GRAFICS: Graph Embedding-based Floor Identification Using Crowdsourced RF Signals

Weipeng Zhuo[1], **Ziqi Zhao**[2], Ka Ho Chiu[1], Shiju Li[3], Sangtae Ha[4], Chul-Ho Lee[3] and S.-H. Gary Chan[1]

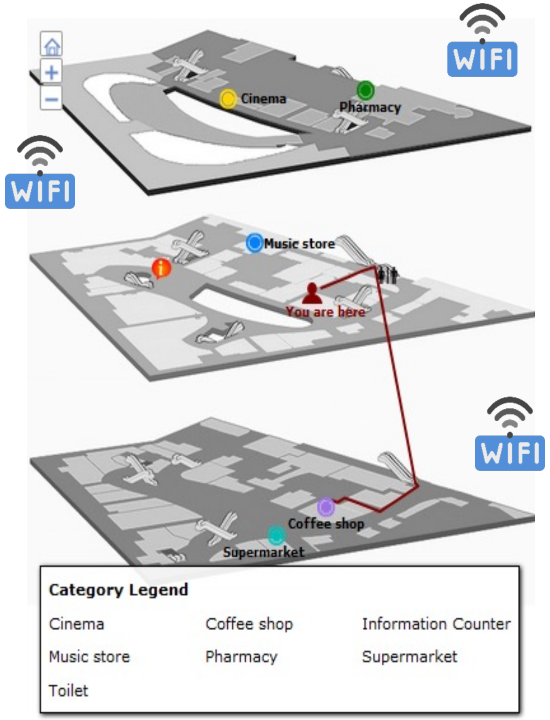
Presenter: Ziqi Zhao
2022.7.12
ICDCS 2022

1. Hong Kong University of Science and Technology (HKUST)
2. École Polytechnique Fédérale de Lausanne (EPFL)
3. Texas State University
4. University of Colorado Boulder

Introduction to Floor Identification

- Radio frequency (RF) signals (e.g., WiFi, iBeacon, UWB) with floor information enables plenty of applications:
  - Multi-floor navigation
  - Geo-fencing
  - Scene construction with unmanned aerial vehicles
  - Robot rescue

- Number of floors is usually available from Google Maps and property managers.



Multi-floor navigation

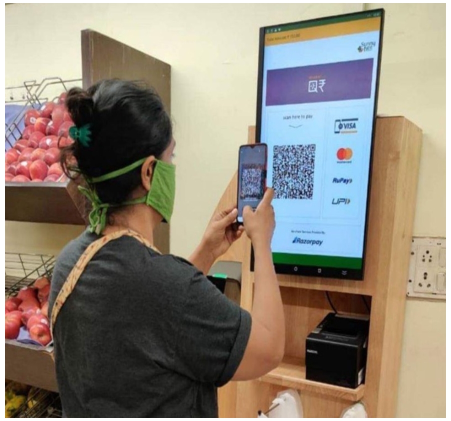
Floor number available

Crowdsourcing for WiFi Data Collection

- Few Floor Labels are Available in Crowdsourcing
  - Only sporadic floor labels are available from activities such as in-shop check-ins and contactless shopping.
  - Most crowdsourced RF signals are unlabeled.

- RF Signal Heterogeneity
  - There are many MAC addresses in the building, but each RF record only senses a small portion of them.
  - The overlap ratio between pairs of RF records is small.

In-shop check-ins



Contactless shopping

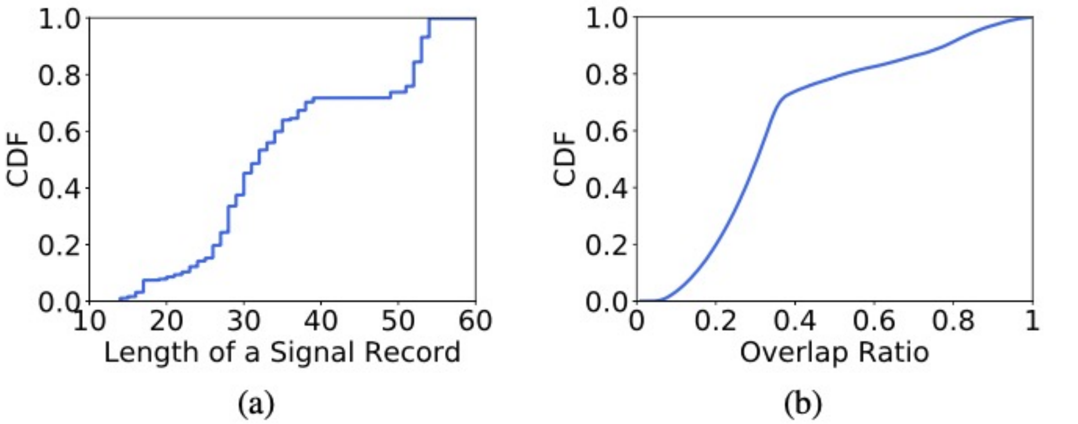
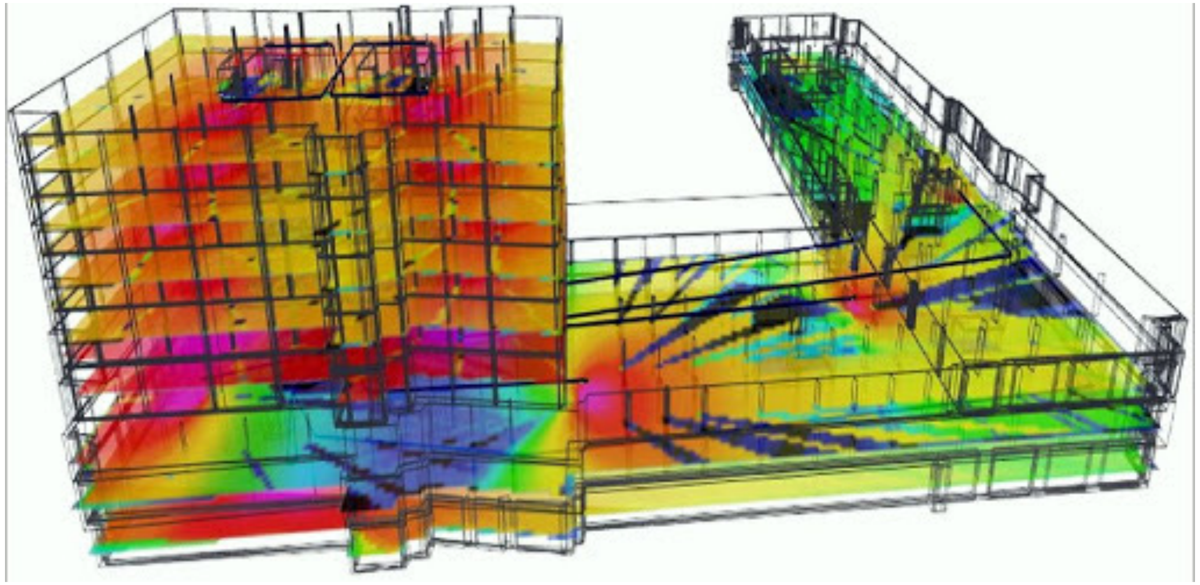


