5GNN: Extrapolating 5G Measurements through GNNs

https://github.com/StrongWeiUMN/5GNN

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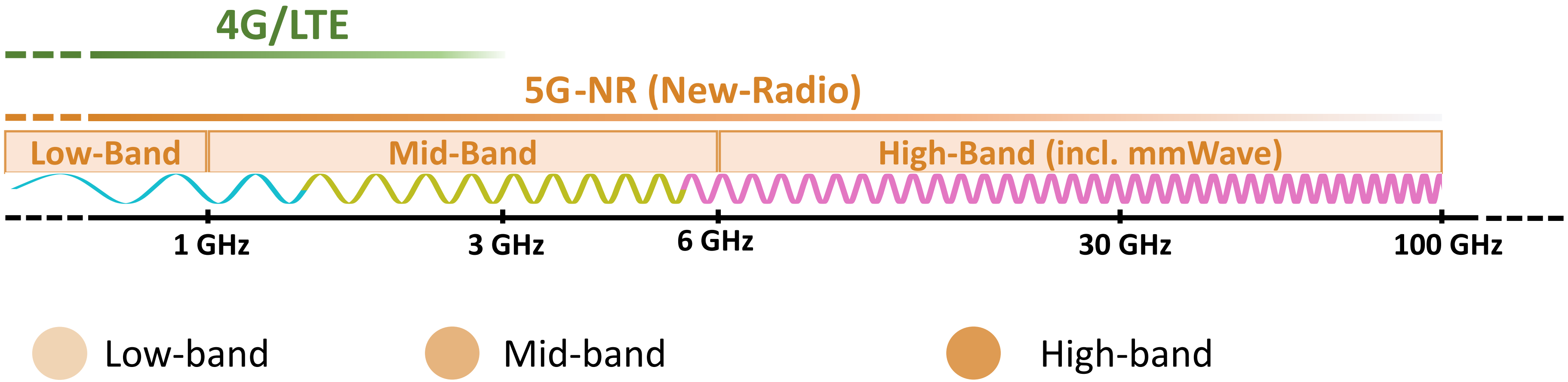
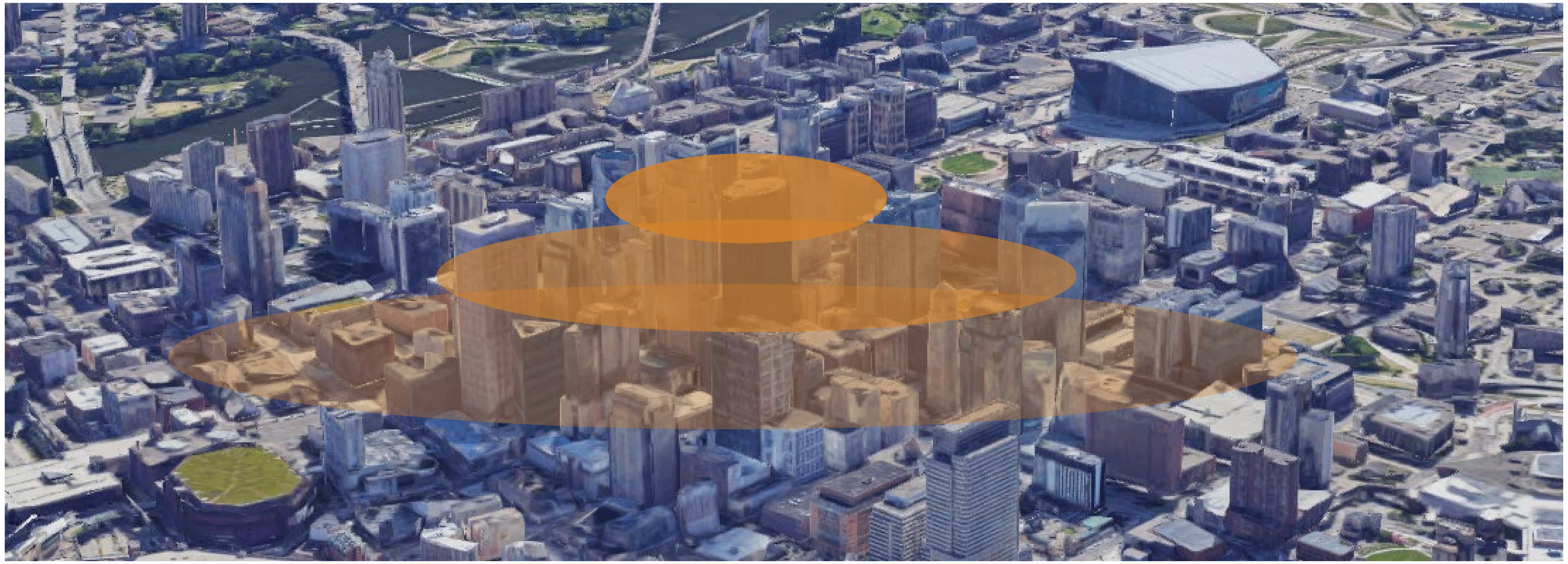
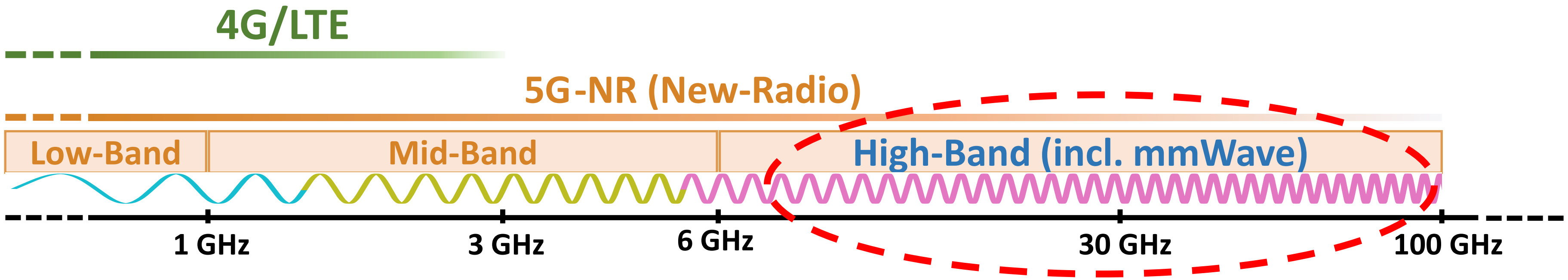
5G Band Is Diverse





