Tsinghua University

Train Once, Locate Anytime for Anyone: Adversarial Learning based Wireless Localization

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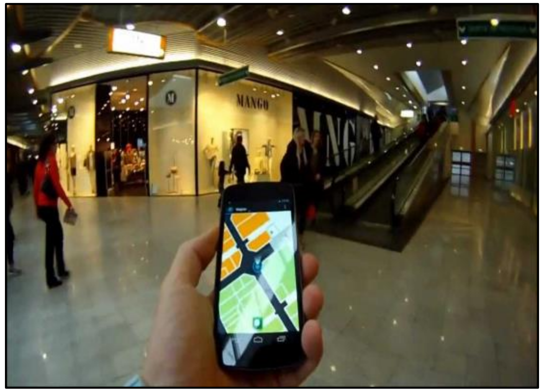
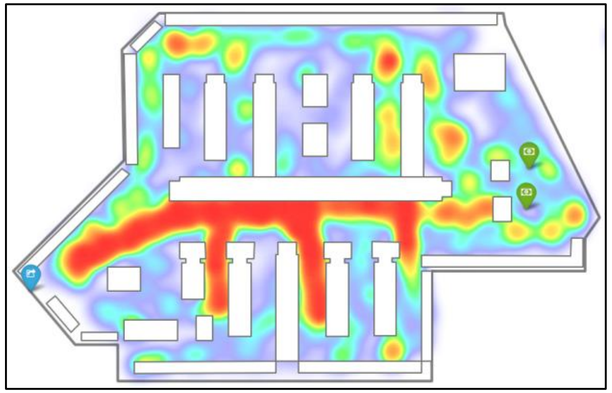
Motivation

- Various location-based ubiquitous applications.



Indoor Location

Navigation

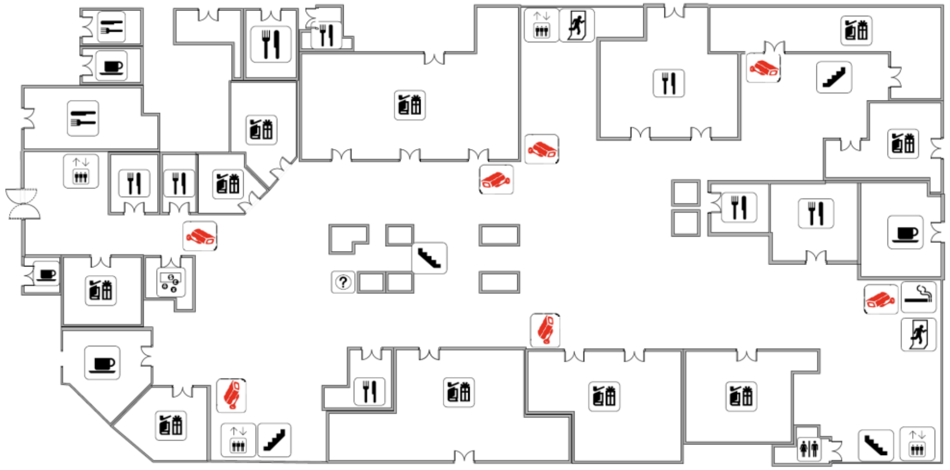


PoI discovery

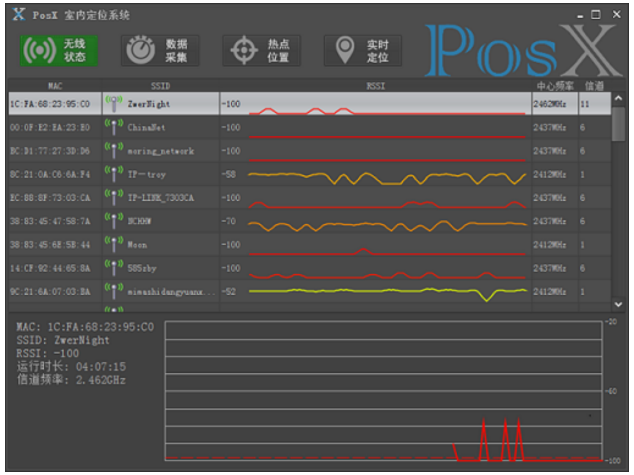
- And locating with Wi-Fi is superior in
  - Ubiquitous: Almost everywhere installed infrastructure.
  - Low-cost: Off-the-shelf Wi-Fi devices.
  - Non-invasive: not required to wear/carry any special devices.
- Attract attention from both academic and industrial communities.

Motivation

- Long-term evaluation of Wi-Fi Localization system.
  - We evaluate the performance of the Wi-Fi fingerprint-based localization system in real business environments across 7 months.



Shopping Mall Indoor Floor-plan

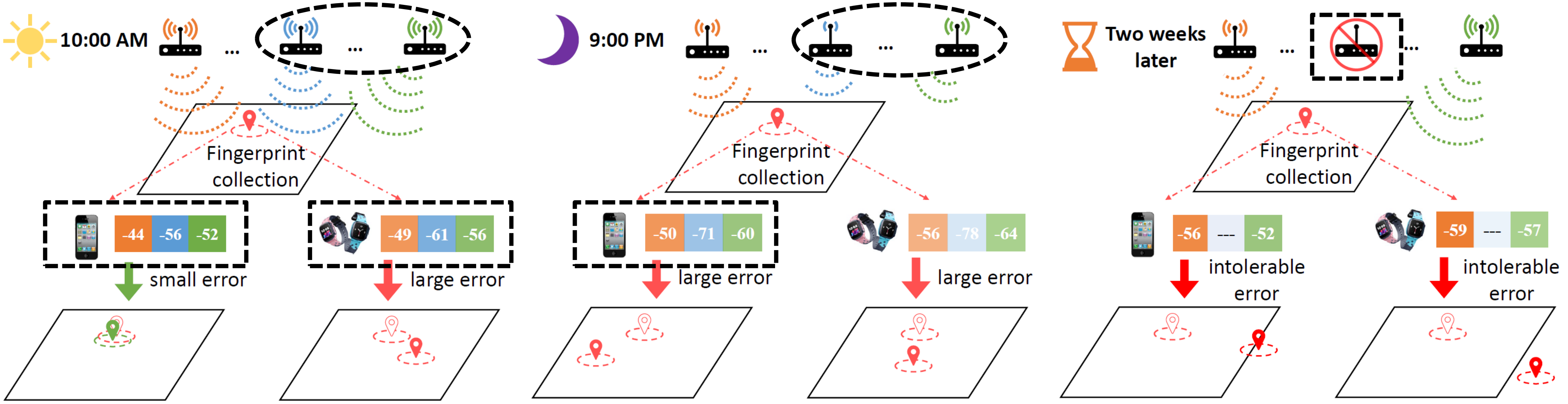


WiFi Collection and Localization System

  - We find three key reasons that lead to frequent large localization bias.

Major Problems

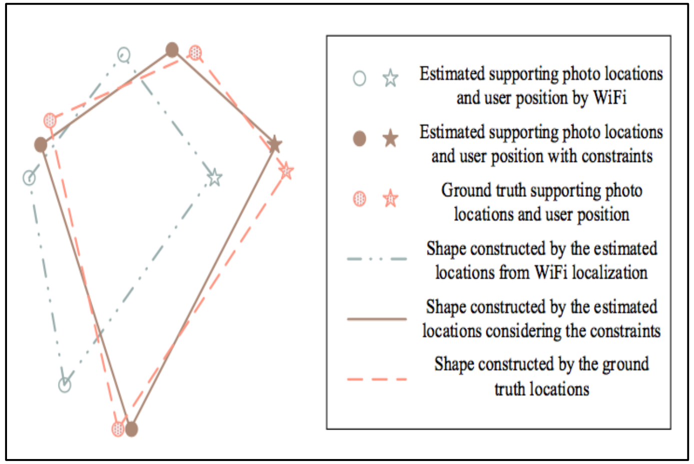
- Three key reasons that lead to frequent large localization bias.



