Qualcomm

NEURAL INFORMATION PROCESSING SYSTEMS

# Deep Learning Frameworks for Unsupervised Indoor Wi-Fi Positioning

**Qualcomm AI Research**

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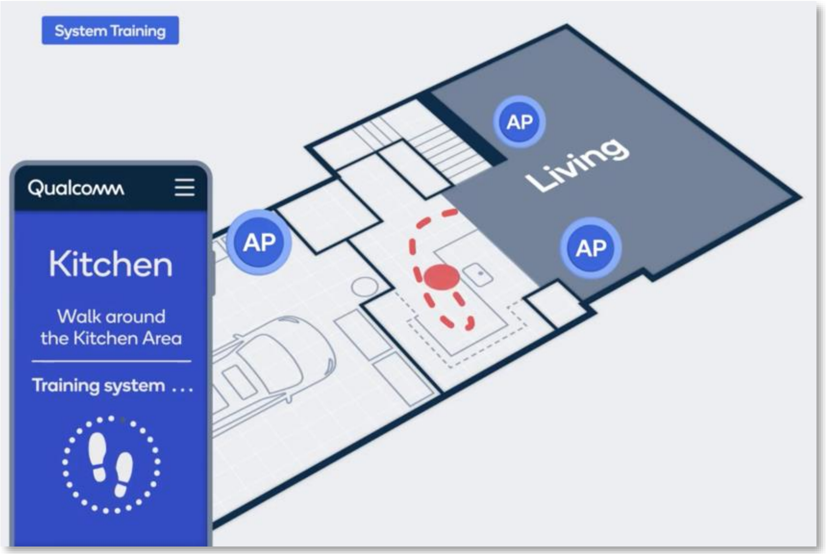
NeurIPS Demo

# Passive Wi-Fi Localization

- Problem: Localizing a person on a floor plan of building using Wi-Fi APs

We assume the following is available:

  - Floor plan – sketch or CAD
  - Sequences of Channel State Information (CSI) while a person walking through the environment
  - For each room, some labeled CSI samples



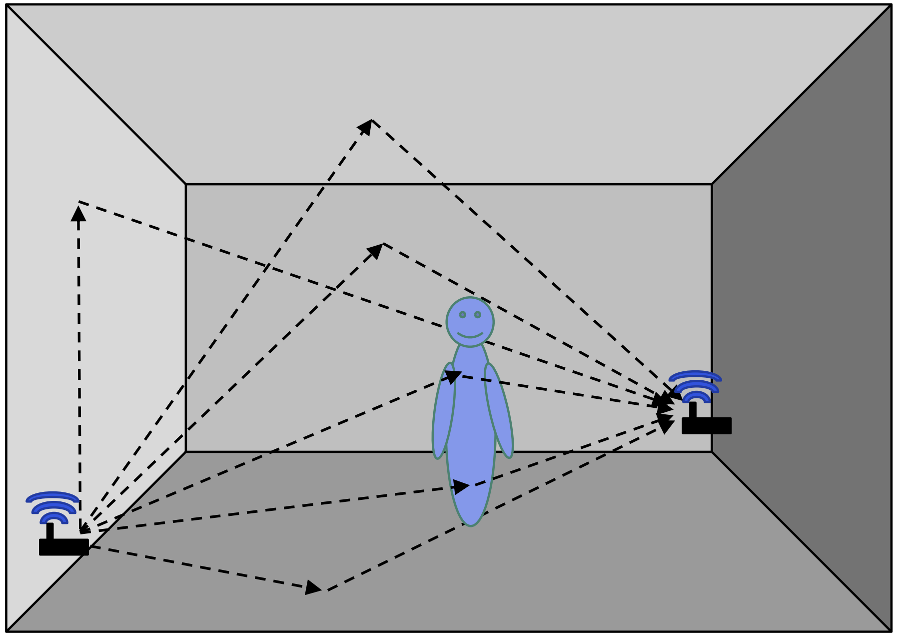

# Multipath effect in passive Wi-Fi sensing:

- The measured Wi-Fi signal is the summation over the many different paths from Tx to Rx
- Channel State Information is defined as:

$$\mathrm{CSI}_i = \sum_{k=0}^{K} r_k \cdot e^{-j2\pi f_i \tau_k}$$

- In equation form:
  - $K$: the number of paths
  - $r_k$: is attenuation
  - $\tau_k$: is the propagation delay (length of path / speed of light)
  - $f_i$: frequency for sub-carrier $i$