5G mmWave Enhance the Human Experience

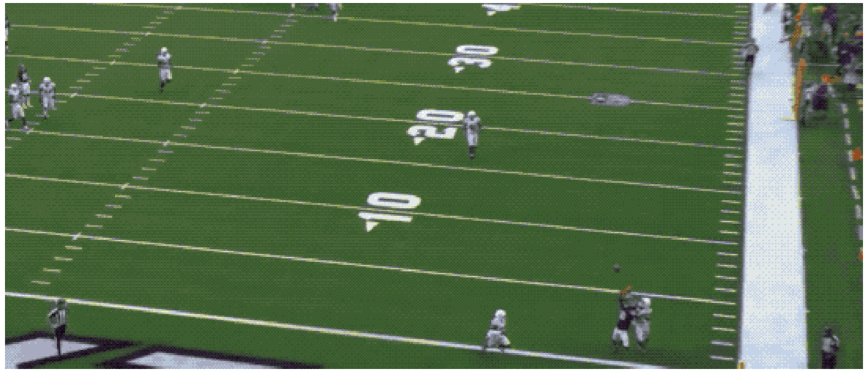


With theoretical throughput up to 20 Gbps!

Key to support apps requiring ultra-high bandwidth

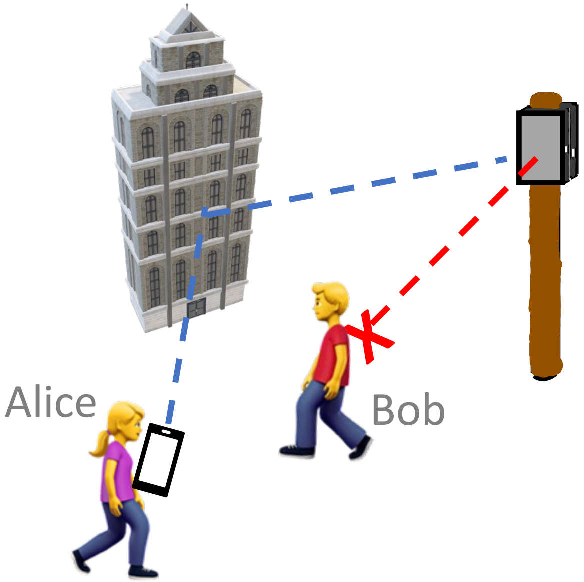
AR/VR Services

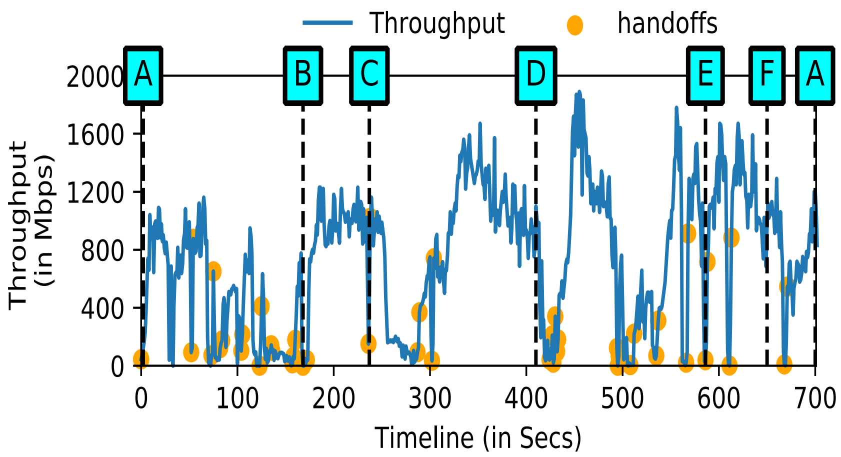
Source: Intel True View

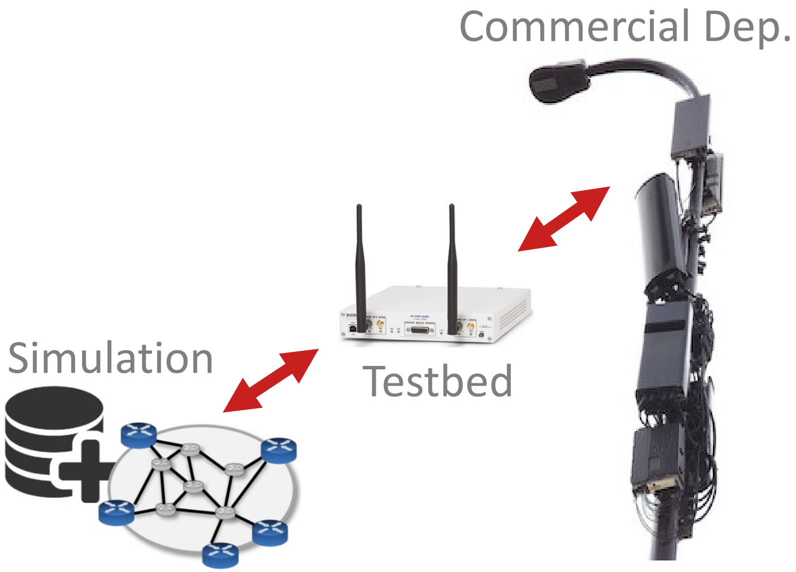


Volumetric Content Delivery

Also Brings New Challenges







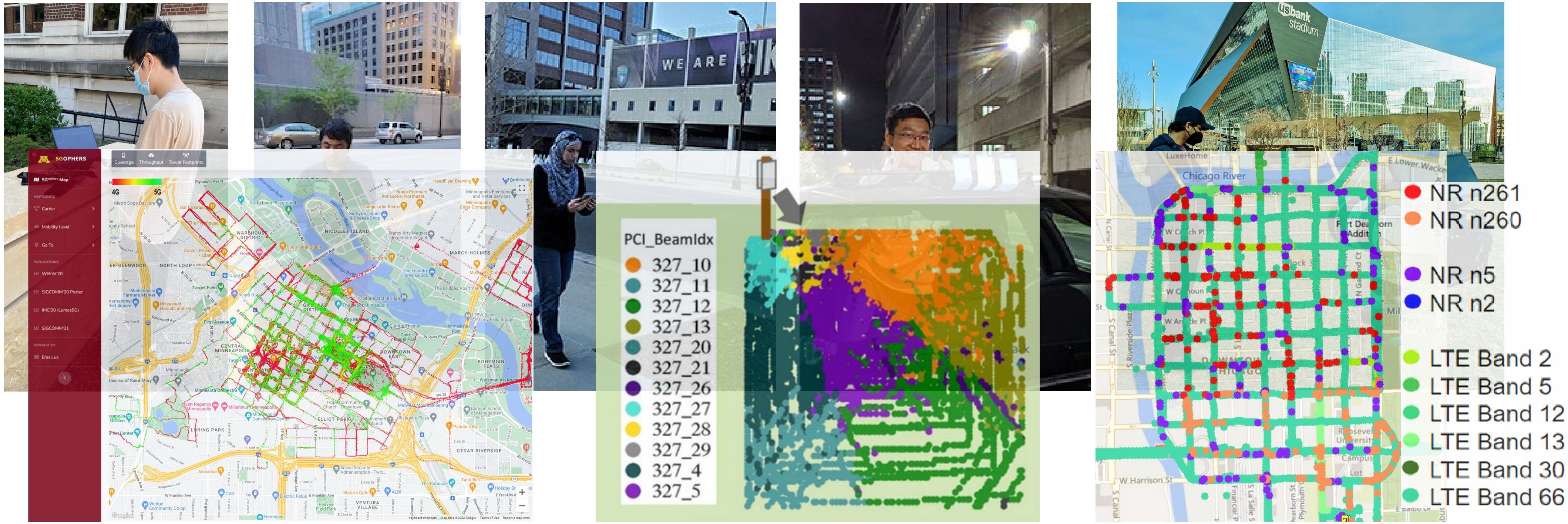
Multi-path signals due to **reflection** and **blockage**

Wild and frequent **fluctuations** in throughput

Gaps among **digital world**, **local testbed**, and **commercial deployment**

- We need **more real-world data** to support the model learning for prediction!

Measurements are Key to Reveal Commercial 5G



5Gopher: Mapping throughput | **5G Beam coverage** | **5G Band study**