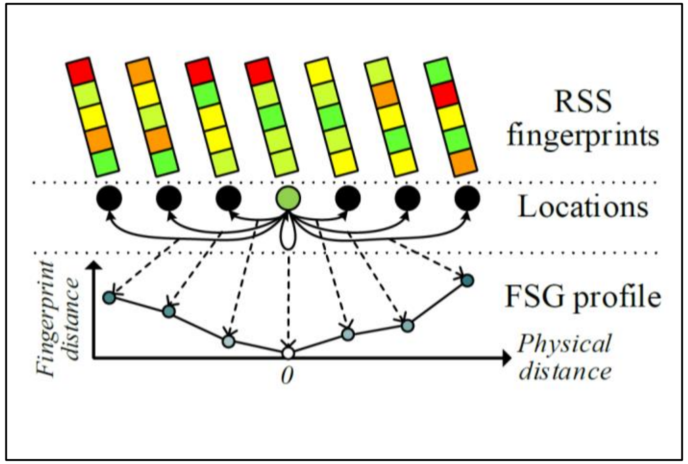
  - Signal variation.
  - Device heterogeneity.
  - Database deterioration.

Existing Arts

- Improve Localization Accuracy and robustness



Argus, Ubicomp '15



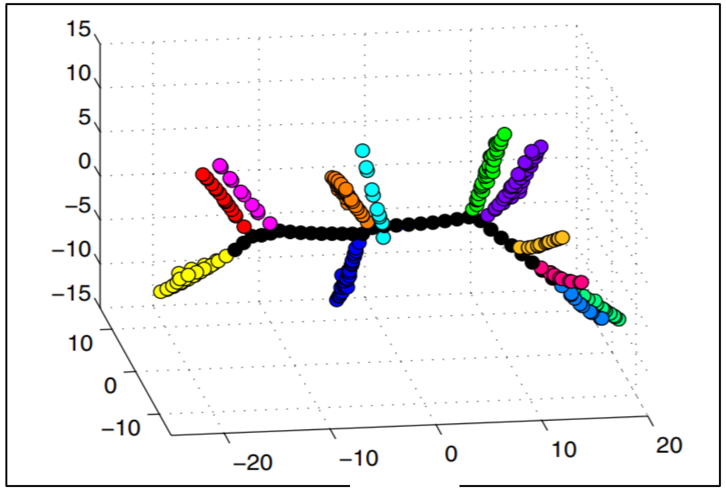
ViVi, Ubicomp '17

Environmental dynamics & device heterogeneity

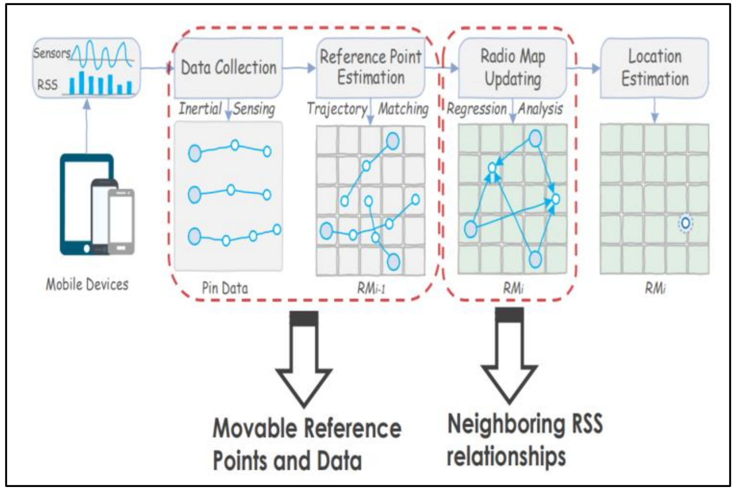
Localization accuracy and cross-device robustness remain low

Existing Arts

- Reduce Maintenance Overhead



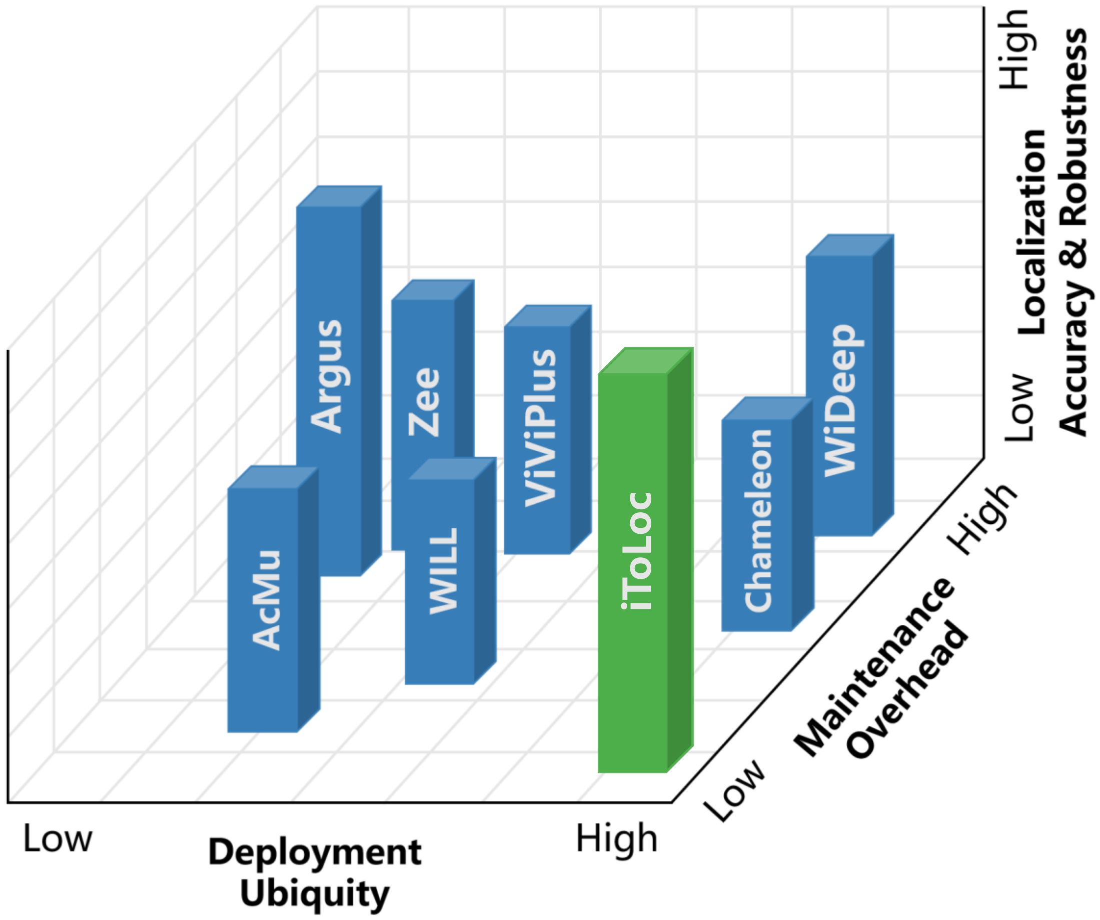
LiFS, MobiCom ’12



AcMu, INFOCOM ’15

reliable update depends on accurate localization → **maintenance overhead has not been obviously reduced**