Fig. 1. Statistics of RF records measured on a floor. (a) CDF of the number of MAC addresses in a signal record; (b) CDF of overlap ratio, given by the ratio of common MAC addresses and distinct MAC addresses, for all pairs of signal records.

Problem Statement

- How to design an efficient and accurate floor identification algorithm under RF heterogeneity with few labels?



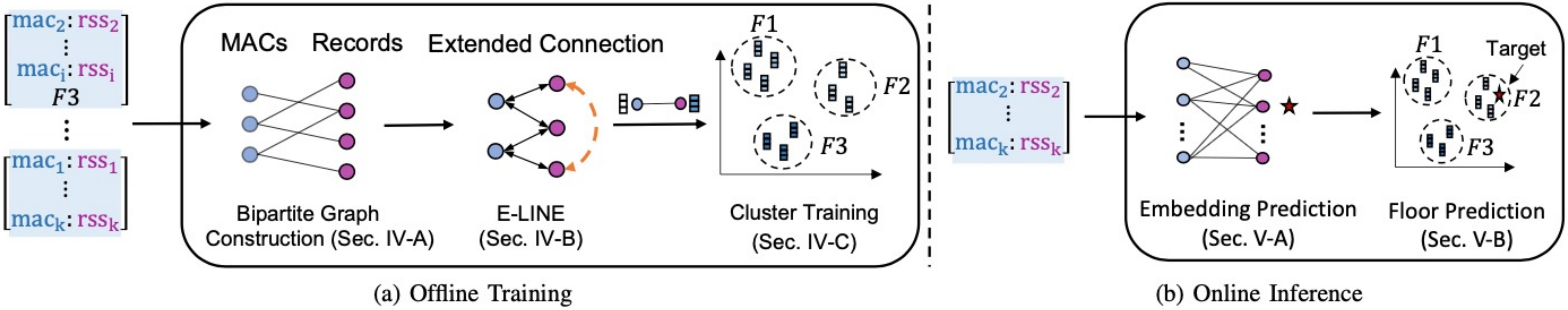
Existing Approaches

- Record IMU (Inertial Measurement Unit) signals for floor transition [1]-[7]: strong assumption on user behavior.
- Requirement of MAC locations [8]-[12]: not easily available in practice.
- Matrix formulation for RF signals [13]-[18]: ad-hoc data imputation to fill in RF signal values that are not available.

Sample\MAC	1	2	3	…	800
1	-50	-60	?	…	-70
2	?	-65	-65	…	?
3	?	?	-58	…	?
4	-72	?	?	…	-67
5	-64	-52	?	…	-68
…	…	…	…	…	…
2000	?	?	?	…	-53

