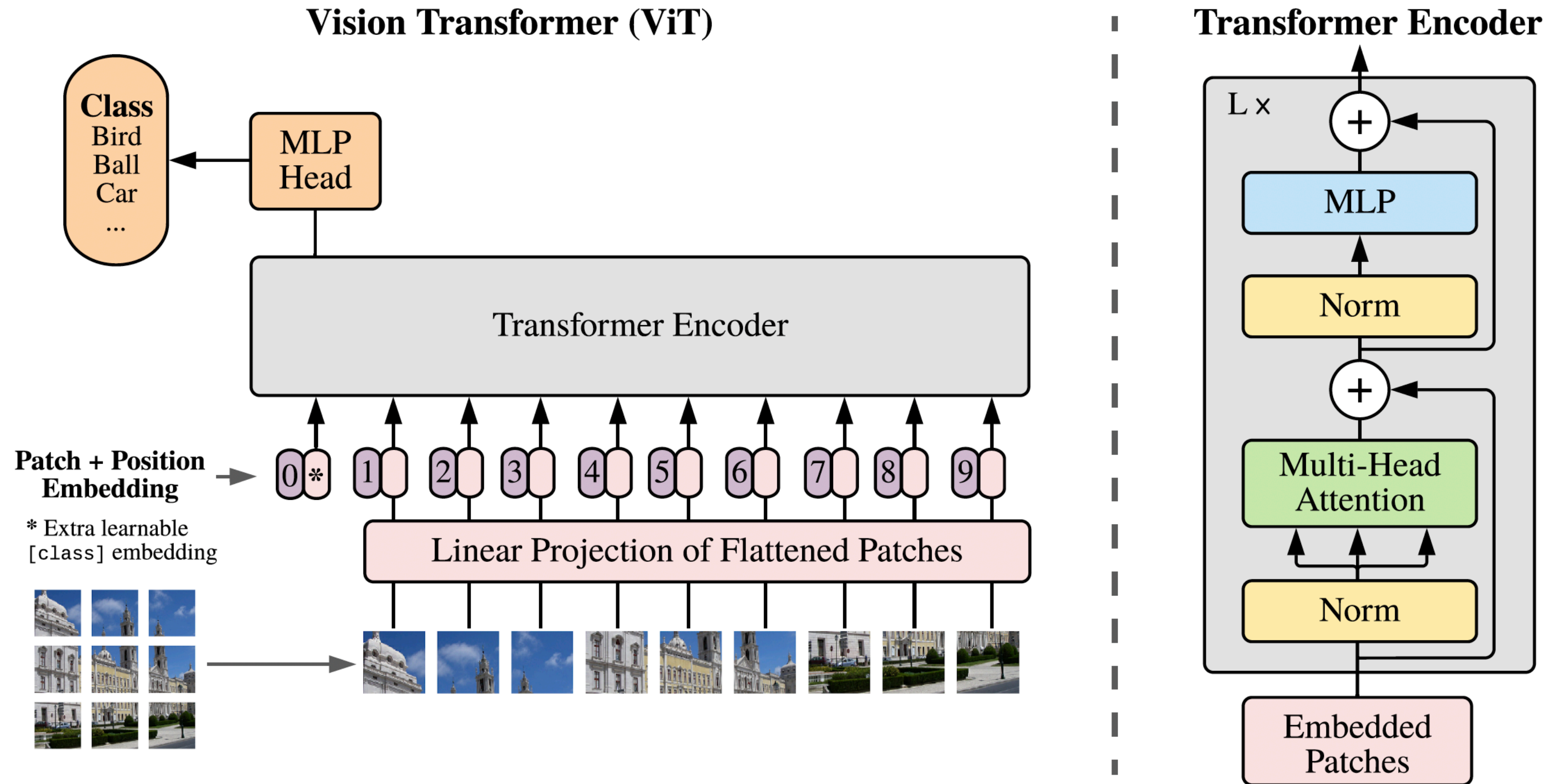
2019 by Meta



- ▶ Pre-trained on large datasets (960h LibriSpeech, 60k hours Libri-Light, 28k hours Common Voice)
- ▶ Can be fine-tuned for many tasks such as ASR and speaker identification

# ViT in computer vision

2021 by Google



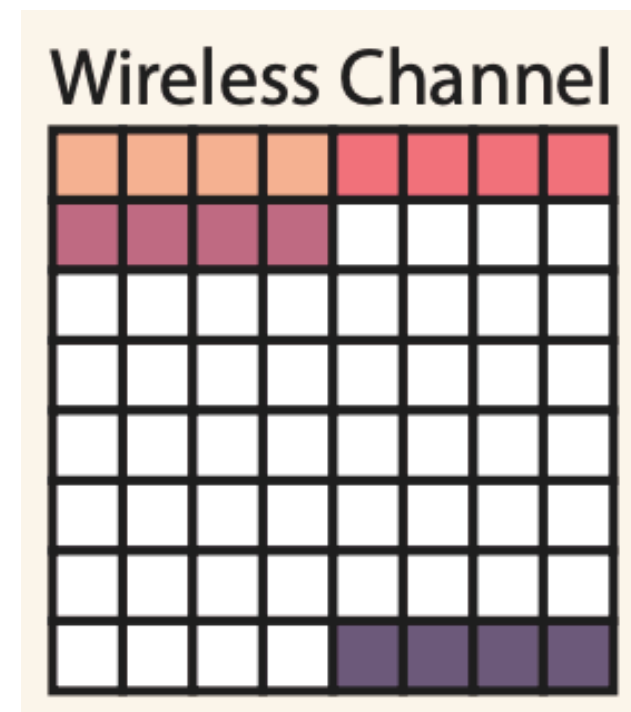
- ▶ Pre-trained on ImageNet-21k (14M images) and JFT-300M (300M images)
- ▶ Can be fine-tuned for many tasks such as image classification and object detection

# **LWMs**

# **Large Wireless Models**



# LWM: World's first foundation model for wireless



Can be  
fine-tuned

LWM 1.0 - LWM 1.1

## communication tasks

LOS/NLOS classification

Beam prediction

Channel estimation

Channel interpolation

Localization

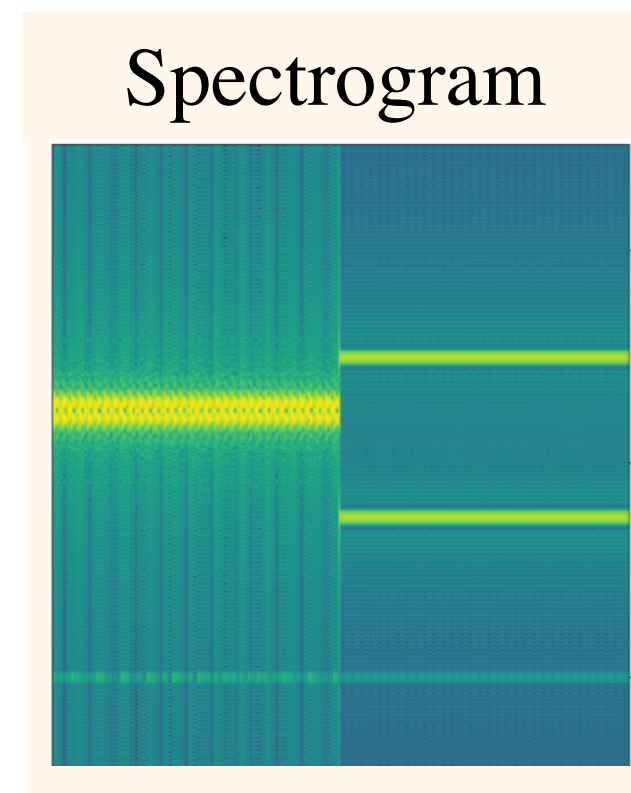
## sensing tasks

Presence detection

Activity recognition

Gesture recognition

Biomarker sensing



Can be  
fine-tuned

(Releasing soon!)

## communication tasks

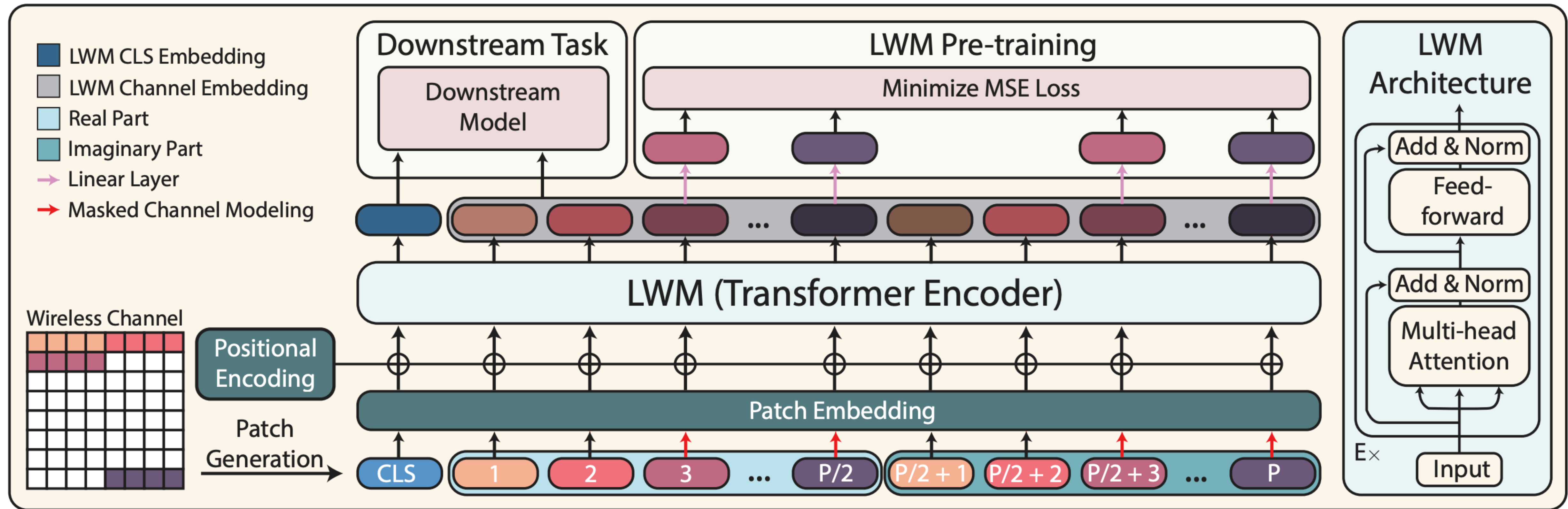
Modulation classification

Signal detection

## sensing tasks

Gesture/activity  
recognition  
without channel  
estimation

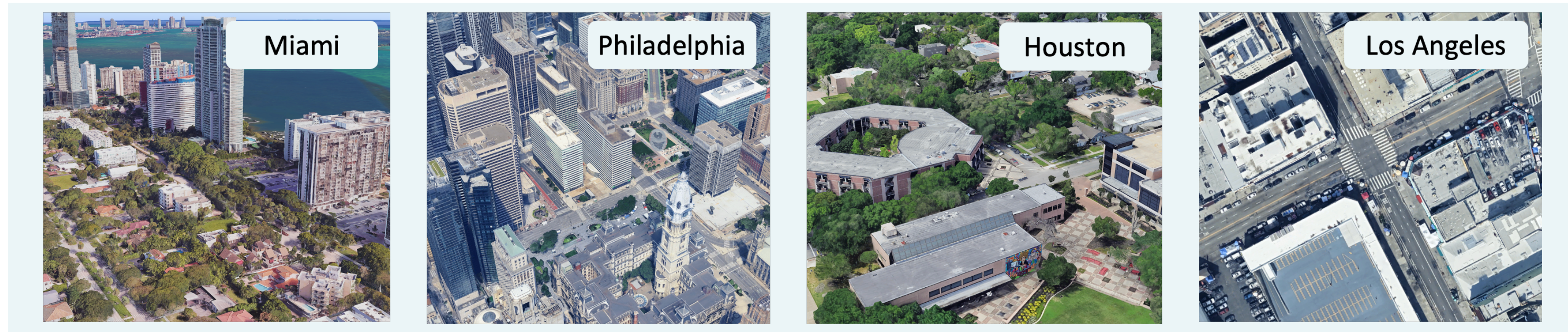
# LWM model architecture



- ▶ The model architecture is similar to ViT while the pre-training strategy is similar to BERT
- ▶ Masked channel modeling (for real/imag. patches) is used for self-supervised pre-training
- ▶ The LWM encoder is based on the standard transformer structure



