UC San Diego
JACOBS SCHOOL OF ENGINEERING
Electrical and Computer Engineering

Mobicom 2020

WCSNG
Wireless Communications Sensing and Networking

Deep Learning based Wireless Localization for Indoor Navigation

Roshan Ayyalasomayajula, Aditya Arun, Chenfeng Wu, Sanatan Sharma, Abhishek Sethi, Deepak Vasisht and Dinesh Bharadia

https://wcsng.ucsd.edu/dloc/

SCAN ME

Outdoor Localization

Outdoor Localization

Navigation

https://play.google.com/

Autonomous Driving

https://www.kvhmobileworld.kvh.com/why-gps-spoofing-is-no-threat-autonomous-navigation/

Delivery Bots

https://medium.com/@miccowang/delivery-robots-as-last-mile-solution-aebebe557ad4

Autonomous Drones

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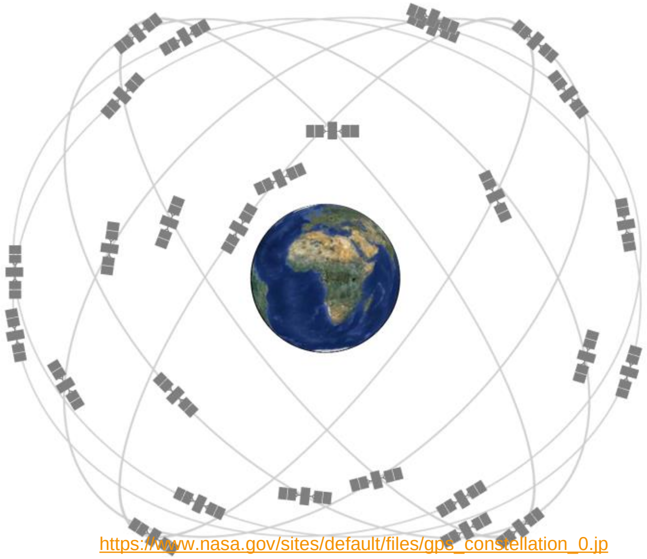

https://www.nasa.gov/sites/default/files/gps_constellation_0.jpg

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Indoor Localization

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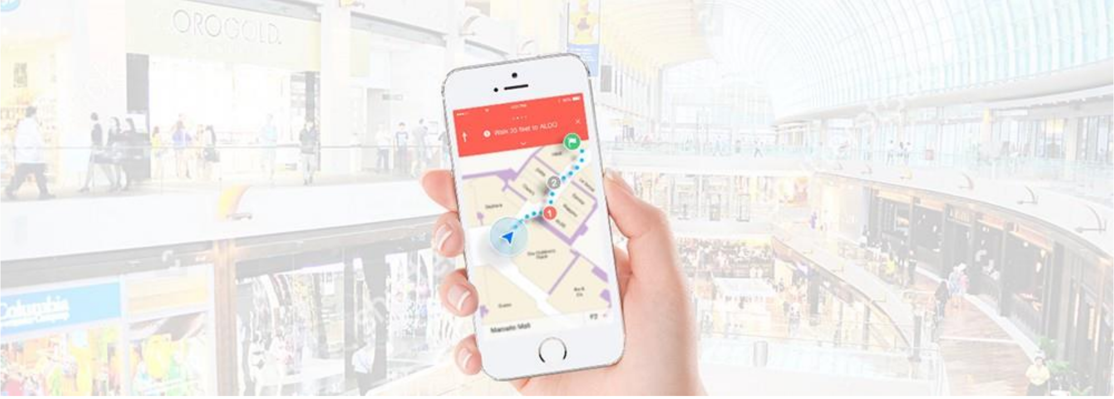

https://medium.com/@brian.moran_91776/top-10-reasons-how-indoor-navigation-helps-shopping-malls-be6376bf3d2

Indoor Localization

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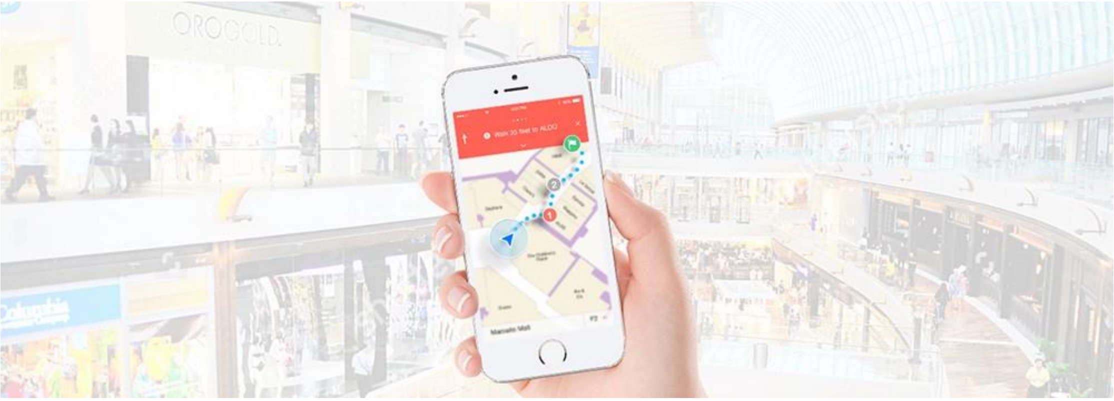

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https://jonnegroni.com/2015/04/15/the-humans-of-wall-e-were-probably-better-off-without-him/

Lack of Context

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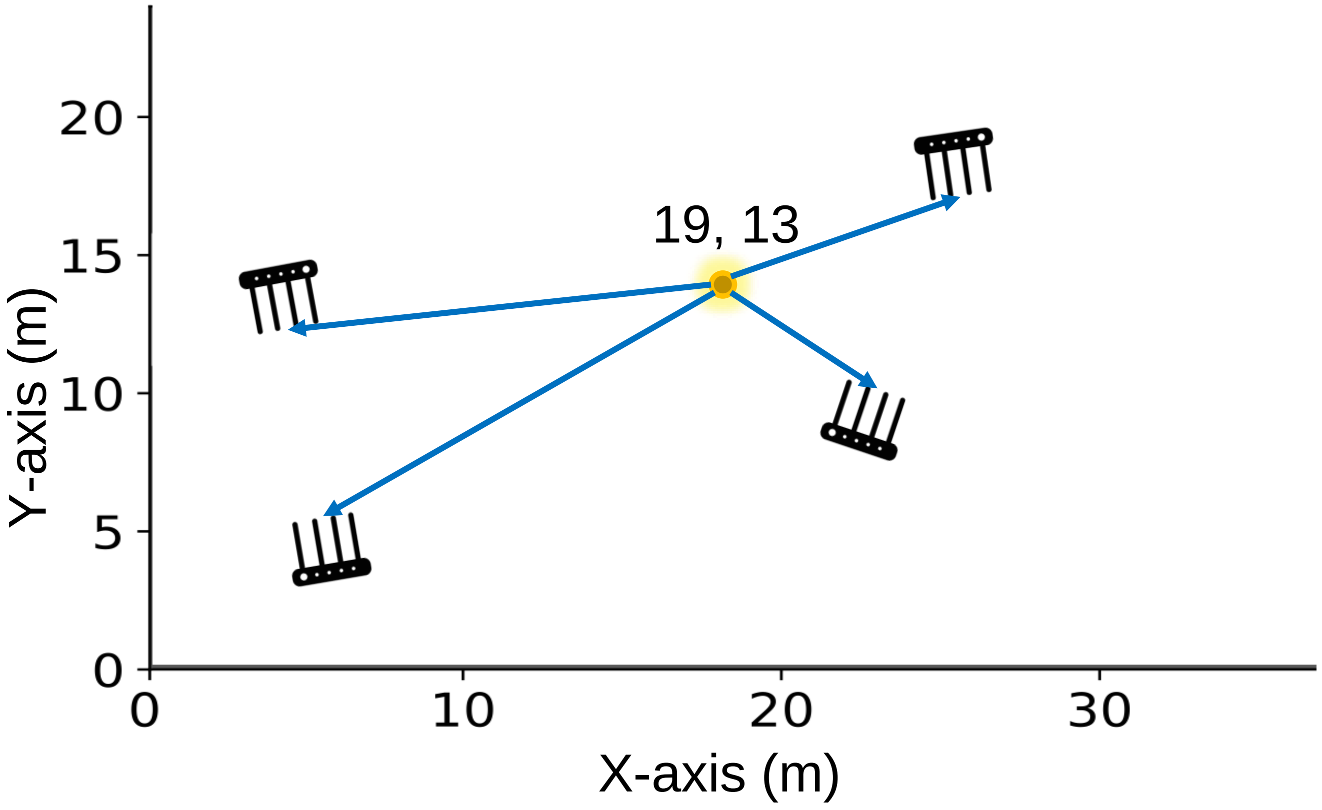

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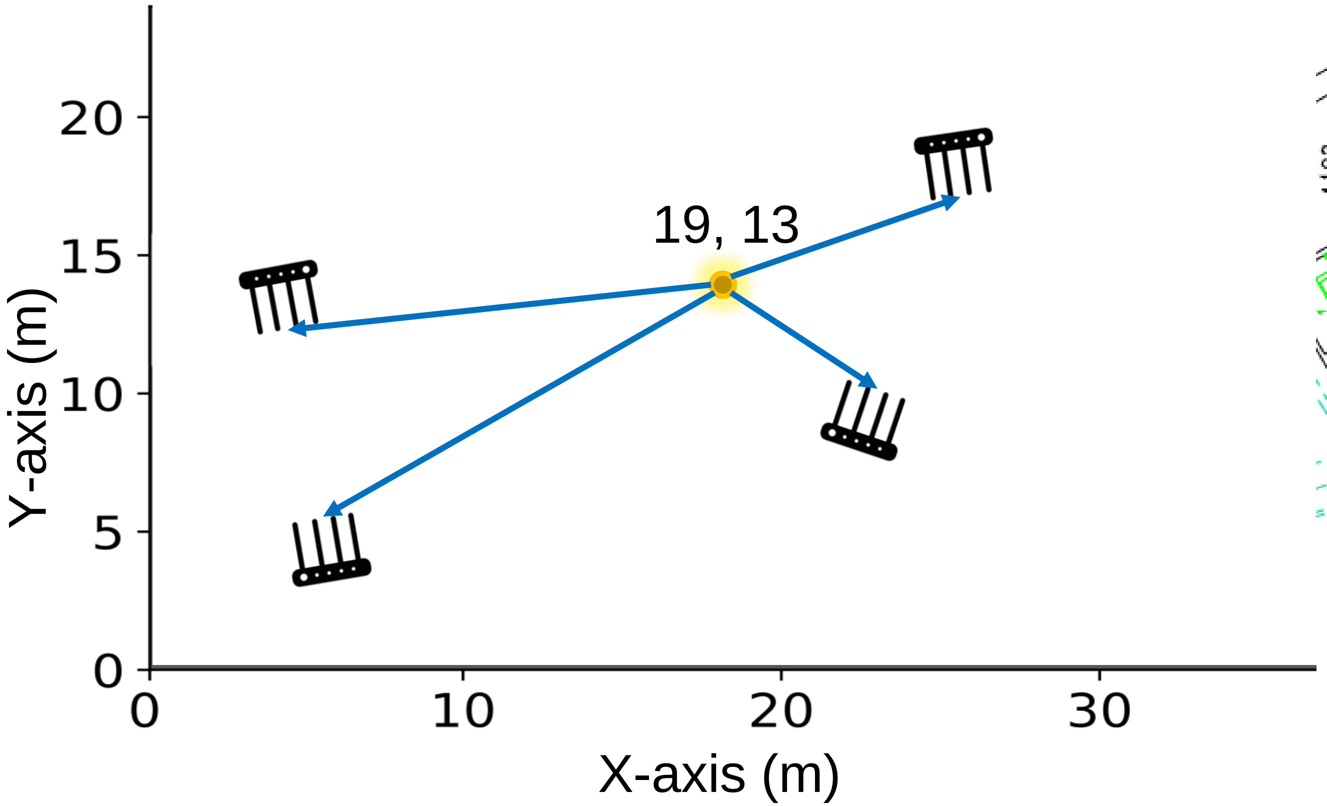