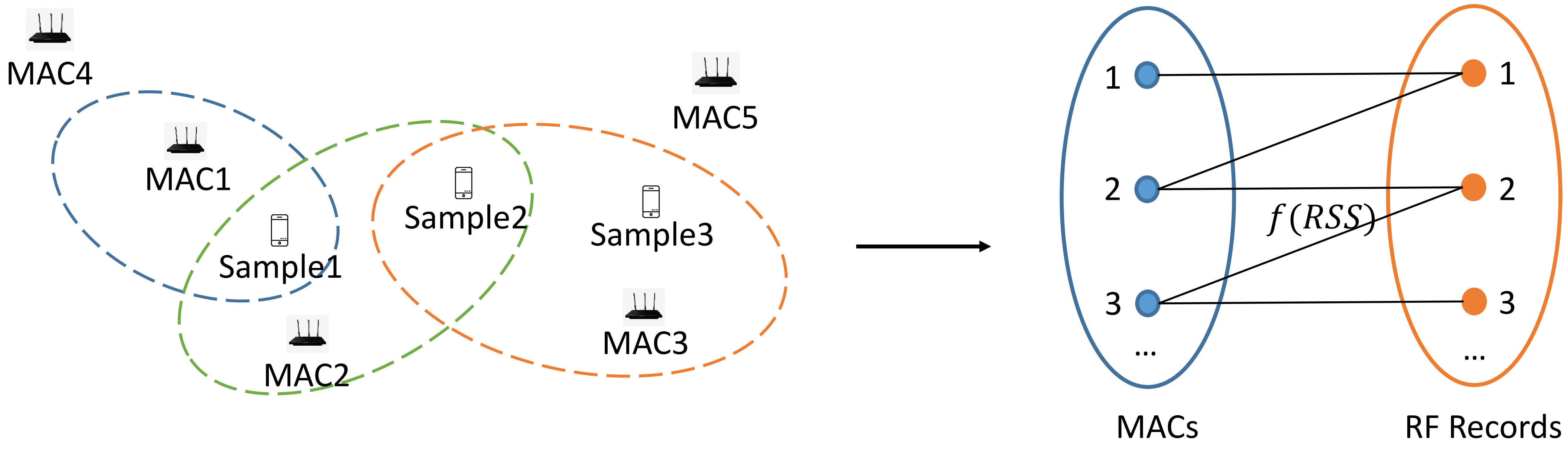
GRAFICS

- **Gra**ph Embedding-based **F**loor **I**dentification Using **C**rowdsourced RF **S**ignals
- No assumption on user behaviors and MAC locations.
- Highly adaptive to RF heterogeneity.
- Well capture the relation between RF signals.
- Works well on sparsely labeled RF signals.



Overview of GRAFICS

Bipartite Graph Modeling for RF Signals



Advantages:

- Model sensed RSS (Received Signal Strength) without any data imputation.
- Highly adaptive to RF heterogeneity.
- Scalable to huge amount of crowdsourced data.

Preliminaries: Embedding Generation with LINE

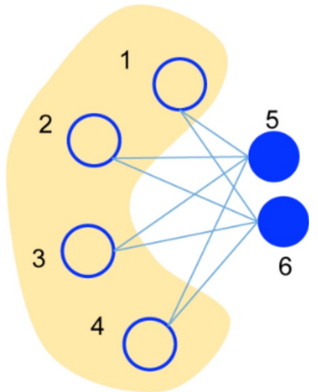
- LINE: Large-scale Information Network Embedding [19]
- Second-order proximity: based on shared neighbors between nodes.
  Two nodes that share similar contexts (neighborhoods) are considered similar.

$$\Pr(\boldsymbol{u}'_j|\boldsymbol{u}_i) := \frac{\exp(\boldsymbol{u}'_j \cdot \boldsymbol{u}_i)}{\sum_{l \in \mathcal{M} \cup \mathcal{V}} \exp(\boldsymbol{u}'_l \cdot \boldsymbol{u}_i)} \longrightarrow \hat{\Pr}(\boldsymbol{u}'_j|\boldsymbol{u}_i) := \frac{c_{ij}}{\sum_{l \in N(i)} c_{il}}$$

Theoretical — Empirical

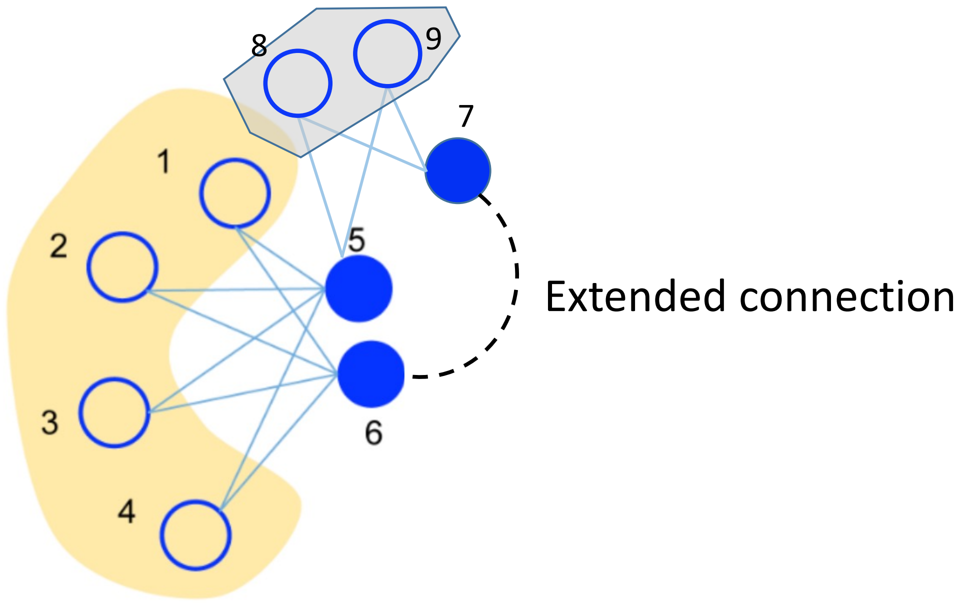
- Objective function

$$\mathcal{O}_1 = -\sum_{i \in \mathcal{M} \cup \mathcal{V}} \sum_{j \in N(i)} c_{ij} \log \Pr(\boldsymbol{u}'_j|\boldsymbol{u}_i)$$



E-LINE: Extended LINE for Multi-hop Connections

- Original LINE: only shared neighbors are considered.
- In our case, two close RF records on the same floor might only be connected through multi-hop connections.
- E-LINE: Extend the embedding learning algorithm to consider multi-hop neighbors.



