Virtual Graph Neural Networks: A Novel Approach for Building-Agnostic Indoor Positioning Systems

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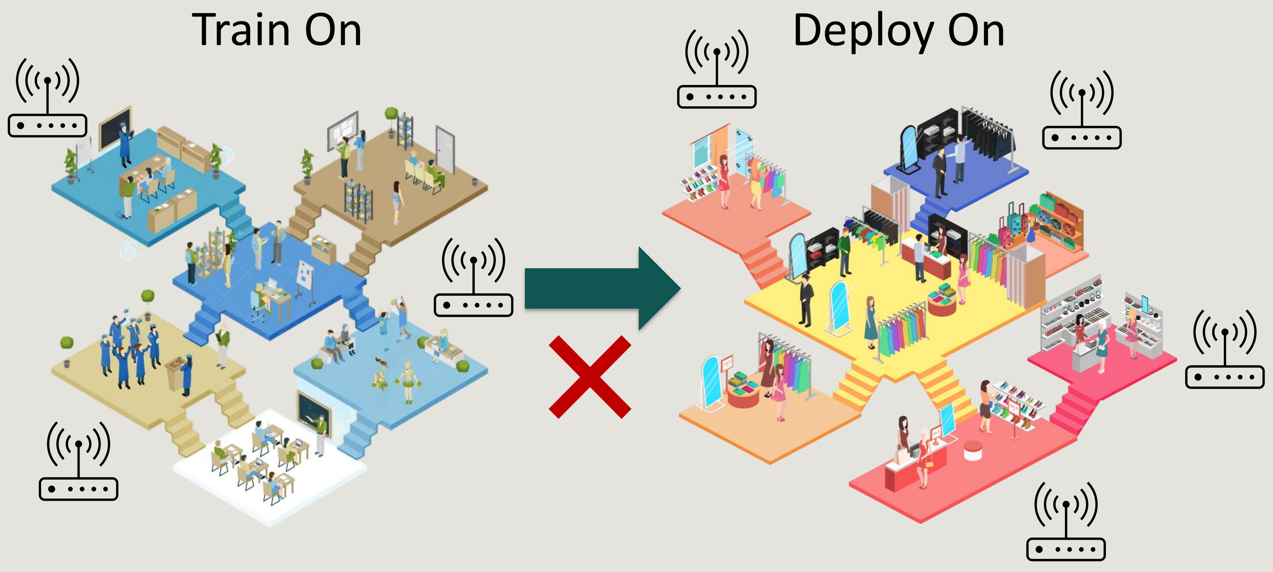
Challenges

Indoor localizations systems often face the following challenges:

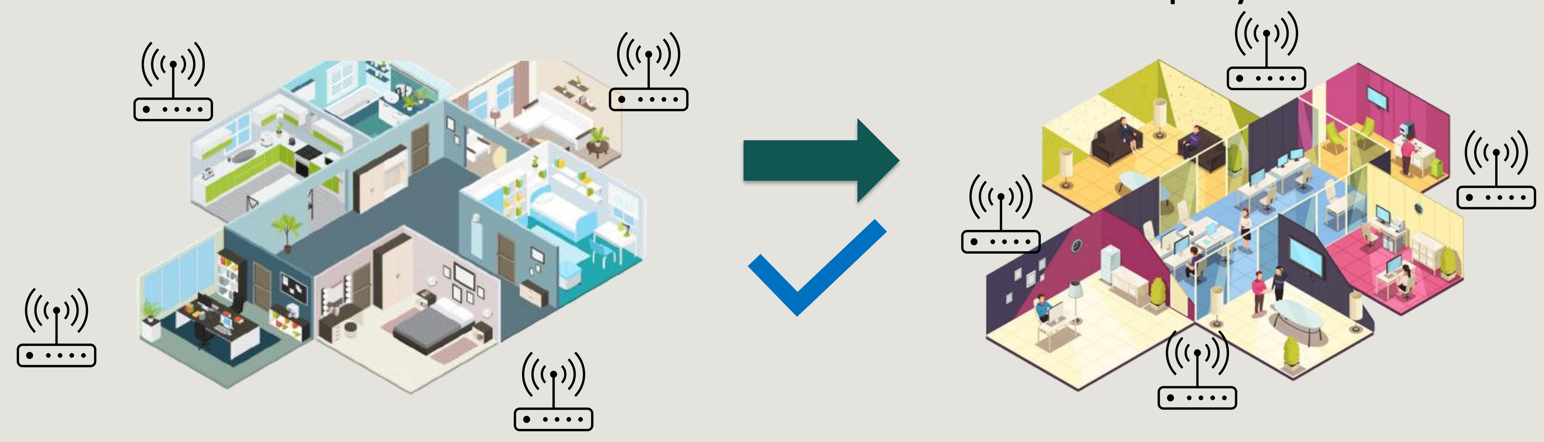
- Network configuration changes lead to performance degradation.
- Lack of generalizability to unseen environment, systems are usually trained and deployed on the same environment.
- Need additional data collection, retraining or fine-tuning to handle changes in environment.