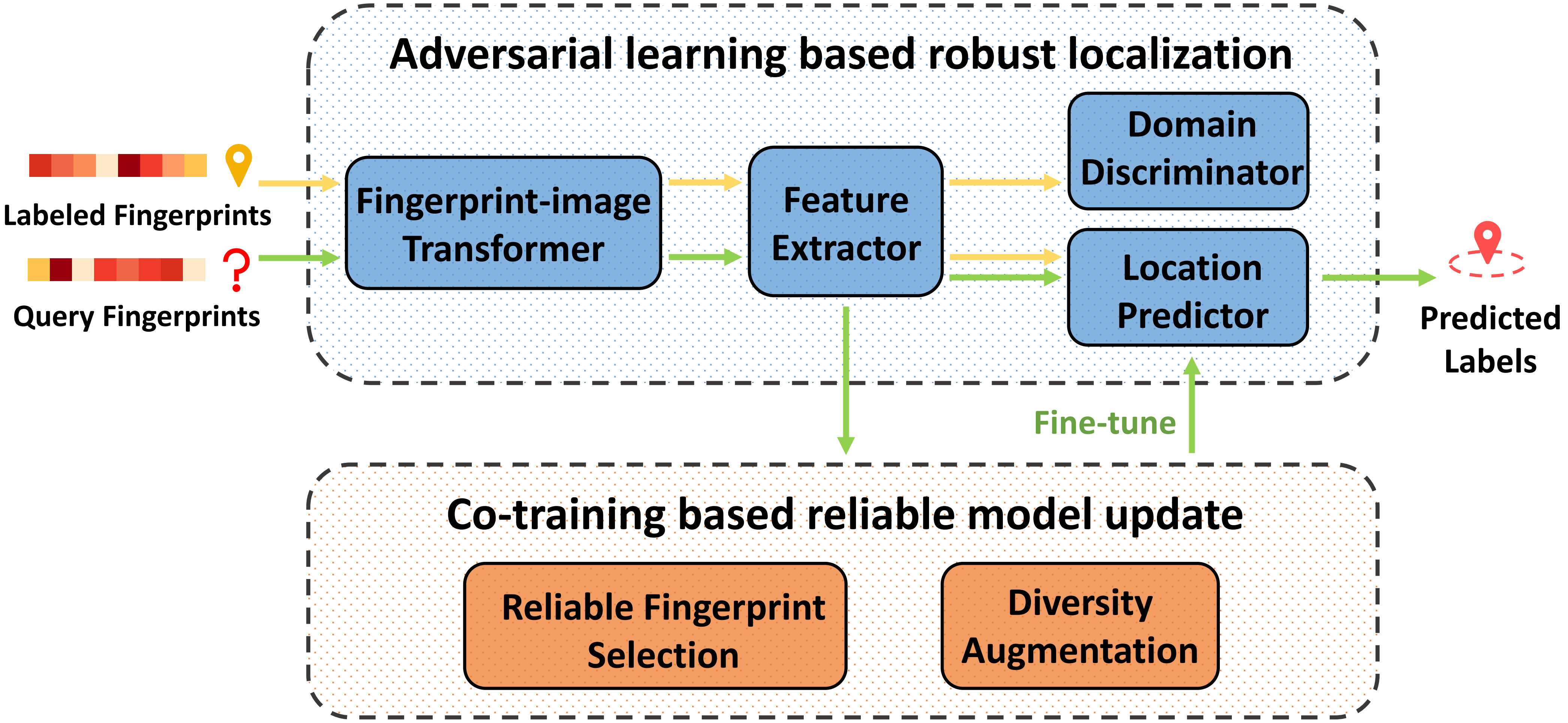
Target System



- Achieve three goals simultaneously.
  - high **localization accuracy**.
  - low **maintenance cost**.
  - delightful **deployment ubiquity**.

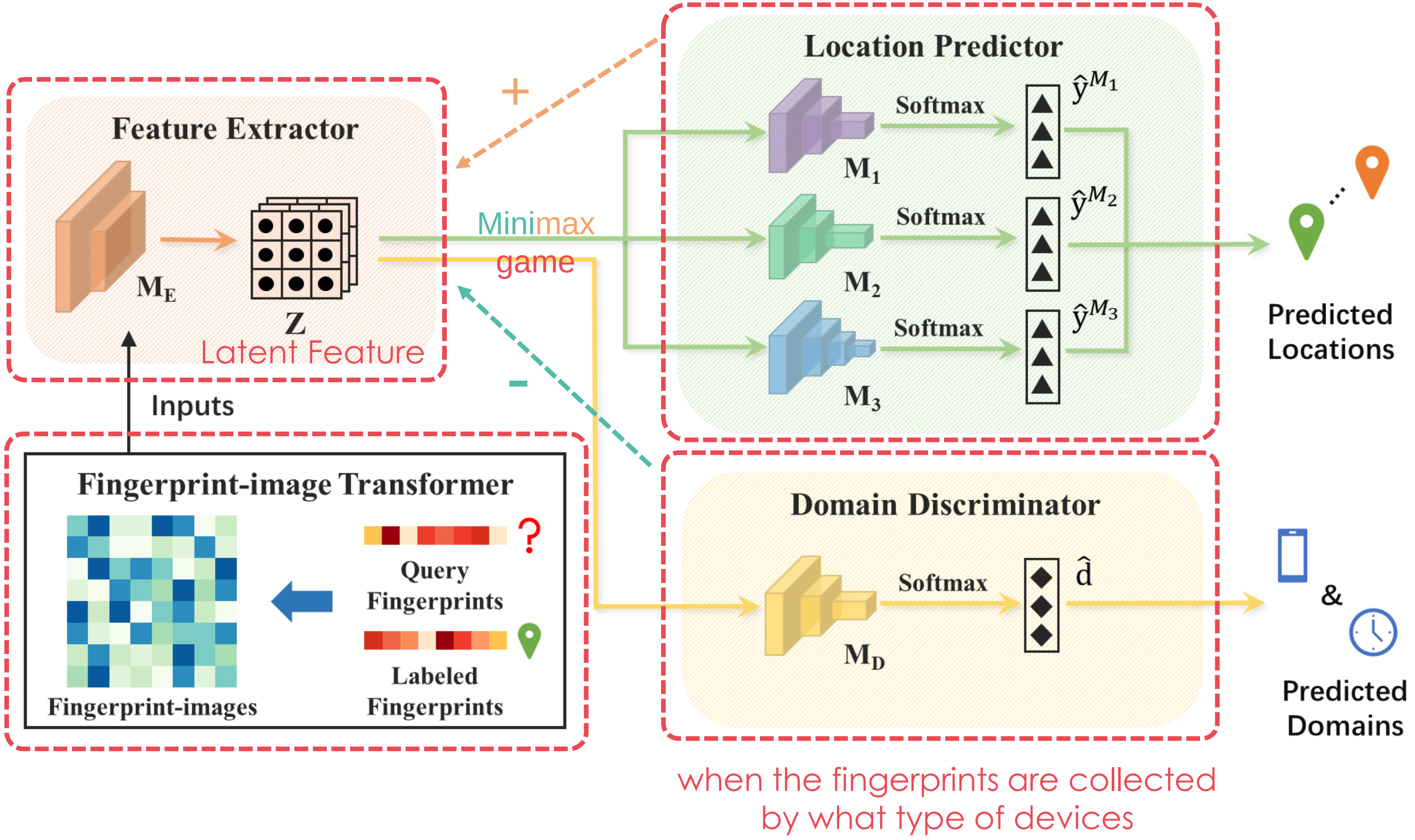
- **iToLoc**: A fine-grained deep learning based **i**ndoor localization system that is able to **T**rain **o**nce, update automatically, **Loc**ate anytime for anyone.

