5GNN: Extrapolating 5G Measurements through GNNs

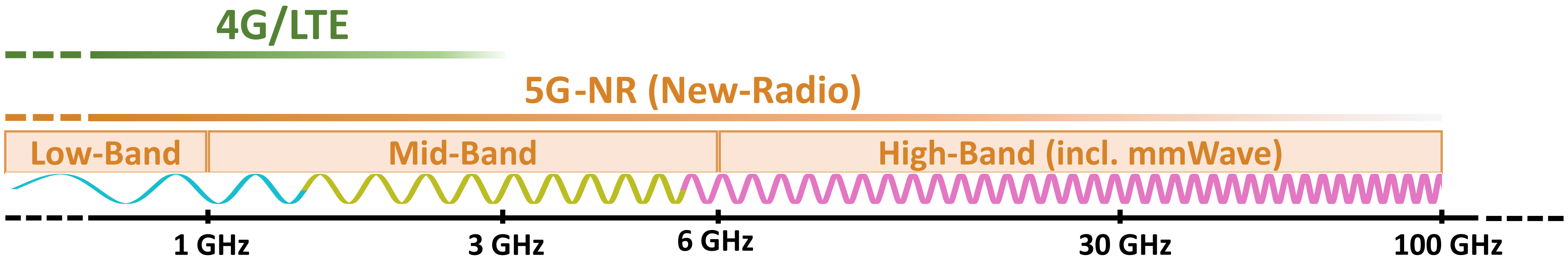
https://github.com/StrongWeiUMN/5GNN

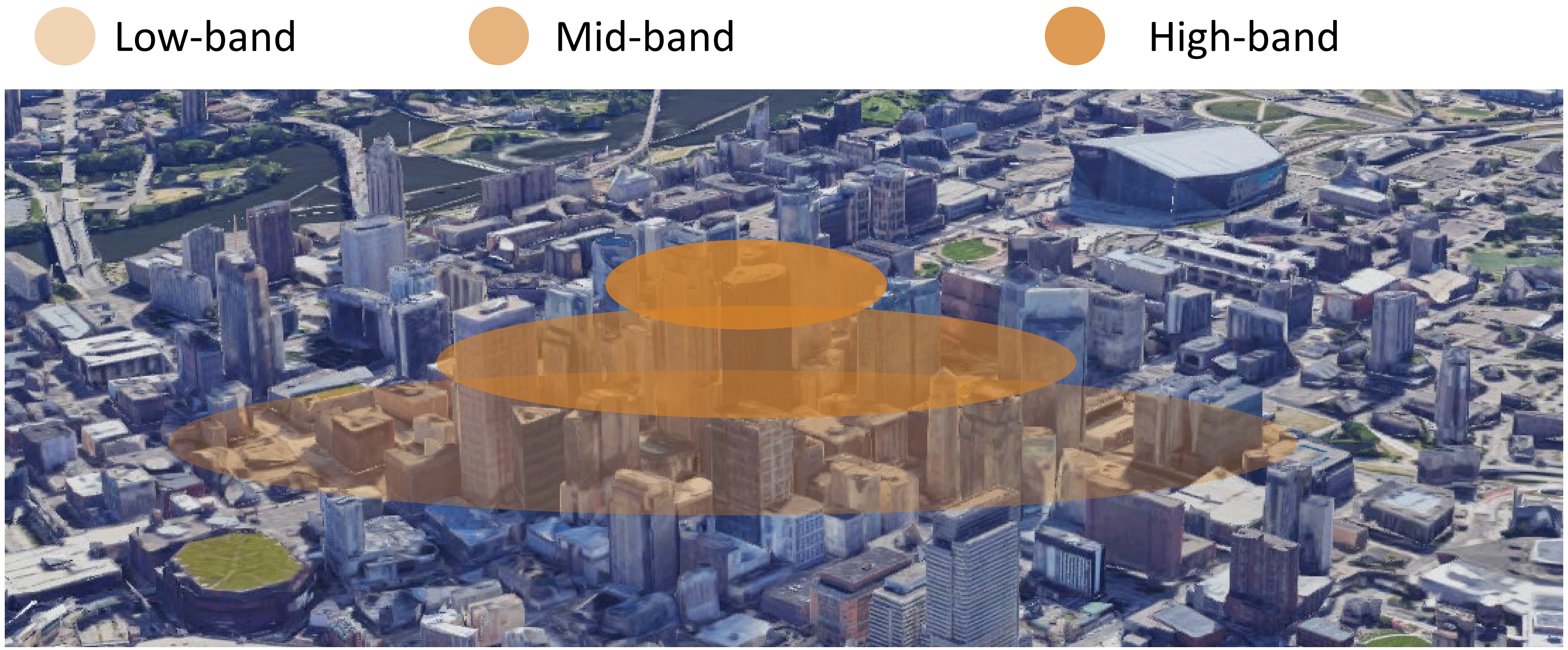
Wei Ye, Xinyue Hu, Tian Liu, Ruoyu Sun,
Yanhua Li, **Zhi-Li Zhang**