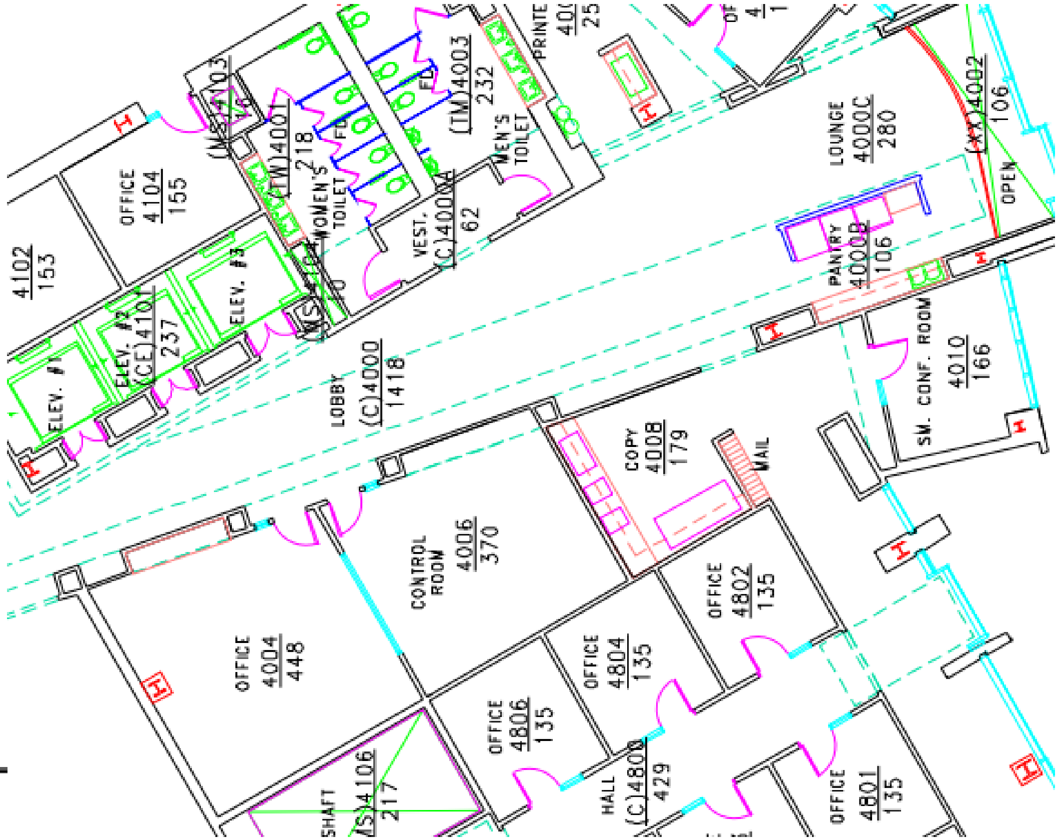

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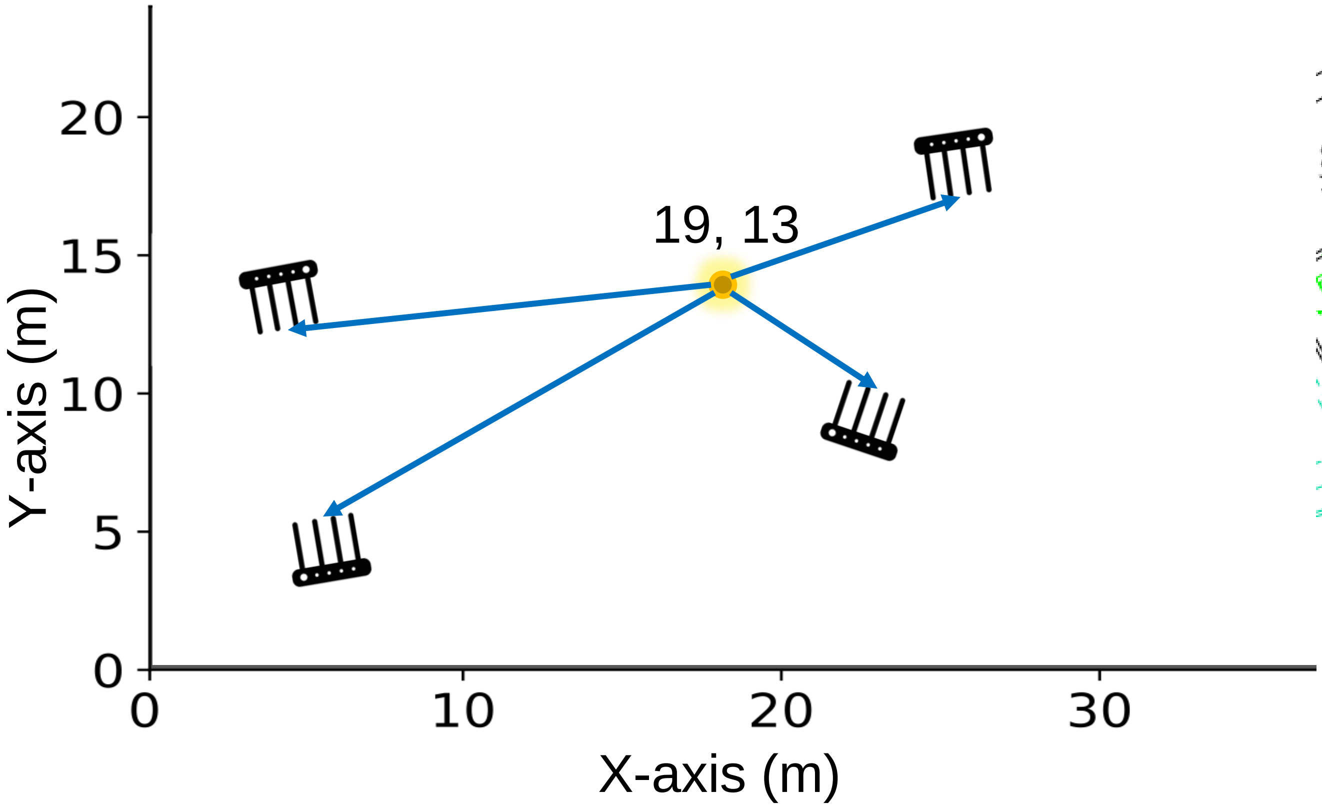

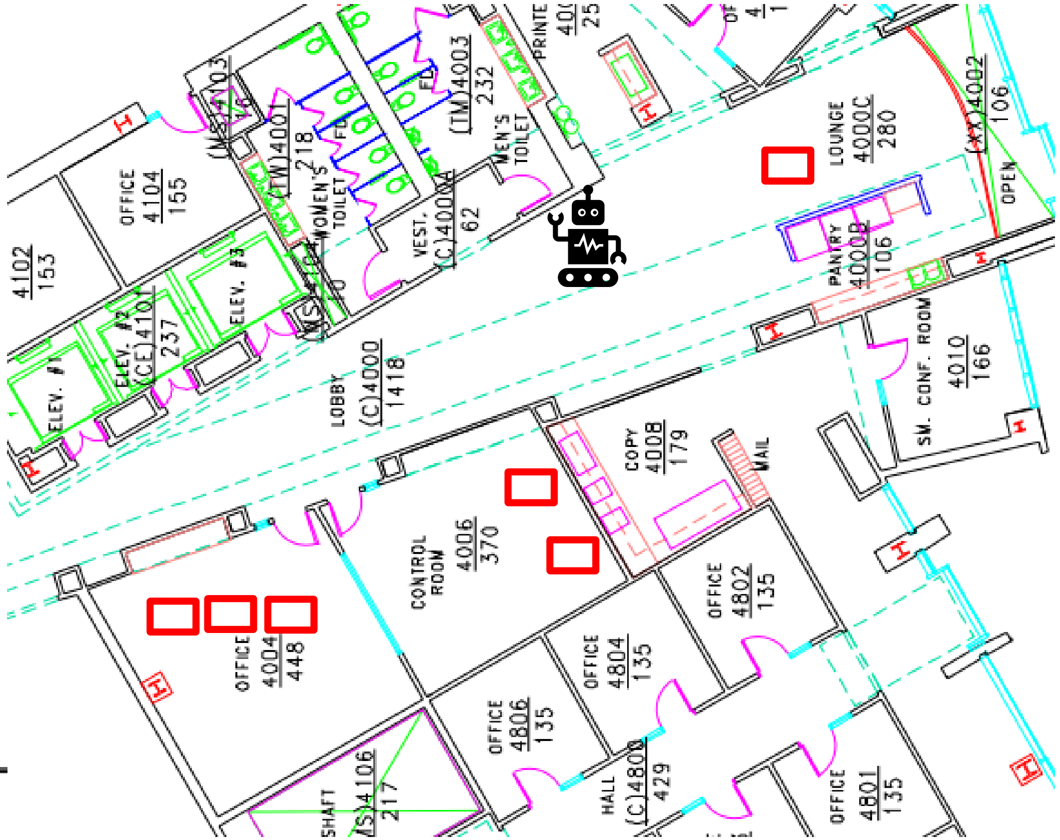

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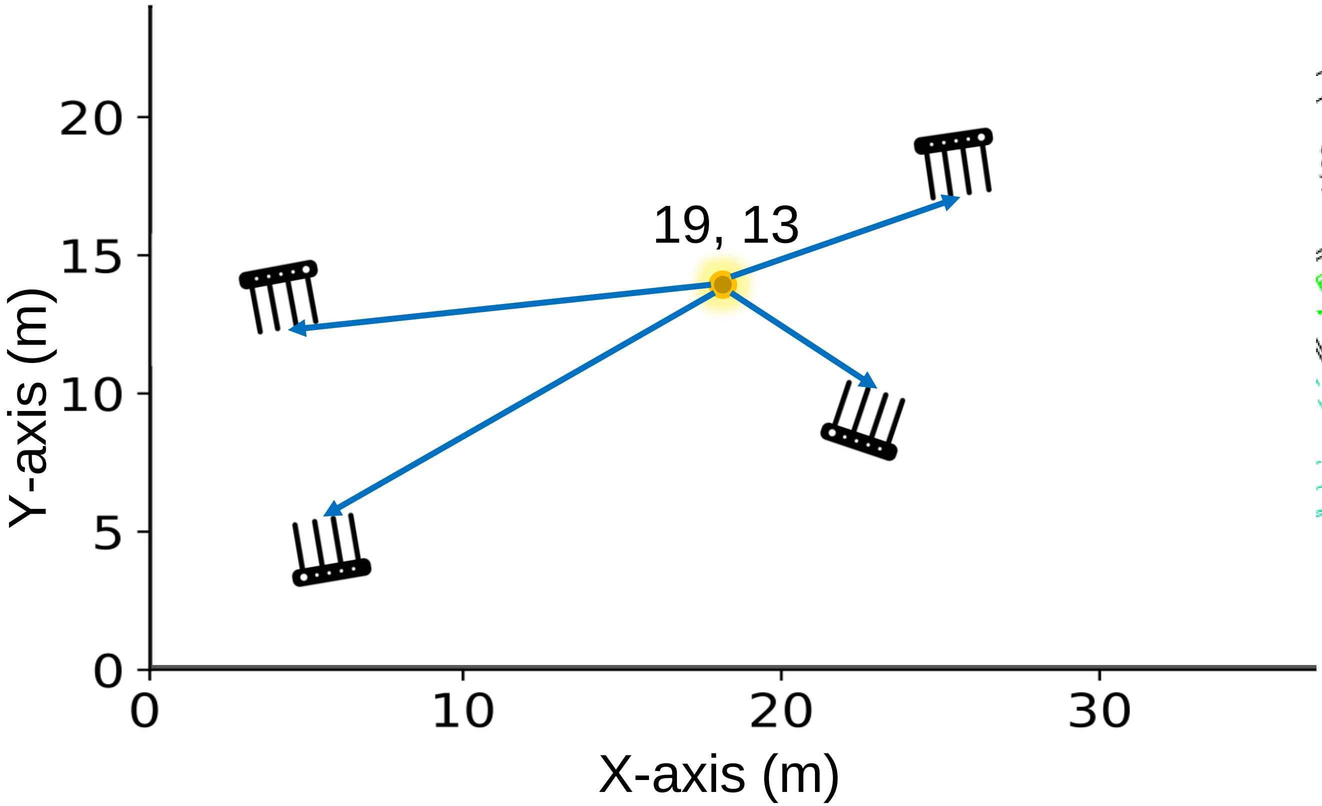
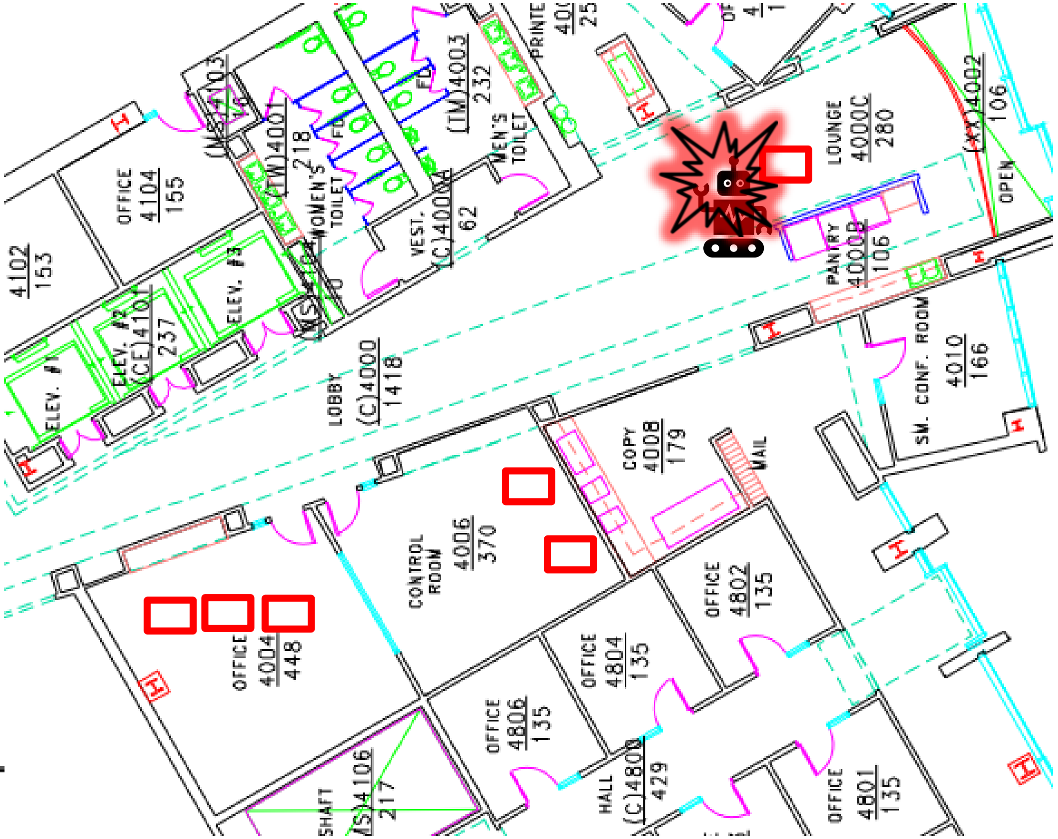


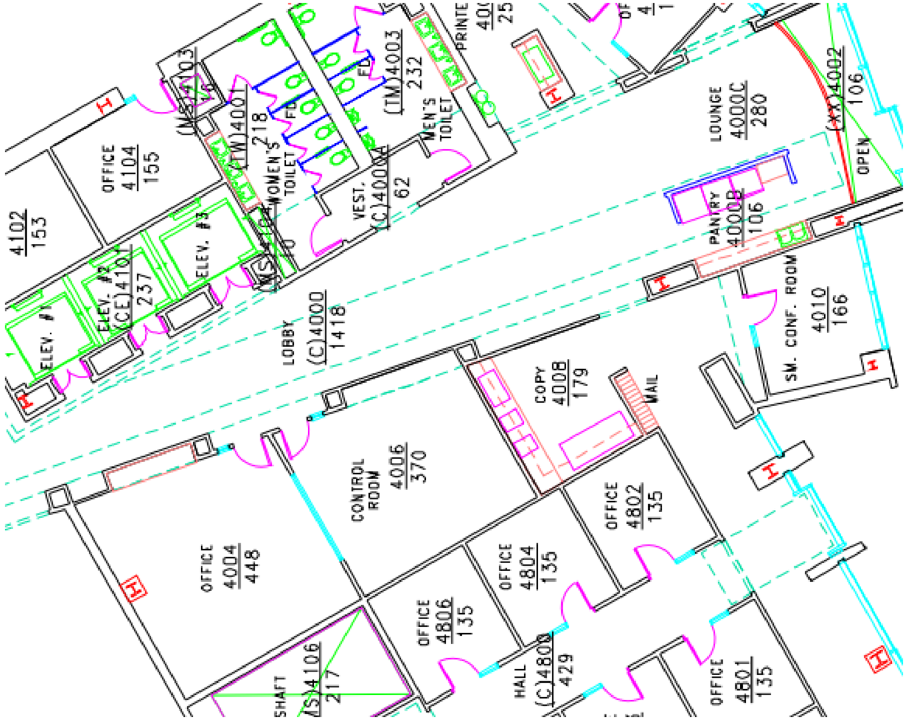


Created by Grafix Point from Noun Project

WiFi based localization

WiFi based localization

MonoLoco MobiSys'18	Chronos NSDI'16	ToneTrack Mobicom'15	SpotFi Sigcomm'15	ArrayTrack NSDI'13