- The detailed **"in-the-field" measurements** are the key to understand the commercial 5G network performance.

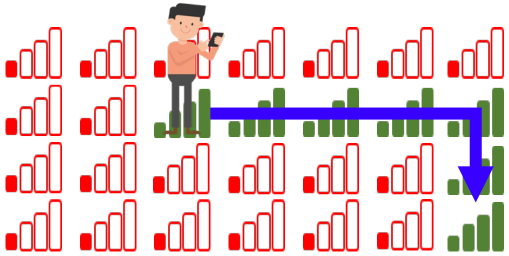
Measurement of Commercial 5G is Low-efficient

However,

(1) Measurement process is **laborious** and **costly**.

(2) Data can only be collected in **limited areas** of (potentially large) space.

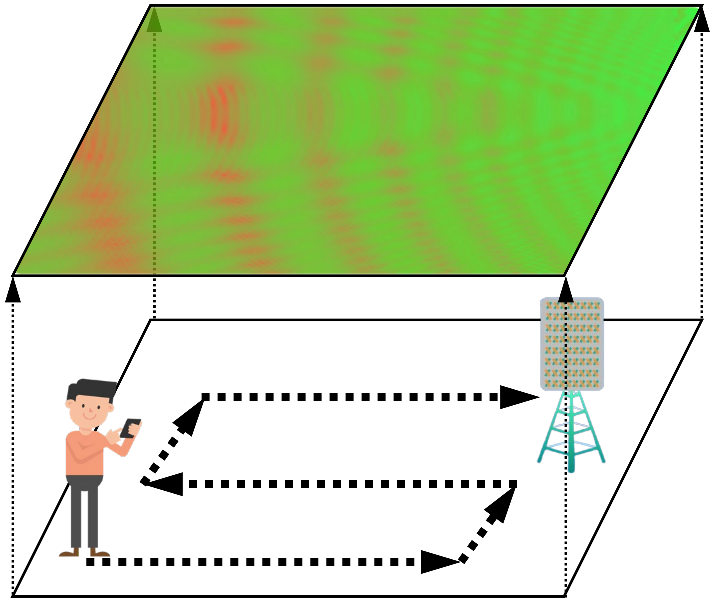
(3) The limited coverage data will **introduce biases** to the model.



5G Measurement Extrapolation Problem

5G Measurement Extrapolation Problem

Given a collection of 5G "signal" measurements collected in the **limited number of locations** in a target 5G coverage area:

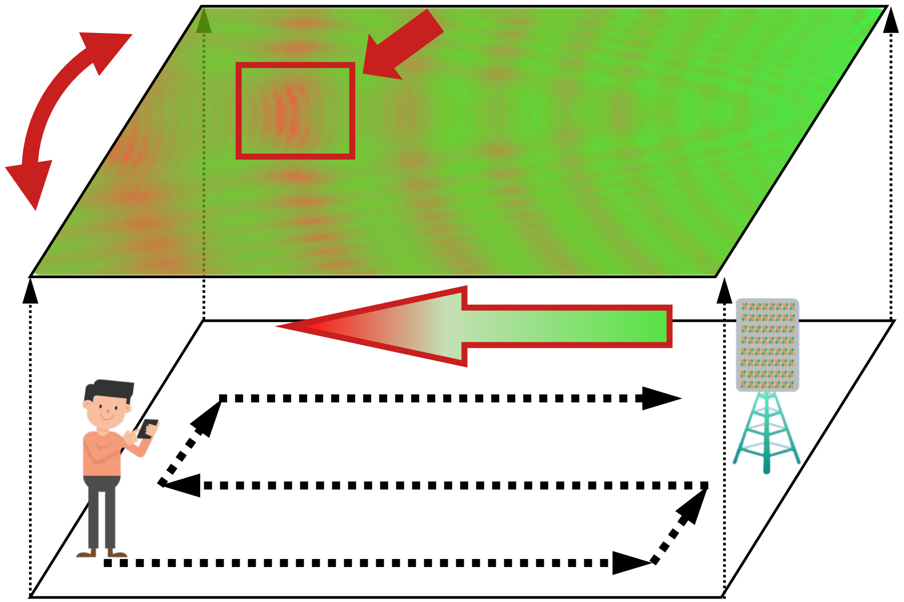


Can we infer or **extrapolate 5G "signals" at other locations** within the area that we do not have samples?

GNN is good at capturing spatial correlations!