University of Minnesota

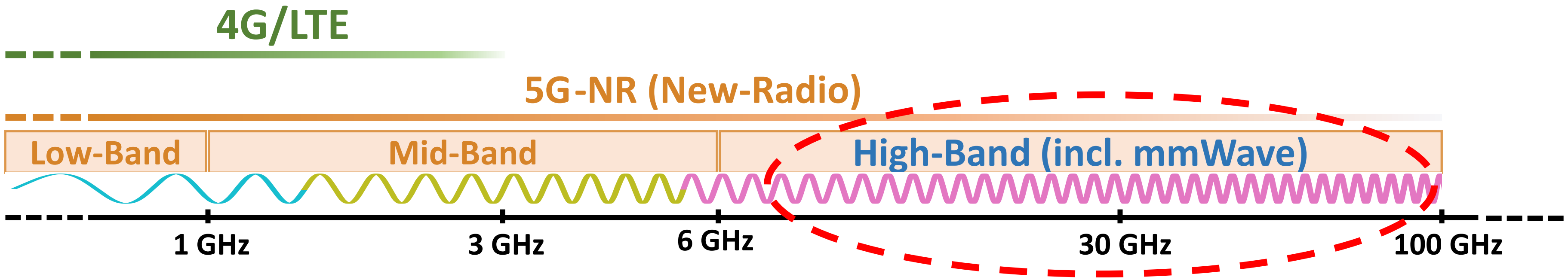
Worcester Polytechnic Institute 1865 Lehr und Kunst

5G Spectrum Bands





5G High Band and mmWave 5G

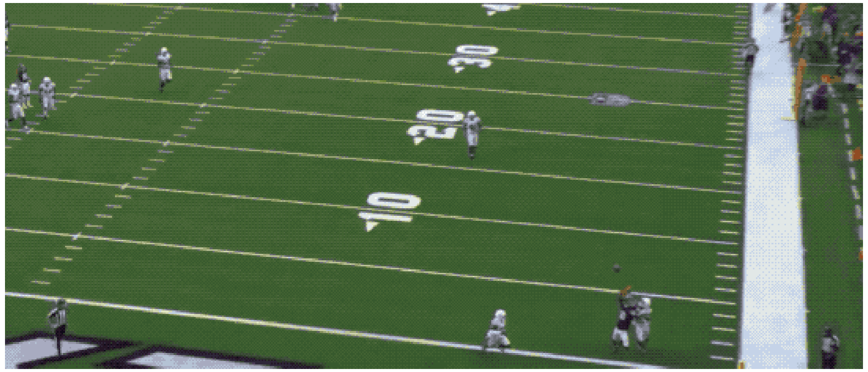


With theoretical throughput up to 20 Gbps!