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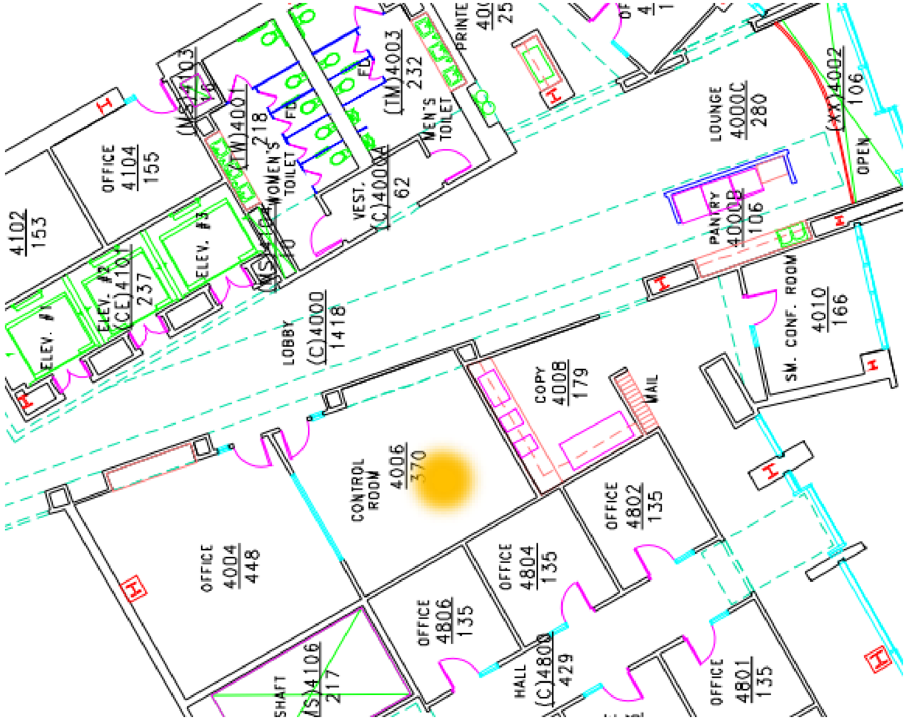

Median: few decimeters

WiFi based localization

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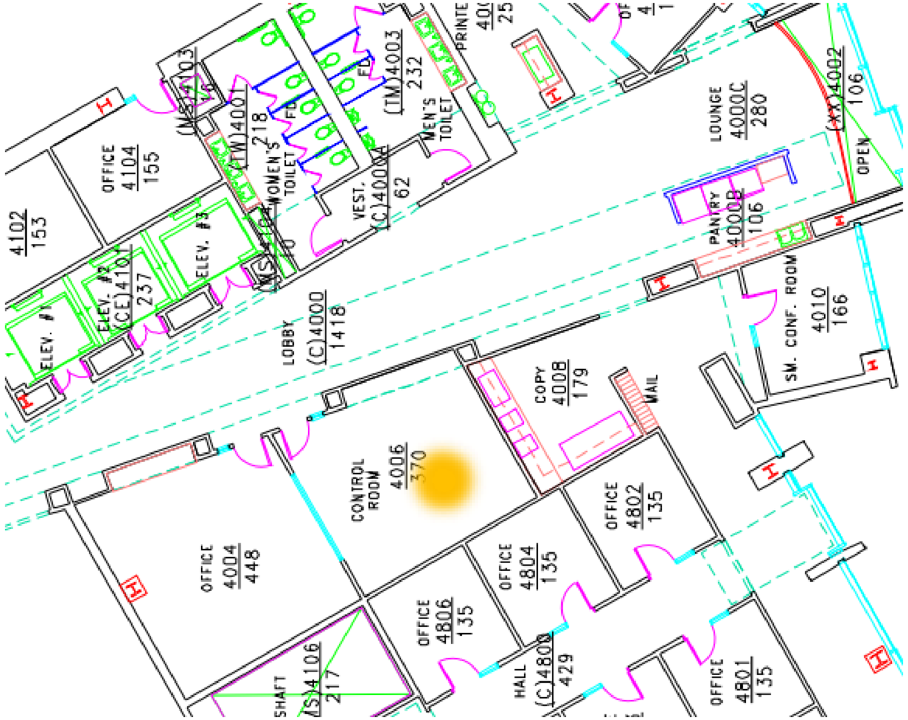

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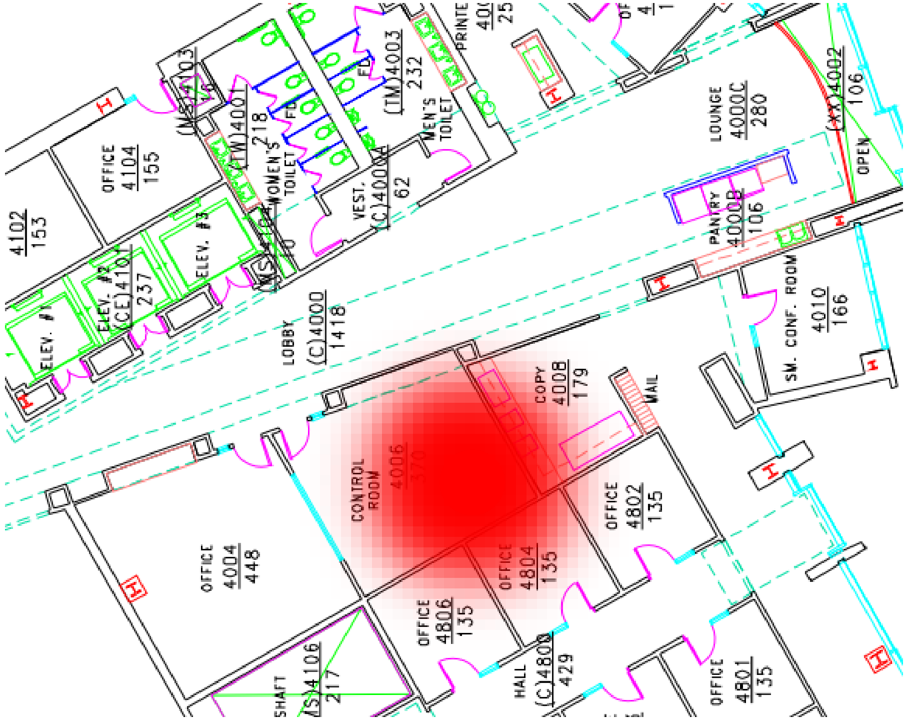

>10% of cases: few meters

Deep Learning based Wireless Localization for Indoor Navigation

DLoc and MapFind

Deep Learning based Wireless Localization

Deep Learning based Wireless Localization

Localization: Novel learning based approach to solve for the environment dependent localization.

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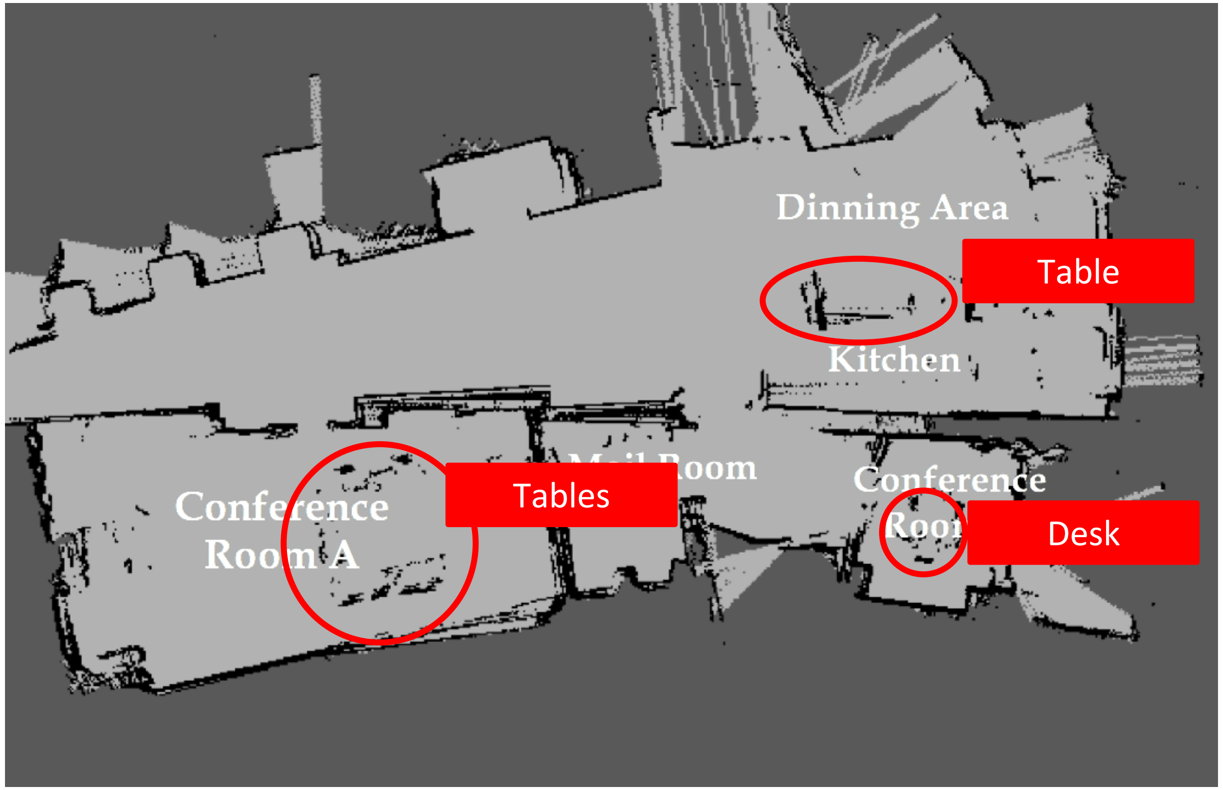
Context: Bot that collects both Visual and WiFi data.



Deep Learning based Wireless Localization

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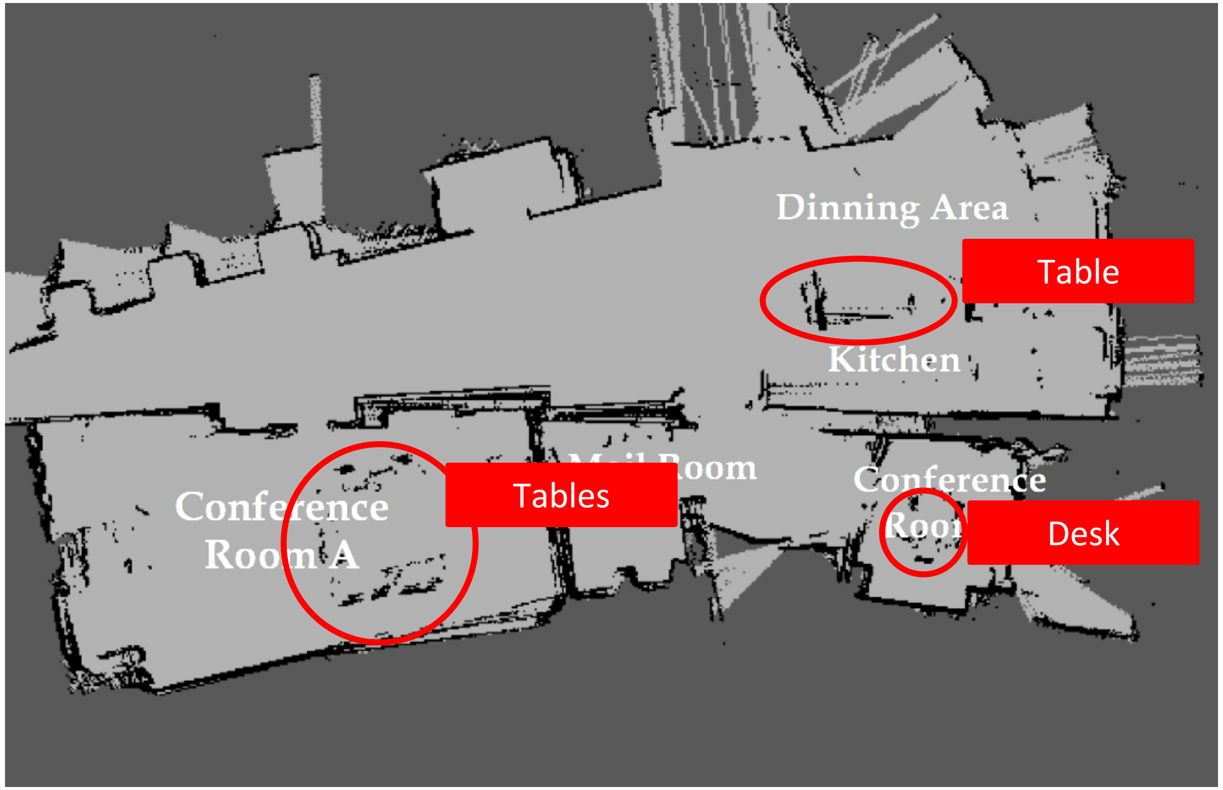


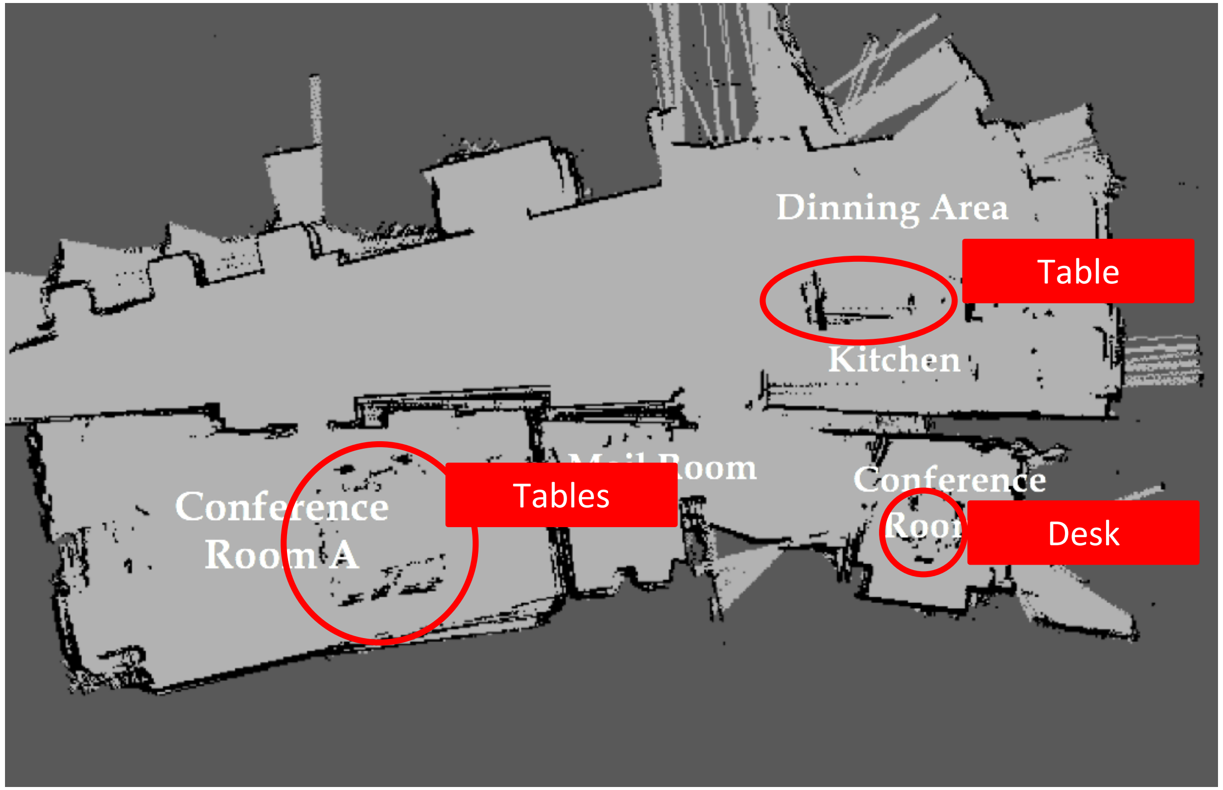
Deep Learning based Wireless Localization

Localization: Novel learning based approach to solve for the environment dependent localization.

Context: Bot that collects both Visual and WiFi data.