Motivation & Objectives

There is an increasing need for robust and accurate indoor localization services that are not only precise but are able to adapt to new environments without additional data collection overhead or model retraining.

We aim to develop a system that can learn environment-invariant features that are robust to changes in network configuration and can **generalize to unseen environments without additional data collection or model retraining**.

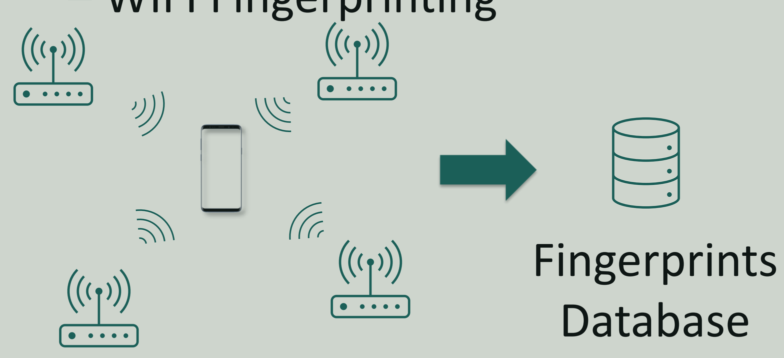


Methodology

Basic Idea

Virtual Representation → Virtual Graph Representation / Heterogeneous Graphs + Graph Neural Network = Building-Agnostic Localization

1 Data Collection at a **single** or more buildings – WIFI Fingerprinting



2 Mapping Scans to **Virtual Representation**

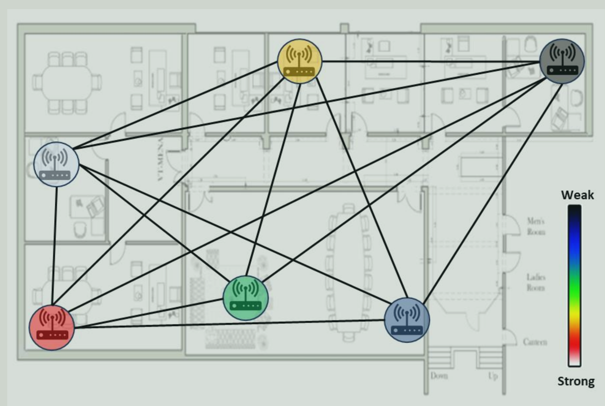
Normalize Coordinates of APs, and scans around AP with strongest RSSI

APs	AP_1	AP_2	AP_3	...	AP_N	AP-(x,y)
AP-(x,y)	1,2	2,2	3,3	...	0, 0	N/A
Scan#1	-30	-20	-21	...	-90	2, 3

APs	AP_1	AP_2	AP_3	...	AP_N	AP-(x,y)
AP-(x,y)	-1,0	0,0	1,1	...	-2, -2	N/A
Scan#1	-30	-20	-21	...	-90	0, 1

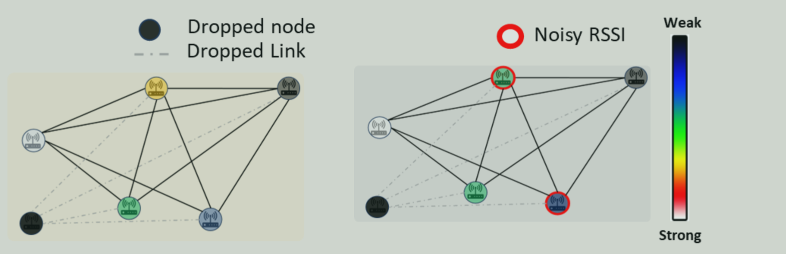
3 **Virtual Graph** Construction

Construct graph using k APs with strongest RSSI values, edges are weighted by distance between AP_i and AP_j