In our experiments:
10 CSI packets
208 sub-carriers
8 antennas



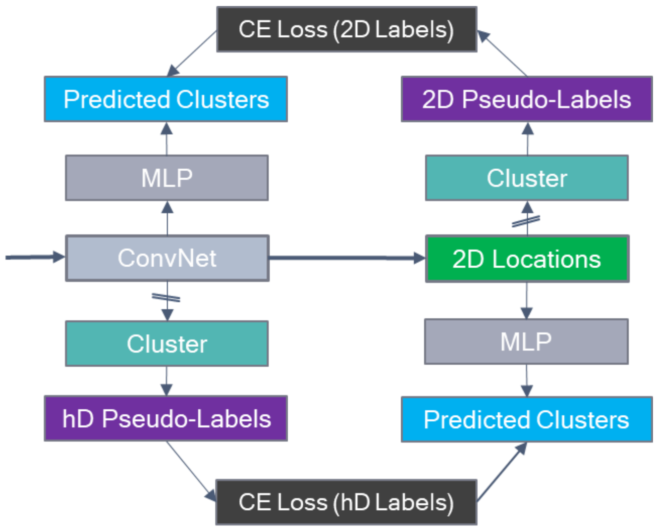
Multipath phenomenon in passive Wi-Fi sensing

# Our solutions:

- Weakly-supervised deep learning frameworks:

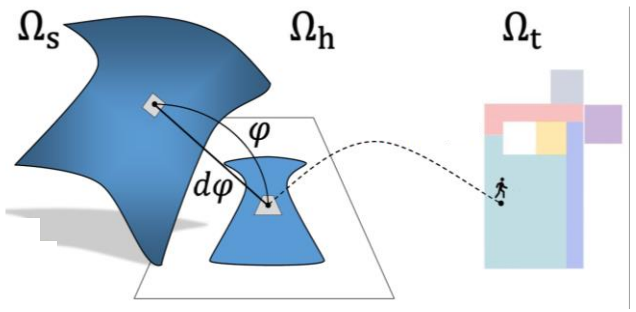
## Wi-Cluster [GLOBECOM 2021]

- Deep metric learning and self-supervised learning




## OT-IsoMap [NeurIPS 2021]

- Manifold learning and optimal transportation



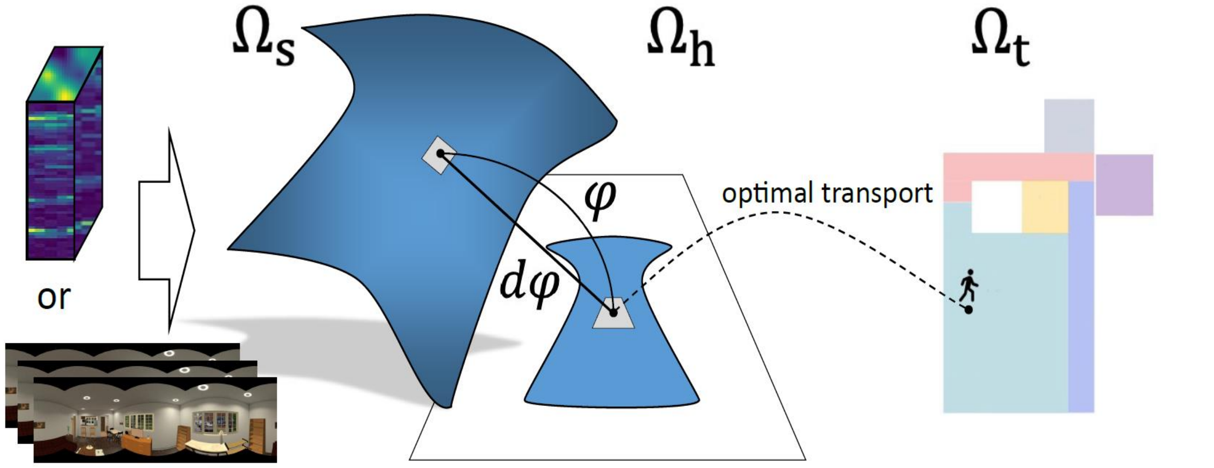
# OT-IsoMap

Modality-agnostic topology aware localization, F. Zanjani et al., NeurIPS 2021

- Weakly supervised passive Wi-Fi positioning
- Framework: manifold learning and optimal transportation