Dataset: Deployed it in 8 different in a Simple and Complex Environment

Results: Shown a 85% improvement compared to state of the art at 90th percentile.



Challenge: Multipath, Non-Line of Sight

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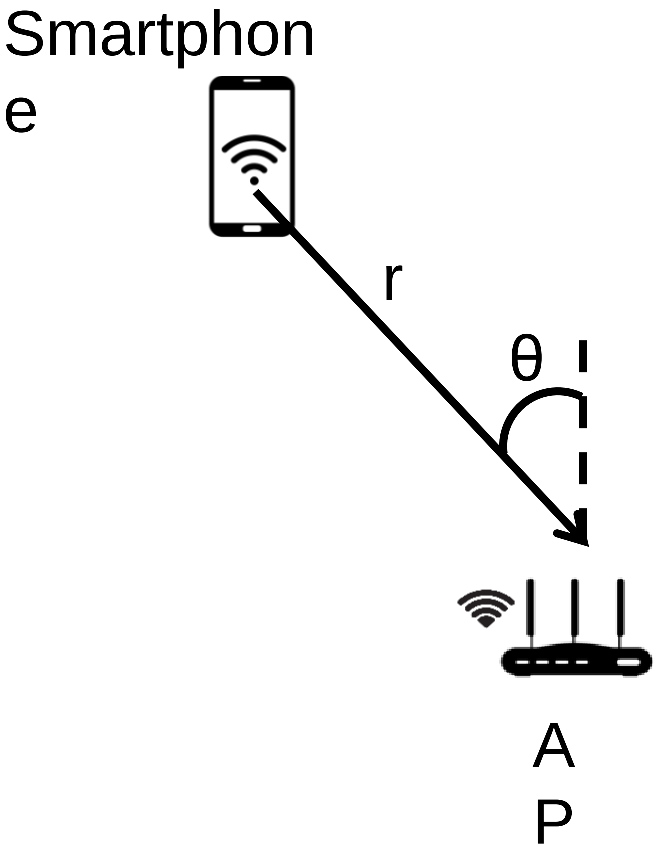

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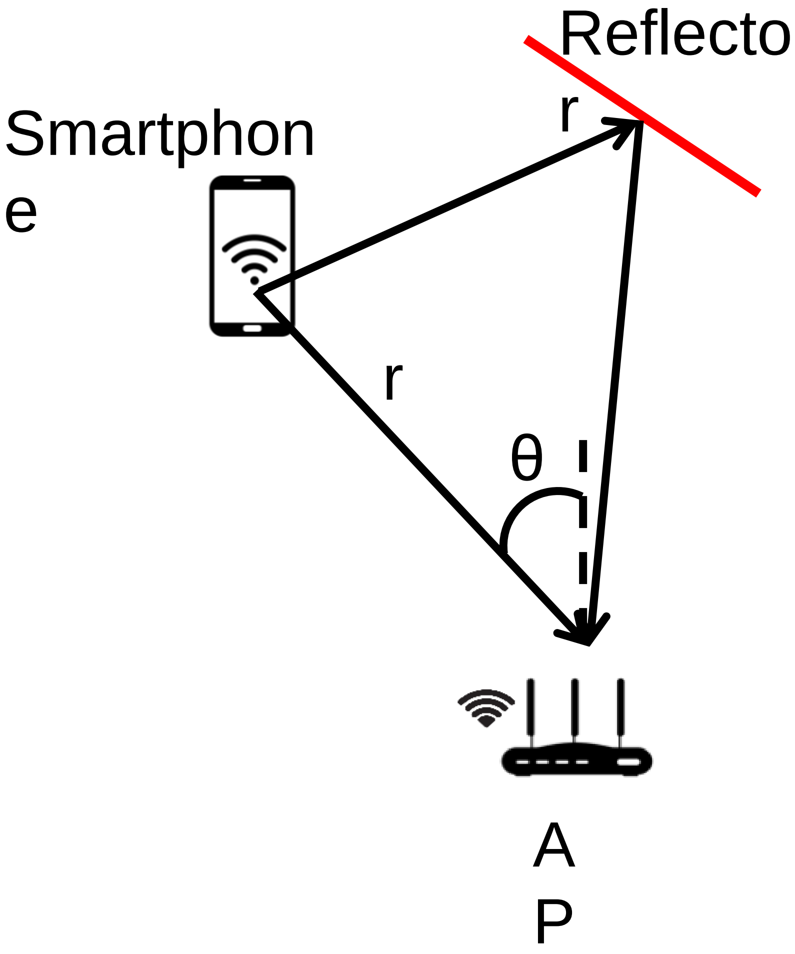

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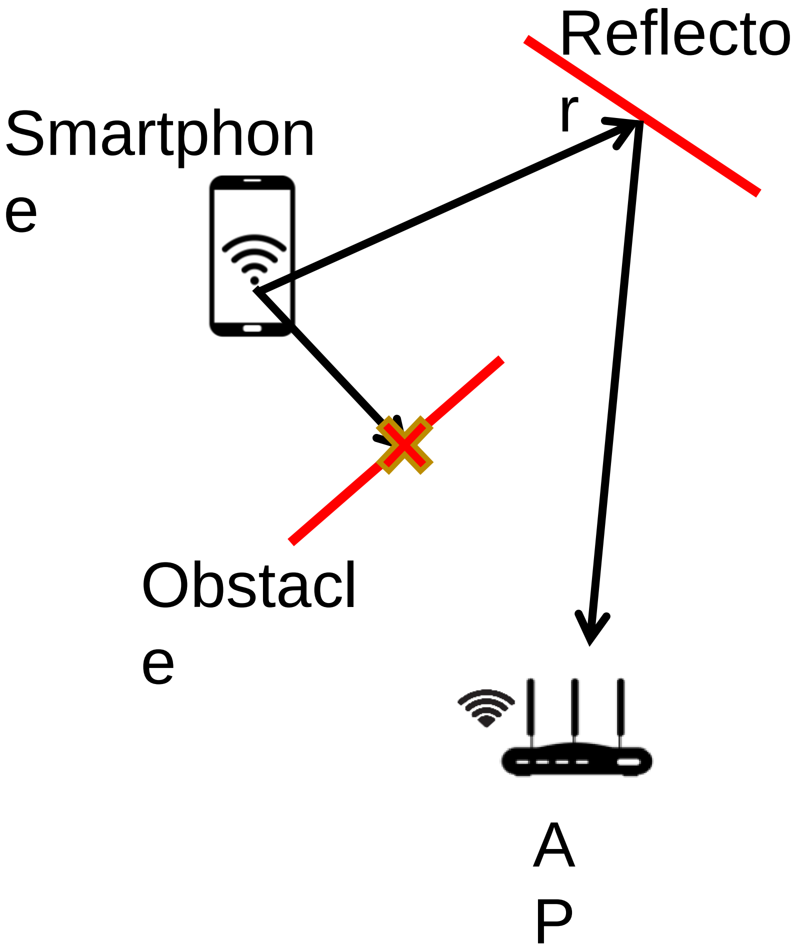

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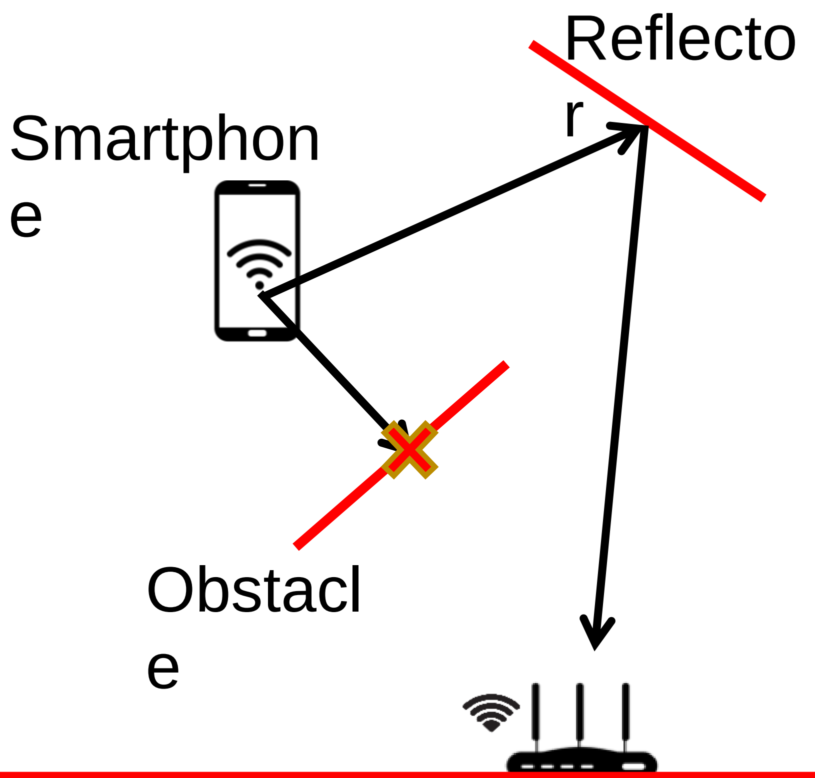


Need Knowledge of Environment

Requirements to design the neural network

Requirements to design the neural network

Input Representation

Requirements to design the neural network

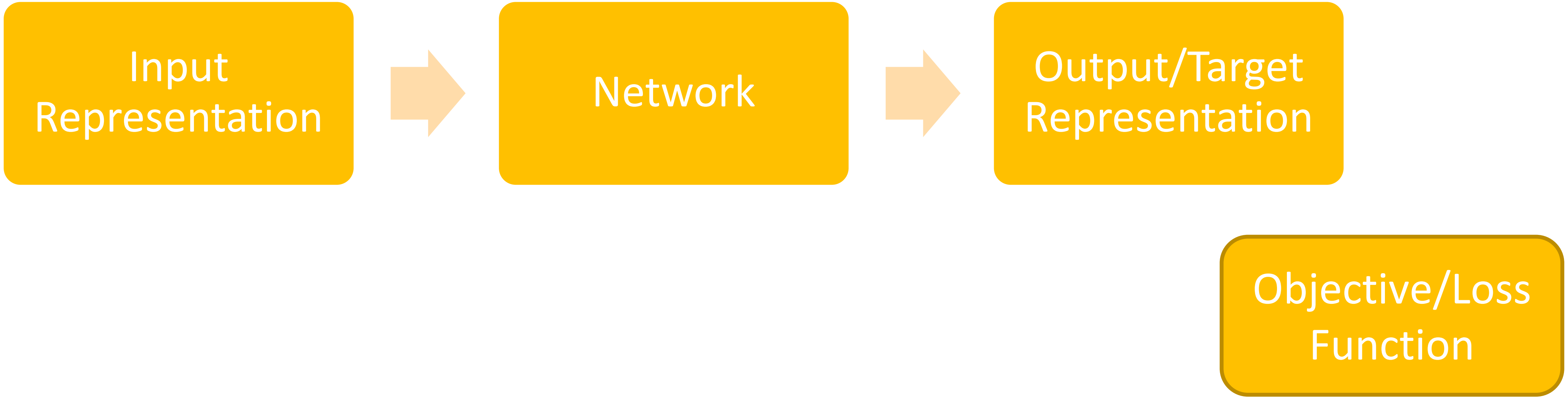
Input Representation

Output/Target Representation

Requirements to design the neural network

Input Representation → Network → Output/Target Representation

Requirements to design the neural network



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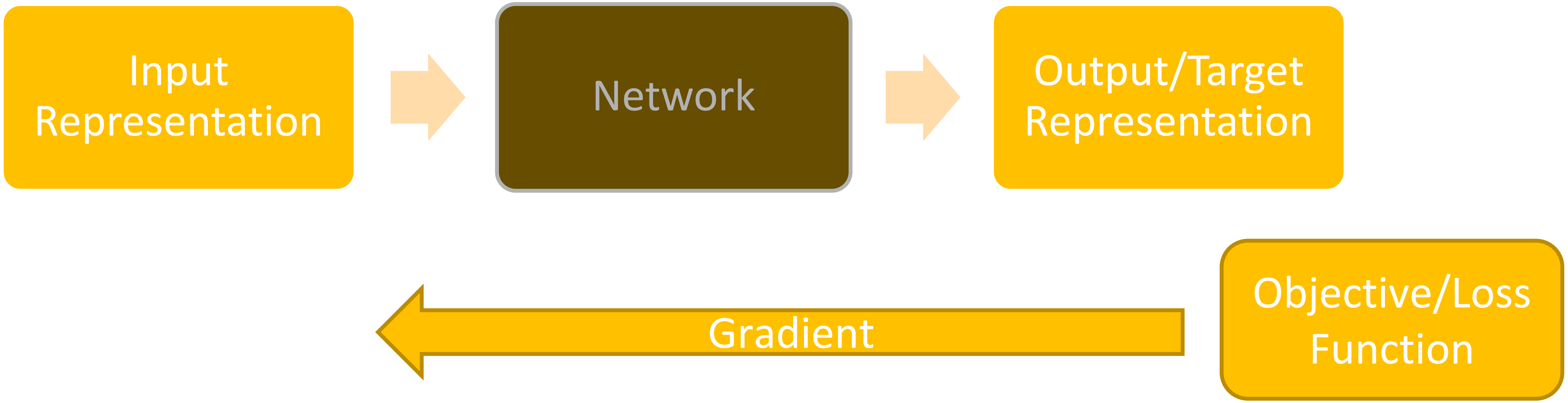

Input Representation: Raw CSI data

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Maximillian Arnold et. al., SCC 2019

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Complex Channel Values and AWG noise

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Complex Channel Values and AWG noise

Can we represent them as images?