System Overview



DANN-based Robust Localization

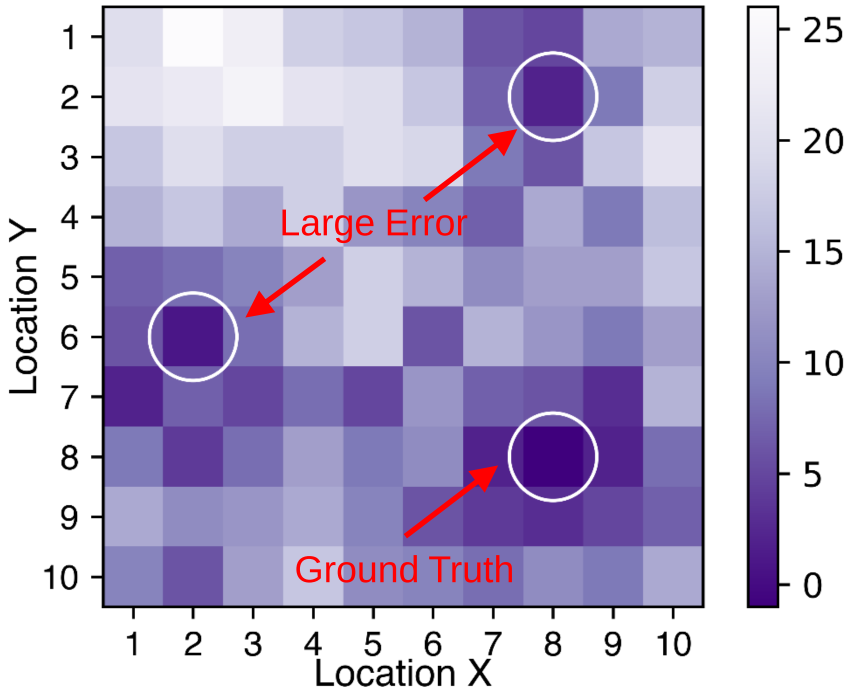
- Domain Adversarial Neural Network



DANN-based Robust Localization

- Spatial Constraint

Spatial Ambiguity: Large localization error



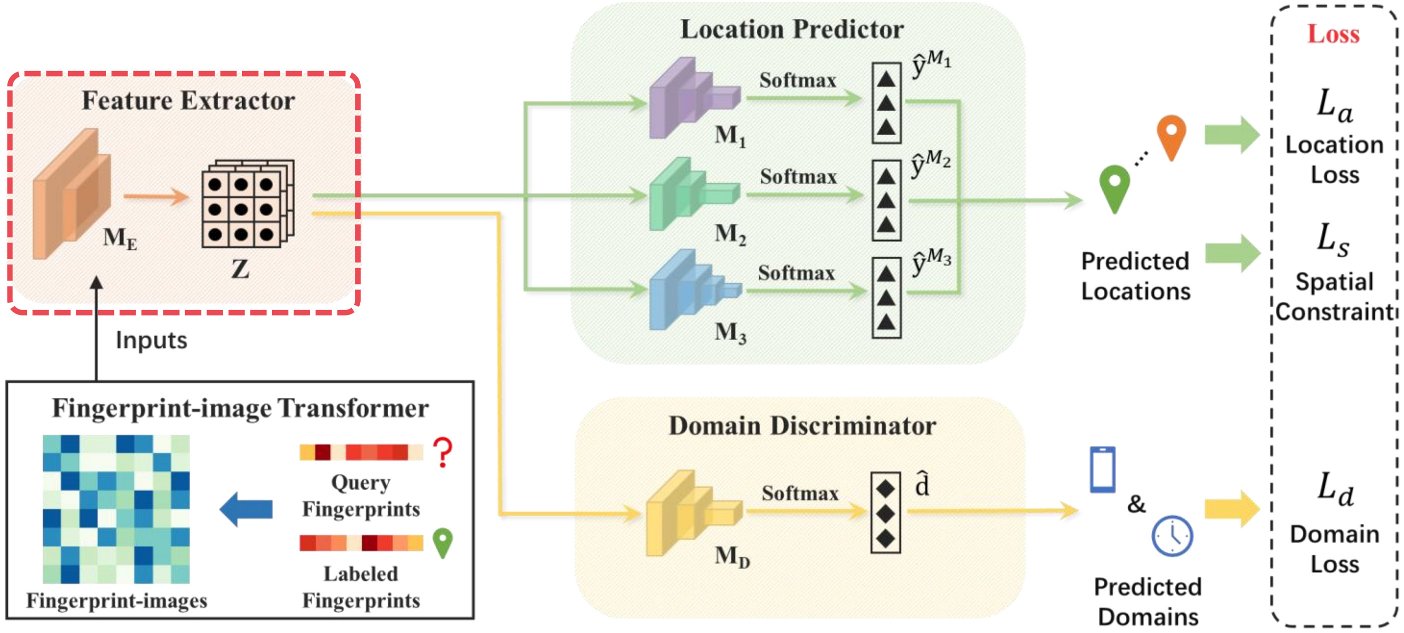
We penalizes $\hat{\mathbf{y}}_i$ when it is inconsistent with and far away from the ground truth $\mathbf{y}_i$.

Spatial Constraint Loss: $L_s = \frac{1}{|\mathbf{X}|}\sum_{i=1}^{|\mathbf{X}|}\sum_{c=1}^{C} w_{y_i c}\hat{\mathbf{y}}_{ic}$

$w_{y_i c}$ is the weight representing the physical distance between the c-th location and ground truth $\mathbf{y}_i$.

DANN-based Robust Localization

- Objective and Training

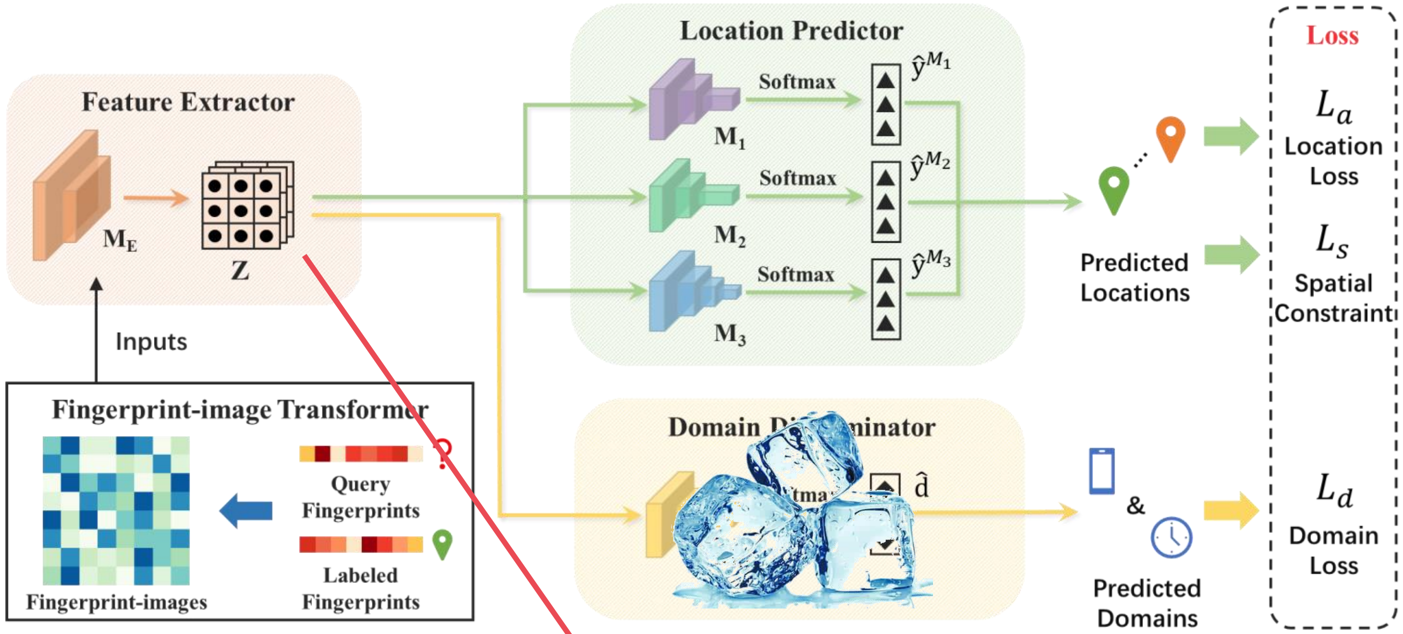


Cheat the domain discriminator but boost the location predictor

$$L = L_a + \gamma L_s - \lambda L_d$$

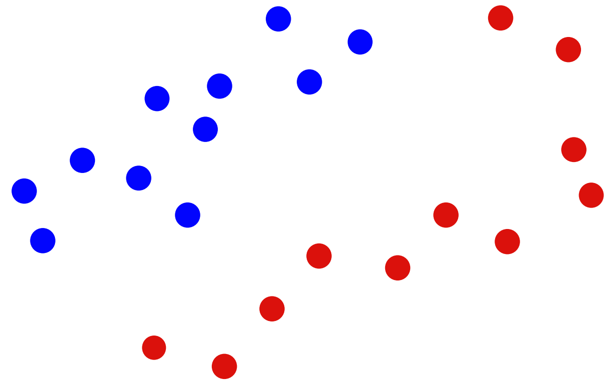
Feature extractor contradicts to domain discriminator. How to train the model?