Key to support apps requiring ultra-high bandwidth

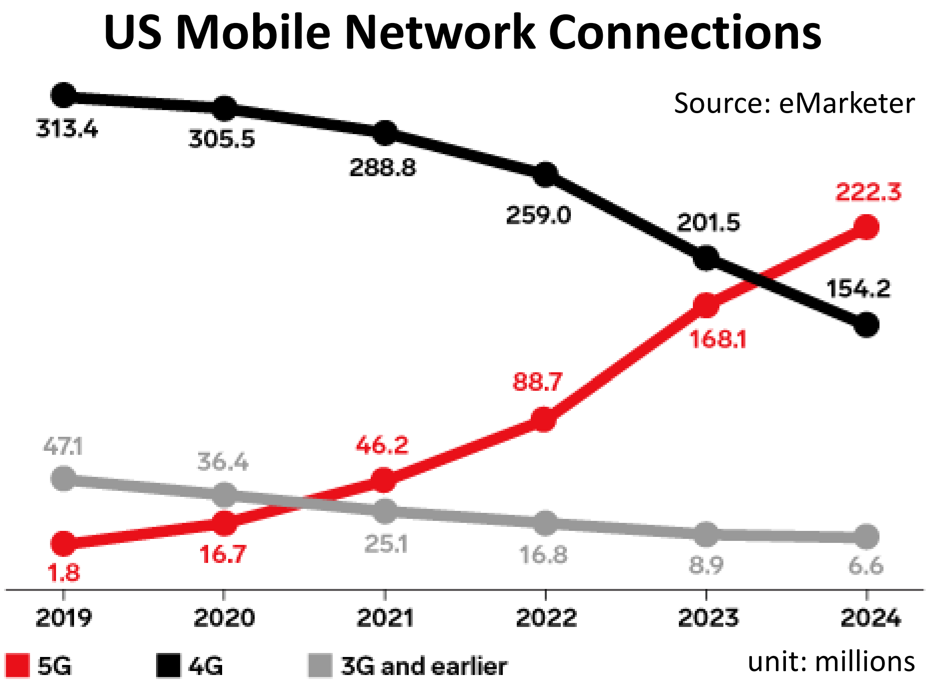
AR/VR Services

Source: Intel True View



Volumetric Content Delivery

Commercial 5G Measurement



5Gopher: Mapping throughput

5G Beam: Beam coverage

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

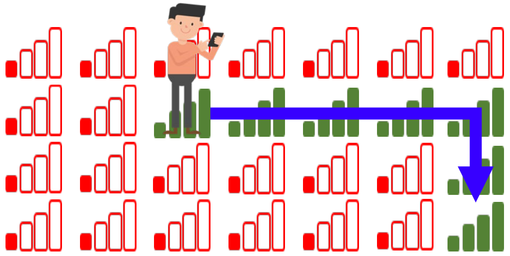
Commercial 5G Measurement - Limitations

However,

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

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

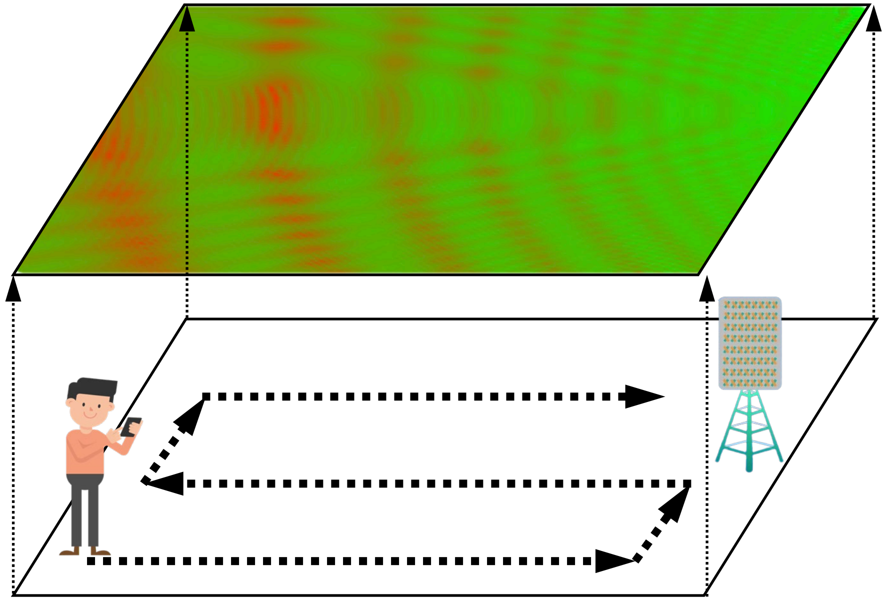
(3) The limited coverage data will **introduce biases** to the model.



5G Measurement Extrapolation Problem and Our Solution → ***5GNN***

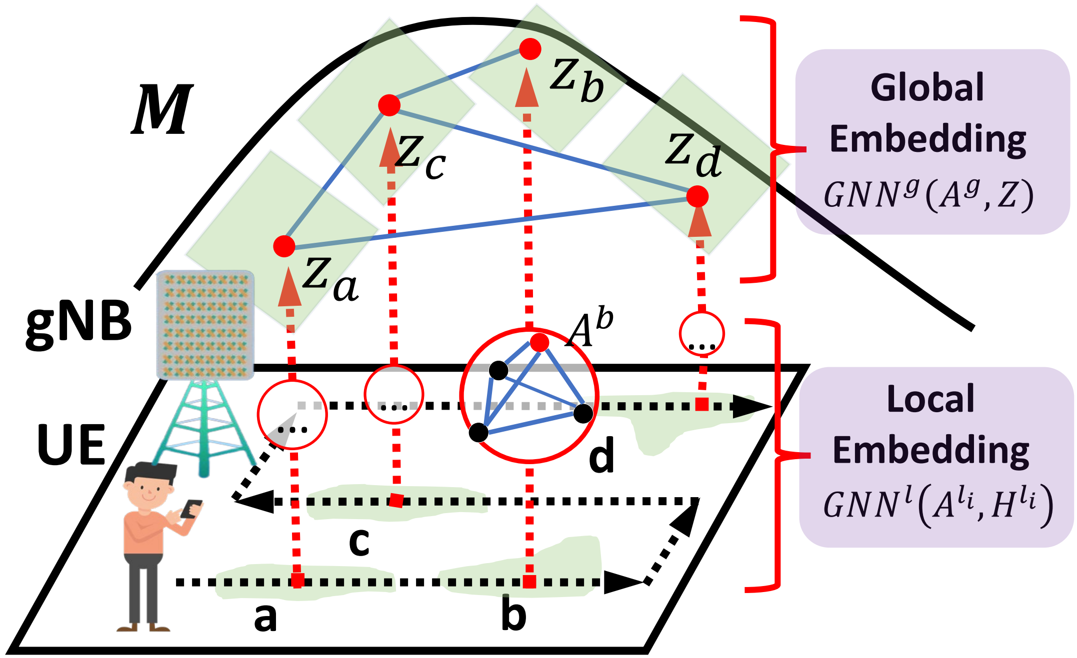
5G Measurement Extrapolation Problem

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?