Input Representation: AoA-ToF images

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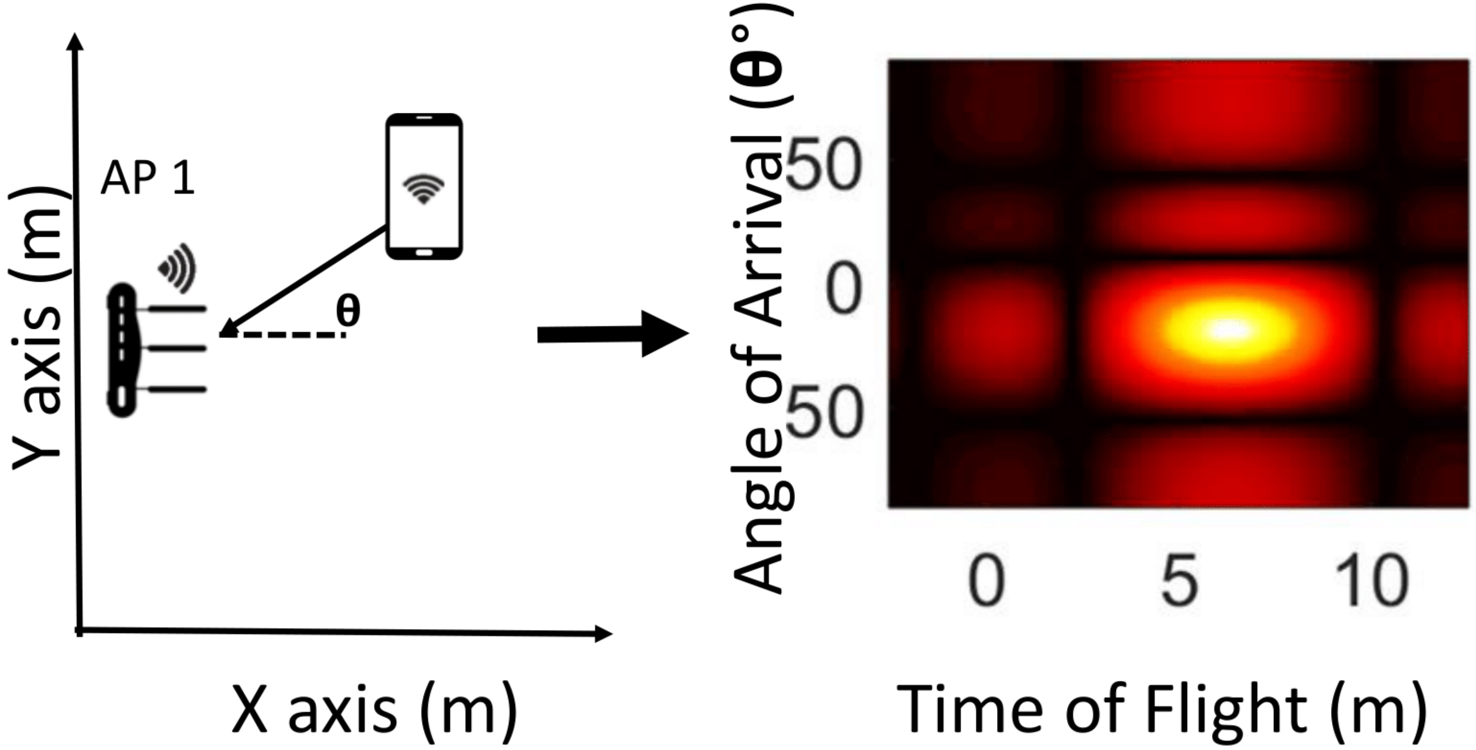

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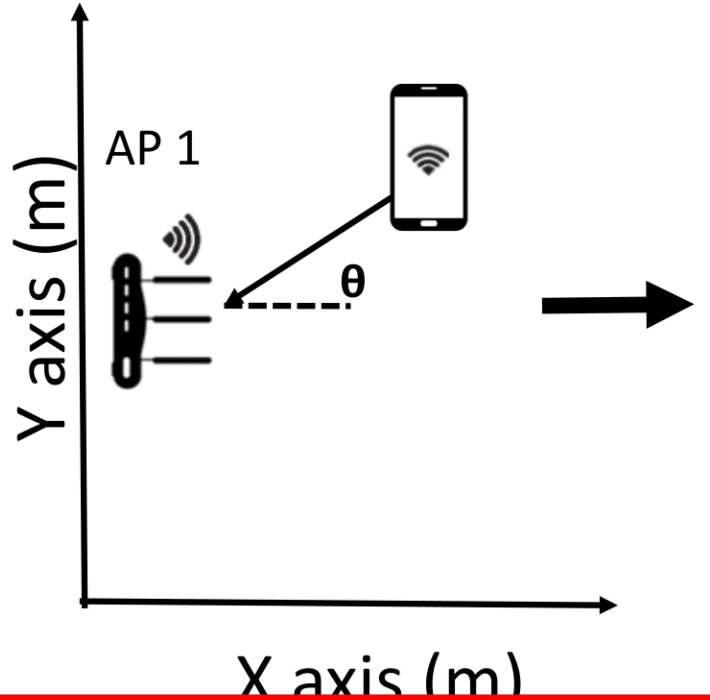
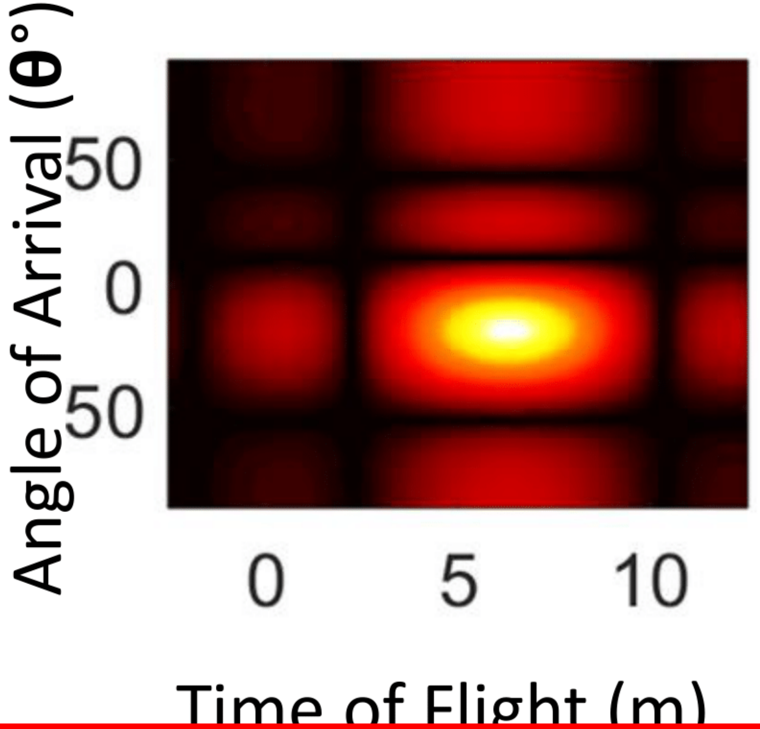
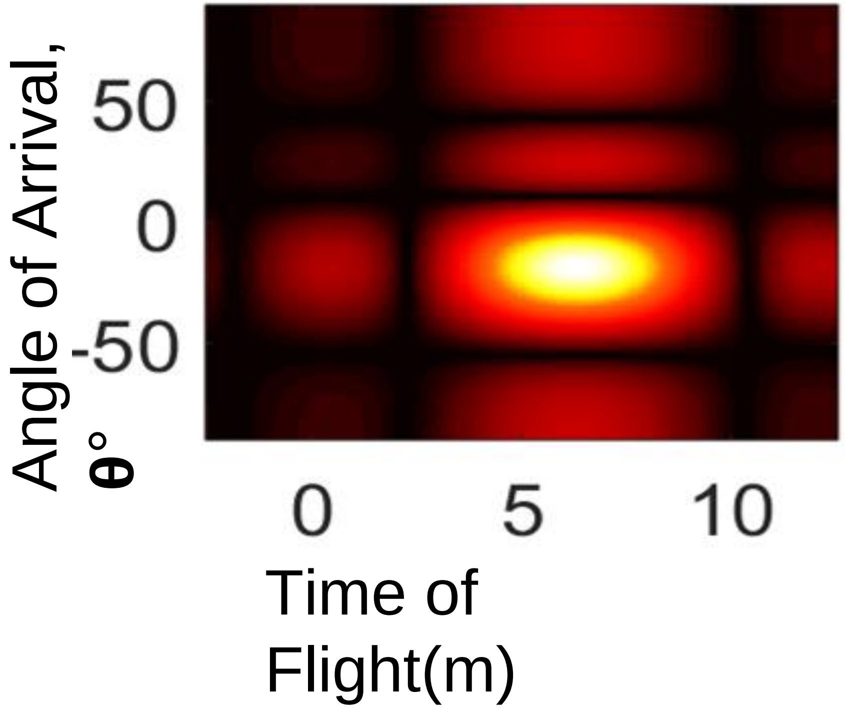




Does not have context of Space and AP locations

Input Representation: XY images

AoA-ToF (Polar) to XY (cartesian)



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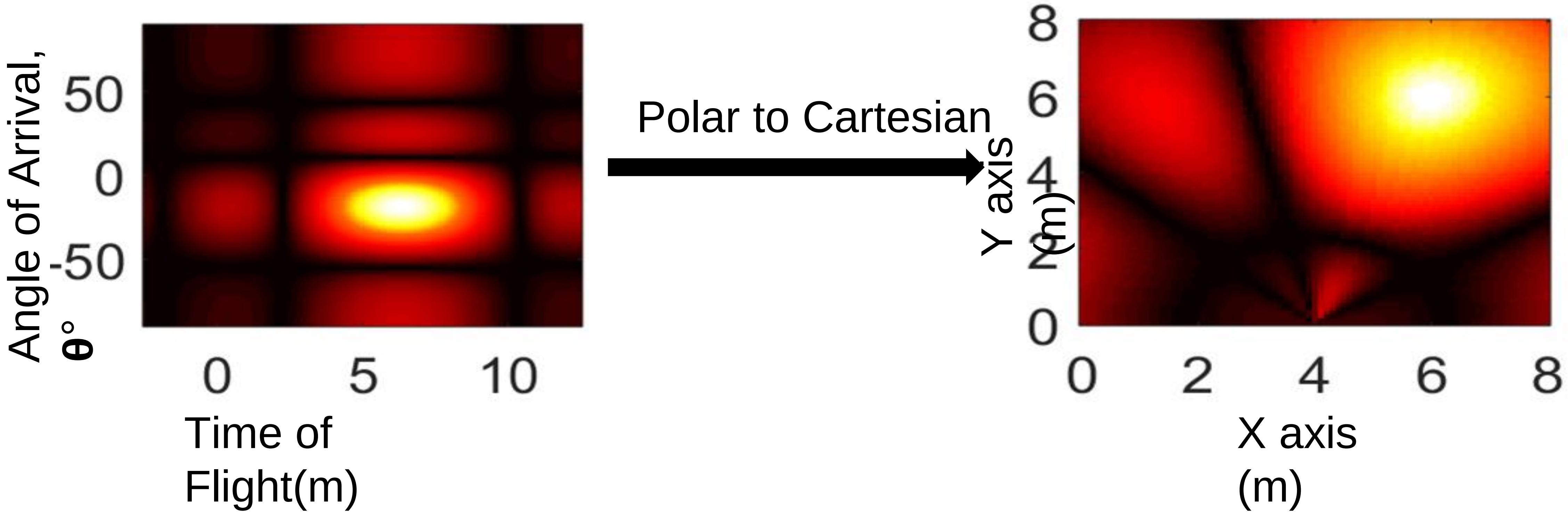

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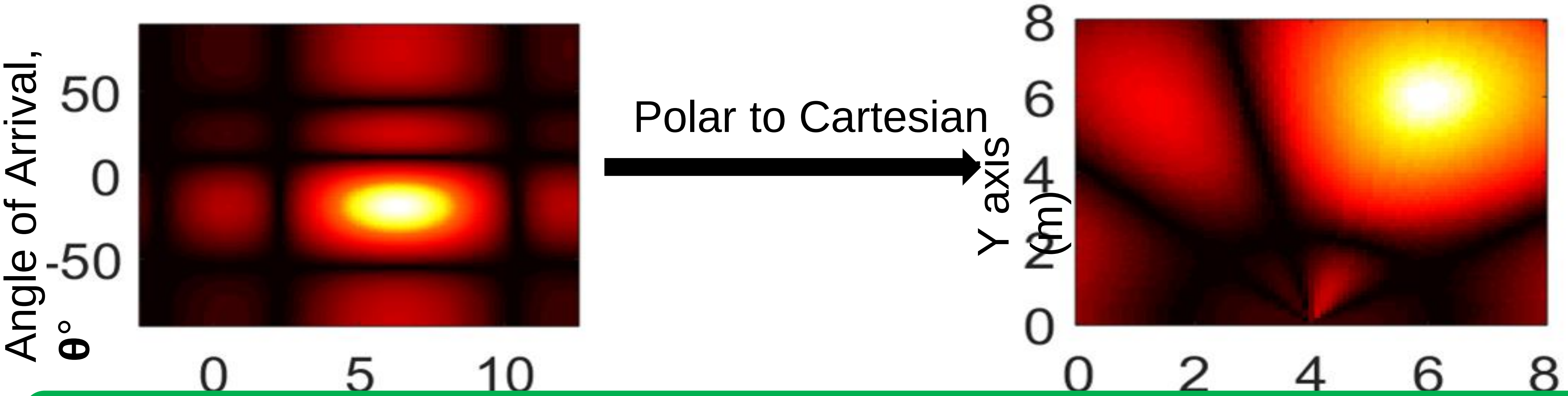
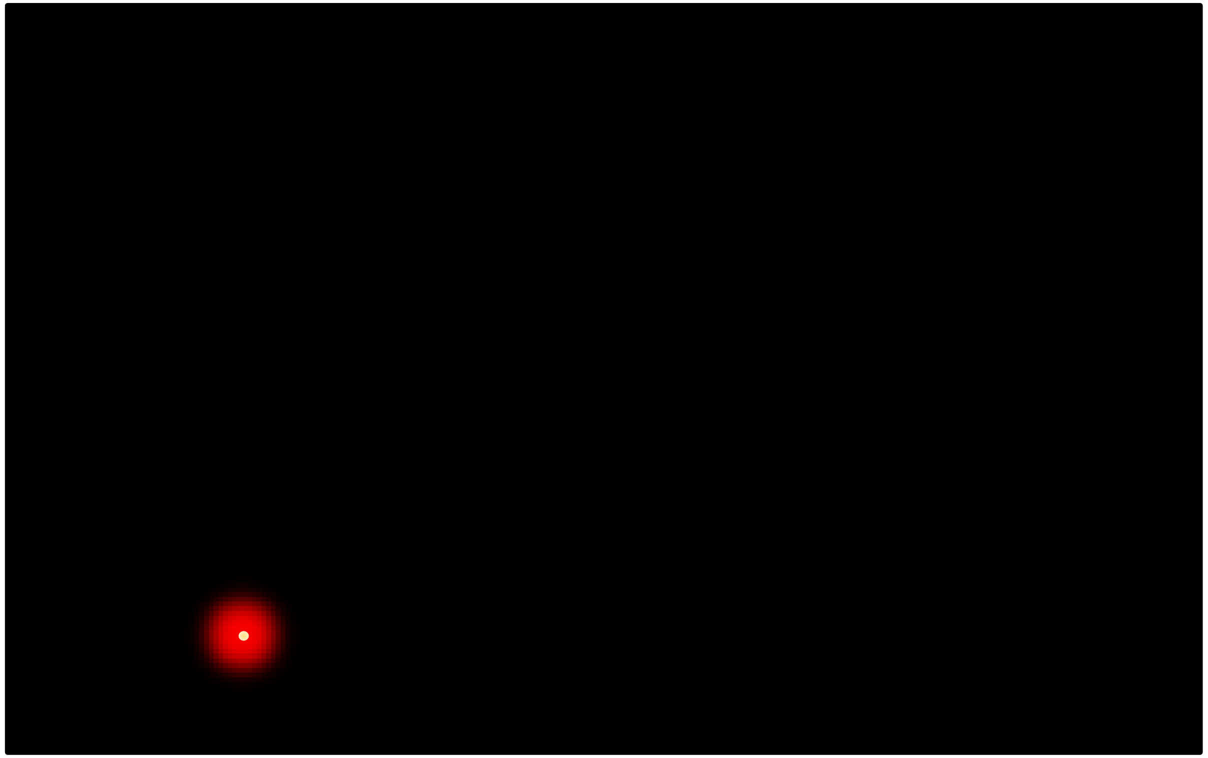