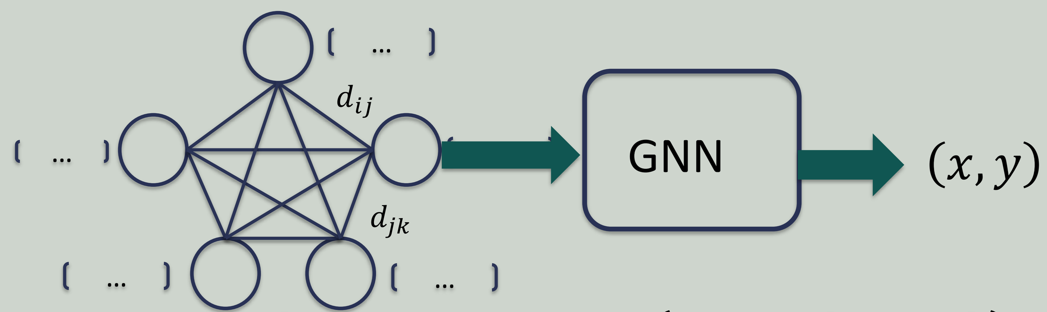
Graph Augmentation

Ensure the online adaptability of the localization models even when specific APs are unavailable using the random AP dropping and noise addition.



4 **Model Trainer**

Train GNN using MSE to predict 2D coordinates relative to AP with the strongest RSSI

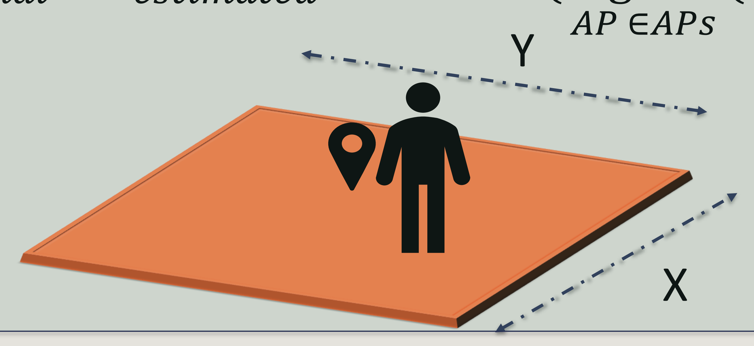


$$l_{estimated} = GNN(Virtual\ Graph)$$

5 **De-Normalize Estimates**

Retrieve the original building g coordinates given the AP with the strongest RSSI.

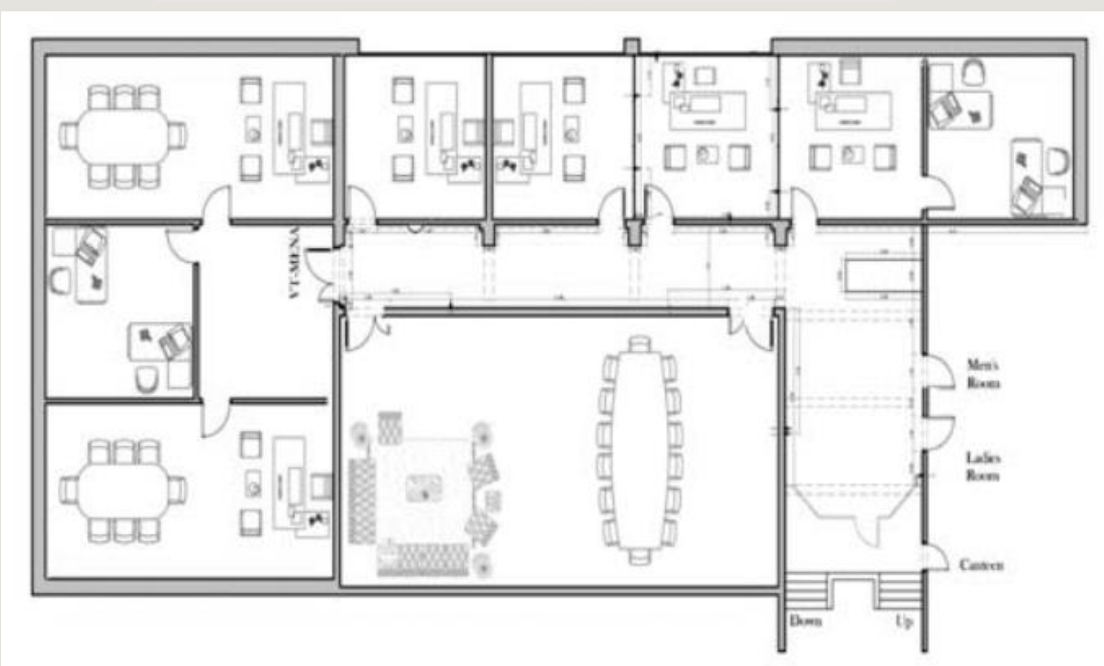
$$l_{final} = l_{estimated} + Coords(\operatorname{argmax}_{AP \in APs}(RSSI(AP)))$$