# OT-IsoMap

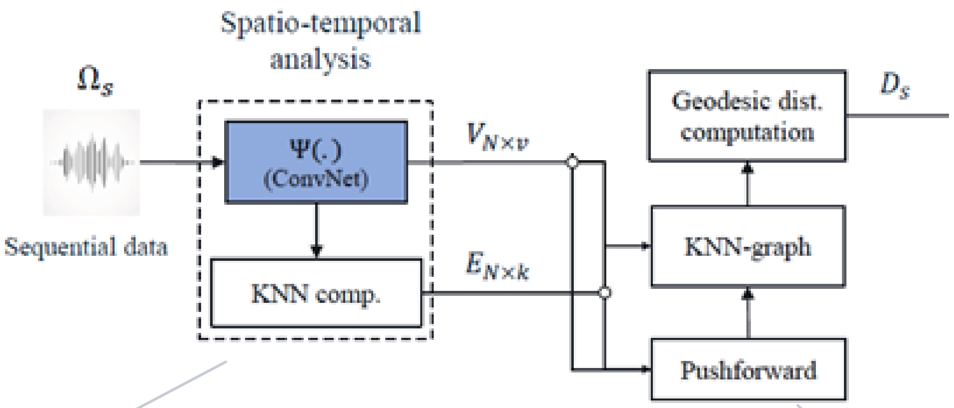
- Displacement of observer in the environment correspondence with 2D/3D intrinsic space of data
- Learning a parametric mapping (Φ) into an isometric 2D space is hard
- Learn a mapping that preserves the isometric while minimizing the transportation cost into a target map




Ambient space of data    2D intrinsic space    Target floor plan

# OT-IsoMap

- 1. Estimating the distance matrix in 2D space
  - Construct a KNN graph after finding KNN samples
  - The distance between adjacent vertices is computed by Mahalanobis distance
  - The distance between non-adjacent vertices is computed by Dijkstra shortest path algorithm