DANN-based Robust Localization



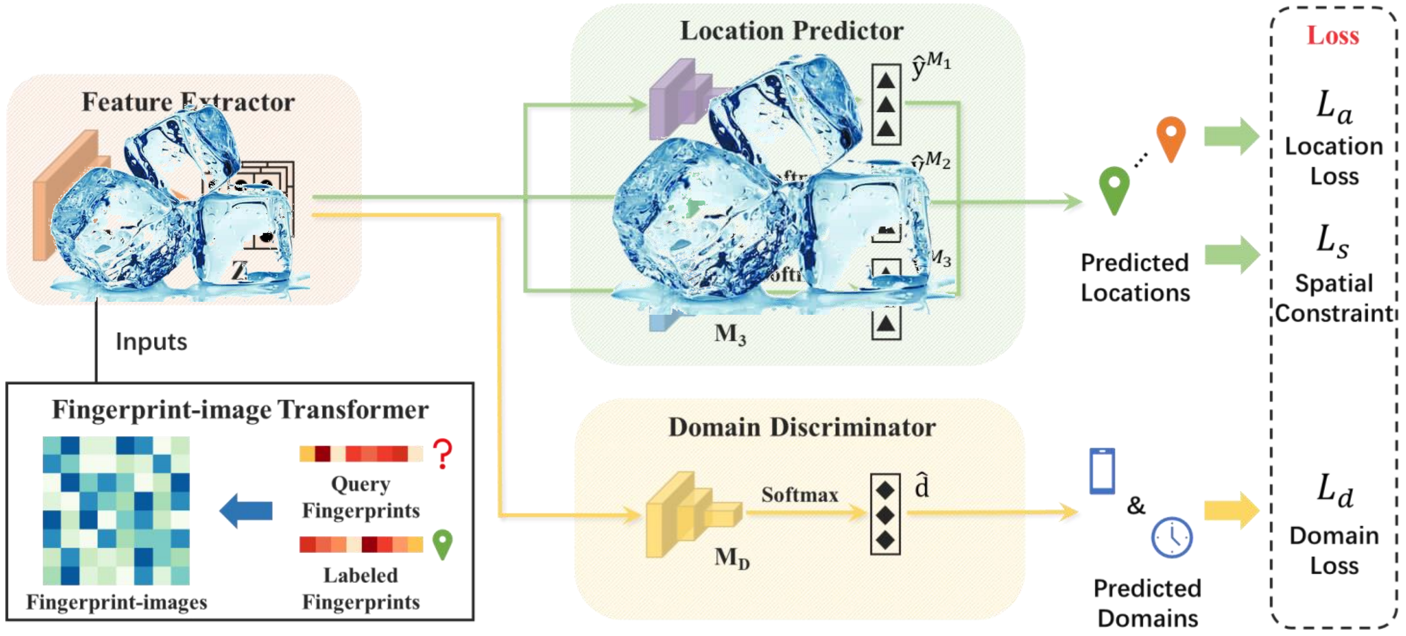
Location From Domain 1

Location From Domain 2



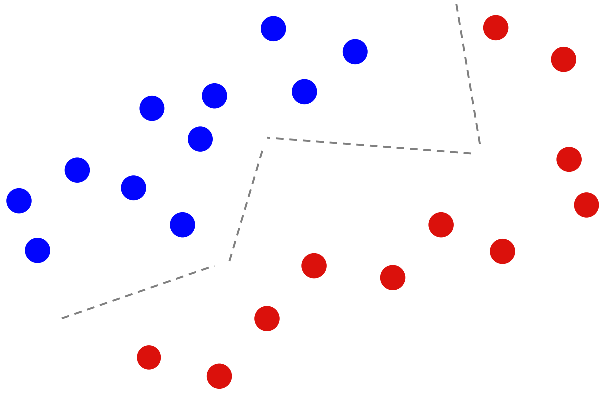
The representation of data from different domains are separate

DANN-based Robust Localization



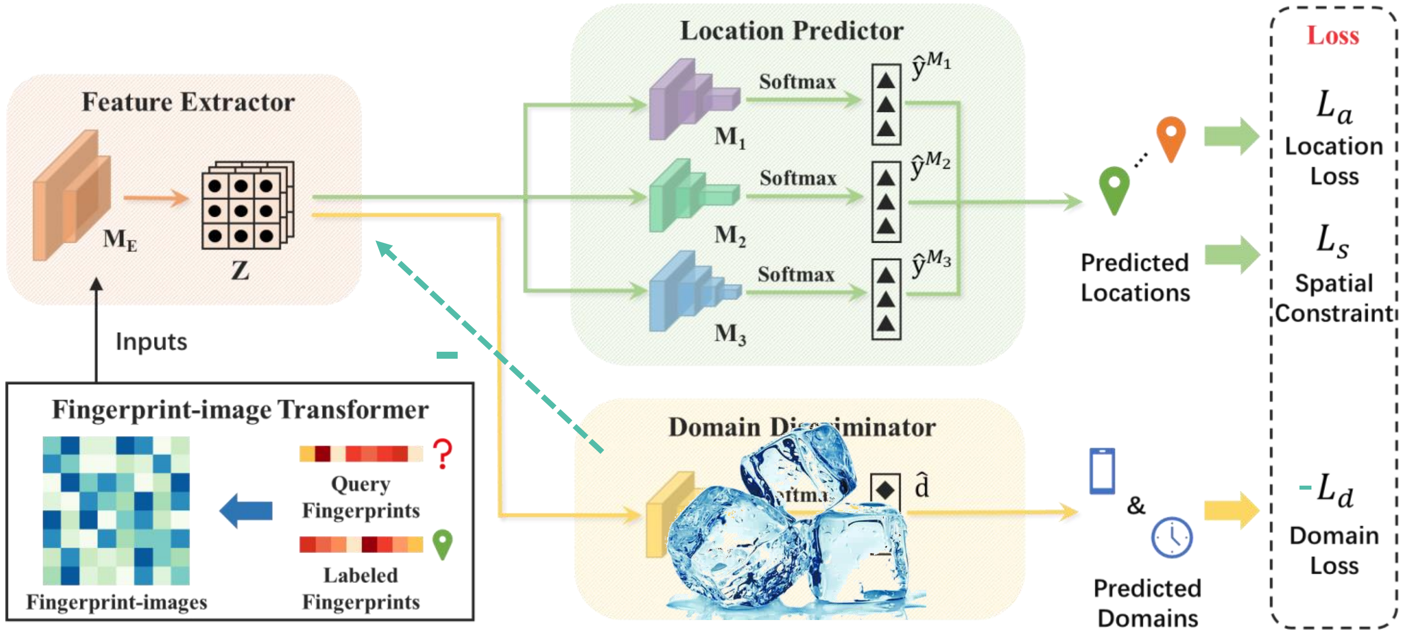
Location From Domain 1

Location From Domain 2



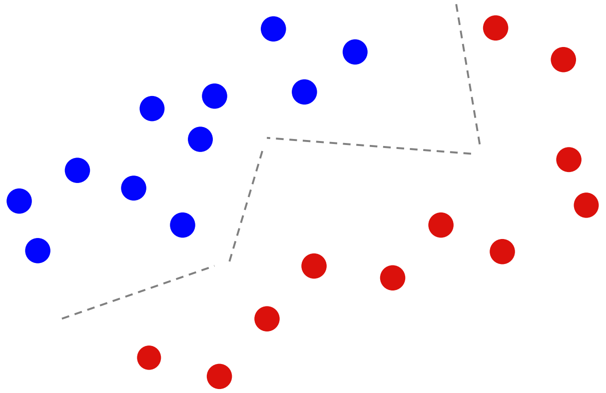
It recognizes the non-linear boundary between domains