Context embedded Input Representation

Location Decoder Output targets

Location Decoder Output targets

Location Decoder Output targets



Location Decoder Output targets

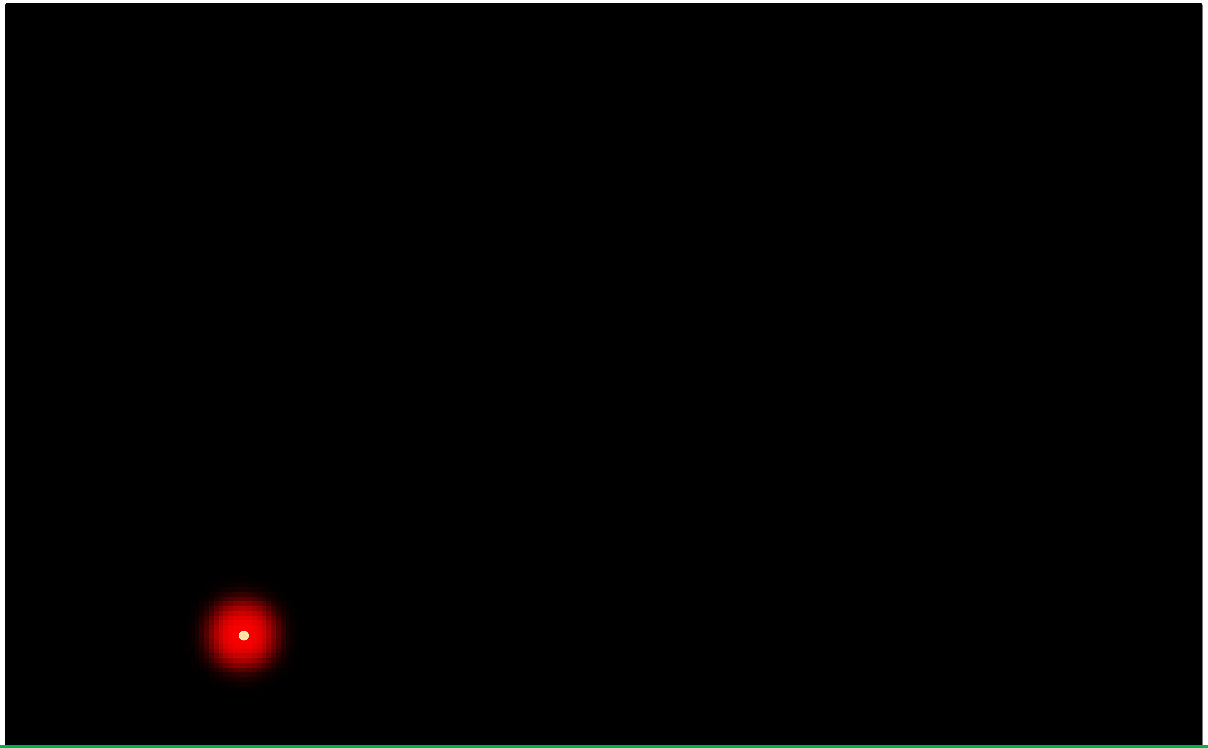
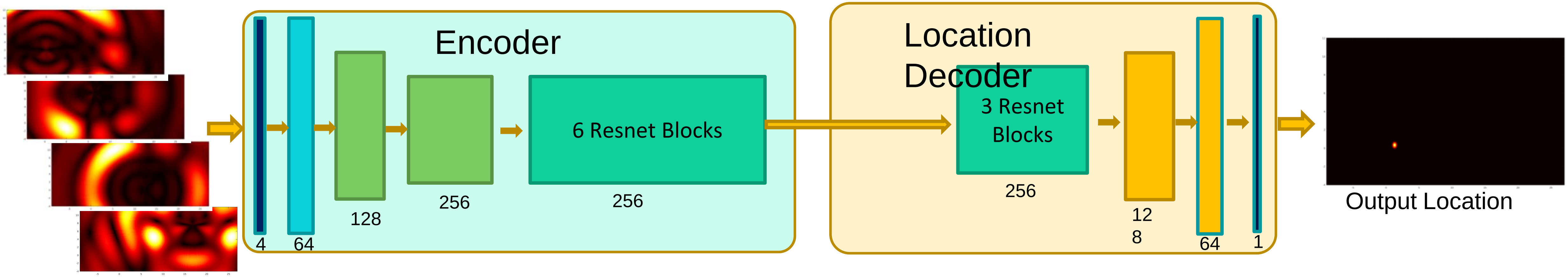


Image-to-Image translation problem

Network Architecture

Network Architecture



Input Images

1. Conv2d [7,7,1,3]
2. Instance norm
3. Tanh

1. Conv2d [7,7,1,3]
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3. ReLU

1. Conv2d [3,3,2,1]
2. Instance norm
3. ReLU

Resnet Block*

1. ConvTranspose2d [3,3,2,1]
2. Instance norm
3. ReLU

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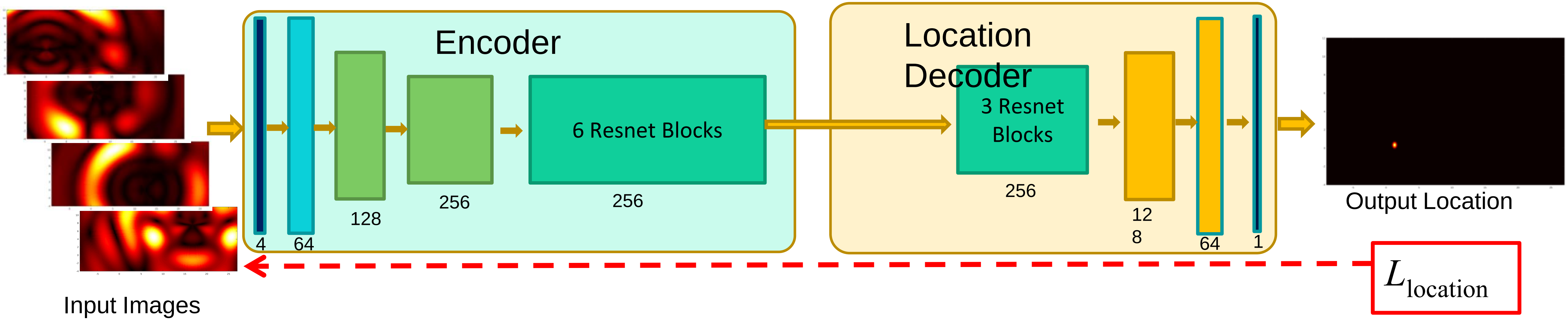
Network Architecture



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Location Loss

Closeness in MSE sense

$$L_{location} = L2[D_{location}E(H) \ - \ T]$$

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Closeness in MSE sense

$$L_{location} = L2[D_{location}E(H) - T]$$

Penalize multiple peaks

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Closeness in MSE sense

$$L_{location} = L2[D_{location}E(H) \; - \; T]$$

Penalize multiple peaks

$$L_{location} = L2[D_{location}E(H) \; - \; T] + \lambda \, L1[D_{location}E(H)]$$

High 90th percentile errors: Asynchronous Clocks

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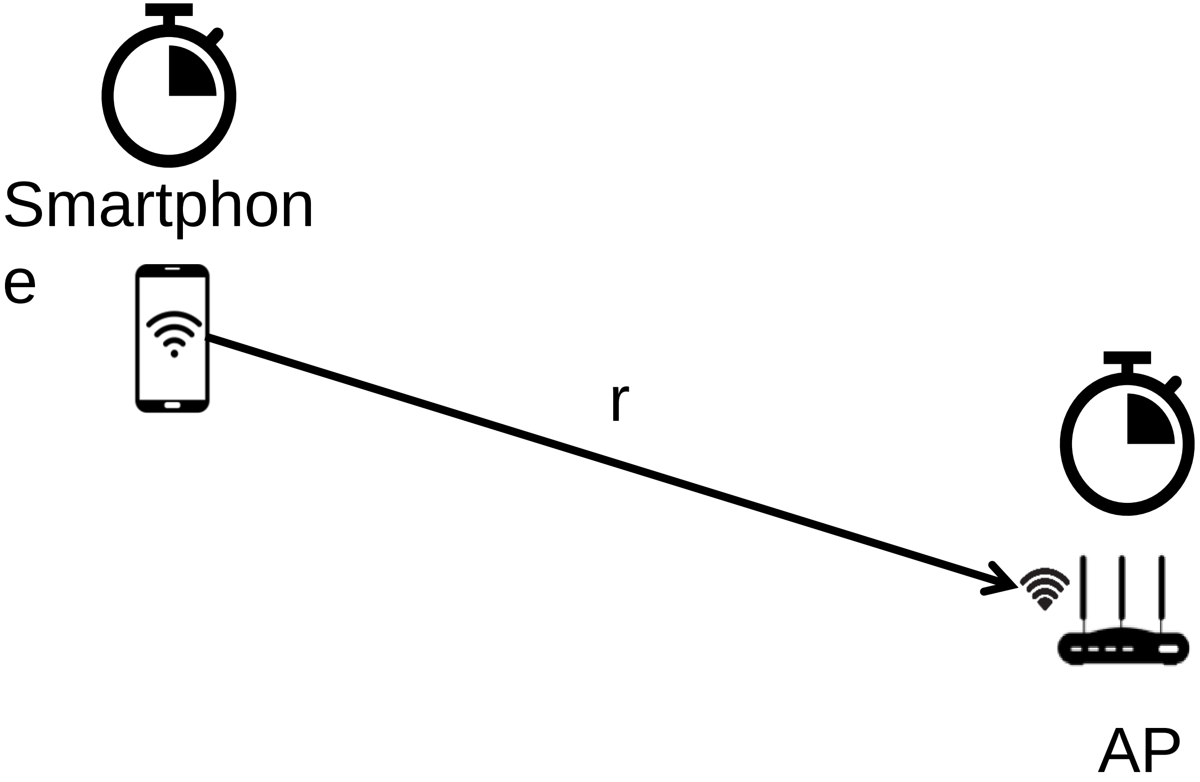
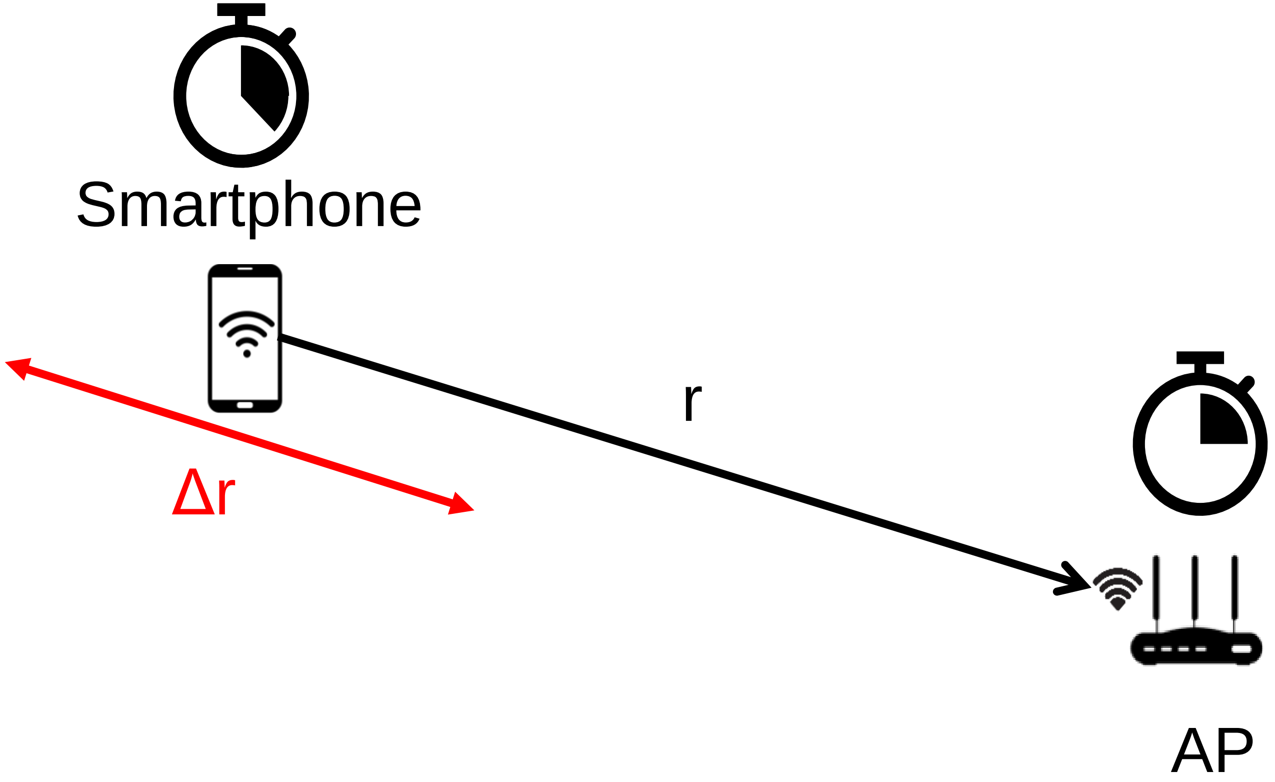
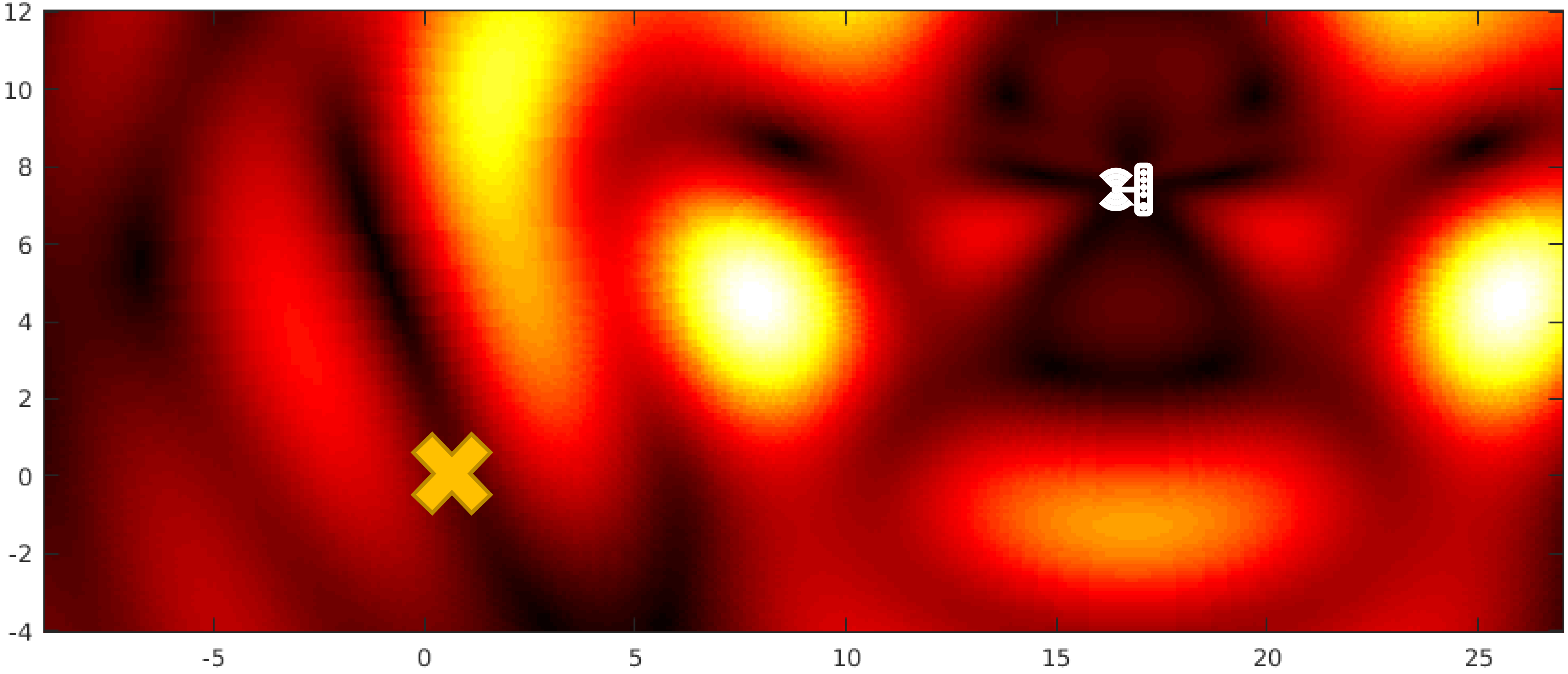