Proposed Method: 5GNN



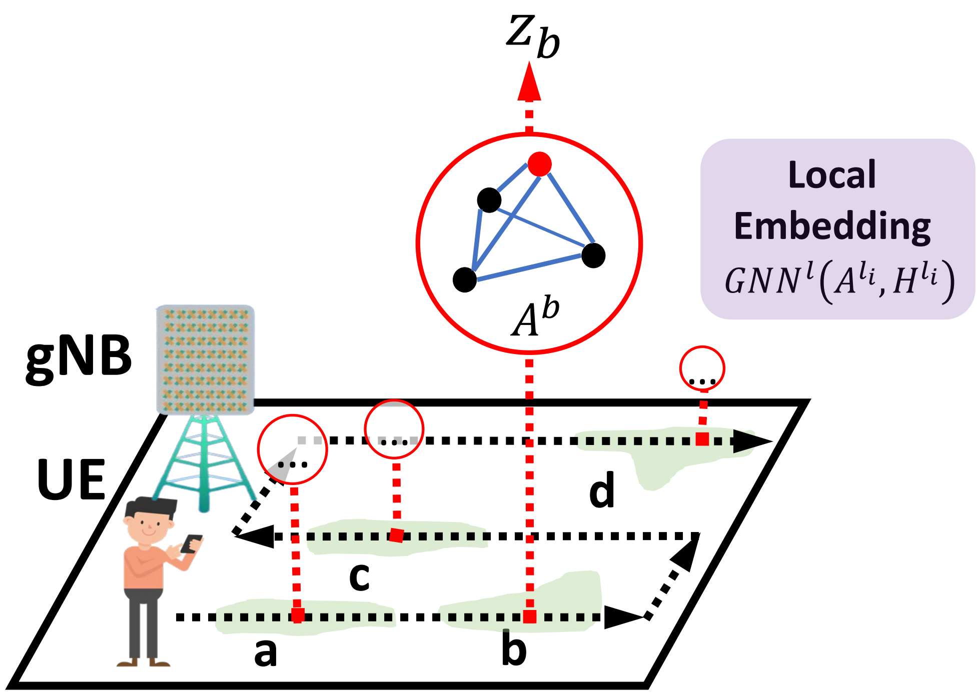
Radio Physical Characteristics

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

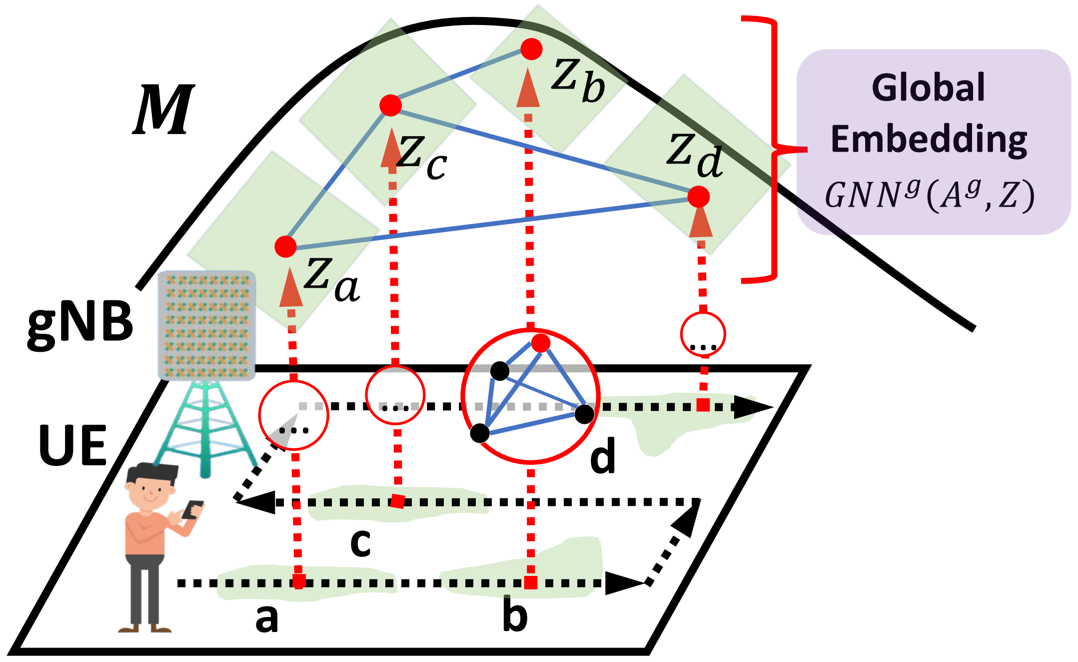
GNN^l is applied on the local graph and can be any off-the-shelf baseline GNN model.

