

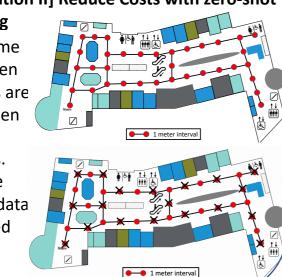
#### **Background & Motivation**

We aim to provide an infrastructure-free, image-based indoor localization system. [Motivation I] Feature Propagation between Views: Existing works working on panorama images. Shouldn't we treat these views differently?



[Motivation II] Reduce Costs with zero-shot

Learning We assume the unseen locations are in-between seen locations. Thus, the training data is reduced by ~50%



## Zero-Shot Multi-View Indoor Localization

## via Graph Location Networks

Prediction

"Location 4

 $\mathcal{Y}_u \subset \mathcal{Y}$ 

GLN-ZS-ATT

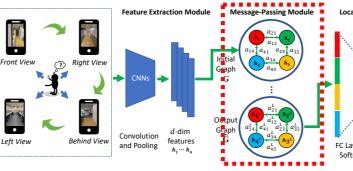
2.02

4.55

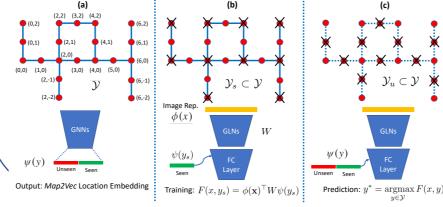
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#### Methodology

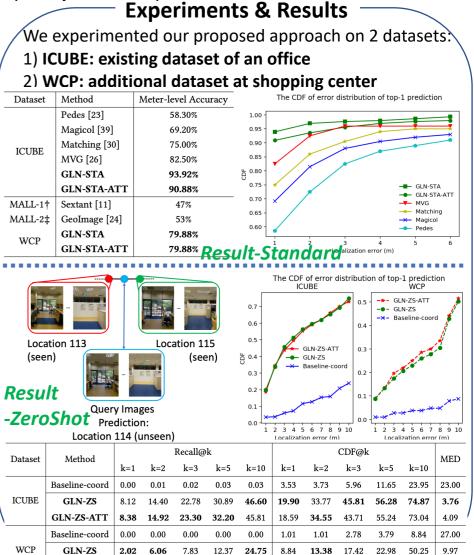
We propose a multi-view image-based localization method that utilizes Graph Neural Networks (GNNs) to propagate distinct features of different views. Message-passing with GNNs



Zero-Shot Indoor Localization: A Three-step framework: 1. Train *Map2Vec* location embeddings (seen & unseen data) 2. Train an inloc system w/ compatibility function (seen data) 3. Perform Inference by picking the most probable location



# ACM multimedia Seattle



13.64

8.33

24.50

9.09

13.38

25.00

19.70

51.52