SOTA GNNs Don’t Utilize RF Physical Characteristics

But, the state-of-art GNNs cannot take fully advantage of **physical characteristics** of 5G radio frequencies:



Global Properties:

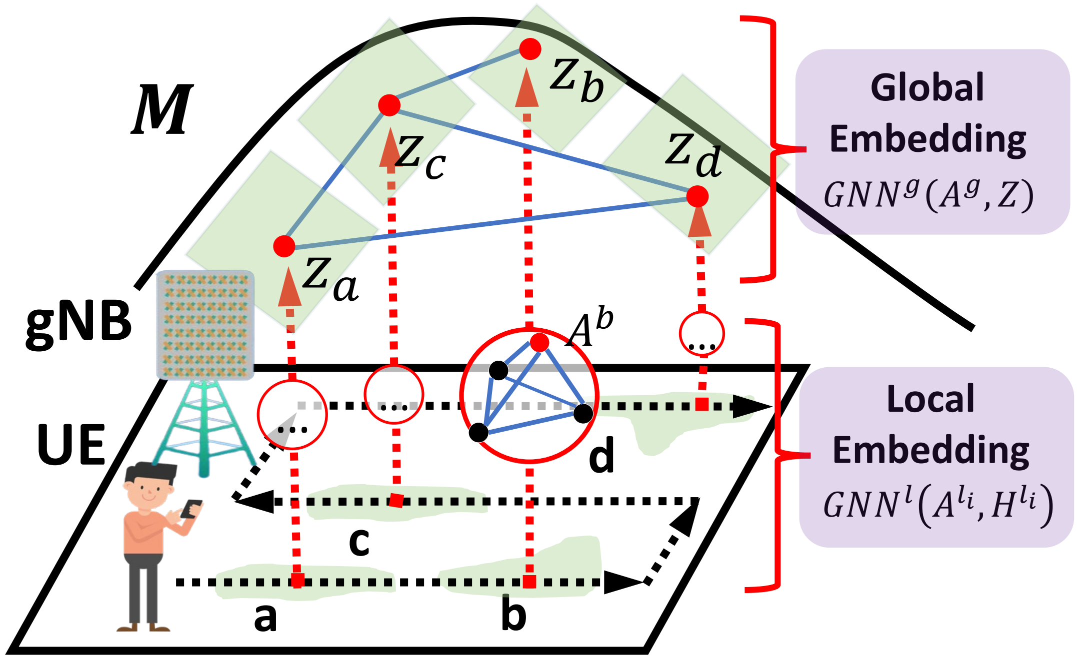
Radio signal propagation, attenuation, fading, and path losses

Local Properties:

signal waveform variations, noise, and interference

Our Solution → ***5GNN***

Proposed Method: 5GNN



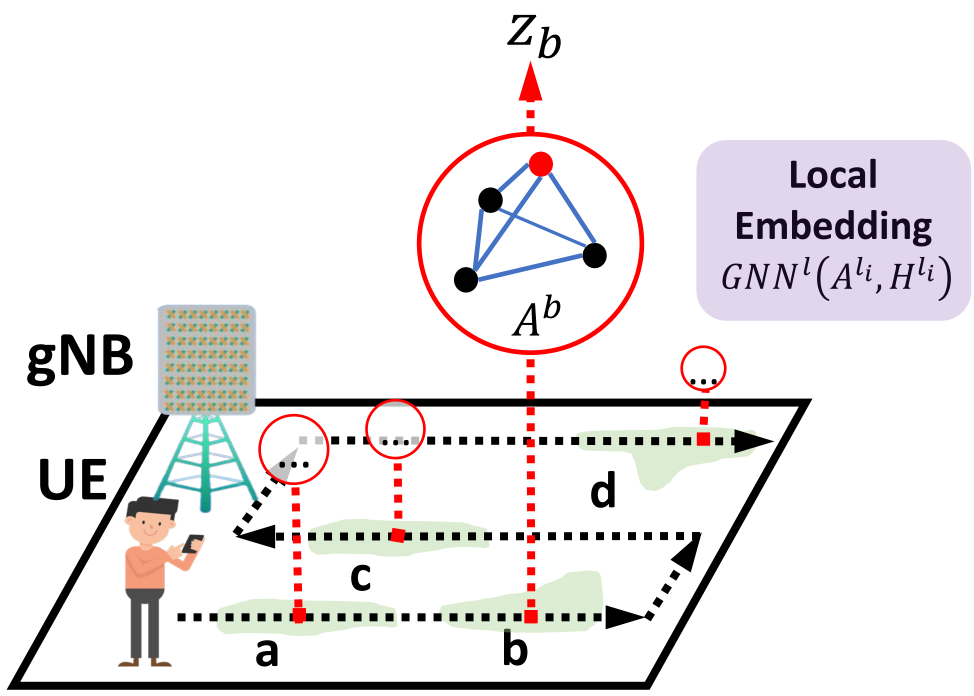
Radio Physical Characteristics

Radio signal propagation, attenuation, fading, and path losses

Local signal waveform variations, noise, and interference

5GNN is a tower information-free, physical-inspired, and graph-based learning approach.

Proposed Method: 5GNN



We aim to **learn a local ("smooth") embedding** of data points lying within a local neighborhood.

Radio signal's local characteristics:

Local signal waveform variations, noise, and interference

Stage 1: Local embedding

$$z_i = F(GNN^l(A^{l_i}, H^{l_i}))$$

$F(.)$ flattens the matrix into vector

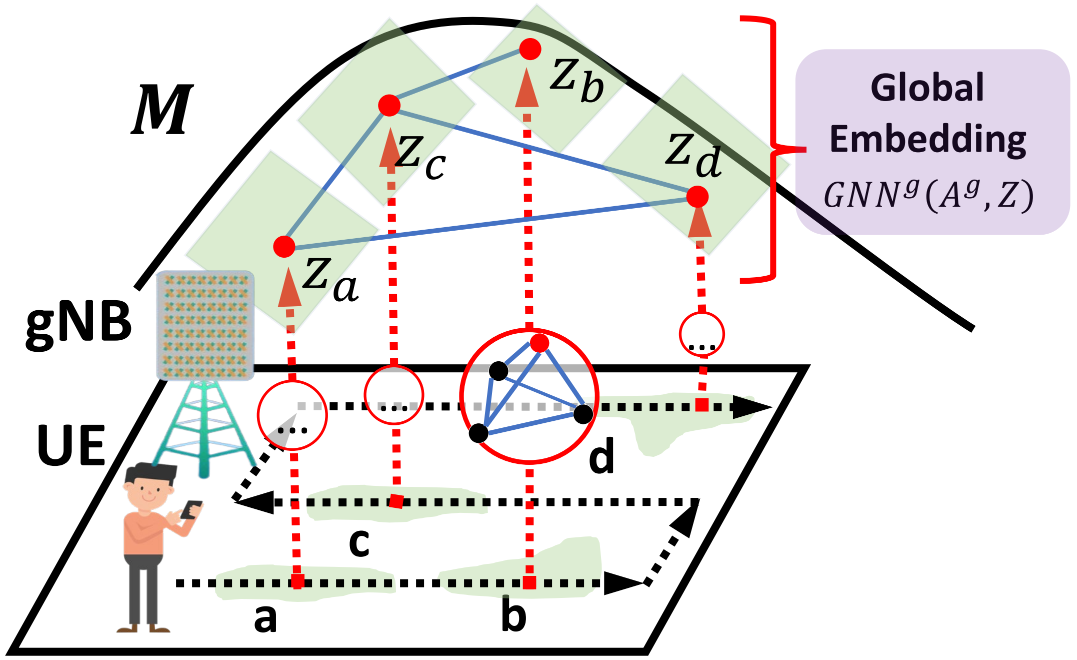
GNN^l is applied on the local graph and can be **any off-the-shelf baseline GNN model.**