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

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

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

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

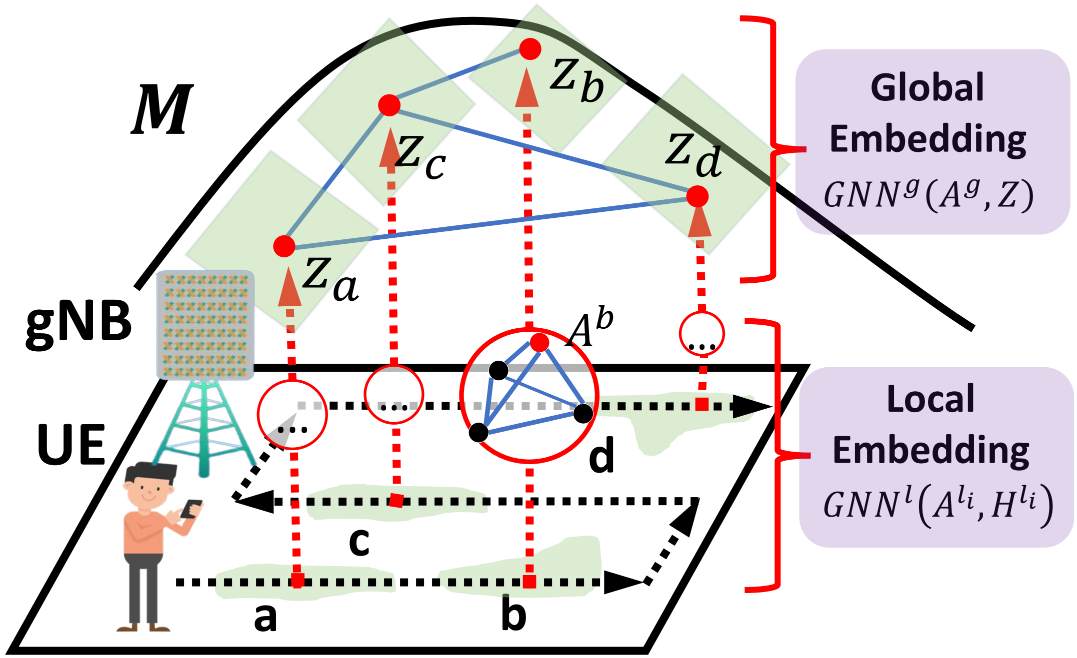
$$\hat{Z} = GNN^g(A^g, Z)$$

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.

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

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

Stage 1: Local embedding

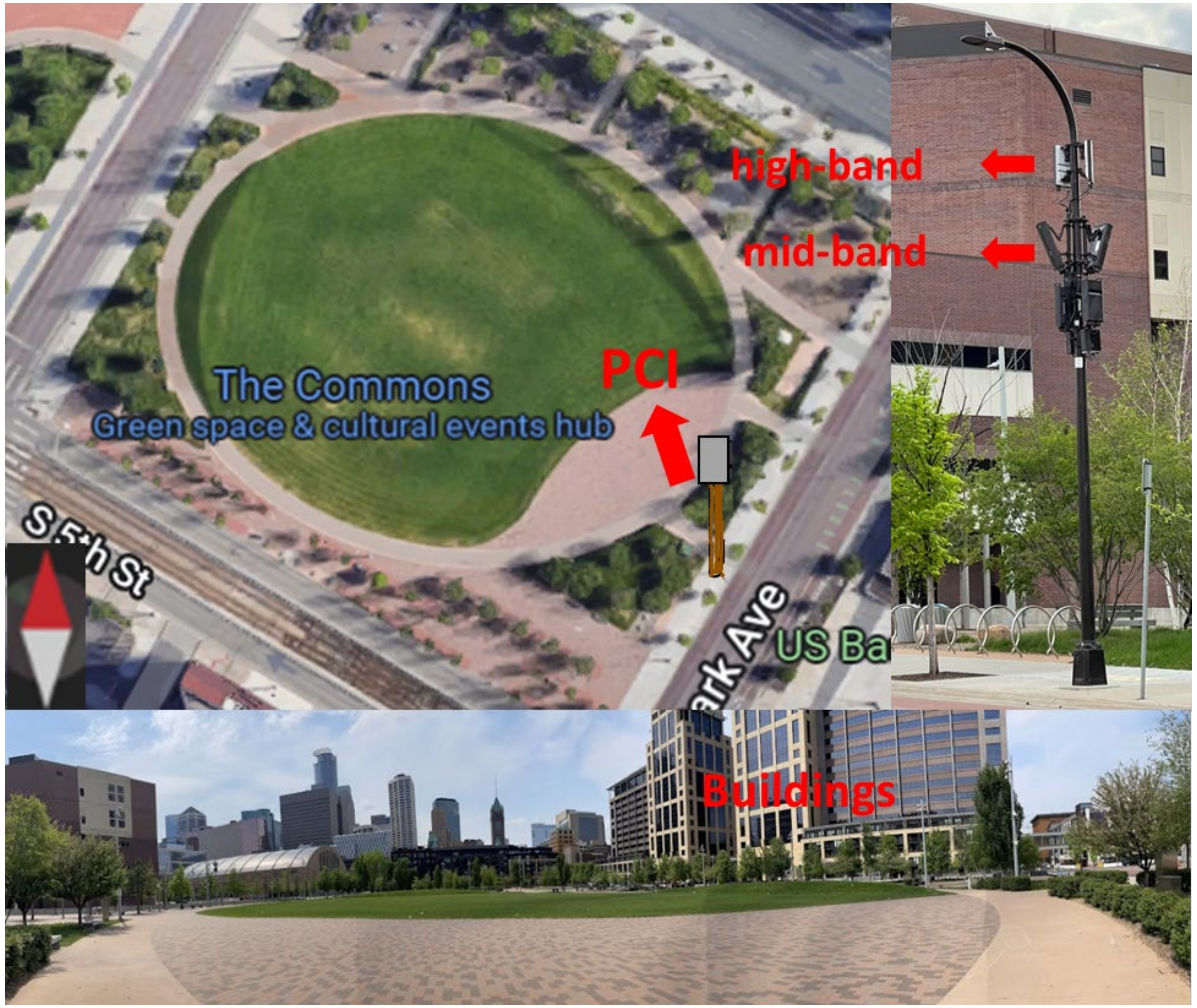
Try to learn a local ("smooth") embedding.