DANN-based Robust Localization

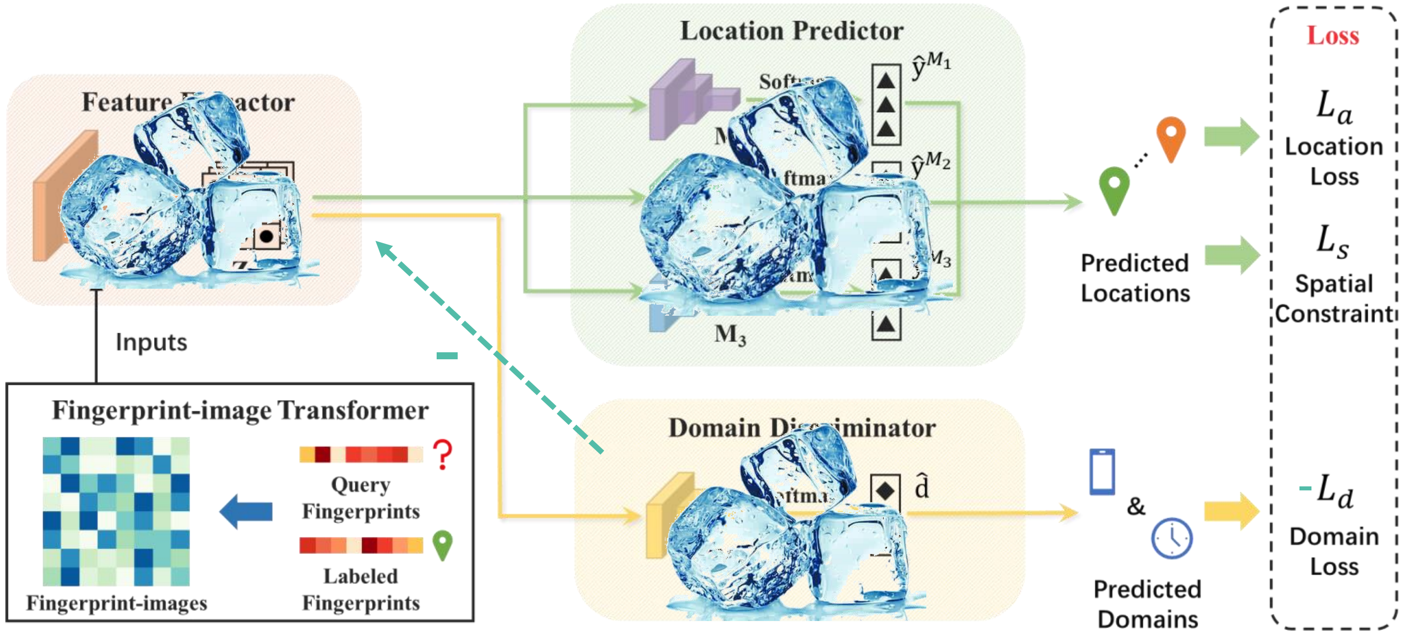


Location From Domain 1

Location From Domain 2

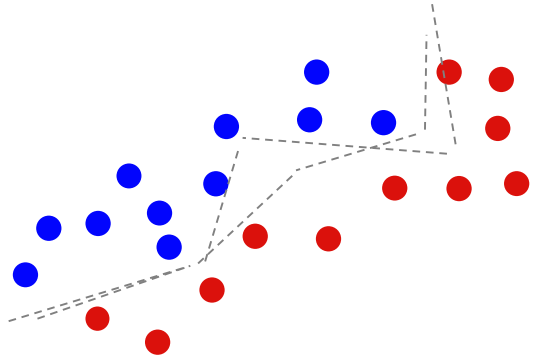


DANN-based Robust Localization



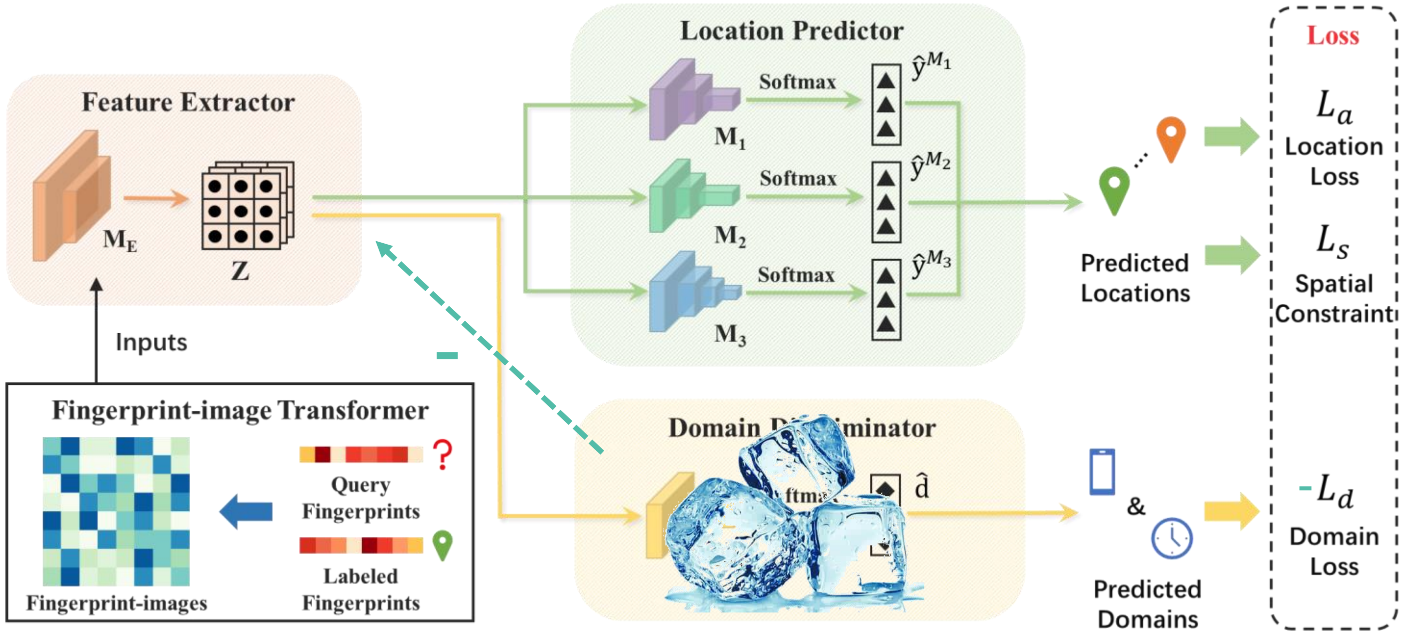
Location From Domain 1

Location From Domain 2



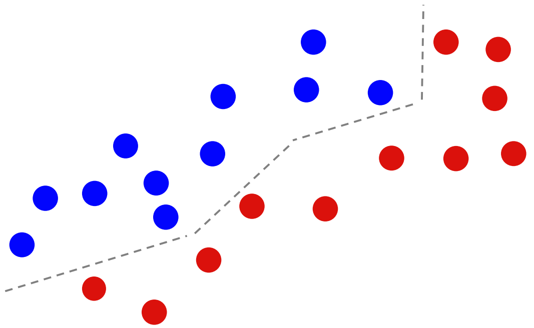
It moves the data towards the boundary of different domains