# LWM pre-training — Dataset

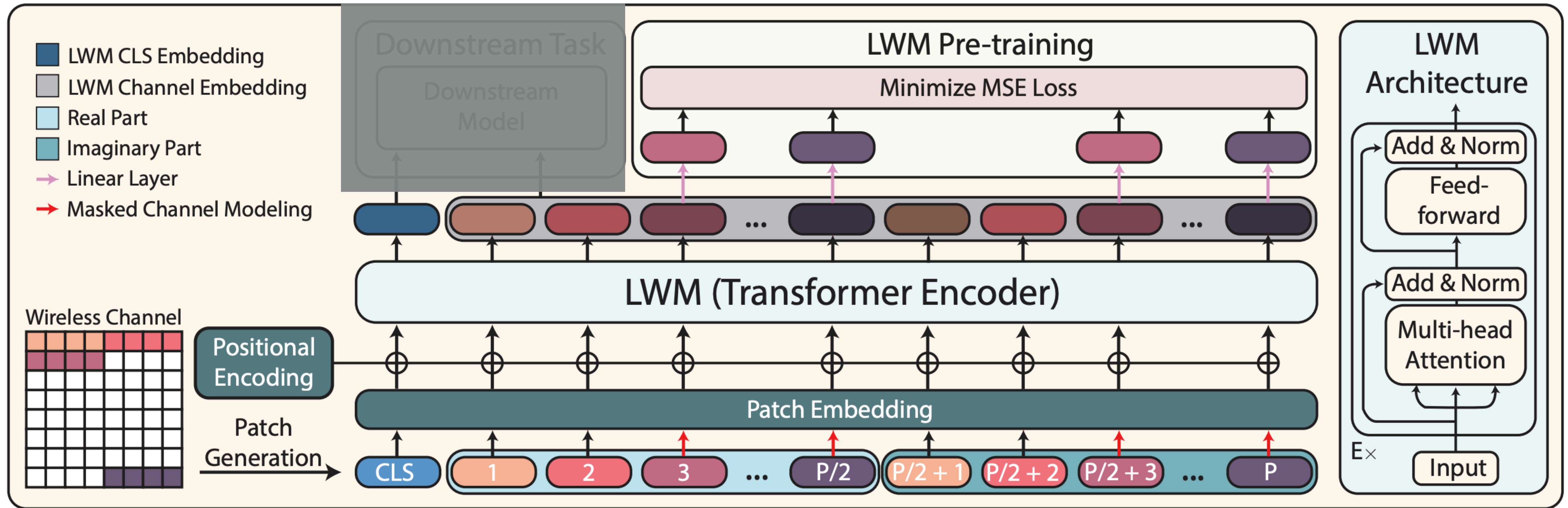


- ▶ The DeepMIMO dataset provides diverse wireless scenarios
  - \* Over **1 million channel samples** are generated from **15 DeepMIMO scenarios**
  - \* Channels cover different number of antennas and subcarriers at basestations
  - \* Channels of varying sizes are used for pre-training, making the model more flexible
- ▶ Large diverse datasets help foundation models to have
  - \* Wide distribution coverage: Reduces domain shift across wireless environments
  - \* Rich embedding space: Learns generalizable, high-rank channel features
  - \* Improved sample efficiency: Boosts downstream performance with few labels

Find a script that generates the full data on [lwm-wireless.net](https://lwm-wireless.net)

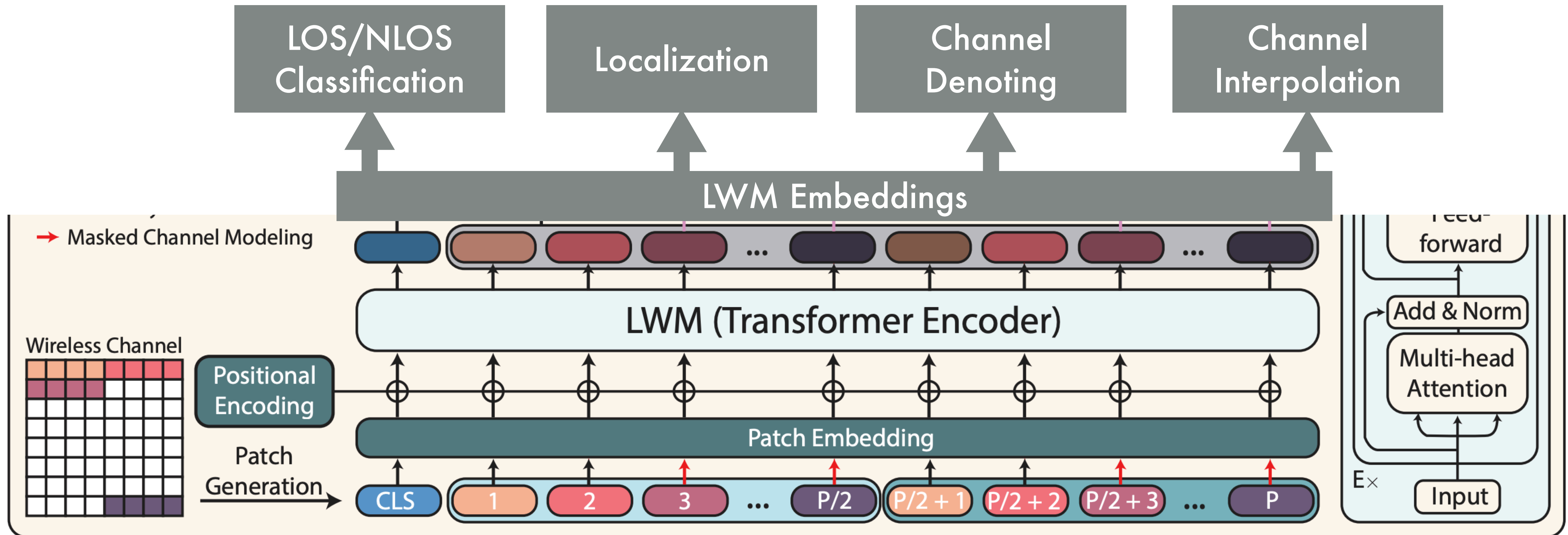


# LWM pre-training — Strategy



- ▶ Given the large hannel dataset, the LWM model is pre-trained end-to-end
  - \* Self-supervised training with masked channels via contextual channel reconstruction
  - \* Objective is to minimize MSE loss
- ▶ Transformer attention/multi-head mechanism implicitly learns spatial/spectral/temporal dependencies

# How to use LWM?



- ▶ The LWM universal embeddings could be used instead of raw-channels
- ▶ LWM embeddings can support many tasks in communications and sensing
- ▶ The model can be refined for each task (**submit LWM variants for ranking & listing**)



# Example LWM Applications

## (Initial Results)

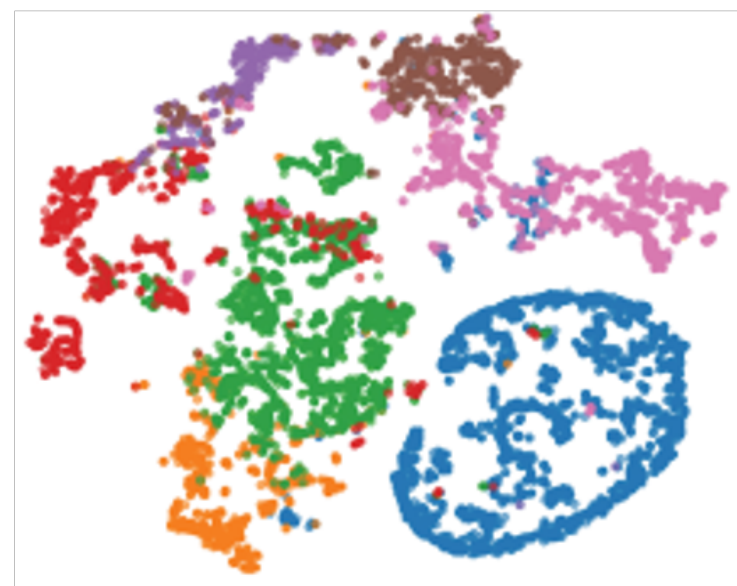
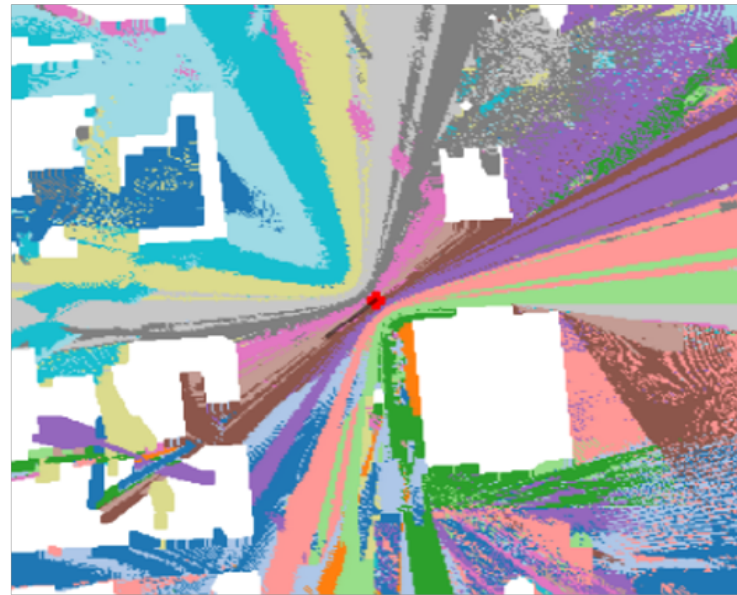
# Example LWM applications