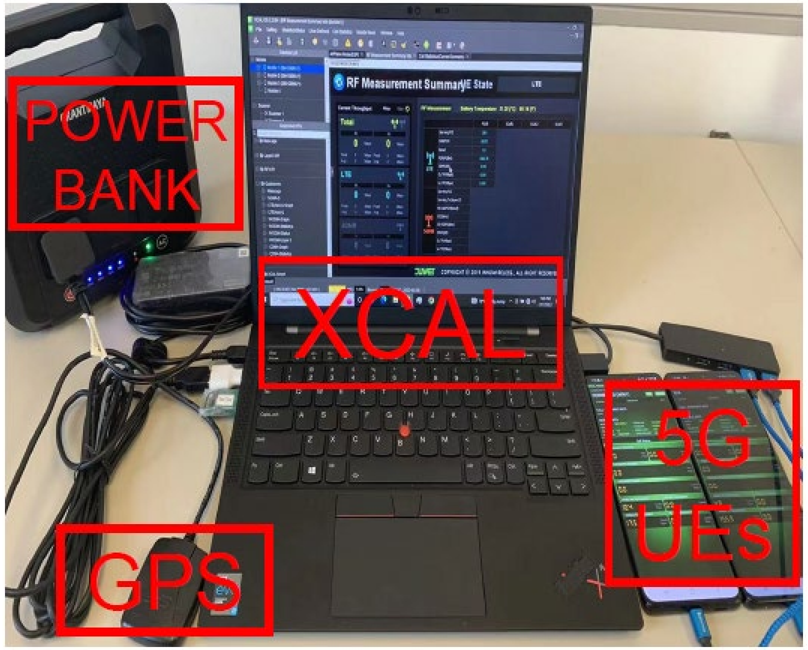
$$z_i = F(GNN^l(A^{l_i}, H^{l_i}))$$

$$A_{jk}^{l_i} = \exp(-\frac{d(c_j, c_k)}{2\sigma^2}) \qquad H^{l_i} = \begin{bmatrix} c_i & 0 & 0 \\ c_j & X_j & y_j \\ \dots & \dots & \dots \end{bmatrix}$$

Back propagation

Measurement Campaigns





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

Datasets

Table 1: Key Statistics of Real-World Datasets

Scenario	Public Square
Total area covered	8,000 m^2
Technologies	4G-lowBand/midBand; 5G-highBand
Data samples	Total 200k+ with 100ms sampling rate
Tasks	Signal strength imputation Channel quality regression