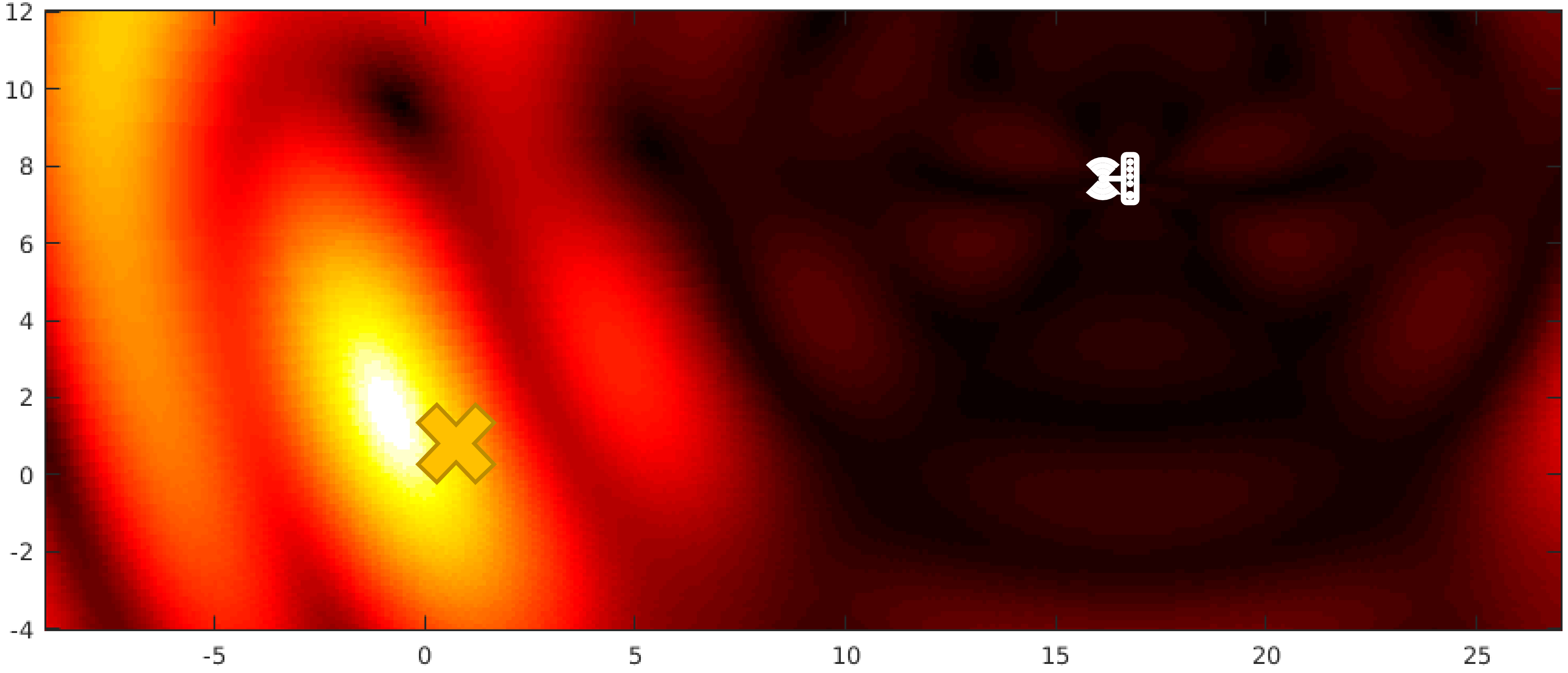
High 90th percentile errors: Asynchronous Clocks