For each data point i, sample the k-nearest neighboring $(j, k \in Nbr(i))$ into a local graph A^{l_i}.

$$A_{jk}^{l_i} = \exp(-\frac{d(c_j, c_k)}{2\sigma^2})$$

$$H^{l_i} = \begin{bmatrix} c_i & 0 & 0 \\ c_j & X_j & y_j \\ \dots & \dots & \dots \end{bmatrix} \begin{array}{l} \leftarrow \text{center node} \\ \leftarrow \text{neighbor node} \\ \end{array}$$

Proposed Method: 5GNN



We aim to **approximate the (global) 5G signal manifold** by patching together the local charts in an appropriate manner.

Radio signal's global characteristics:

Radio signal propagation, attenuation, fading, and path losses.

Stage 2: Global embedding

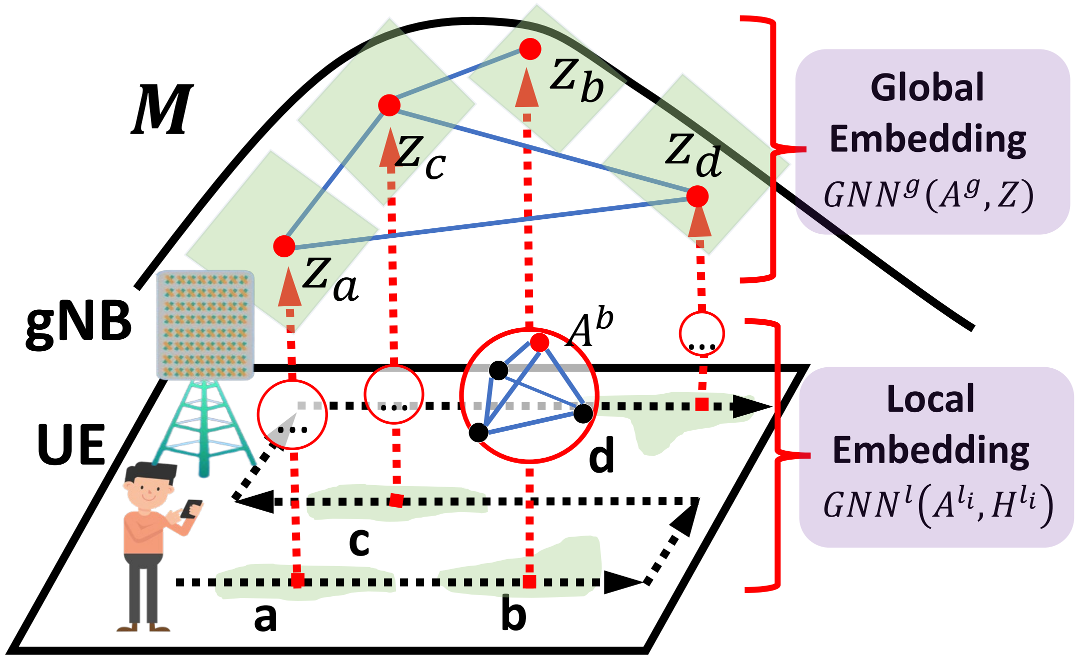
$$\hat{Z} = GNN^g(A^g, Z)$$

GNN^g is applied on the global graph and can be **any off-the-shelf baseline GNN model**.

We build a global kNN graph A^g over all the local charts.

$Z = [z_0, z_1, \dots, z_N]^T$ is the feature matrix

Proposed Method: 5GNN



Stage 3: Joint Training

$$\arg\min_{\theta} \; Loss(\boldsymbol{y}_{pred}, \boldsymbol{y}_{true})$$
$$\boldsymbol{y}_{pred} = MLP([\hat{Z}||Z])$$

Stage 2: Global embedding

Try to approximate the (global) 5G signal manifold.