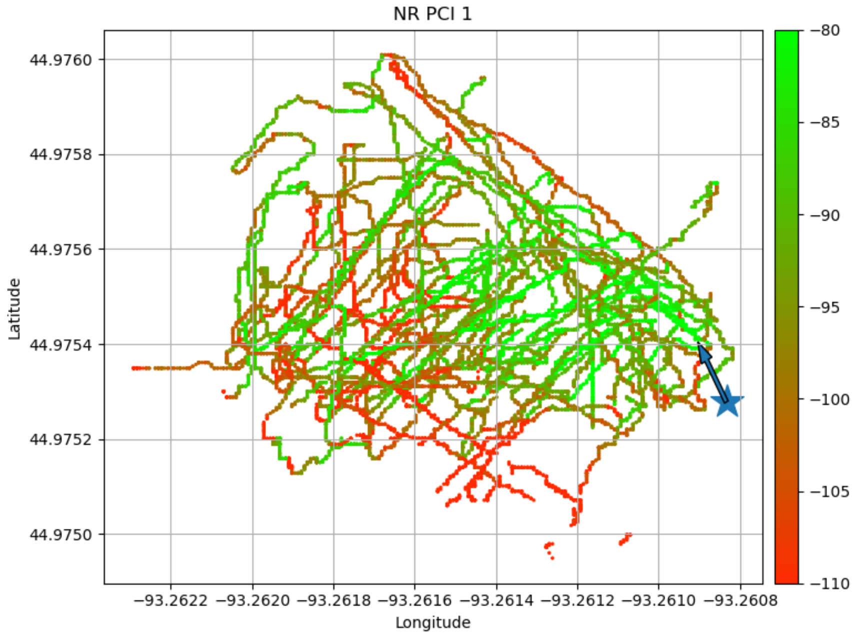


Table 2: Fields of signal strength imputation task.

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

Table 3: 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

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

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

- *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

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

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

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

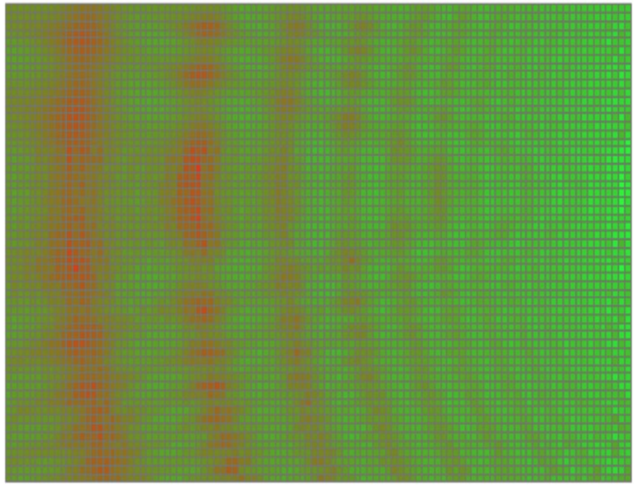
Results of Channel Quality Regression Task

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

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

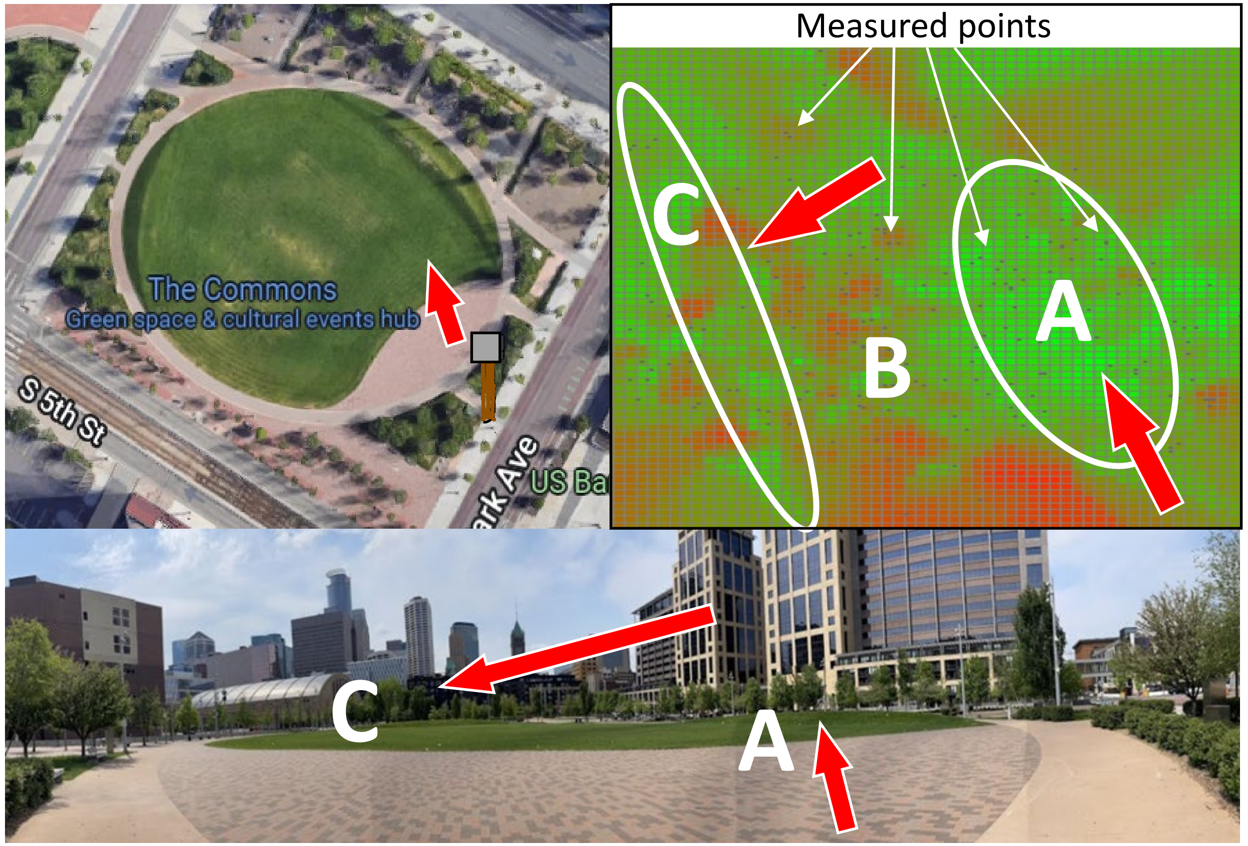
- *5GNN* reduces errors up to **9.2%** on the regression task.
- *5GNN* is a better choice for signal imputation and channel quality regression tasks by efficiently capturing signals' **local and global spatial correlations**.