DANN-based Robust Localization

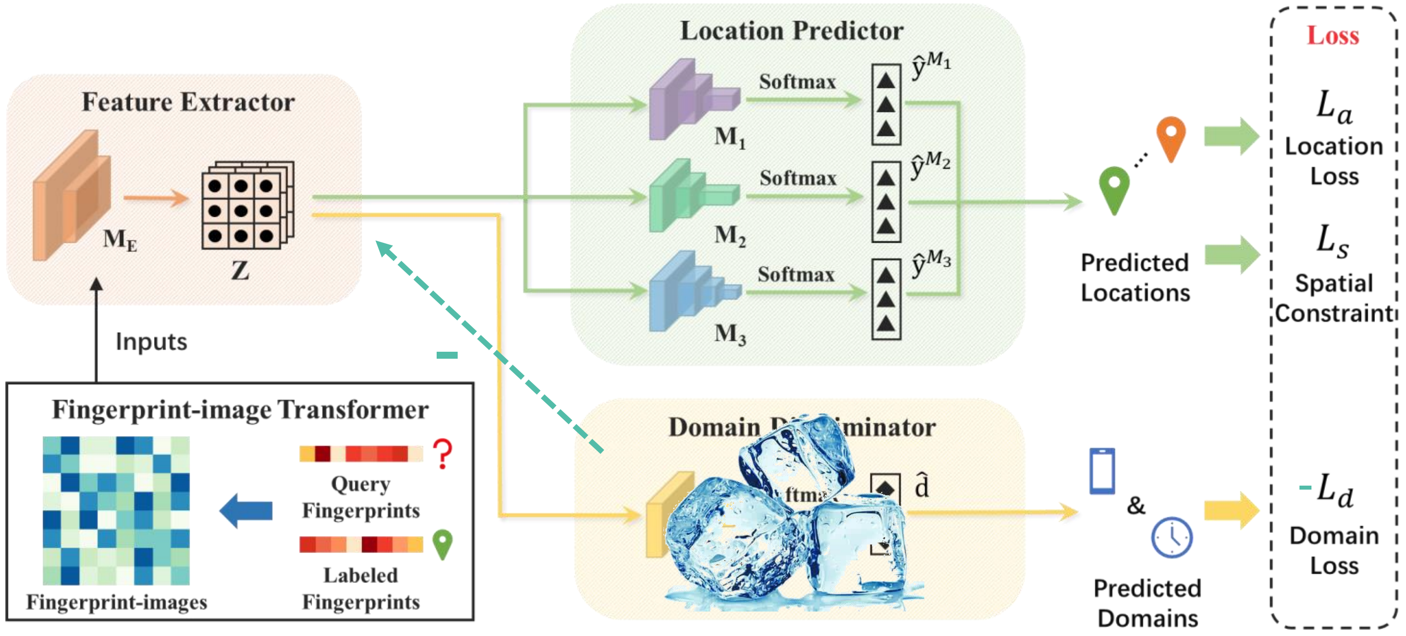


Location From Domain 1

Location From Domain 2

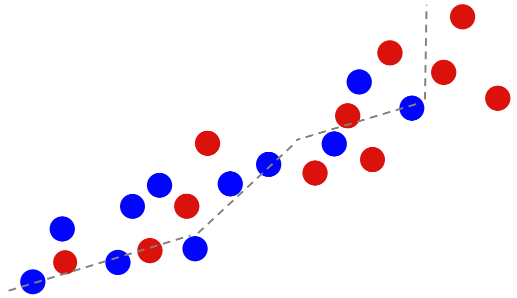


DANN-based Robust Localization



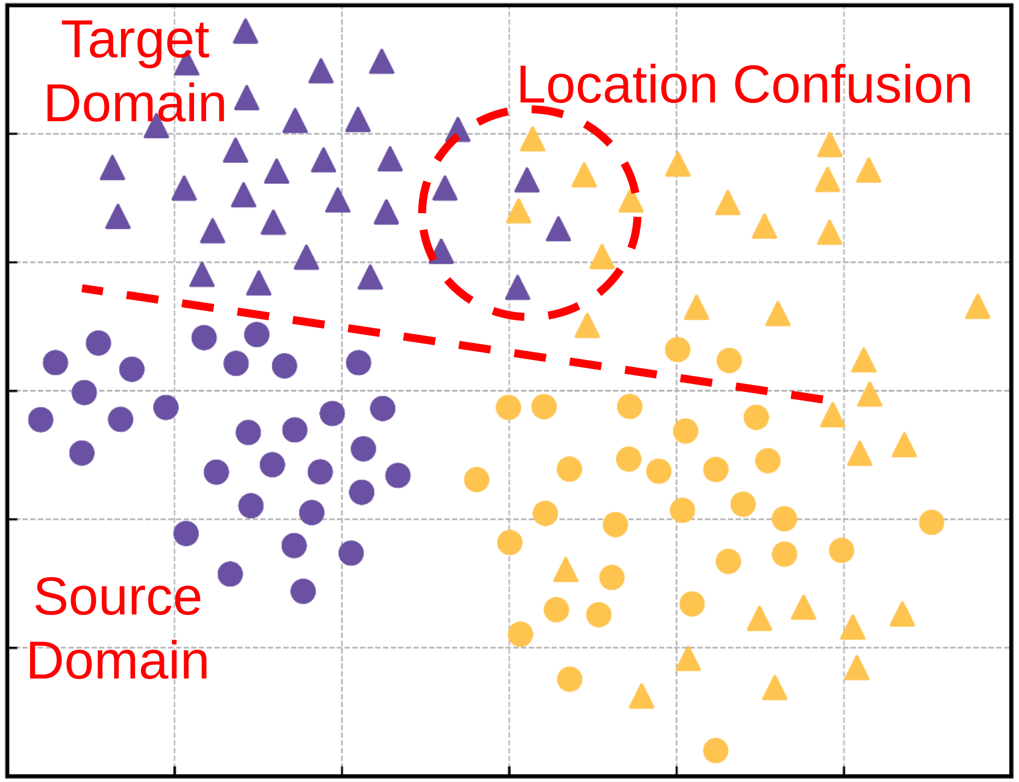
Location From Domain 1

Location From Domain 2

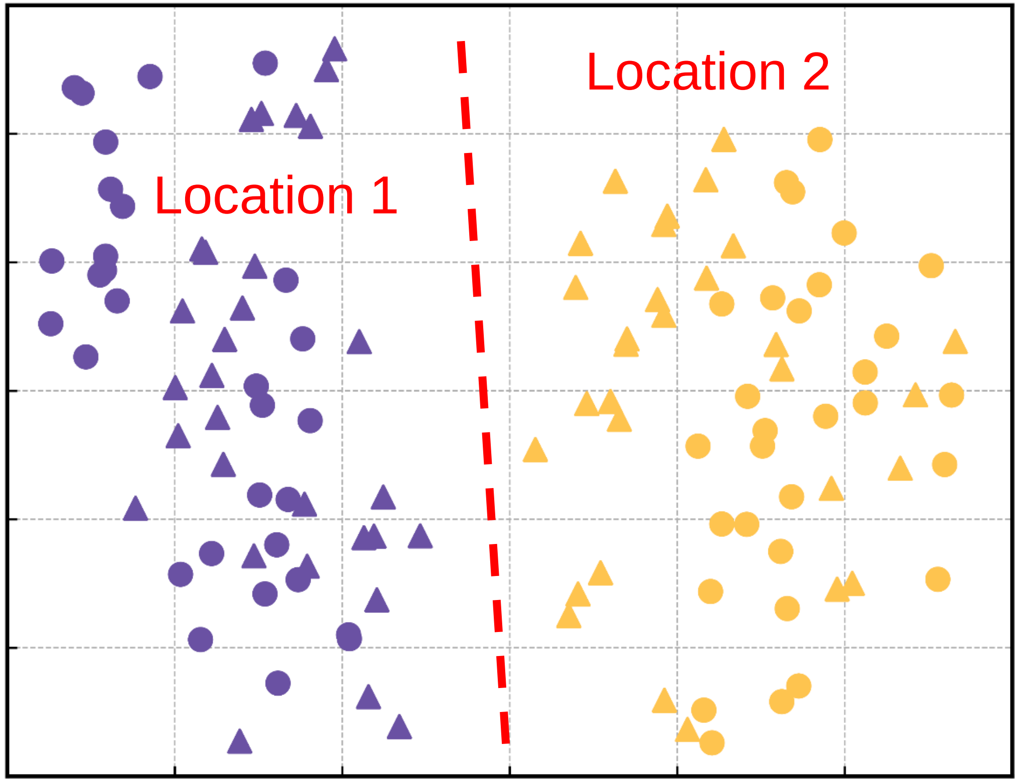


DANN-based Robust Localization

- Latent Representation



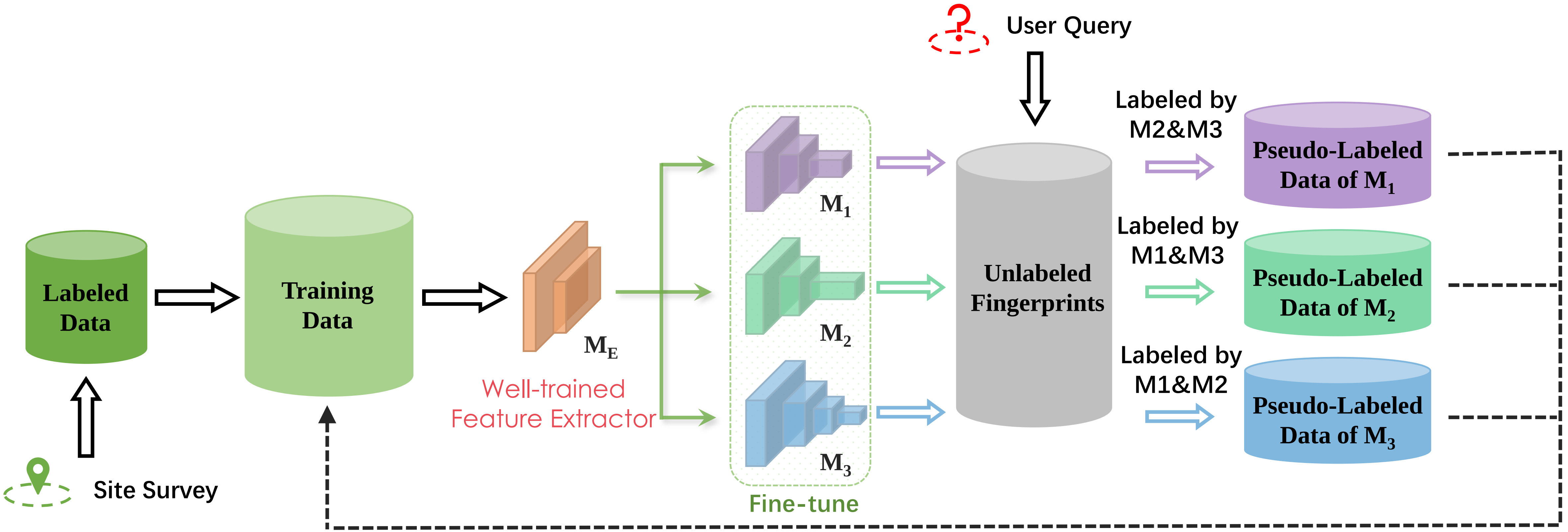
Without Adversarial Learning



With Adversarial Learning

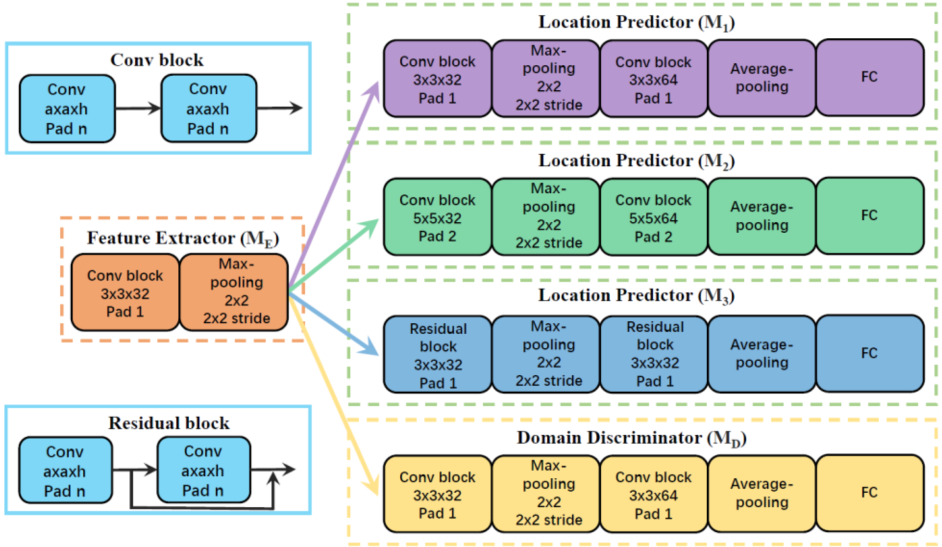
Co-training Based Model Update

- Training process of model update



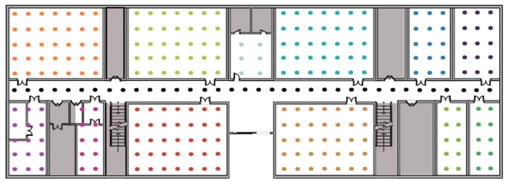
Experiment

- Experimental Methodology
  - 3 scenarios.
  - 8 devices.
  - 7 months.
  - 2 evaluation metrics.

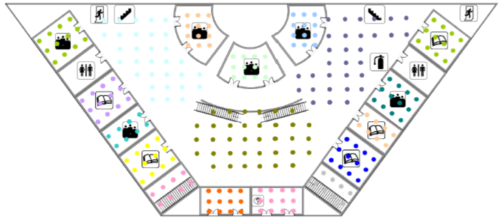


The architecture of ***iToLoc***

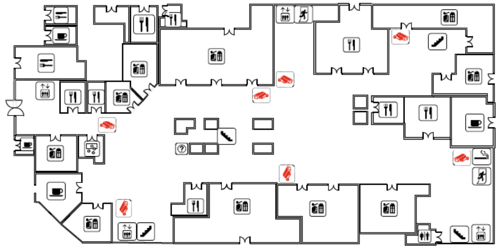
#	Building type (Areas)	Size(m^2)	Density	Devices	Region	Samples	Duration
1	Office (Whole floor)	600	1m × 1m	HUAWEI P10 * 2, Phab2, Nexus 6p * 2/7, Millet 6/9	13	72K	2 weeks
2	Classroom (Whole floor)	1,360	1.5m × 1.5m	HUAWEI P10 * 2, Phab2, Nexus 6p * 2/7, Millet 6/9	18	96K	2 weeks
3	Shopping mall (Public areas)	2,130	——	HUAWEI P10 * 2, Phab2, Nexus 6p * 2/7, Millet 6/9, imoo Z5/Z6	30	288K	7 months



(a) Office building