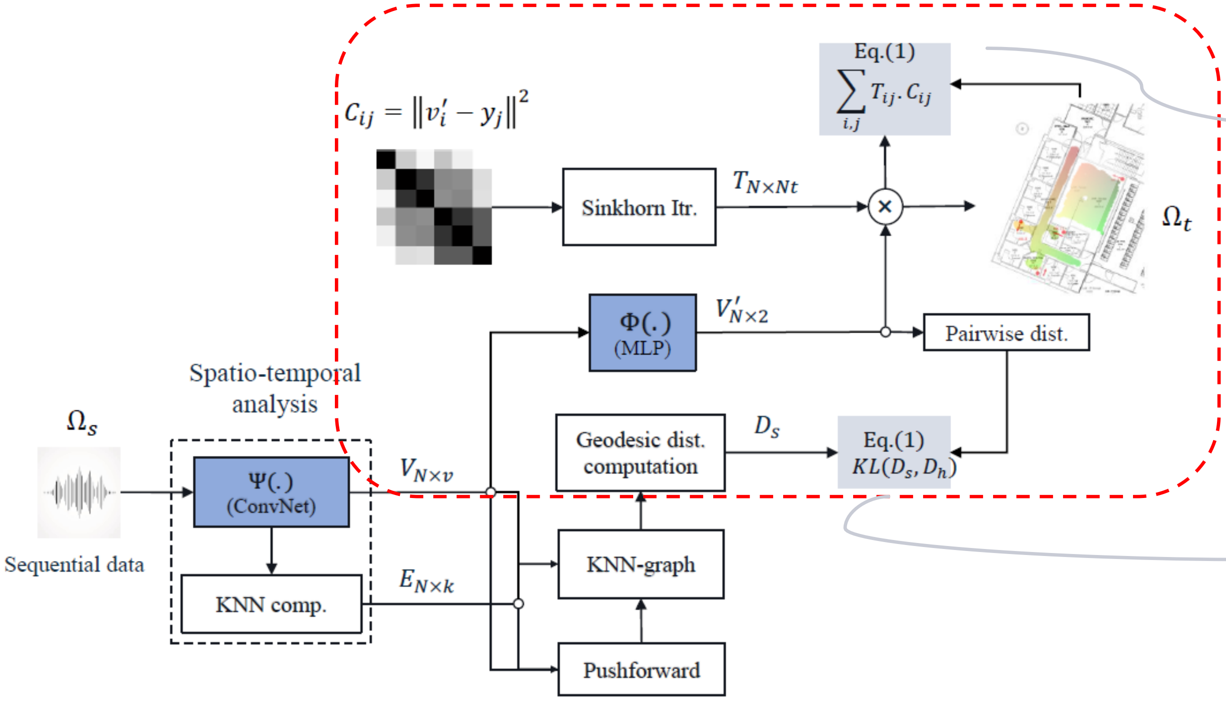



$$\mathcal{L}(x_i^a, x_i^p, x_i^n) = max\Big(0, d(h_i^a, h_i^p) - d(h_i^a, h_i^n) + \alpha\Big) \quad \text{where} \quad h_i = \Psi(x_i).$$

$$d \cong \frac{1}{2}\,[x_i - x_j]^T \cdot [\Sigma^{-1}(x_i) + \Sigma^{-1}(x_j)] \cdot [x_j - x_i]$$

# OT-IsoMap

1. Estimating the distance matrix in 2D space
2. Learning a parametric map ($\Phi$) into 2D space
   - Isometric embedding: distances should have similar distribution
   - Layout similarity: minimal cost under optimal transportation


## Layout similarity

$$T(C,p,q) = \underset{T \in \gamma(p,q)}{argmin}\langle T, C\rangle - \frac{1}{\lambda}H(T)$$

Cost matrix $C_{ij} = \|\Phi(x_i) - y_j\|^2$

(Densely) sampled points from $\Omega_t \in \mathbb{R}^2$

## Isometric embedding

$$\min_{\Phi} D_{KL}(D_s||D_h), \quad \text{where } D_s, D_h \in \mathbb{R}^{N_s\times N_s}$$