E-LINE: the New Objective

- Recall LINE's second order proximity:

$$\Pr(\boldsymbol{u}'_j|\boldsymbol{u}_i) := \frac{\exp(\boldsymbol{u}'_j \cdot \boldsymbol{u}_i)}{\sum_{l \in \mathcal{M} \cup \mathcal{V}} \exp(\boldsymbol{u}'_l \cdot \boldsymbol{u}_i)}$$

- To enable information flow in multi-hop neighborhoods, E-LINE defines a new conditional probability:

$$\Pr(\boldsymbol{u}_j|\boldsymbol{u}'_i) = \frac{\exp(\boldsymbol{u}_j \cdot \boldsymbol{u}'_i)}{\sum_{l \in \mathcal{M} \cup \mathcal{V}} \exp(\boldsymbol{u}_l \cdot \boldsymbol{u}'_i)}$$

- A new objective:

$$\mathcal{O}_2 = -\sum_{i \in \mathcal{M} \cup \mathcal{V}} \sum_{j \in N(i)} c_{ij} \log \Pr(\boldsymbol{u}_j|\boldsymbol{u}'_i)$$

E-LINE: the Full Objective and Loss Function

- Combined with the objective function of LINE:

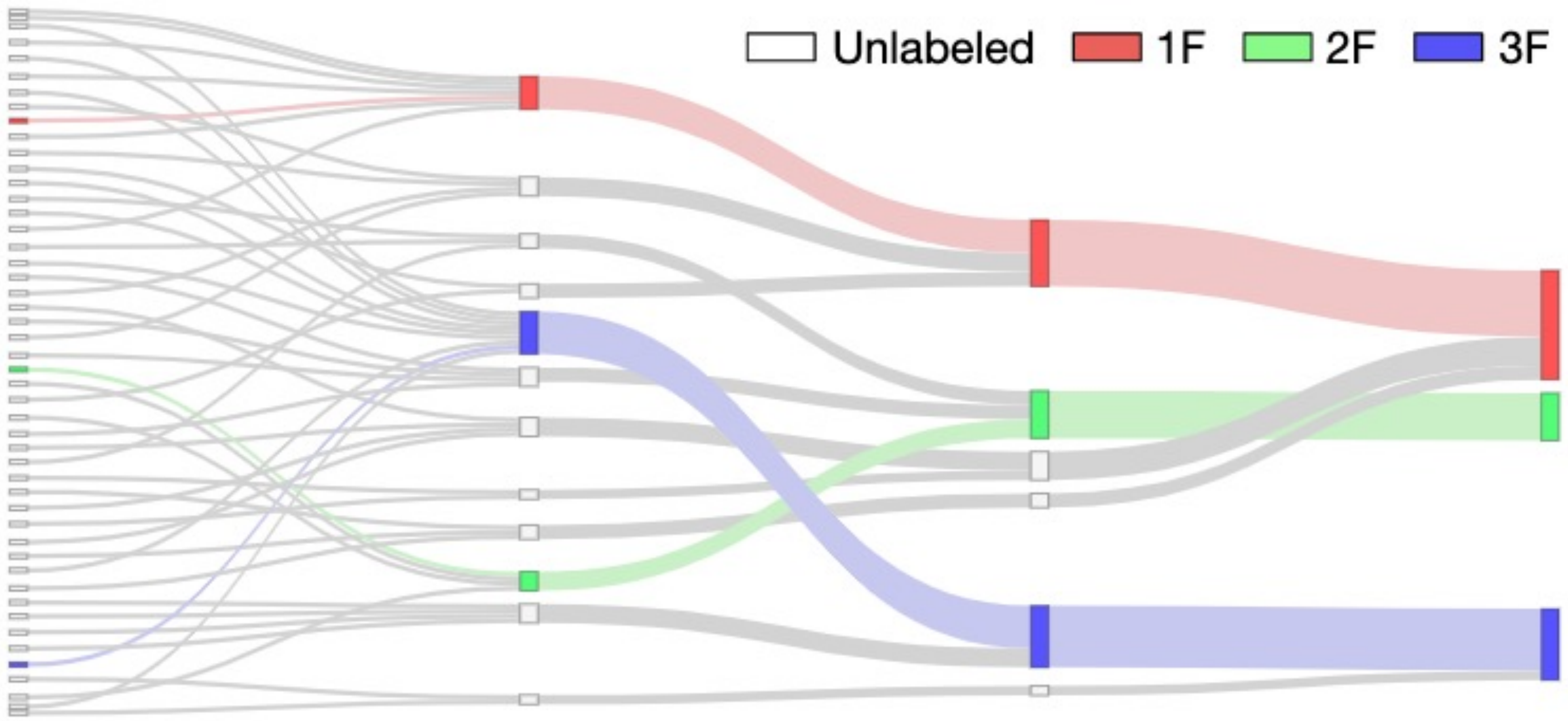
$$\mathcal{O}_3 = \mathcal{O}_1 + \mathcal{O}_2 \quad = - \sum_{i \in \mathcal{M} \cup \mathcal{V}} \sum_{j \in N(i)} c_{ij} \left(\log \Pr(\boldsymbol{u}'_j | \boldsymbol{u}_i) + \log \Pr(\boldsymbol{u}_j | \boldsymbol{u}'_i) \right)$$