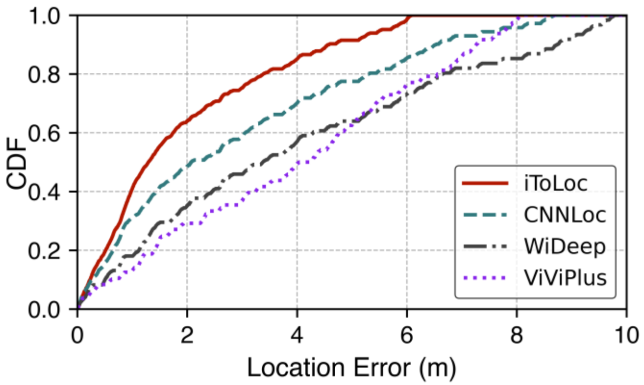
(b) Classroom building



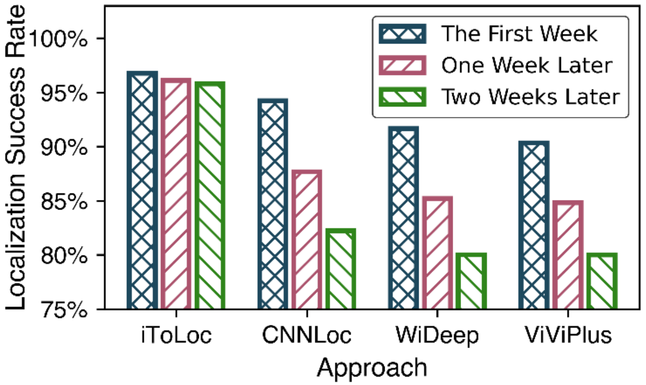
(c) Shopping mall

Experiment

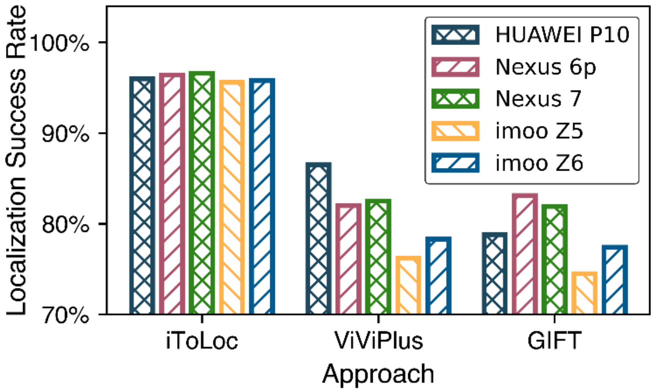
- Overall Performance



Accuracy comparison



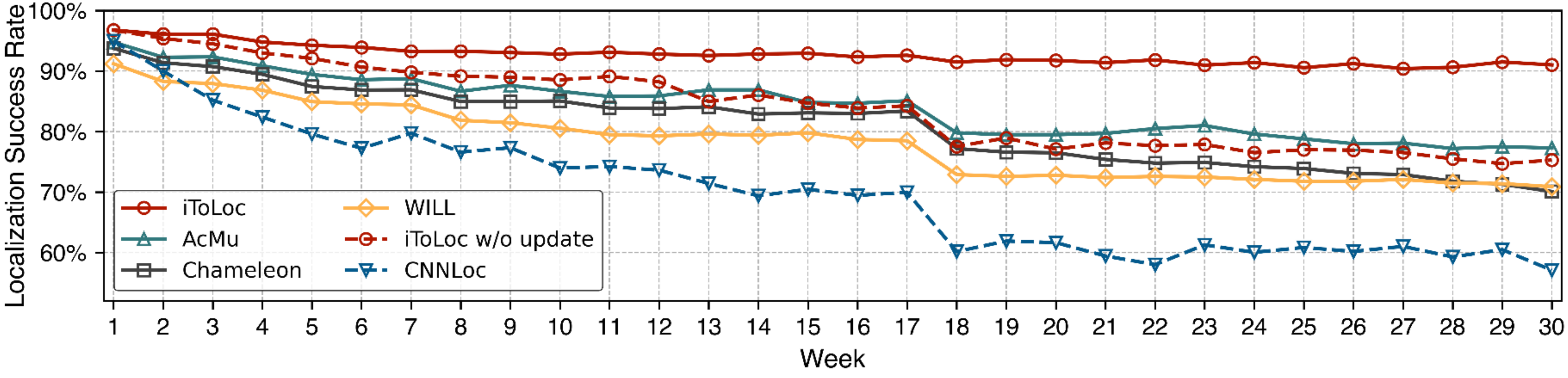
Temporal robustness



Cross-device robustness

Experiment

- Overall Performance



Long-term performance comparison

Conclusion & Contribution

- We design a novel **adversarial network based localization framework**. Based on the in-depth understanding of RSS fingerprints and efficient design of the network model, the proposed framework is able to extract **device-independent** and **dynamics-resistant feature** for robust localization.

- We provide a fresh perspective to solve the radio-map automatic adaption problem based on semi-supervised learning. Compared with existing methods, we **first fill the gap between robust localization and reliable model update**.

- We prototype ***iToLoc*** on 8 different types of devices in real environments for 7 months. Encouraging results demonstrate that ***iToLoc*** makes a great progress towards fortifying WiFi fingerprint-based localization to an entirely practical service for wide deployment.

Thanks!
Q&A

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