## LoS/NLoS classification



Context-aware  
LOS/NLOS  
inference via global  
token semantics

## Sub6GHz channel to mmWave Beam prediction



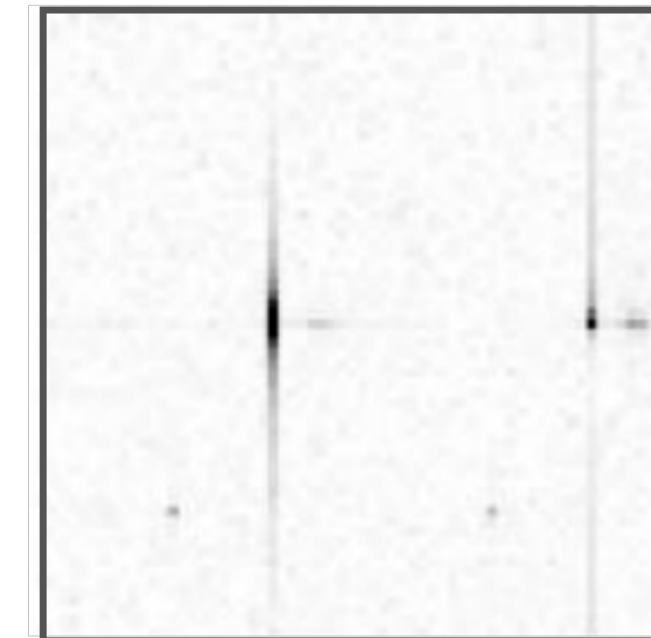
Frequency-domain  
knowledge transfer  
for mmWave beam  
index estimation

## User localization

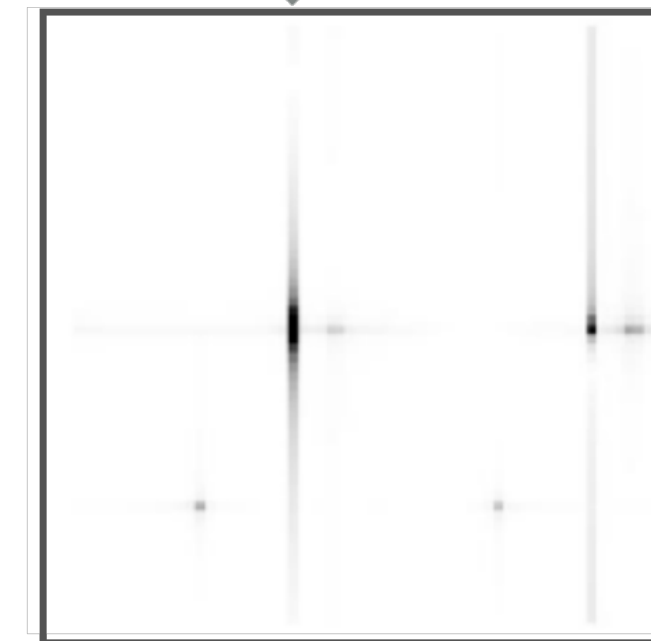


Geometric inference  
from spatially-  
encoded channel  
embeddings

## Channel estimation

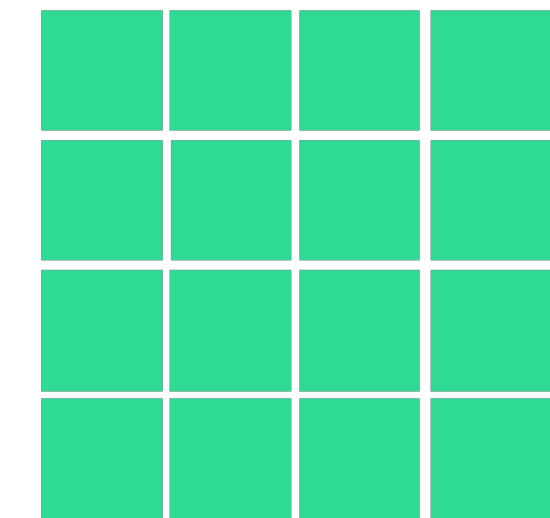
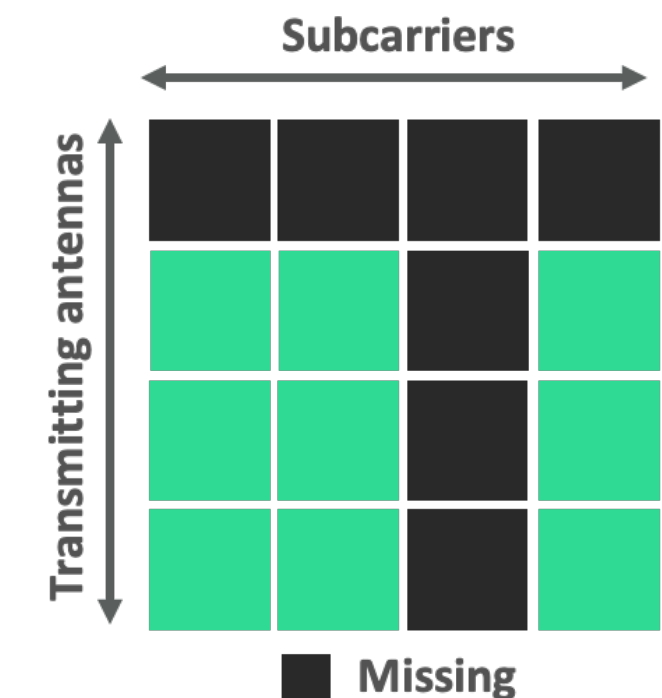


denoising



Self-supervised  
reconstruction of  
imperfect CSI via  
masked modeling

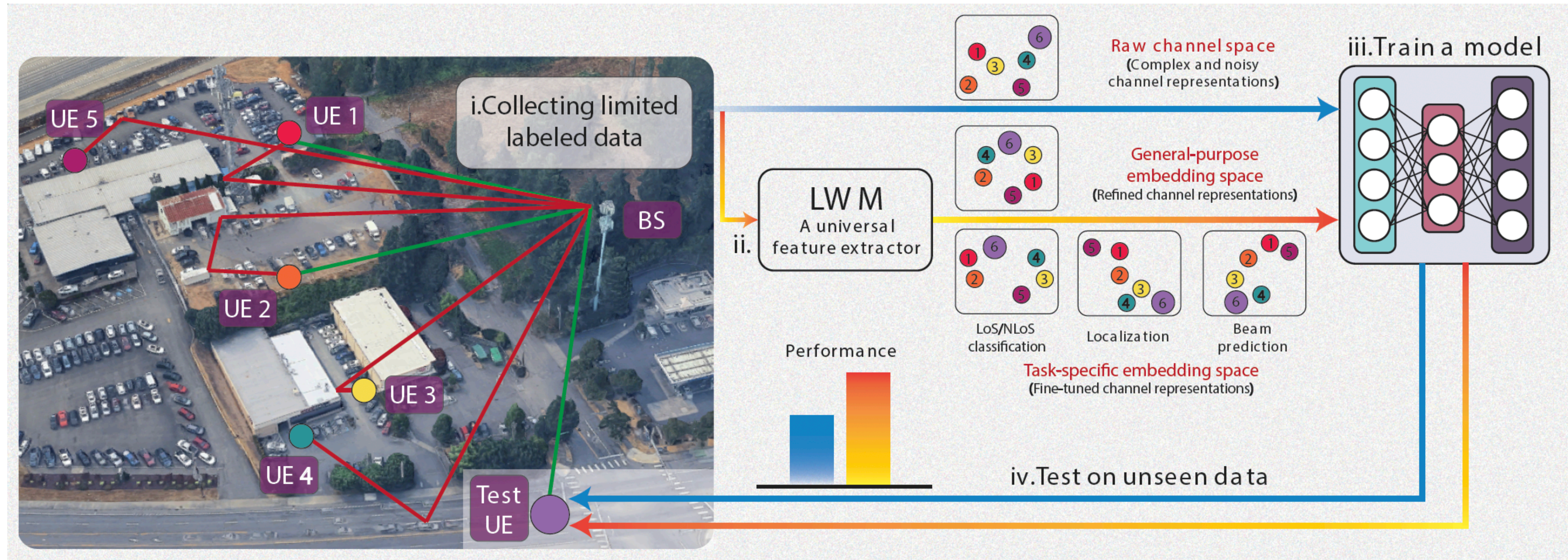
## Channel interpolation



Self-Attention driven  
interpolation of  
missing antennas  
and subcarriers



# Evaluation process

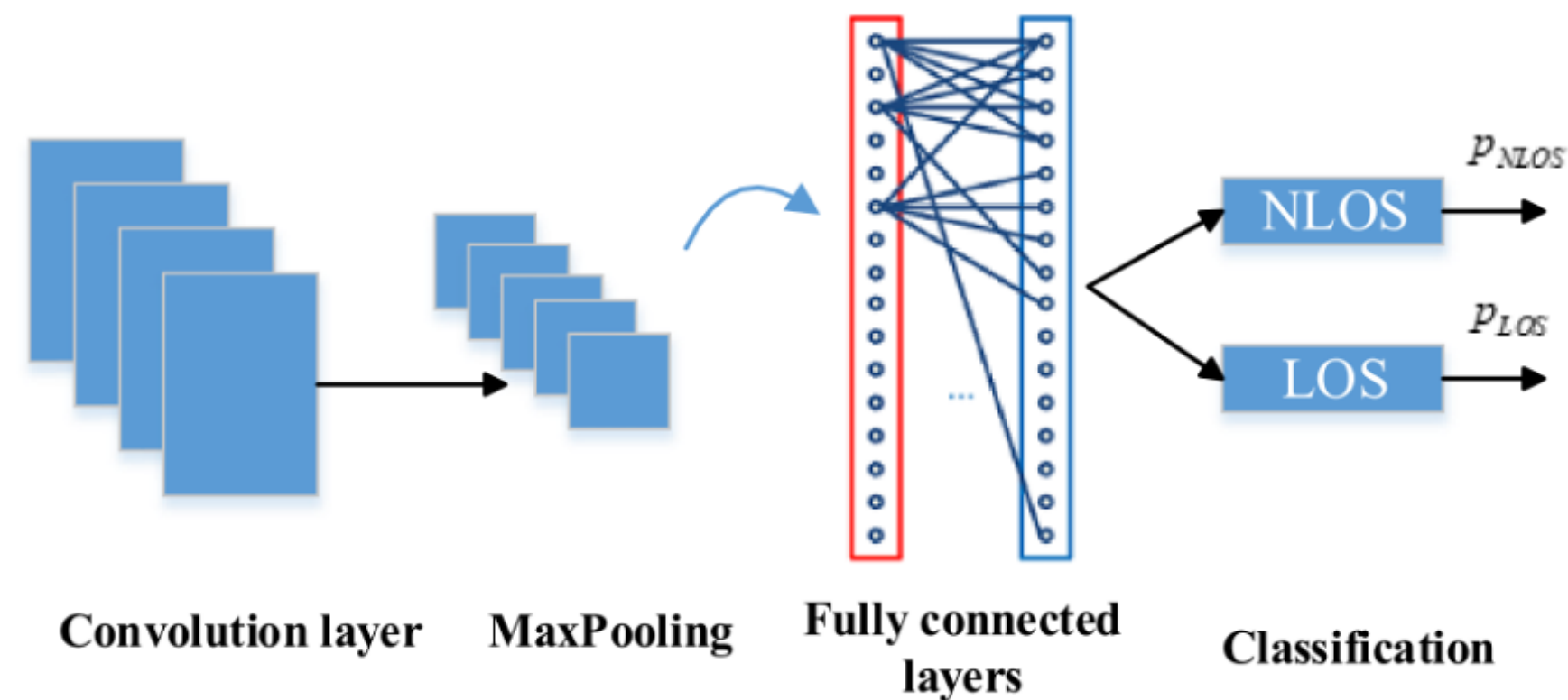


- ▶ For LWM:
  - \* Flattened embeddings with simple ML model generalize well
  - \* No specialized hyper-parameter tuning
- ▶ For the comparison
  - \* Adopt state of the art models (complex models and optimized training)