- After negative sampling we get:

$$\begin{aligned} \mathcal{L}_{\mathcal{G}} := - \sum_{i \in \mathcal{M} \cup \mathcal{V}} \sum_{j \in N(i)} c_{ij} \Big(& \log \left[\sigma(\boldsymbol{u}'_j \cdot \boldsymbol{u}_i) \sigma(\boldsymbol{u}_j \cdot \boldsymbol{u}'_i) \right] \\ & + K \mathbb{E}_{z \sim \Pr(z)} \left[\log \left(\sigma(-\boldsymbol{u}'_z \cdot \boldsymbol{u}_i) \sigma(-\boldsymbol{u}_z \cdot \boldsymbol{u}'_i) \right) \right] \Big) \end{aligned}$$

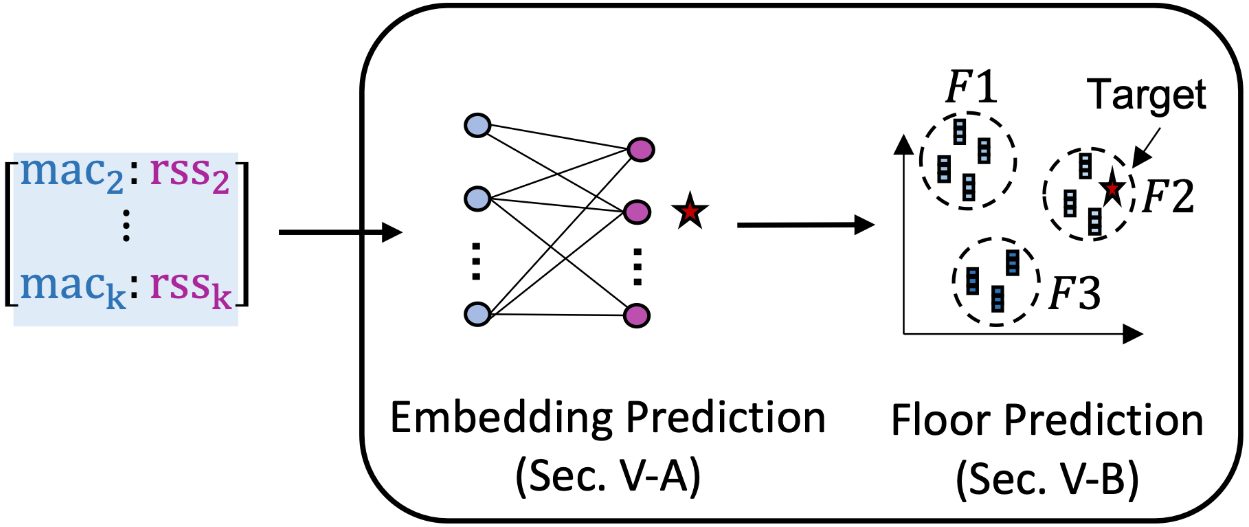
Semi-supervised Hierarchical Clustering

- Clustering on embeddings generated for each RF record.
- Stop when each cluster has exactly one floor-labeled RF record.



Inference of New RF Signals

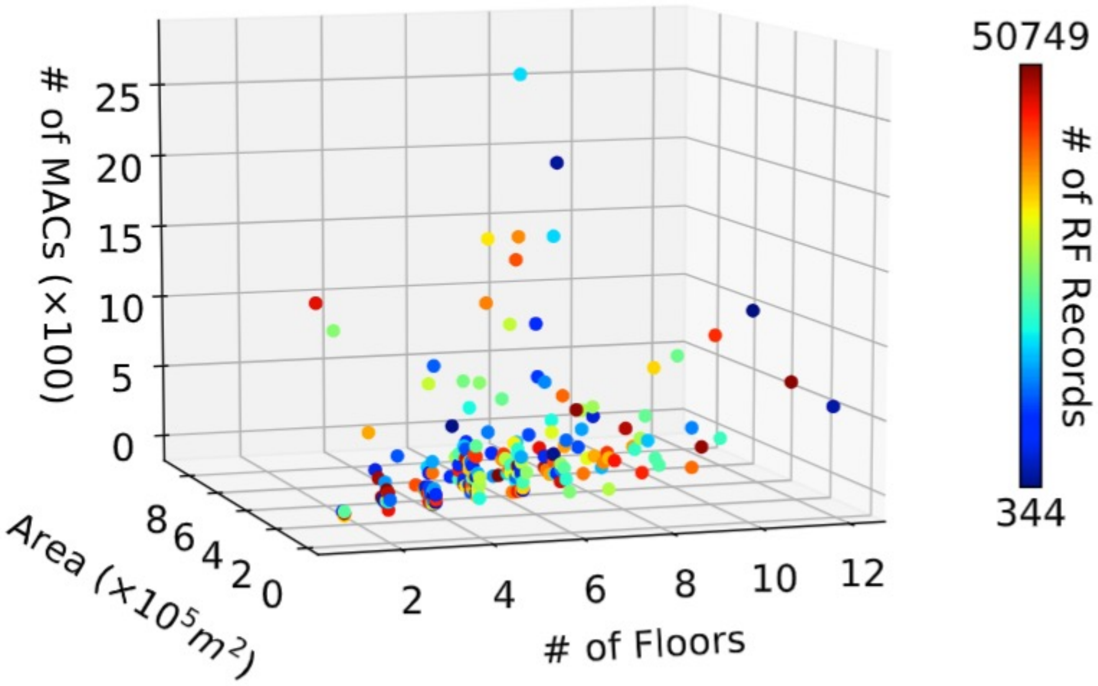
- Add the signal to the bipartite graph.
- Fix existing embeddings, minimize the loss function on newly added nodes.
- Get the embeddings of the RF signals for clustering.
- In the hierarchical clustering model, determine the label of each embedding by finding the closest cluster in the model.