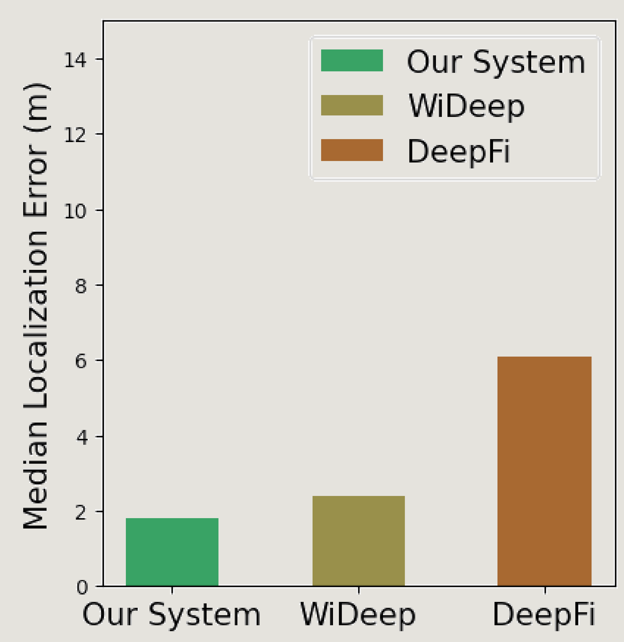
Evaluation

Training Building

Method	Precision
Area	$37m \times 17m$
# Points	29
# APs	122
# Samples	7200

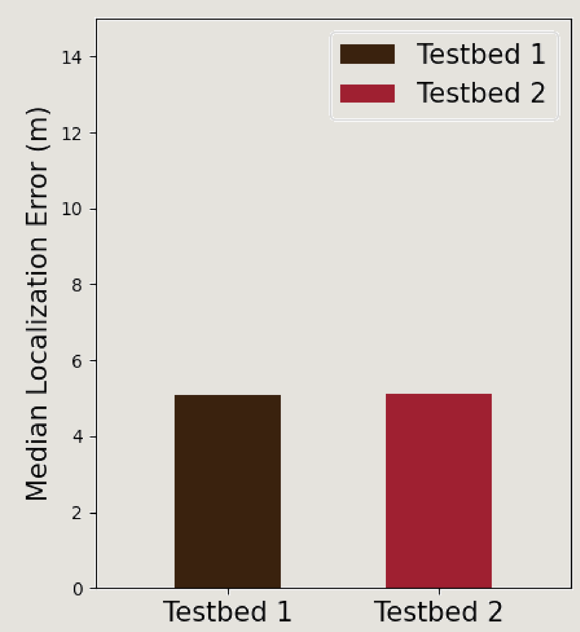


Evaluation on Same Building



System outperforms WiDeep[1] and DeepFi[2] by **136%** and **340%** respectively.

Evaluation on Unseen Buildings



Median Error Increases slightly but **consistent** performance across buildings.

Conclusion

We proposed a novel approach to indoor localization that can generalize to unseen environments without additional data collection, retraining or fine-tuning. The system learns environment invariant features by utilizing virtual representations and Graph Neural Networks. The approach outperforms other systems and can generalize to unseen buildings.