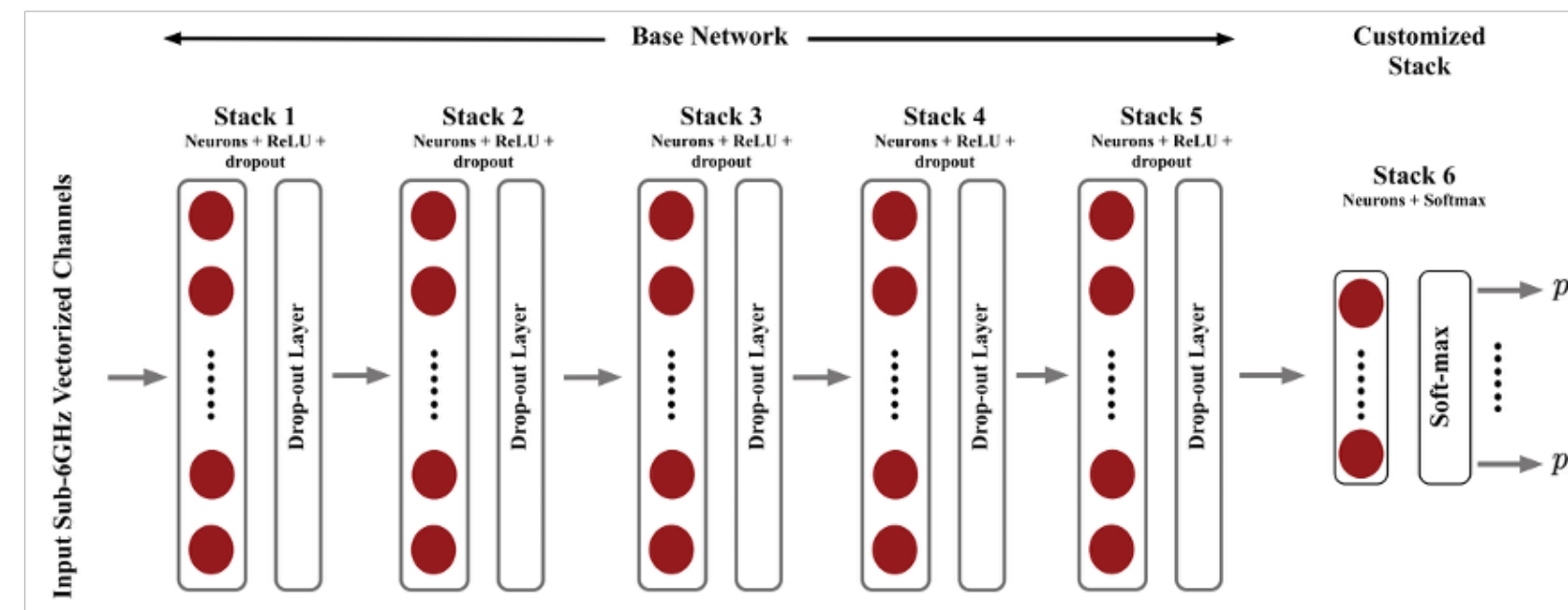


# Considered state-of-the-art models

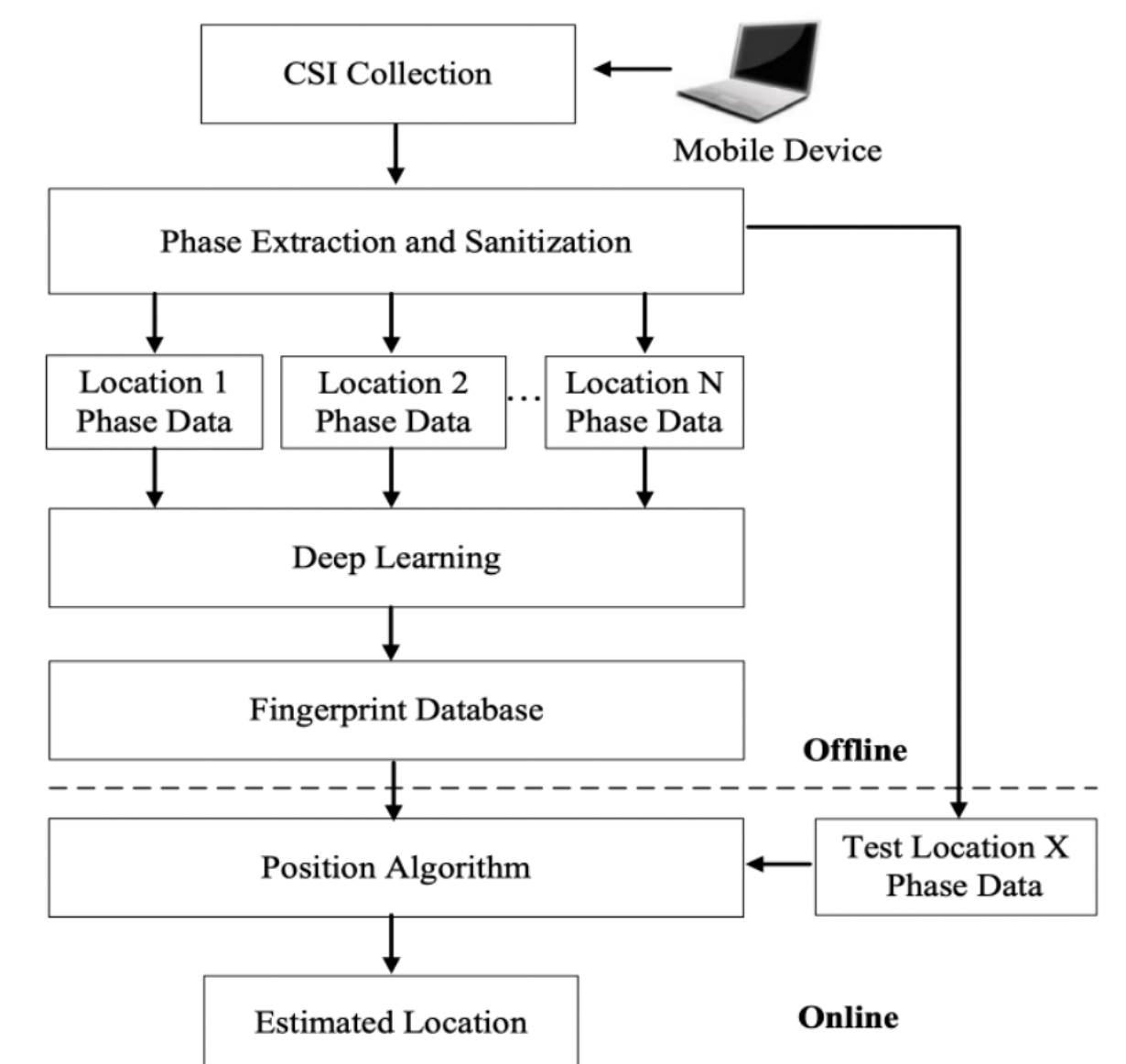
## LOS/NLOS Classification CNN



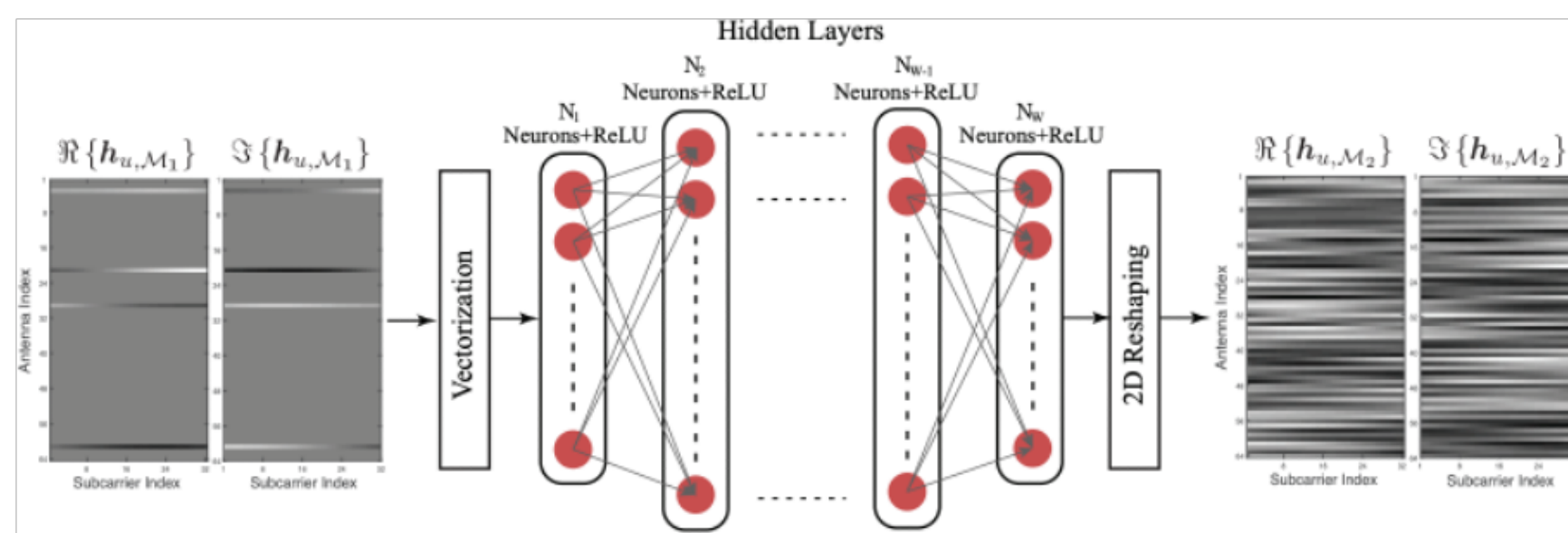
## Sub-6 GHz to mmWave Beam Prediction Complex FCN