(b) Online Inference

Experiment Setup

- Microsoft Kaggle dataset:
    - 204 buildings
- Hong Kong dataset:
    - 5 buildings
- Floor number ranges from 2 to 12.
- Each floor has around 1000 RF samples.



Statistics of the dataset

State-of-the-art Comparison Schemes

- SAE (Stacked Auto Encoder) [13]
- Scalable-DNN [14]
- Auto Encoder
- MDS (Multidimensional Scaling)

Evaluation Metrics: Precision, Recall, F-score

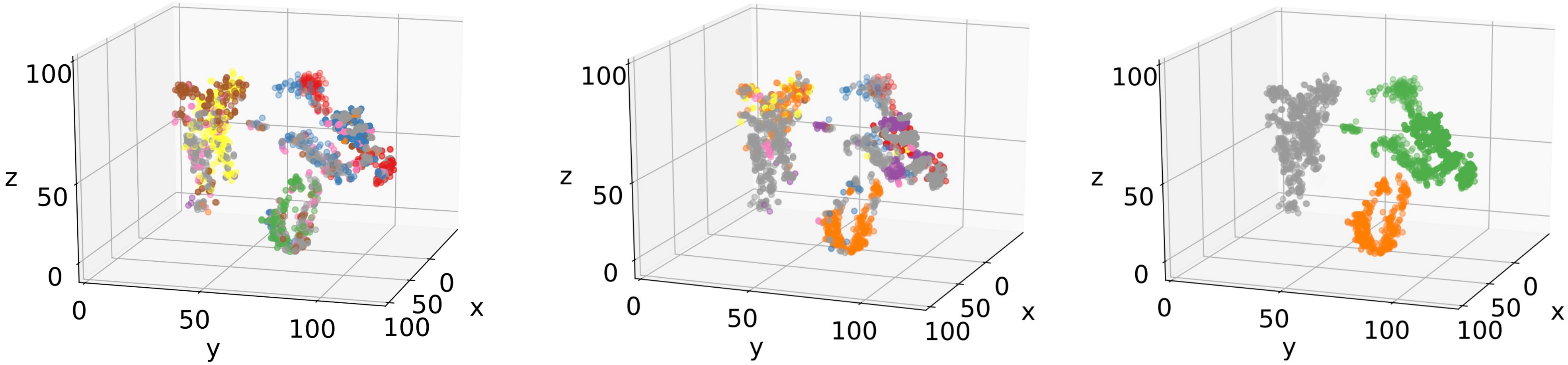
$$P_i = \mathrm{TP}_i/(\mathrm{TP}_i + \mathrm{FP}_i) \qquad R_i = \mathrm{TP}_i/(\mathrm{TP}_i + \mathrm{FN}_i)$$

Micro: treat each sample equally Macro: treat each class equally

Micro	Macro
$\text{micro-}P = \frac{\sum_{i=1}^{n} \mathrm{TP}_i}{\sum_{i=1}^{n}(\mathrm{TP}_i + \mathrm{FP}_i)}$	$\text{macro-}P = \frac{\sum_{i=1}^{n} P_i}{n}$
$\text{micro-}R = \frac{\sum_{i=1}^{n} \mathrm{TP}_i}{\sum_{i=1}^{n}(\mathrm{TP}_i + \mathrm{FN}_i)}$	$\text{macro-}R = \frac{\sum_{i=1}^{n} R_i}{n}$
$\text{micro-}F = 2\frac{\text{micro-}P \times \text{micro-}R}{\text{micro-}P + \text{micro-}R}$	$\text{macro-}F = 2\frac{\text{macro-}P \times \text{macro-}R}{\text{macro-}P + \text{macro-}R}$