Visualization of Radio Maps



Reconstruction results of DeepMIMO mid-band, where we can observe signal's local and global patterns

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



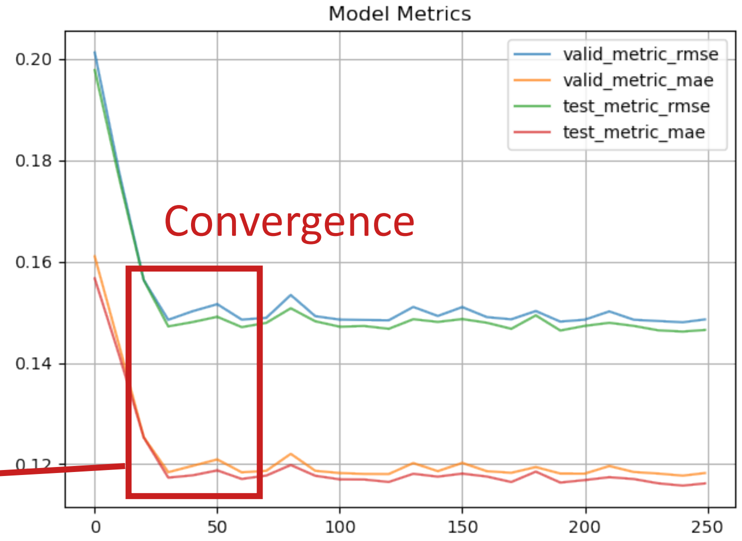
Reconstruct results of commercial 5G high-band

Discussions on Running Time

We use 64 vCPU cores for universal kriging, while 8 vCPU cores with 1 GPU for other GCN-based methods. Those machines **cost the same price** on AWS as a fair comparison.

	Training Time		Inference Time
UK	182.4 s		0.135 ms/sample
GCN-P1	0.39 s/epoch	45 epochs	0.006 ms/sample
GCN-P2	0.18 s/epoch	42 epochs	0.178 ms/sample
GCN-5GNN	0.29 s/epoch	46 epochs	0.183 ms/sample

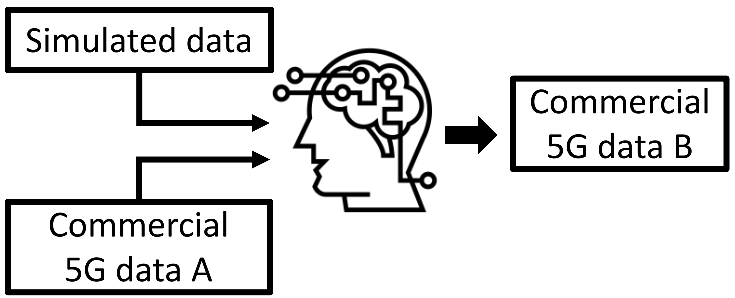
Note: P1 denotes PE-GNN paradigm; P2 is Kriging-GNN paradigm.

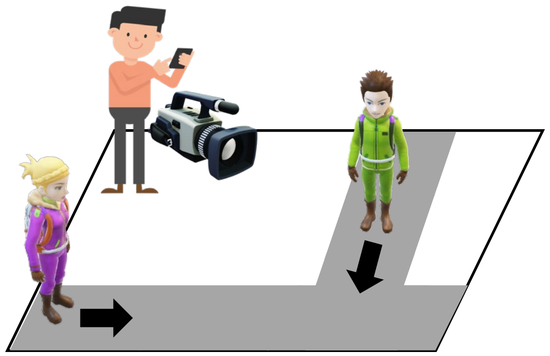


- Different learning paradigms have **different characteristics** of training/inference time.

- *5GNN* is competitive with other methods and can **meet the requirements** for real-world measurement, considering each measurement run usually takes tens of minutes.

Ongoing and Future Works





Machine learning model generalization ability

Real-time environmental perception

AI-assisted measurement route recommendation

Summary

Address the **5G measurement extrapolation problem**.

Argue for the need to account for both **local** and **global** dependencies in 5G signal and feature maps.

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, compared to other state-of-art methods on both synthetic and real-world datasets.

Conduct field experiments to collect the **commercial 5G network data** for this study.

For dataset access and more info, visit us @

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University of Minnesota

Worcester Polytechnic Institute