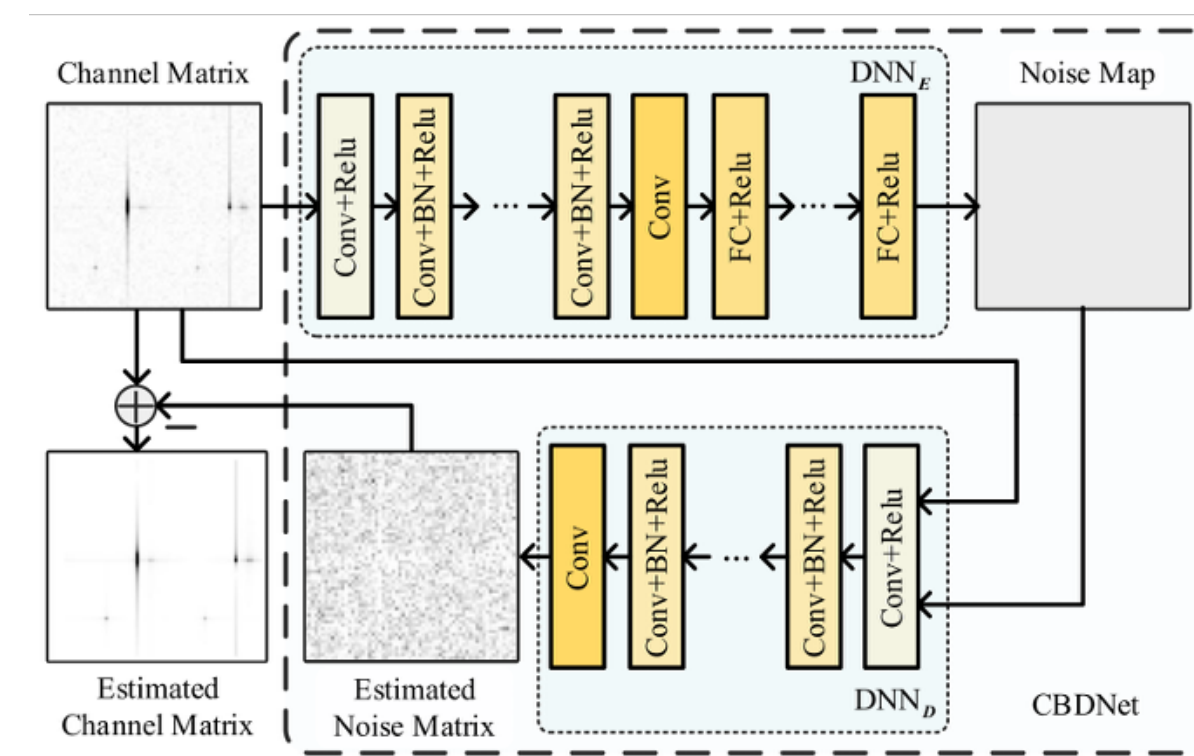
## Localization Complex FCN & data processing



## Channel Interpolation Complex FCN



## Channel estimation/denoising Complex CNN and data processing



X. Wang et al., UWB NLOS/LOS Classification, IEEE GLOBECOM, 2019.  
Alrabeiah & Alkhateeb, Deep Learning for TDD/FDD Channel Mapping, Asilomar, 2019.  
X. Wang, L. Gao, S. Mao and S. Pandey, "CSI-Based Fingerprinting for Indoor Localization: A Deep Learning Approach," in *IEEE Transactions on Vehicular Technology*, 2017.  
J. Guo et al., Convolutional Neural Network based Multiple-Rate Compressive Sensing for Massive MIMO CSI Feedback: Design, Simulation, and Analysis, arXiv:1906.06007, 2019.

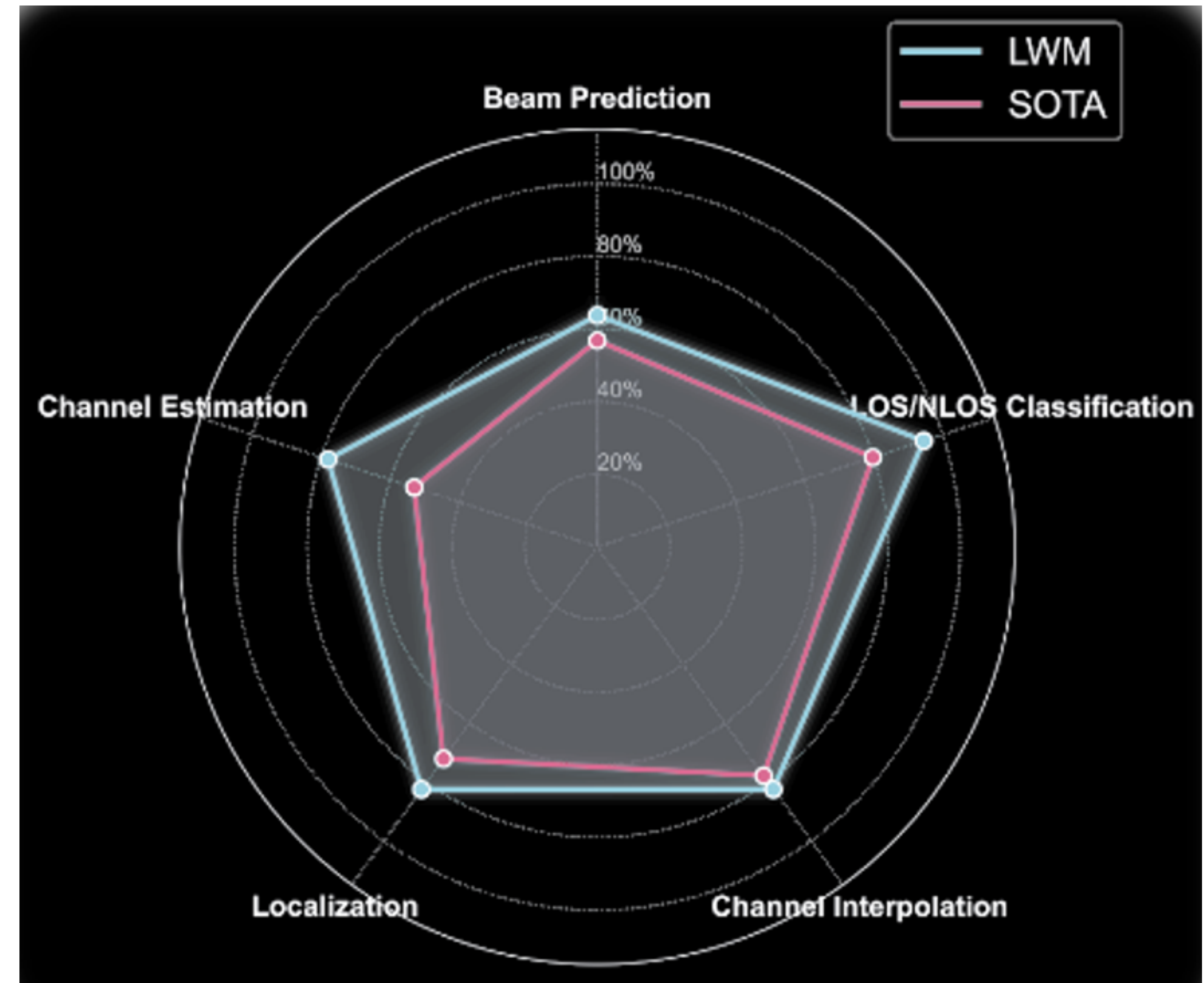
Typically relies on complex task and data specific designs with increased risk of overfitting with limited data

# Initial LWM results

LWMs lead to

- Better gains
- Simple downstream model design
- Simple training

Huge room for optimization!