Visualization of Clustering Process

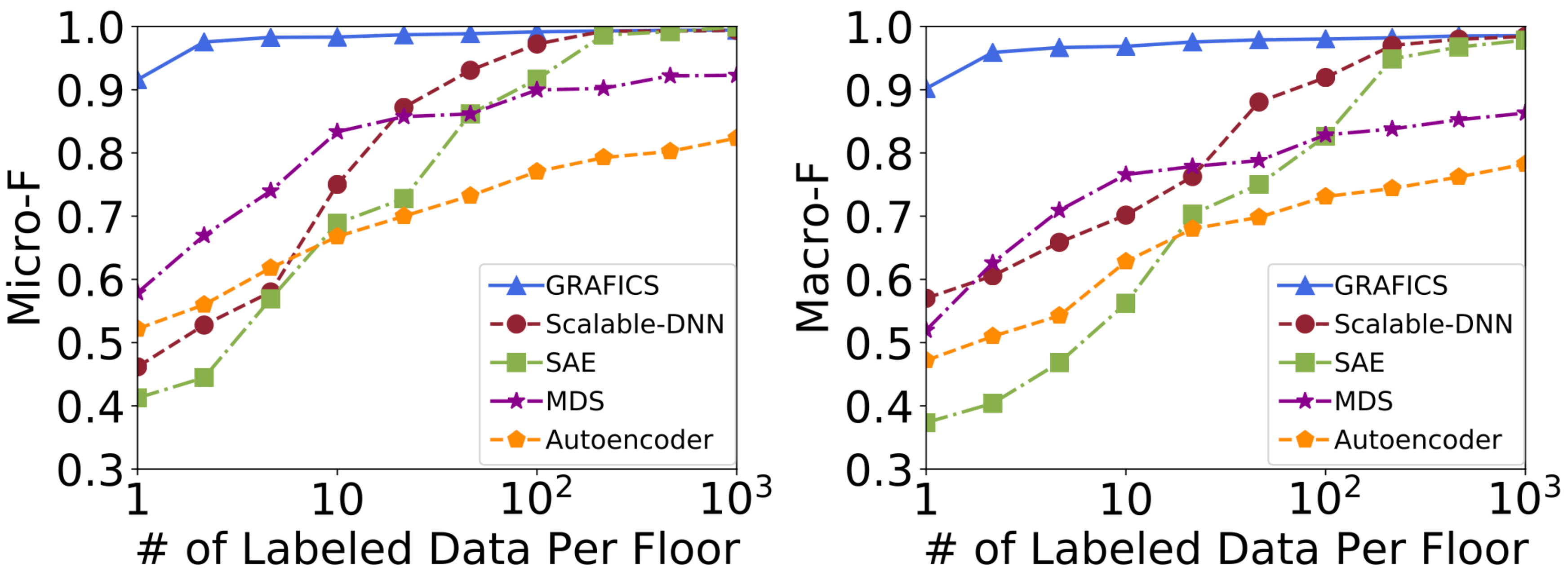
- GRAFICS gradually clusters the RF signal samples from the same floors in a three-story building, when only four samples are labelled for each floor.



40% 80% 100%

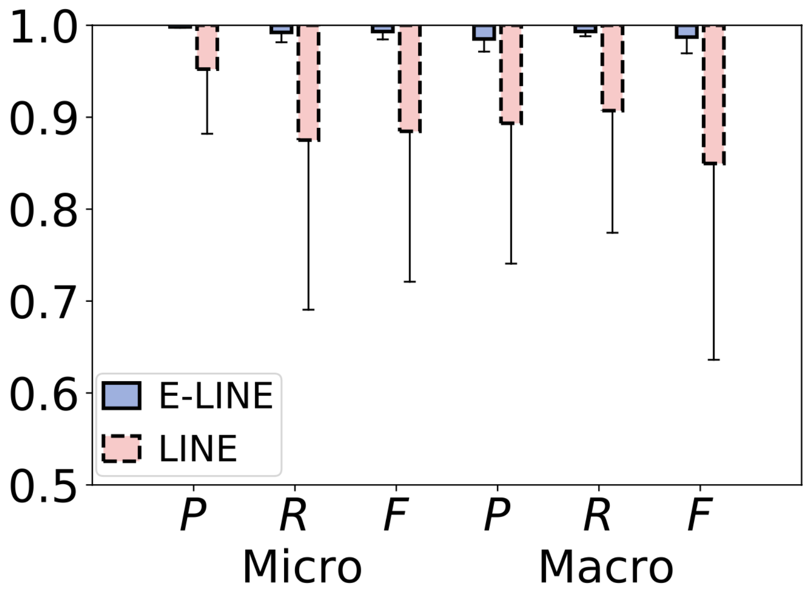
GRAFICS Outperforms SOTA Methods

- GRAFICS already achieves high F-scores when where are few floor labels
- Scalable-DNN and SAE achieve comparable performance with ≈100x labels.
- MDS and auto encoder perform better than supervised ones when there are only few labels.