$D_s$ : Geodesic distance matrix of samples in $\mathbb{R}^M$

$D_h$ : Euclidean distance matrix of samples in $\mathbb{R}^2$

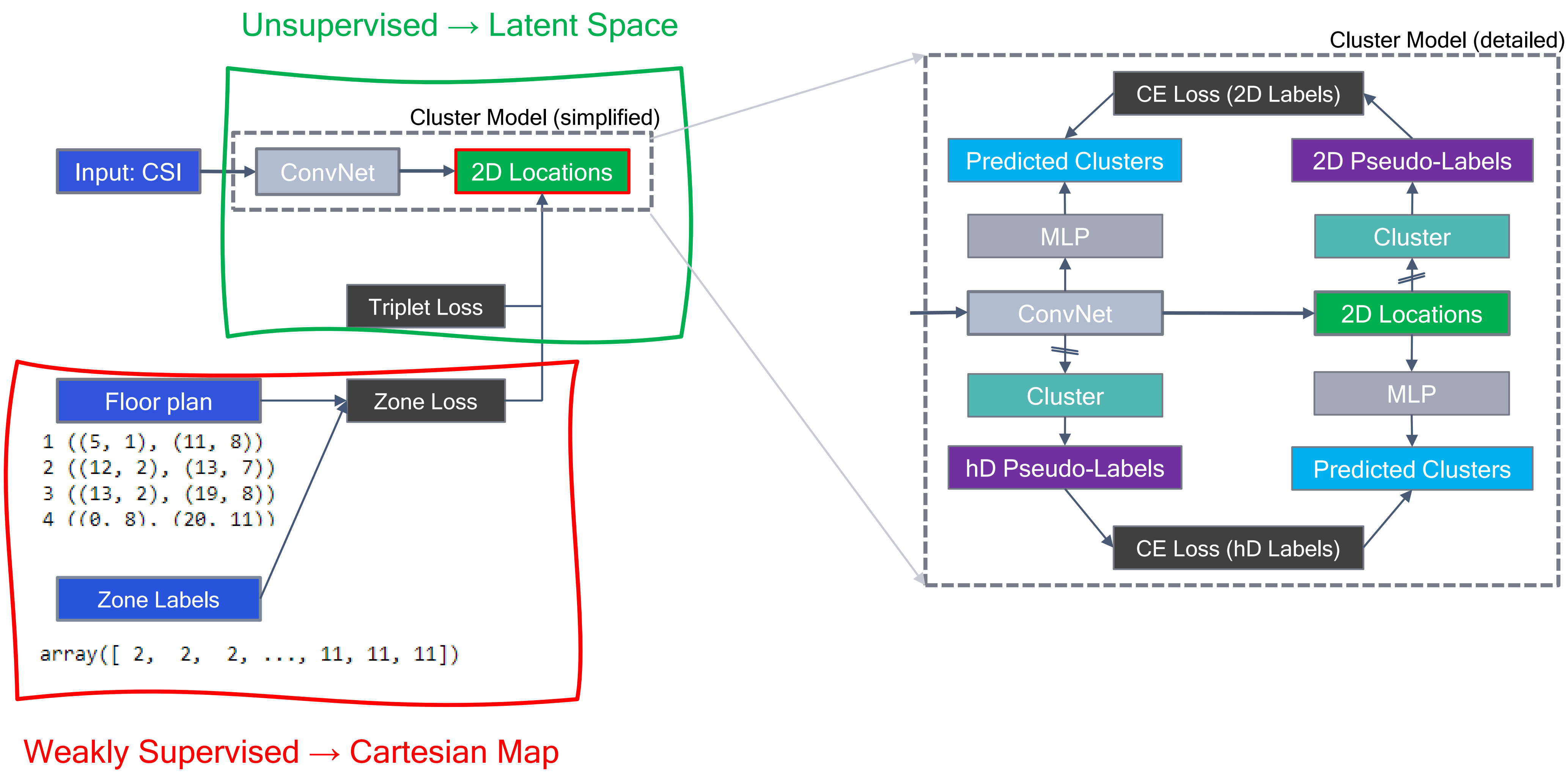
# WiCluster

WiCluster: Passive Indoor 2D/3D Positioning using Wi-Fi without Precise Labels, I. Karmanov et al. GLOBECOM 2021

- Weakly supervised passive Wi-Fi positioning
- Framework: Deep metric and self-supervised learning

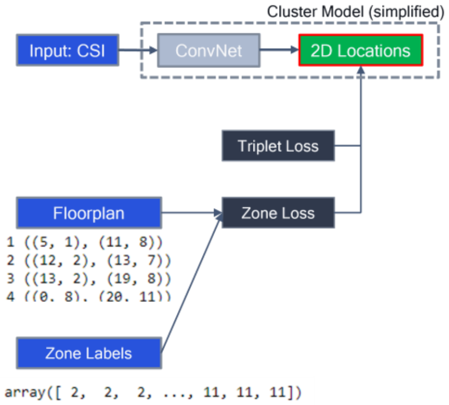
# WiCluster

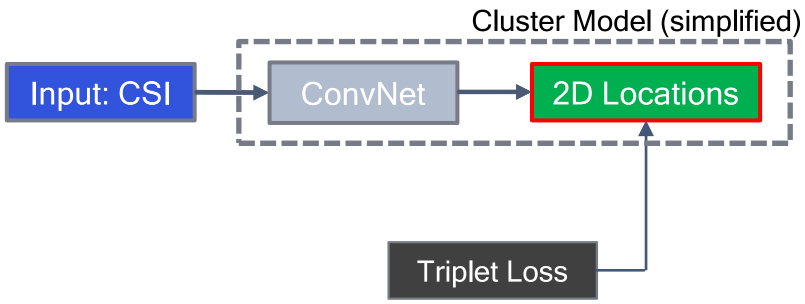
## Full Architecture Diagram

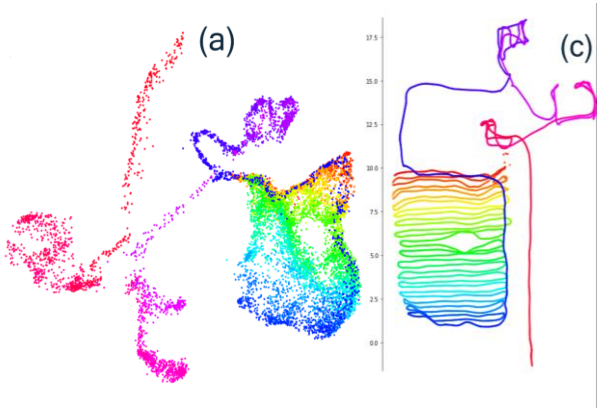


# WiCluster Architecture

## Unsupervised Component




### Cluster Loss

$$\min_{C \in \mathbb{R}^{d \times k}} \frac{1}{N} \sum_{n=1}^{N} \min_{y_n \in \{0,1\}^k} \| f_\theta(x_n) - C y_n \|_2^2 \quad \text{s.t.} \quad y_n^\top 1_k = 1$$