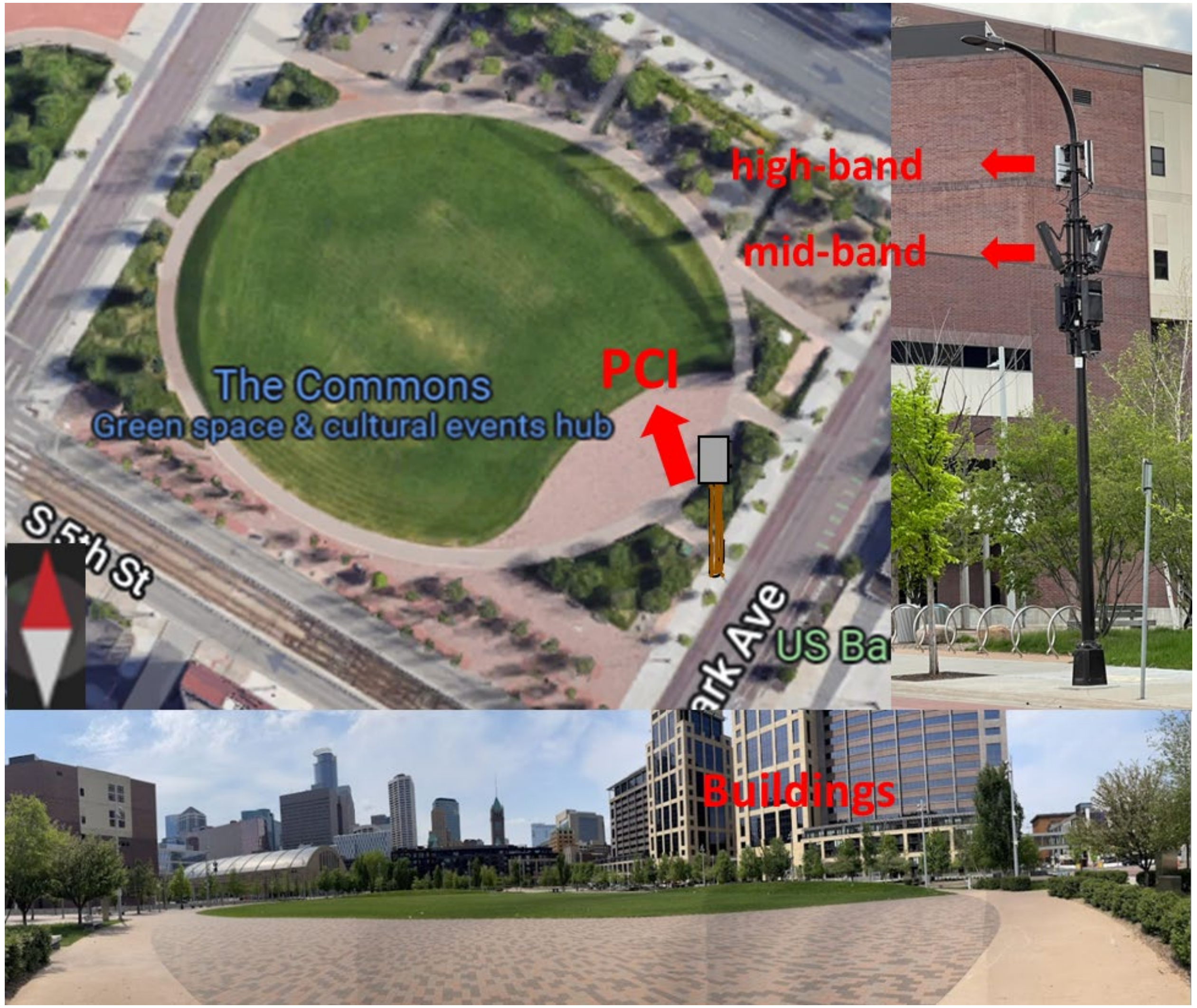
$$\hat{Z} = GNN^l(A^g, Z)$$
$$Z^g = kNN(\{\boldsymbol{p} \text{ in } \boldsymbol{Batch}\}) \qquad Z = [z_0, z_1, \ldots, z_N]^T$$

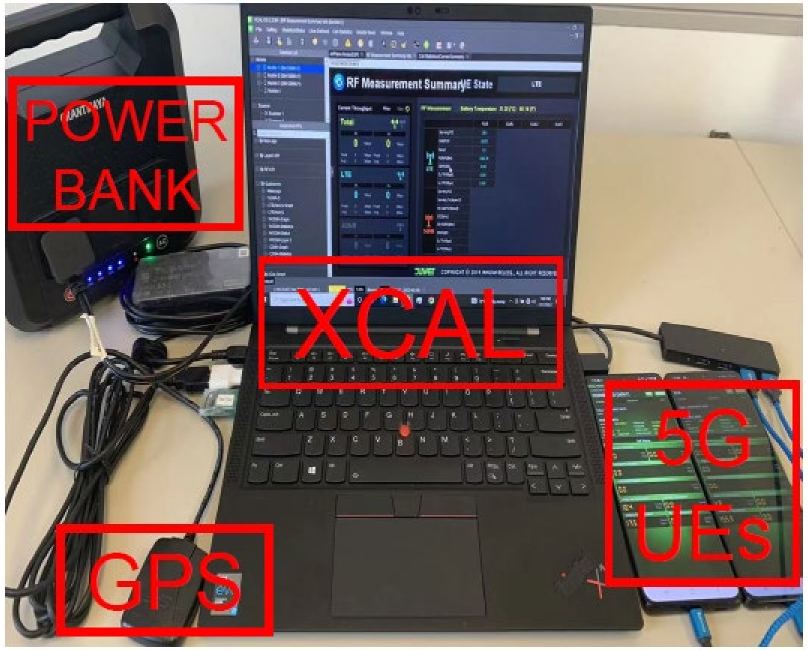
Stage 1: Local embedding

Try to learn a local ("smooth") embedding.

$$z_i = F(GNN^l(A^{l_i}, H^{l_i}))$$
$$A^{l_i}_{jk} = \exp(-\frac{d(c_j, c_k)}{2\sigma^2}) \qquad H^{l_i} = \begin{bmatrix} c_i & 0 & 0 \\ c_j & X_j & y_j \\ \ldots & \ldots & \ldots \end{bmatrix}$$

Measurement Campaigns



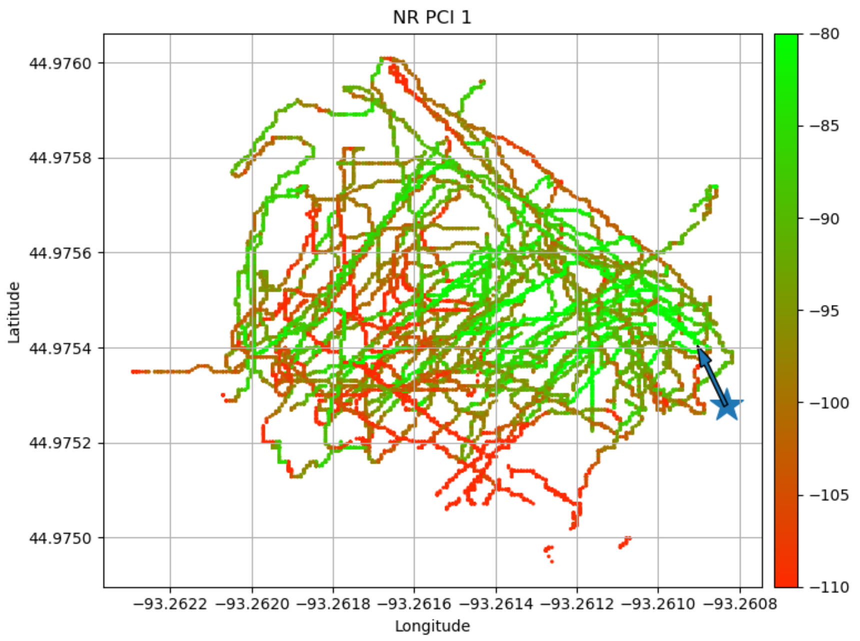


We conducted the **comprehensive measurement campaigns** with the professional tools at the public park covered by diverse 4G/5G bands.