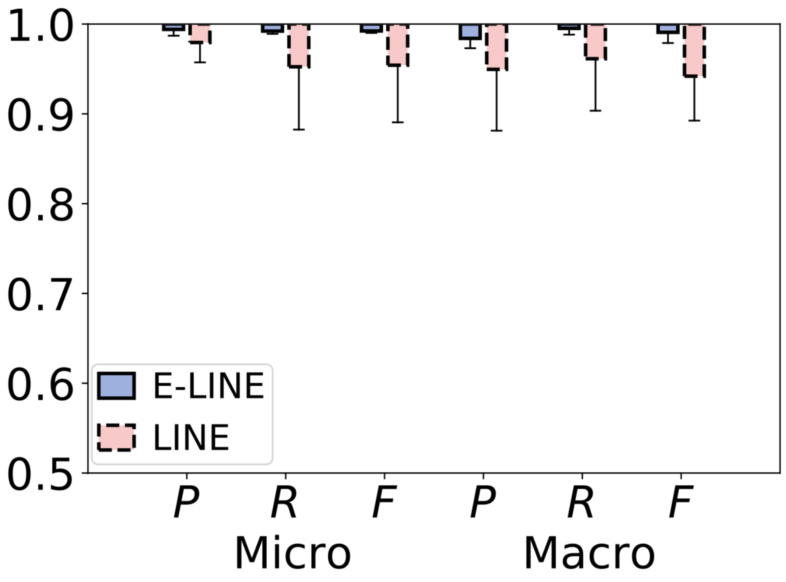


E-LINE Generates Better Embeddings over LINE

- Run 10 times for each setup.
- When each floor only has 4 labels, GRAFICS with LINE exhibits a high variance.
- GRAFICS with LINE performs much better when there are more labels.



Microsoft (#label = 4)



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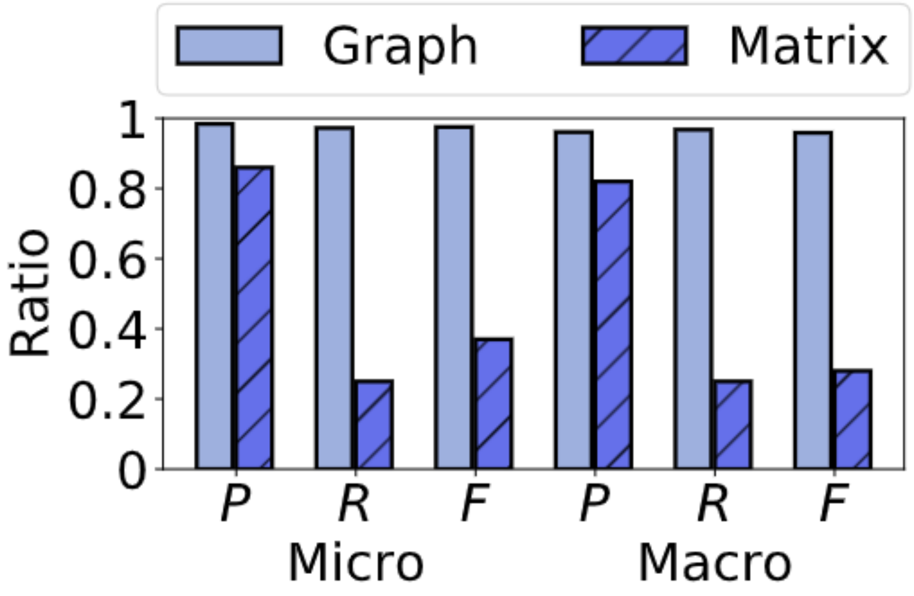
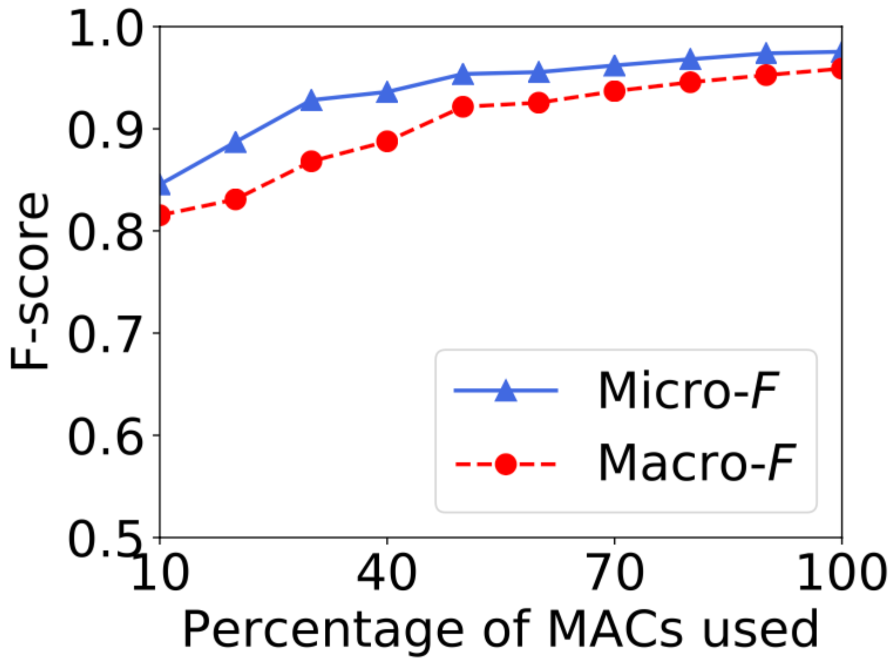
Graph Modeling Handles RF Heterogeneity

- Missing values in the matrix representation are filled with -120dBm.
- Graph modeling significantly outperforms the matrix representation, demonstrating its superiority in handling RF signal heterogeneity.



GRAFICS is Robust to Dynamic RF Environment

- GRAFICS can already achieve a high F-score when only 10% of MACs are used and 90% of MACs are removed.
- When there are ≈50% of MACs, GRAFICS can almost perform as well as the full model.



Conclusion

- Propose to use bipartite graph to model RF signals.
- Propose E-LINE to learn better embedding for each graph node.
- Propose semi-supervised hierarchical clustering to do floor identification.
- Extensive experiment results show significant improvement over state-of-the-art schemes.

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Thank you!