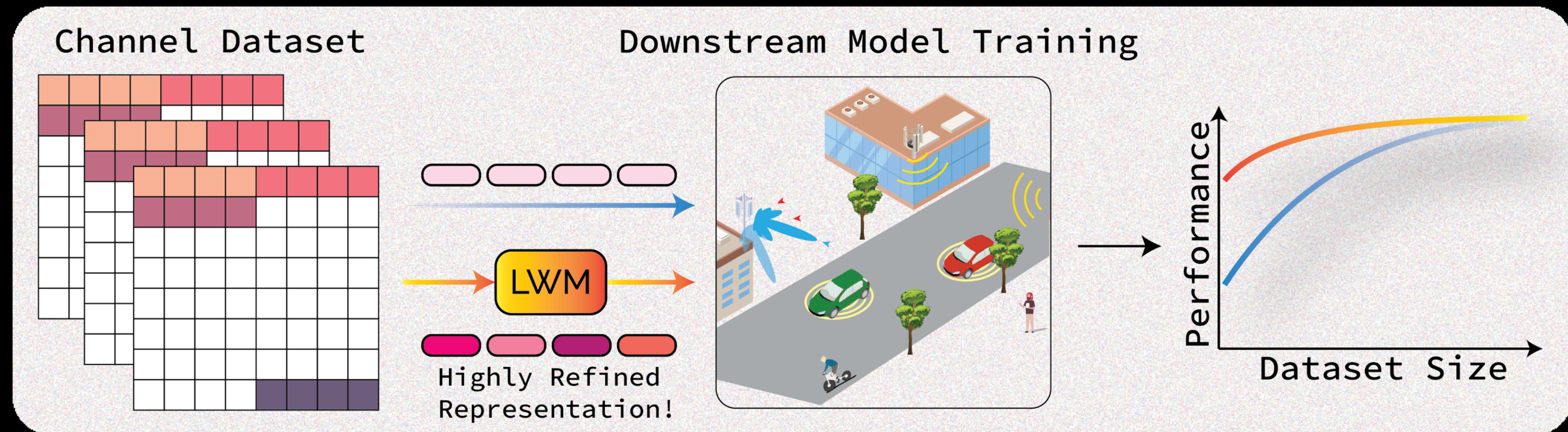


**LWM ITU ML Competition**



# ITU ML Challenge 2025

## LWM Multi-Task Optimization



Wireless Intelligence Lab

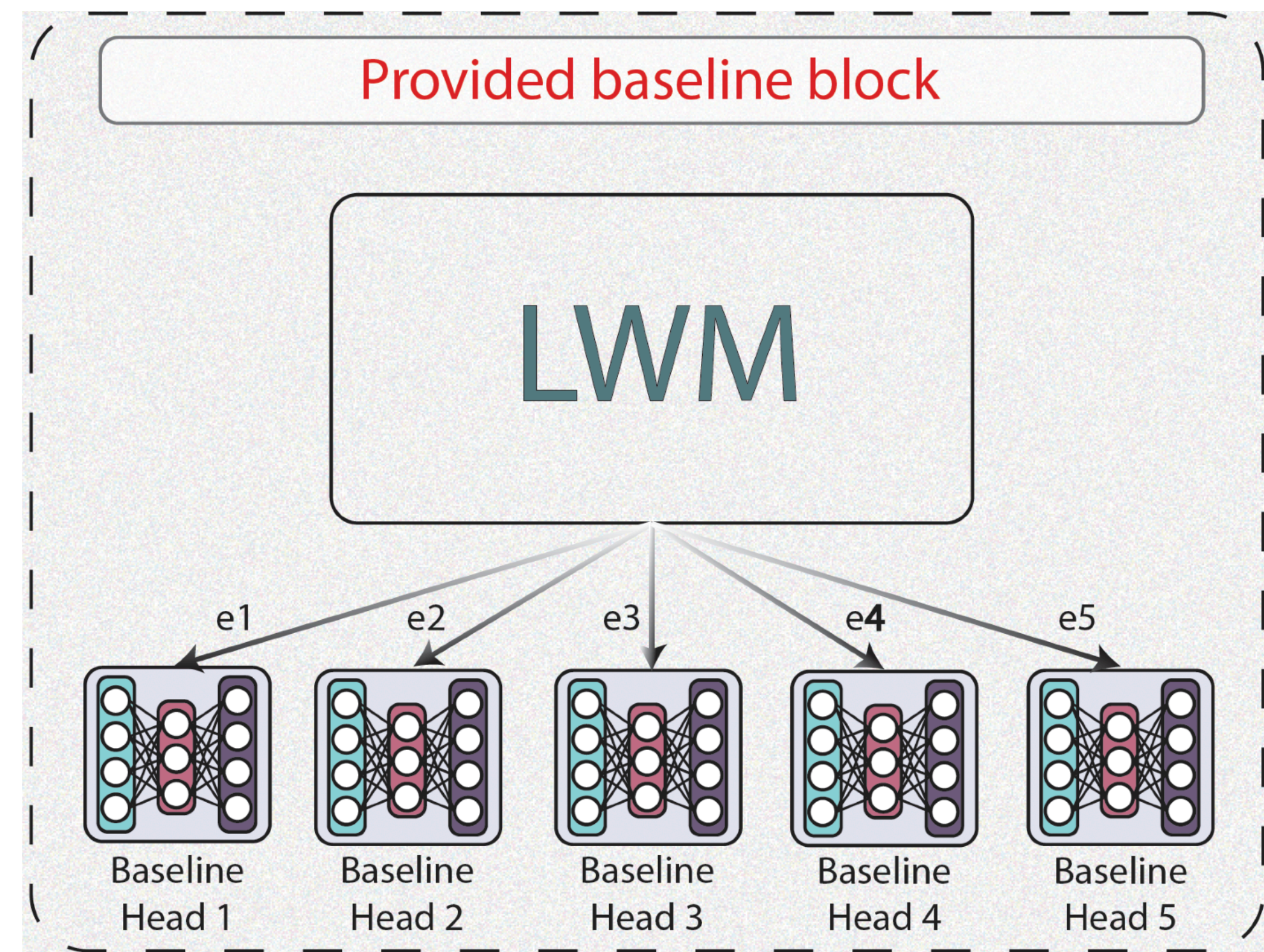


AI for Good



# Problem Statement

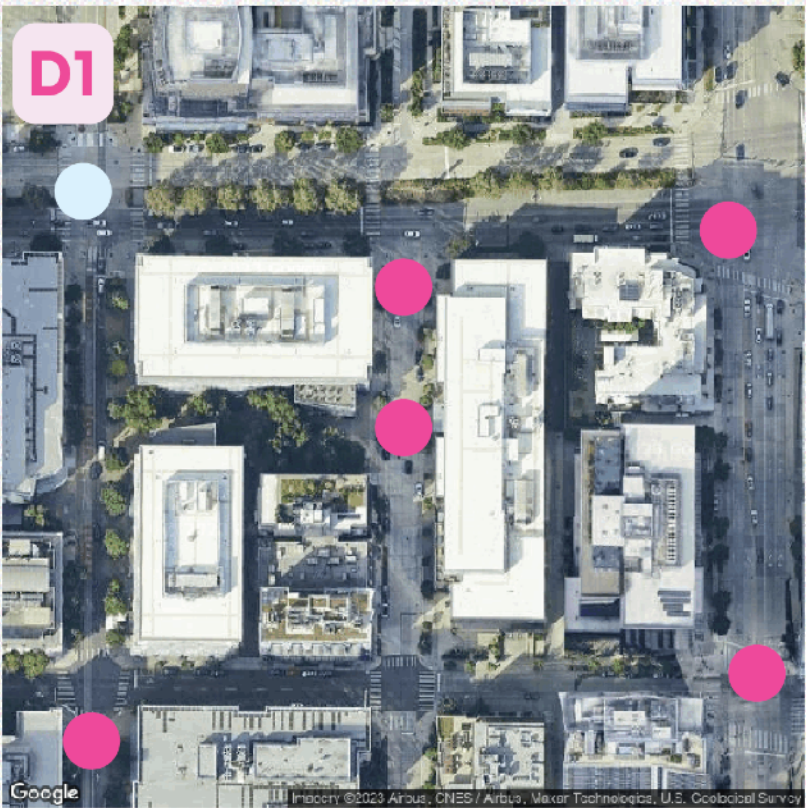
- ▶ Participants will be provided with
  - ▶ A baseline pre-trained LWM 1.1 model
  - ▶ Baseline models for five downstream tasks
  - ▶ Limited training/test sets for the five tasks