$$L_C = -\frac{1}{N} \sum_{i=1}^{N} \log p(y_i | x_i)$$

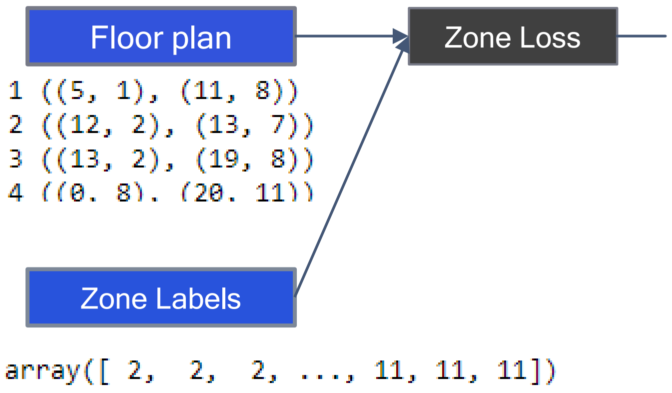
### Triplet Loss

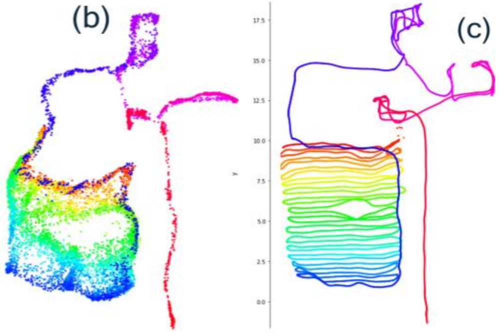
$$L_T = \frac{1}{N} \sum_{(i,j,k) \in \mathcal{T}} \max(0, (d(x_i, x_j) - d(x_i, x_k) + M_t))$$

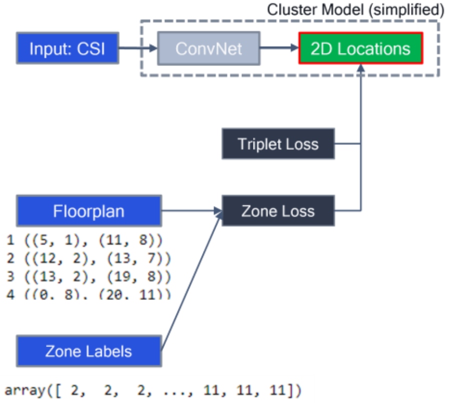
$$d(x, x') = \| f_\theta(x) - f_\theta(x') \|$$

# WiCluster Architecture

## Weakly-supervised Component




**Zone Loss**

$$L_Z = \frac{1}{N}\sum_{i=1}^{N} \max\left(0, d_m(x_i, B)\right)$$

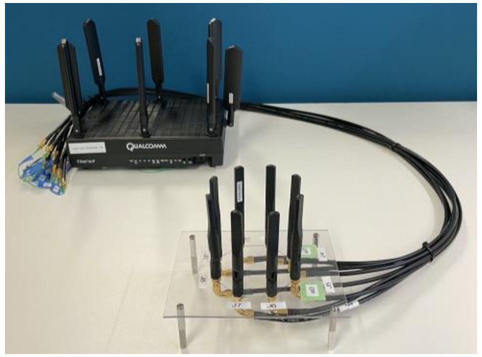
$$[B_{zone}] = ([x_0, y_0], [x_1, y_1])$$