Datasets

Summary of Collected Dataset

Total area covered	8000 m^2
Technologies	4G-lowBand/midBand; 5G-mmWave
Data samples	Total 200k+ with 100ms sampling rate



Data Fields of Signal Imputation Task

c	Longitude; Latitude Angle: the orientation angle of UE
y	BRSRP: filtered beam reference signal received power [dBm]

Data Fields of Channel Quality Regression Task

c	Longitude; Latitude Angle: the orientation angle of UE
X	ss-RSRP: synchronize signal reference signal received power [dBm] ss-RSRQ: synchronize signal reference signal received quality [dB] csi-RSRP [SSBRI]: CSI reference signal received power [dBm] csi-RSRP [CRI]: CSI reference signal received power [dBm] SINR: signal to interference & noise ratio [dB] Pathloss: reduction in power density as signal propagates [dB] BLER: block error rate [%]
y	CQI: channel quality indicator

We use the **collected commercial 5G data** and **DeepMIMO simulated data** for evaluation.

Evaluation Setup

- We compare 5GNN with other **Two** state-of-the-art learning **Paradigms** (*PE-GNN [NeurIPS-ws'22]* and *Kriging-GNN [AAAI'20]*) for "geography inference" problems.

- We consider **Three** representative **baseline GNNs** (*GCN [ICLR'17], GraphSAGE [NeurIPS'17],* and *GIN [ICLR'19]*) to combine with above learning paradigms.

- We also consider **one** widely-used classical statistics-based method (Universal Kriging).

Error rate of *5GNN* vs. state-of-art learning paradigms

Results of Signal Imputation Task

Note: P1 denotes PE-GNN paradigm; P2 is Kriging-GNN paradigm.

Datasets	Metrics	RK	GCN		
			P1	P2	5GNN
DeepMIMO_Mid	RMSE	0.0465	0.0584	0.0451	**0.0440**
	MAE	0.0342	0.0444	0.0334	**0.0320**
DeepMIMO_High	RMSE	0.0767	0.0722	0.0720	**0.0701**
	MAE	0.0584	0.0552	0.0550	**0.0535**
4G_Signal_Low	RMSE	0.1840	0.1216	0.1129	**0.1076**
	MAE	0.1430	0.0955	0.0864	**0.0784**
4G_Signal_Mid	RMSE	0.0899	0.0943	0.0849	**0.0806**
	MAE	0.0684	0.0740	0.0662	**0.0616**
5G_Signal_High	RMSE	0.1588	0.1598	0.1453	**0.1366**
	MAE	0.1201	0.1297	0.1156	**0.1015**

- *5GNN* is **consistently** superior other graph-based learning **Paradigms**.
- It reduces errors up to **12.8%** on the imputation task.

Results of Signal Imputation Task

Note: P1 denotes PE-GNN paradigm; P2 is Kriging-GNN paradigm.

Datasets	Metrics	RK	GCN P1	GCN P2	5GNN
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	MAE	0.1201	0.1297	0.1156	**0.1015**

- *5GNN* also outperforms the Kriging methods and reduces up to **25.3%** error rates on the **5G high band**.

Results of Channel Quality Regression Task

Note: P1 denotes PE-GNN paradigm; P2 is Kriging-GNN paradigm.

Datasets	Metrics	RK	GCN P1	GCN P2	GCN 5GNN
4G_CQI_Low	RMSE	0.1840	0.1859	0.1710	**0.1611**
	MAE	0.1430	0.1518	0.1365	**0.1259**
4G_CQI_Mid	RMSE	0.1435	0.1387	**0.1328**	**0.1328**
	MAE	0.1092	0.1113	0.1053	**0.1017**
5G_CQI_High	RMSE	0.1926	0.1818	0.1724	**0.1643**
	MAE	0.1516	0.1523	0.1417	**0.1287**

- *5GNN* reduces errors up to **9.2%** on the regression task.
- *5GNN* can efficiently capture signals' **local and global spatial correlations**.