**Limited labeled channel datasets**


**Task 1**  
LoS/NLoS  
classification

D1



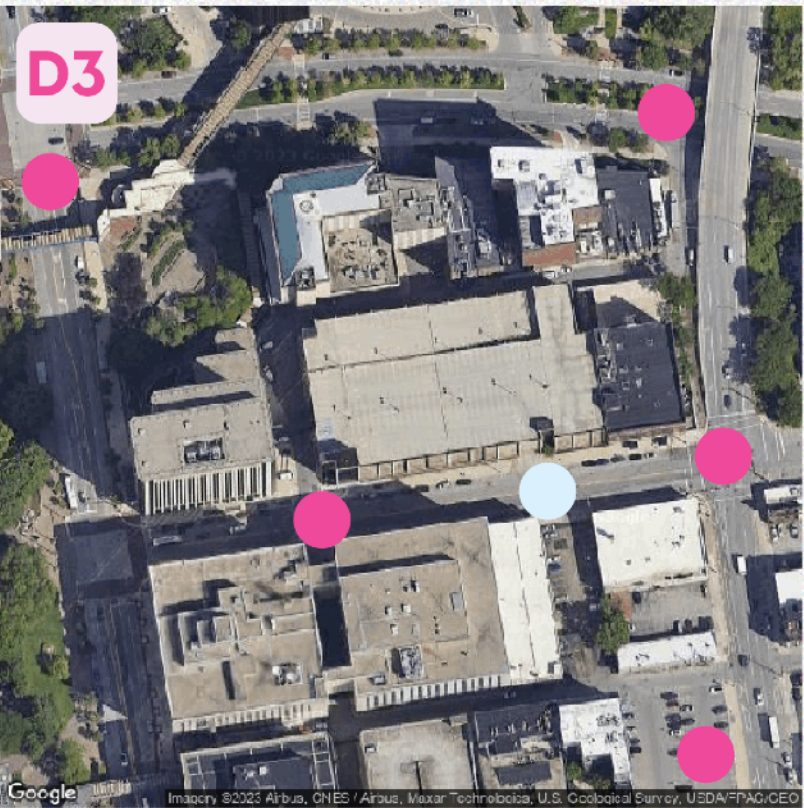
**Task 2**  
Beam  
prediction

D2



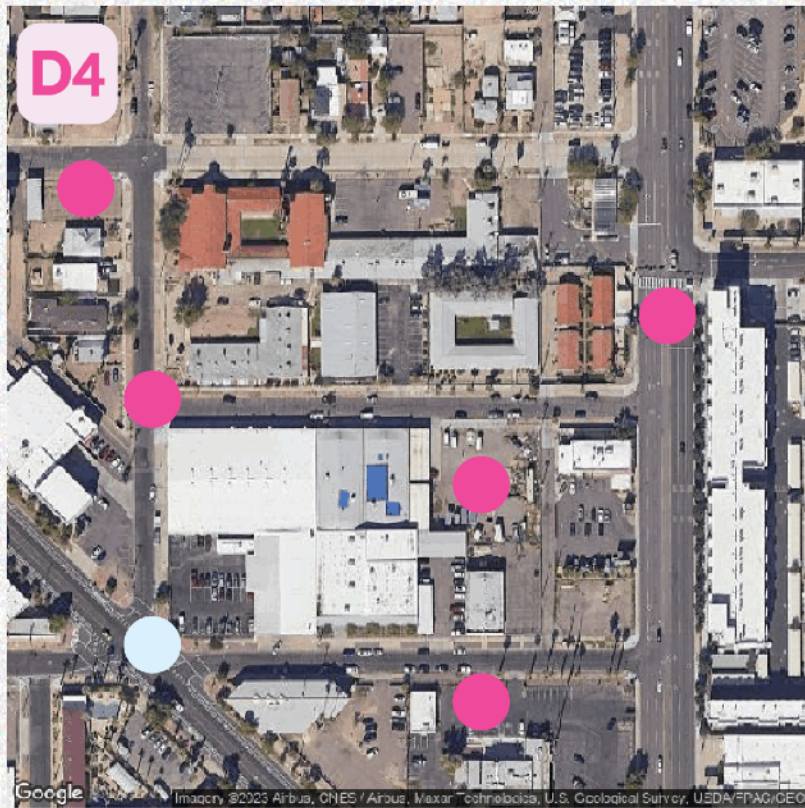
**Task 3**  
CSI  
interpolation

D3



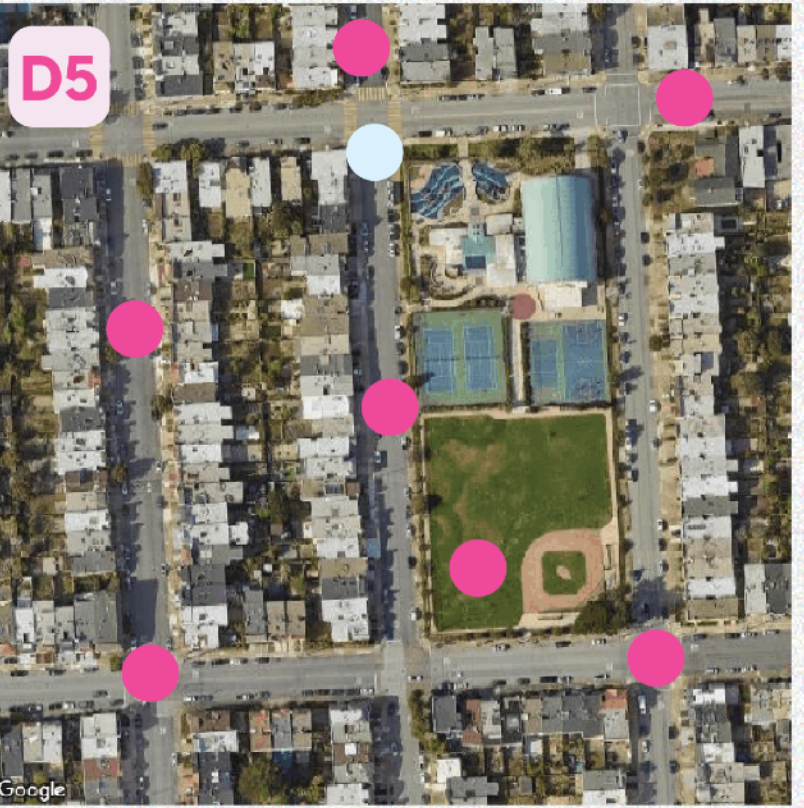
**Task 4**  
Channel  
estimation

D4



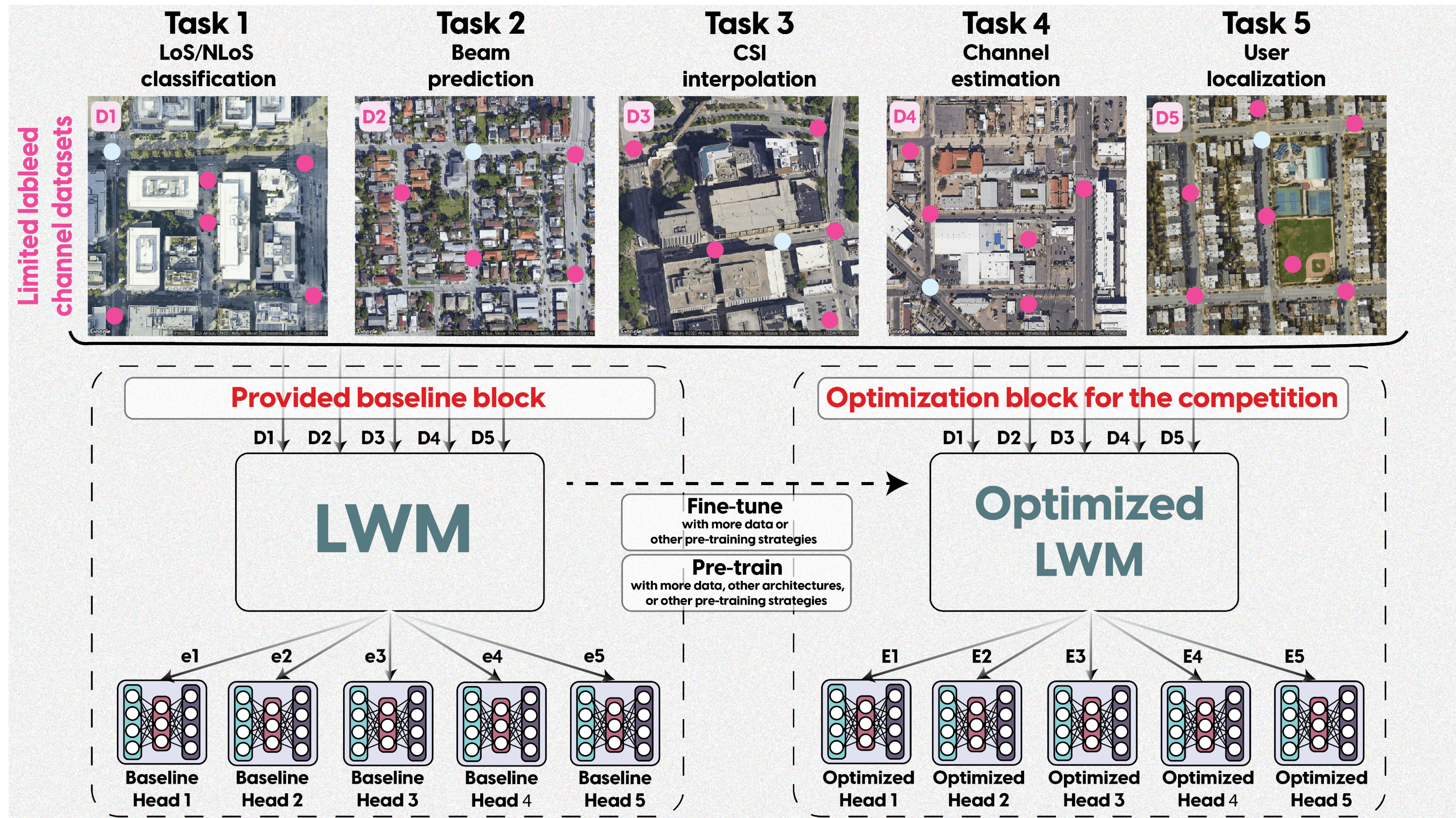
**Task 5**  
User  
localization

D5





# Problem Statement

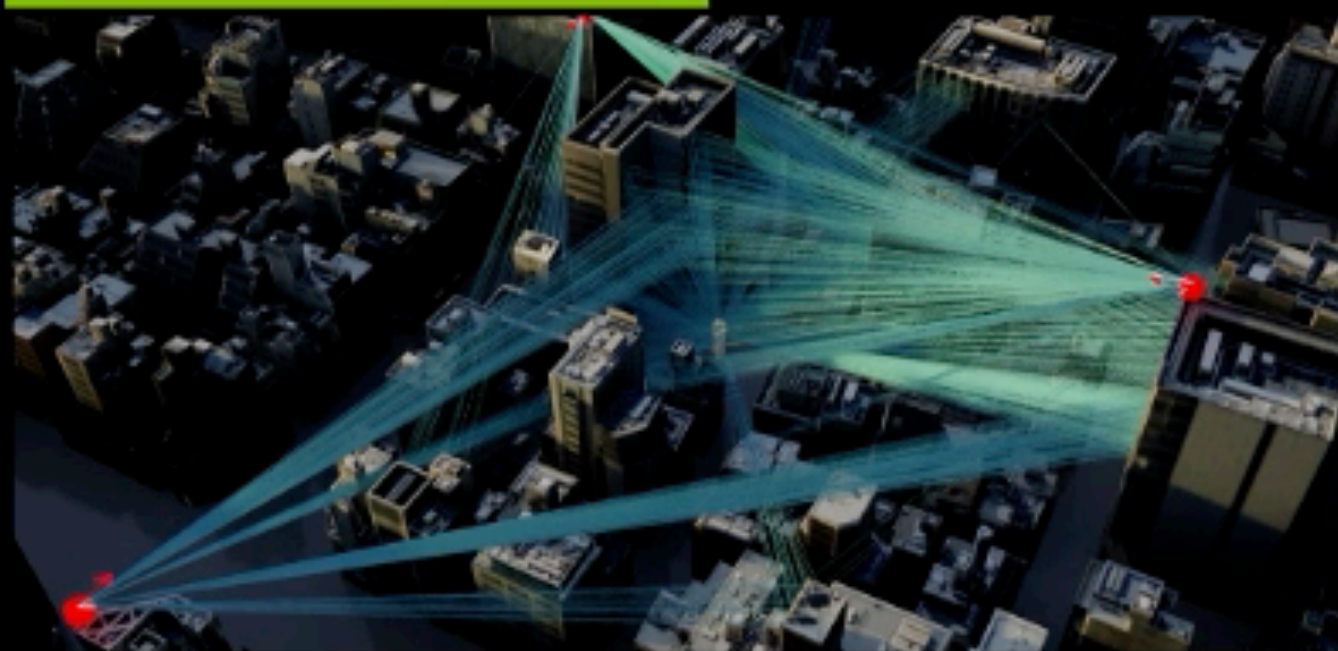


Participants can refine the LWM or downstream task models/training

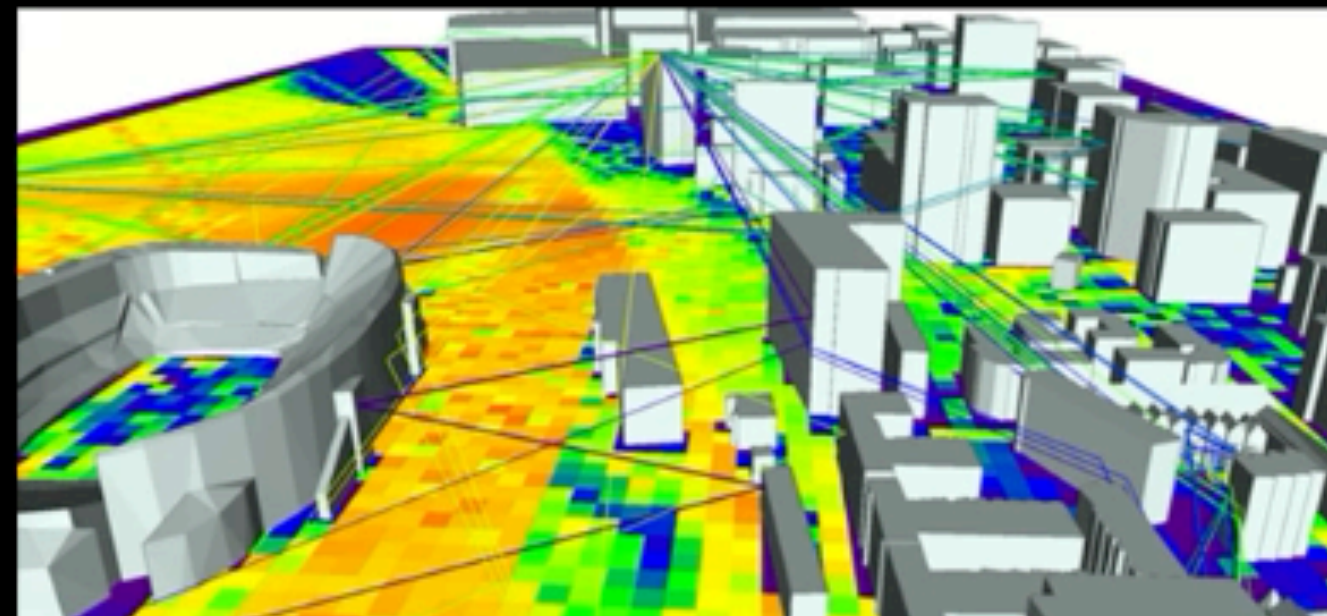




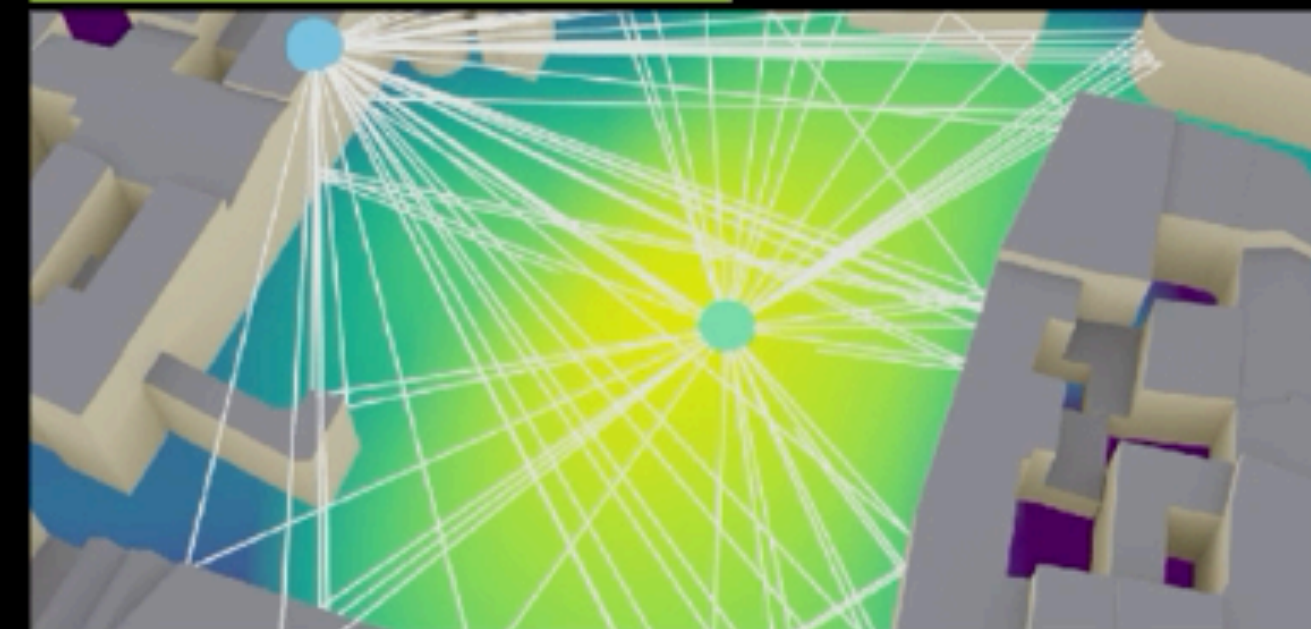
AODT



InSite



Sionna RT



DeepMIMO Parameters

```
# DeepMIMO Dataset Parameters 'S'
parameters = {
    "selected_basestations": ...,
    "selected_users": ...,
    "basestation_antenna_configuration":
    ...,
    "user_antenna_configuration": ...,
    # ...
    "ofdm_params": ...,
}
```

Unified DeepMIMO Scenario

DeepMIMO Generator



DeepMIMO Dataset

Participants get  
**early access**  
to  
DeepMIMO v4



Sionna



NeoRadium

DeepMIMO

Processing & Plotting



Made with Lottielab



DeepMIMO v4  
with 200+ datasets

## Version 4 Scenarios

Facilitating  
community contributions



**asu\_campus\_3p5**

A scenario for asu\_campus\_3p5



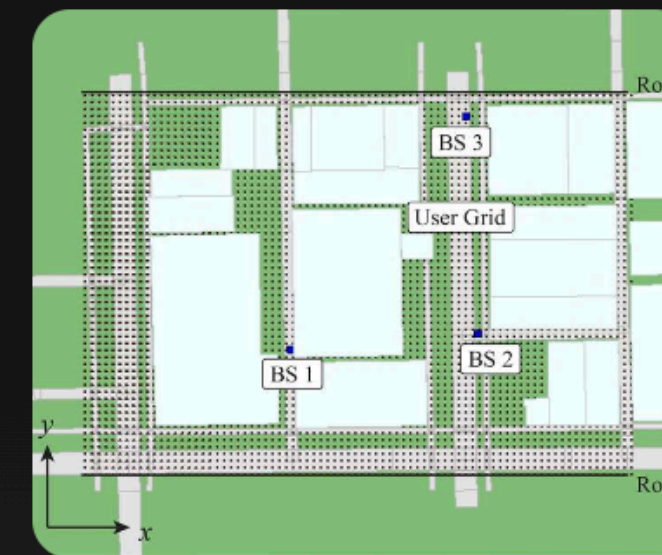
**city\_0\_newyork\_3p5**

A scenario for city\_0\_newyork\_3p5