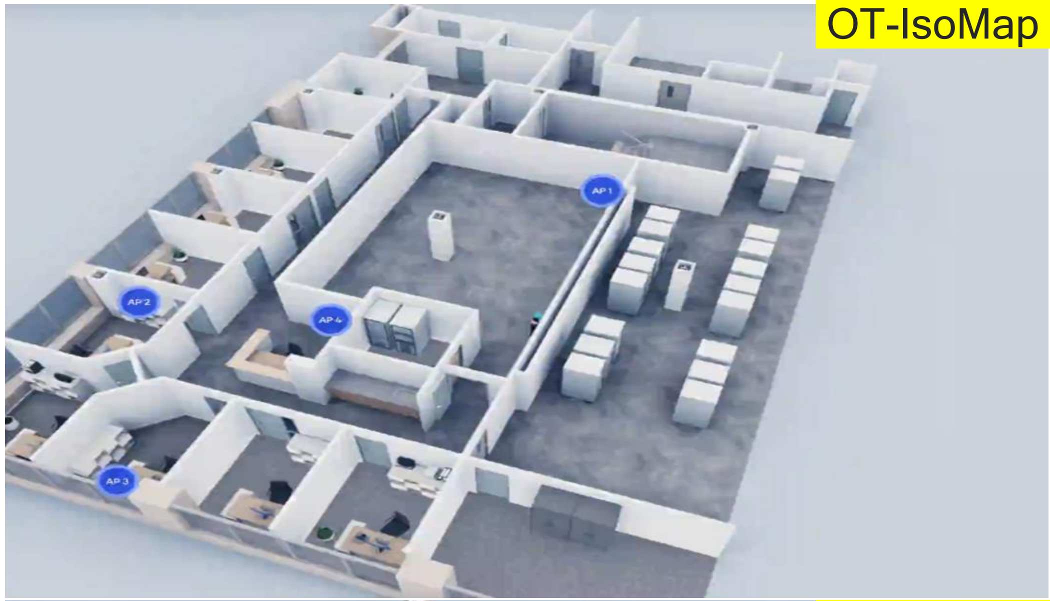
$$d_m(x, x')$$

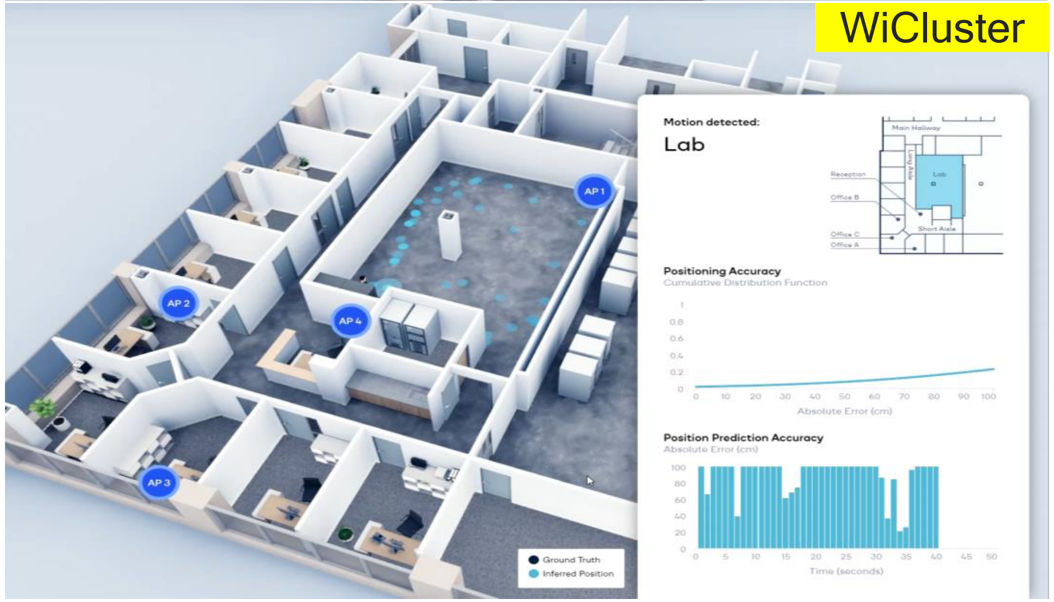
# Experiments

- Localization in Wi-Fi

  - **Four** commercial IEEE 802.11 access points (AP), **5** GHz band
  - Sensing area: **14×20** meters
  - Tx antenna: **1**
  - Rx antennas: **8**
  - Circular array with **4**cm radius
  - BW: **80** MHz
  - **208** frequency tones
  - Packet rate: **100** Hz
  - Mean error: **1.2** m





# Summary

- Weakly supervised learning shown meter level accuracy in Wi-Fi positioning
- The models only require the floor plan image and the zone-level labels
- Advances in Wi-Fi sensing can enable many applications such as surveillance, smart house, automation, etc.

- References:

  - Modality-agnostic topology aware localization, F. G. Zanjani et al., NeurIPS 2021
  - WiCluster: Passive Indoor 2D/3D Positioning using Wi-Fi without Precise Labels, I. Karmanov et al., GLOBECOM 2021

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# Thank you

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