5GNN is Compatible with Different GNNs

Signal Imputation Task

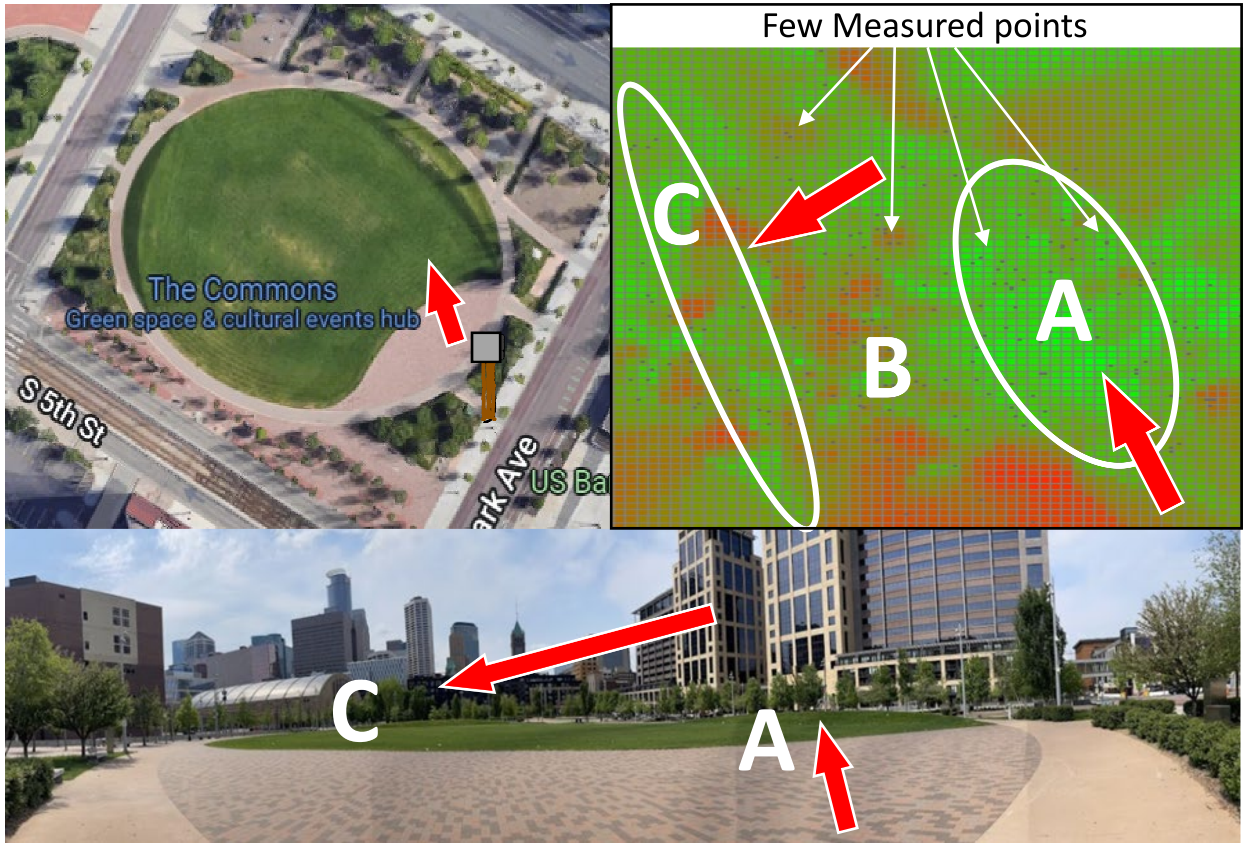
Datasets	Metrics	UK	GCN			GraphSAGE			GIN		
			P1	P2	5GNN	P1	P2	5GNN	P1	P2	5GNN
DeepMIMO_Mid	RMSE	0.0465	0.0584	0.0451	0.0440	0.0559	0.0438	0.0437	0.0531	0.0458	**0.0436**
	MAE	0.0342	0.0444	0.0334	0.0320	0.0423	**0.0315**	**0.0315**	0.0410	0.0344	0.0316
DeepMIMO_High	RMSE	0.0767	0.0722	0.0720	0.0701	0.0723	0.0696	**0.0690**	0.0722	0.0719	0.0703
	MAE	0.0584	0.0552	0.0550	0.0535	0.0552	0.0524	**0.0519**	0.0555	0.0545	0.0537
4G_Signal_Low	RMSE	0.1250	0.1216	0.1129	0.1076	0.1039	**0.1018**	0.1020	0.1223	0.1130	0.1071
	MAE	0.0915	0.0955	0.0864	0.0784	0.0771	0.0758	**0.0745**	0.0964	0.0874	0.0787
4G_Signal_Mid	RMSE	0.0899	0.0943	0.0849	0.0806	0.0887	0.0796	**0.0795**	0.0939	0.0851	0.0816
	MAE	0.0684	0.0740	0.0662	0.0616	0.0688	**0.0603**	**0.0603**	0.0735	0.0663	0.0622
5G_Signal_High	RMSE	0.1588	0.1598	0.1453	0.1366	0.1218	0.1194	**0.1187**	0.1574	0.1457	0.1361
	MAE	0.1201	0.1297	0.1156	0.1015	0.0889	0.0863	**0.0855**	0.1260	0.1157	0.1009

Channel Quality Regression

Datasets	Metrics	UK	GCN			GraphSAGE			GIN		
			P1	P2	5GNN	P1	P2	5GNN	P1	P2	5GNN
4G_CQI_Low	RMSE	0.1840	0.1813	0.1710	0.1611	0.1754	**0.1594**	0.1605	0.1809	0.1712	0.1602
	MAE	0.1430	0.1460	0.1365	0.1259	0.1416	**0.1234**	0.1252	0.1472	0.1370	0.1247
4G_CQI_Mid	RMSE	0.1435	0.1336	0.1328	0.1328	0.1310	0.1278	**0.1276**	0.1345	0.1364	0.1329
	MAE	0.1092	0.1042	0.1053	0.1017	0.1029	0.0982	**0.0972**	0.1045	0.1076	0.1015
5G_CQI_High	RMSE	0.1926	0.1730	0.1724	0.1643	0.1751	0.1645	**0.1629**	0.1748	0.1726	0.1638
	MAE	0.1516	0.1455	0.1417	0.1287	0.1469	**0.1279**	**0.1279**	0.1493	0.1422	0.1292

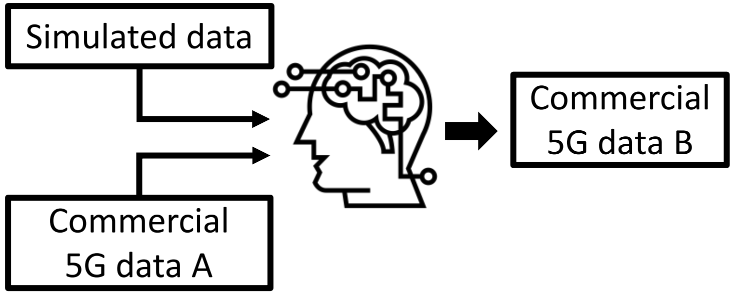
- *5GNN* is **consistently** superior over different baseline GNNs.

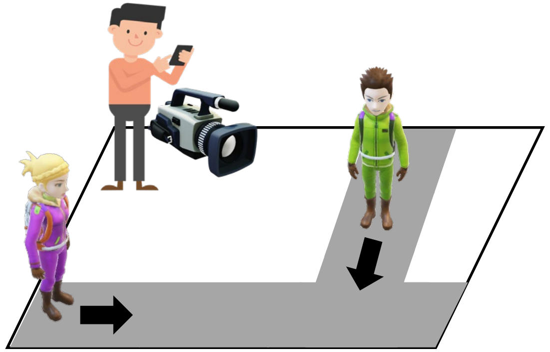
Visualization of Radio Maps



5GNN can efficiently **generate the radio map** based on the **few** measured data points, thus assisting future measurements.

Ongoing and Future Works





Machine learning model generalization ability

Real-time environmental perception

AI-assisted measurement route recommendation

Summary

- Put forward the **5G measurement extrapolation problem**
  - Demonstrate 5G measurement is low efficient.
  - Argue for the need to account for **local** and **global** dependencies in extrapolation problem.
- Propose ***5GNN***
  - A tower information-free, physical-inspired, and graph-based learning paradigm.
  - *5GNN* reduces the error rates (up to) **12.8%** and **9.2%** on the signal imputation task and channel quality regression task.
- Conduct comprehensive **Experiments**
  - Collect the commercial 5G network data.
  - For dataset access, codes and more info, visit us @

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