**city\_1\_losangeles\_3p5**

A scenario for city\_1\_losangeles\_3p5



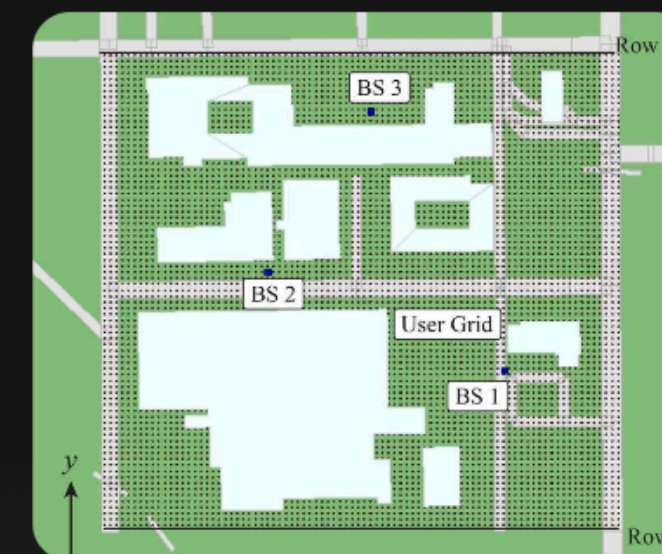
**city\_2\_chicago\_3p5**

A scenario for city\_2\_chicago\_3p5



**city\_3\_houston\_3p5**

A scenario for city\_3\_houston\_3p5

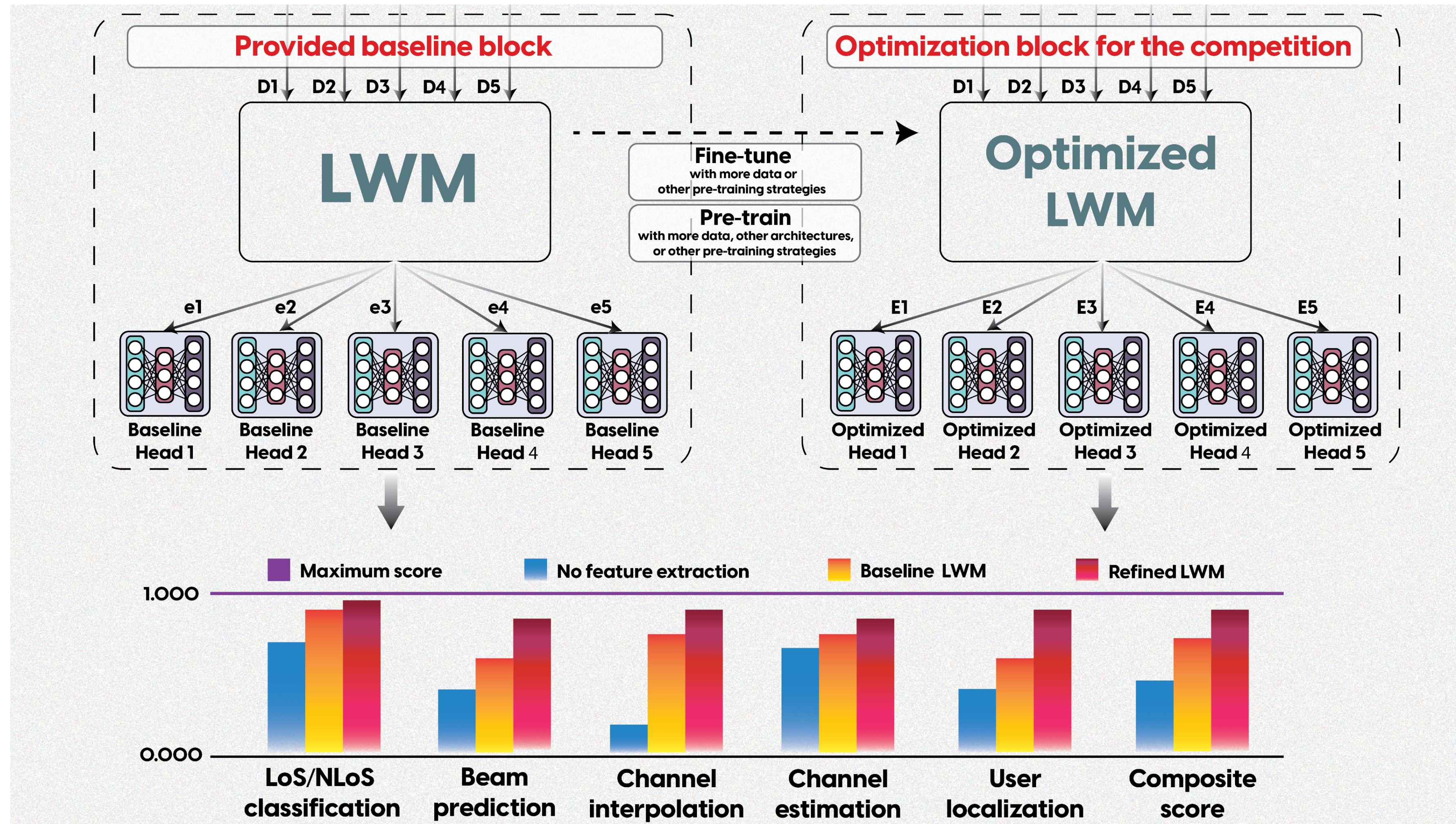


**city\_4\_phoenix\_3p5**

A scenario for city\_4\_phoenix\_3p5



# Problem Statement



Registration is  
now open!

Final models will  
be ranked on the  
LWM website!

Participants will submit refined models and prediction results

Evaluation will be based on the composite score of the five tasks



# Conclusion

- ▶ Complex communication/sensing ML tasks are challenging
  - \* Require large datasets (site-specific)
  - \* Non-trivial model architectures and training optimization
- ▶ LWMs: World's first foundation model for wireless
  - \* Enable complex tasks with small datasets and simple downstream models
  - \* Support many communication and sensing tasks
  - \* Stay tuned for more LWM releases coming soon!

**Registration is now open for the  
ITU ML Challenge 2025 on LWMs**

[www.LWM-wireless.net](http://www.LWM-wireless.net)

[www.WI-Lab.net](http://www.WI-Lab.net)

[www.DeepMIMO.net](http://www.DeepMIMO.net)



# Thank You!

## Questions?

[www.DeepSense6G.net](http://www.DeepSense6G.net)

[www.WI-Lab.net](http://www.WI-Lab.net)

[www.DeepVerse6G.net](http://www.DeepVerse6G.net)