ToF offset

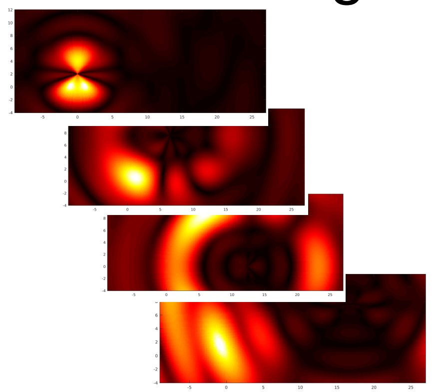


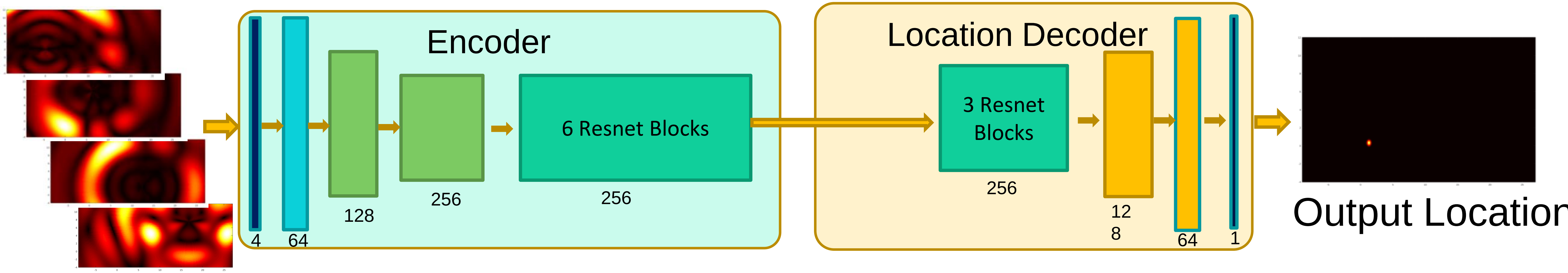
ToF offset compensation



DLoc: Network Architecture

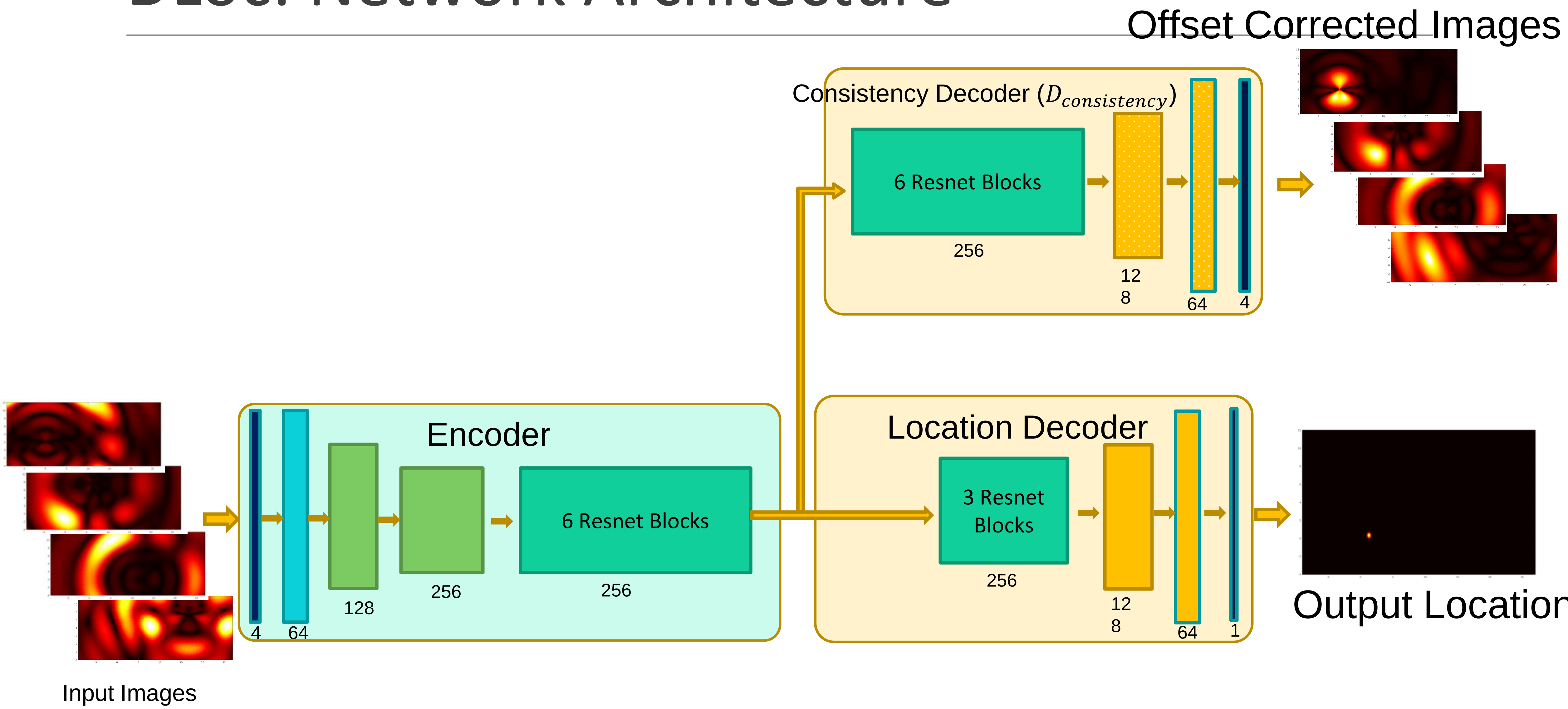
Offset Corrected Images



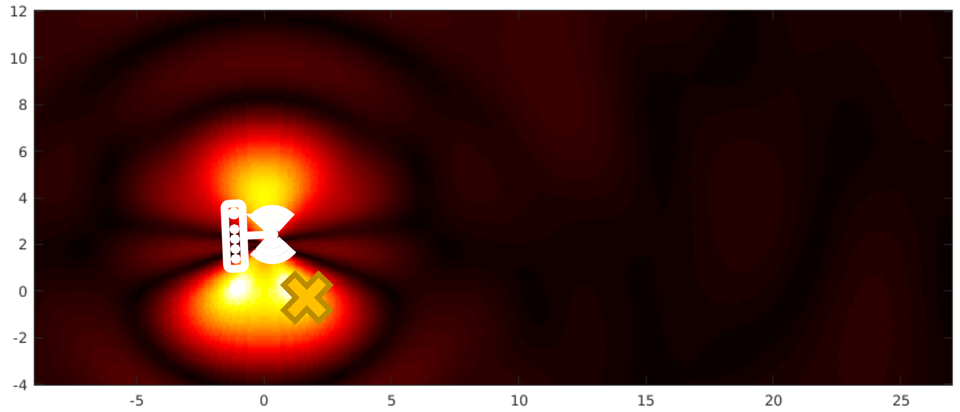


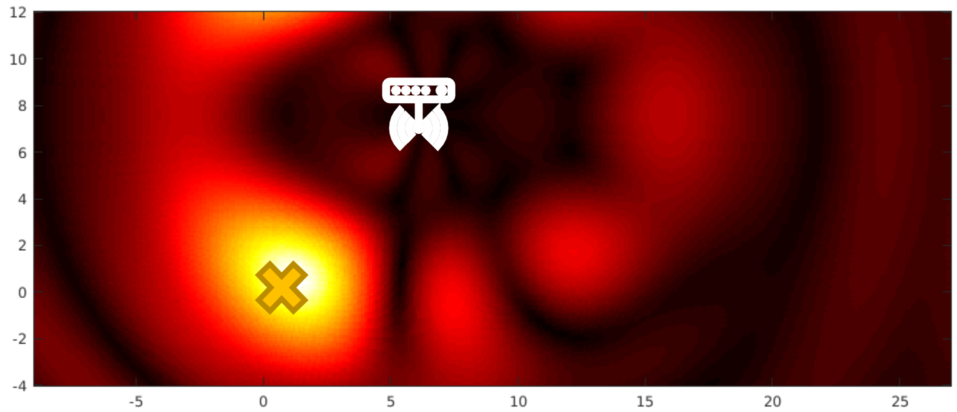
Input Images

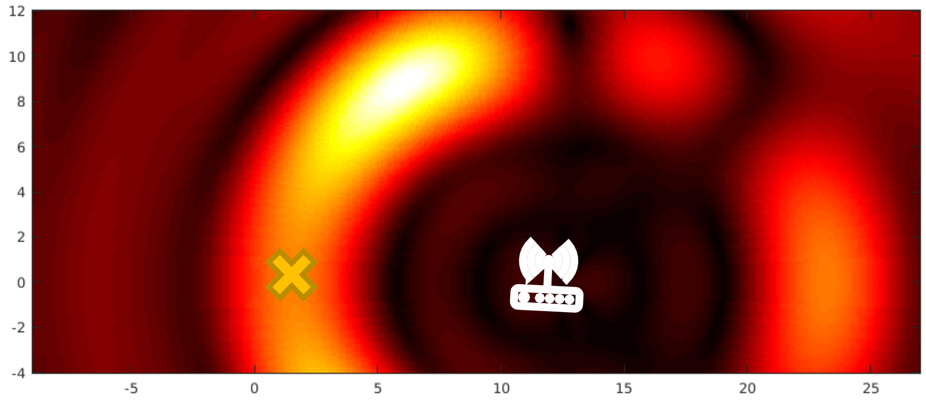
DLoc: Network Architecture

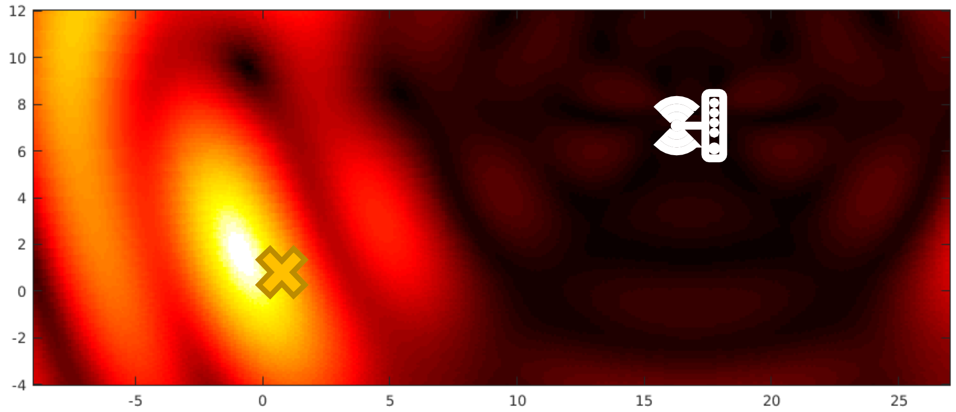


Insight: Single source









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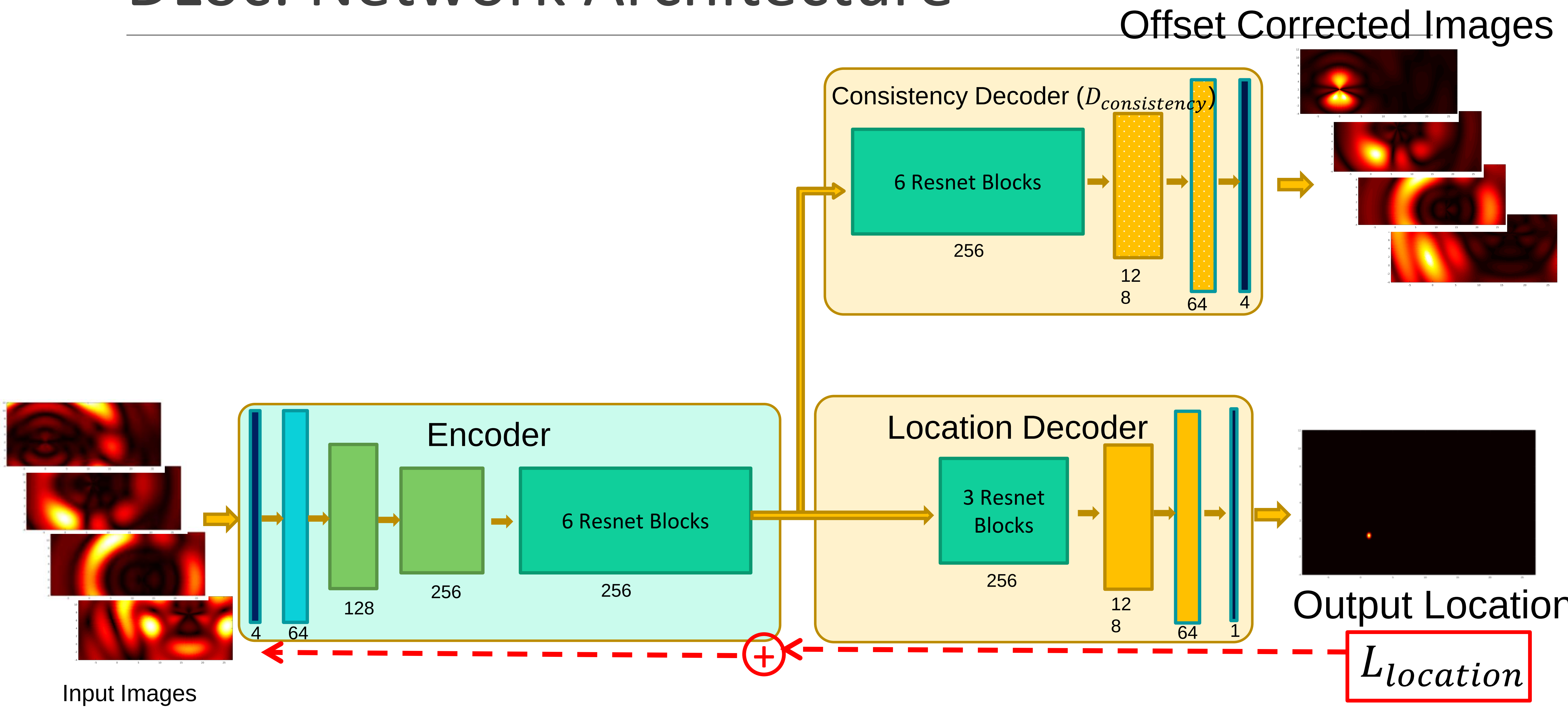

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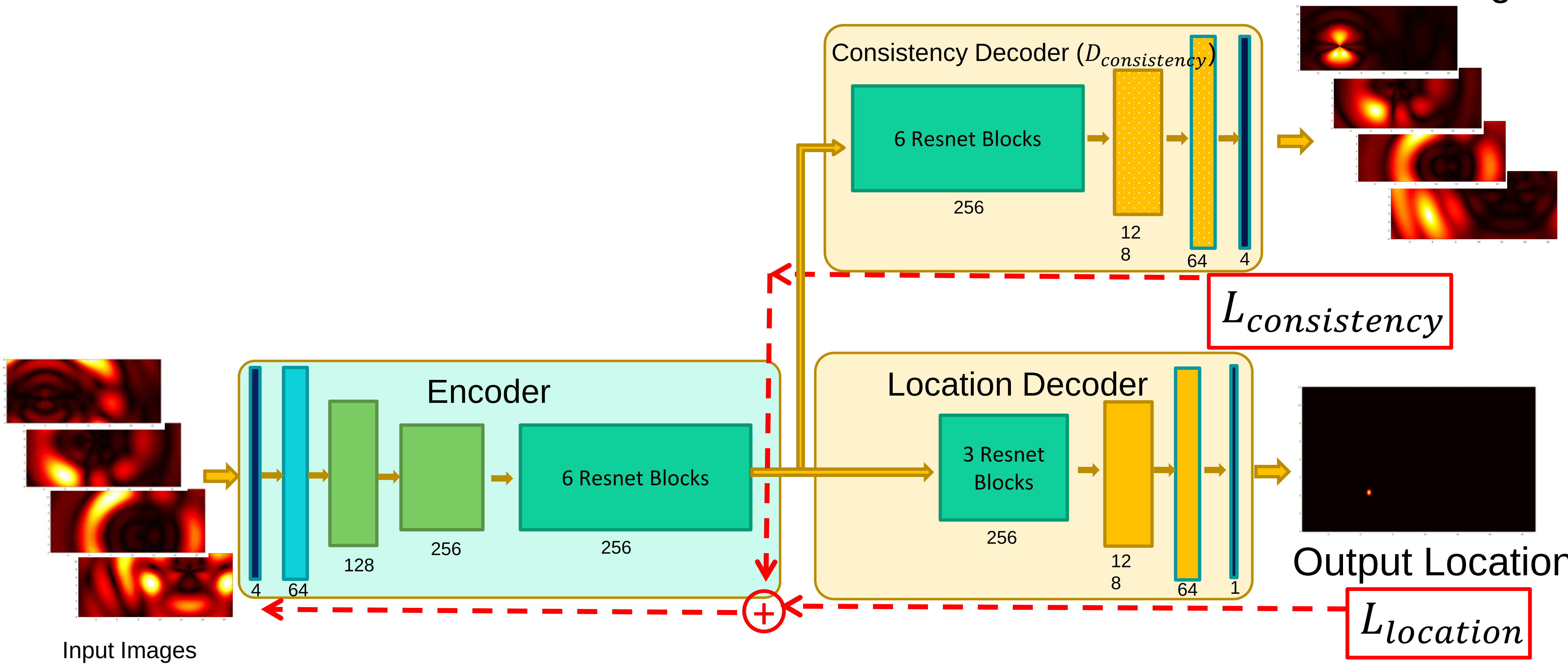

Offset Compensation Loss

Defines consistency across images

$$L_{consistency} = \frac{1}{N_{AP}} \sum_{i=1}^{N_{AP}} L2[D_{consistency}(E(H)) - T_{consistency}]_i$$

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Defines consistency across images

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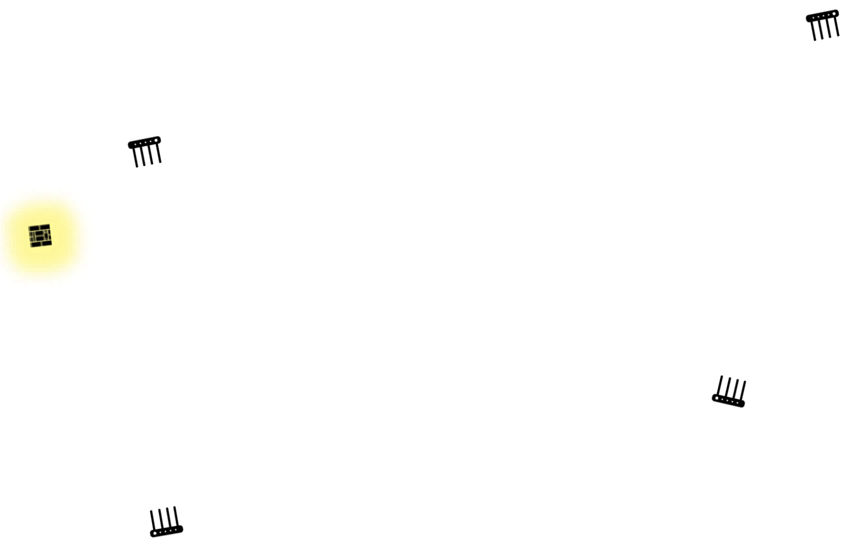
Context: MapFind



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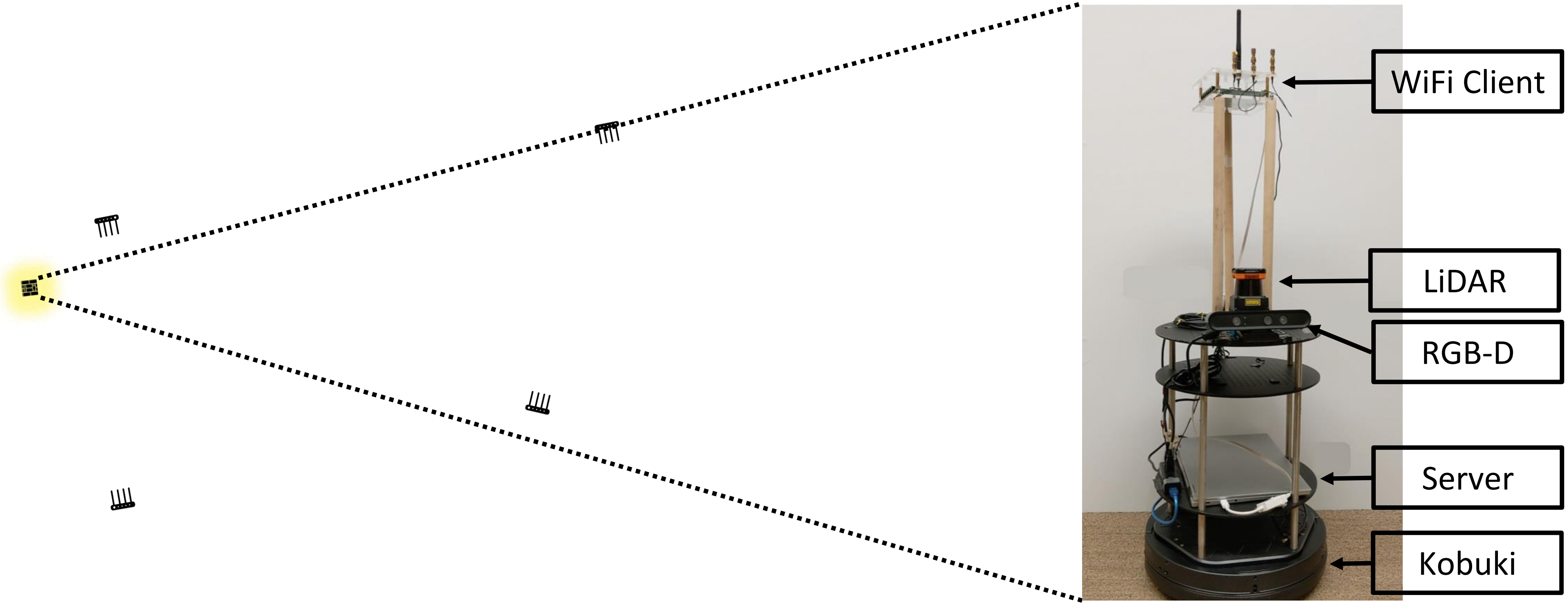

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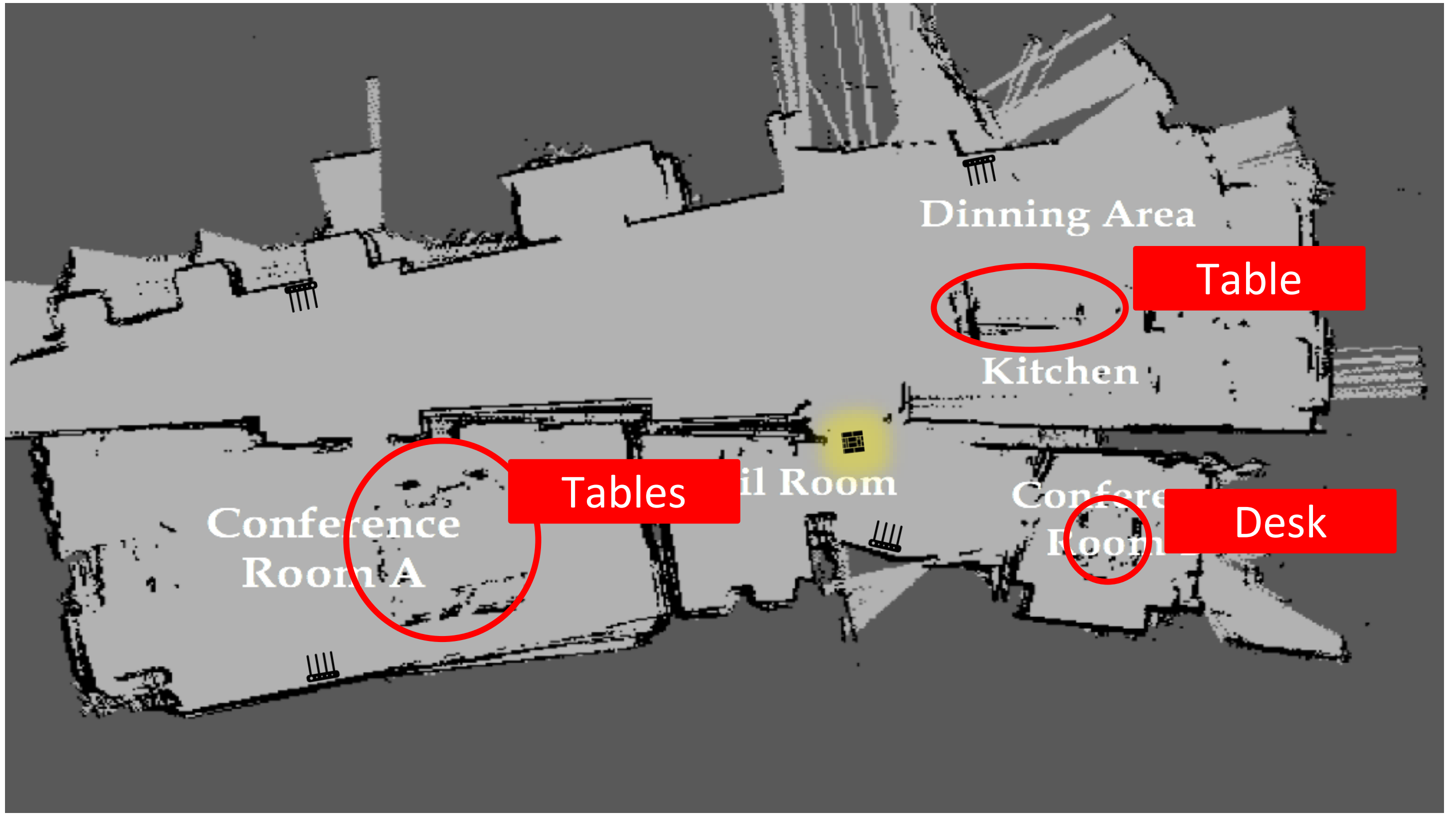

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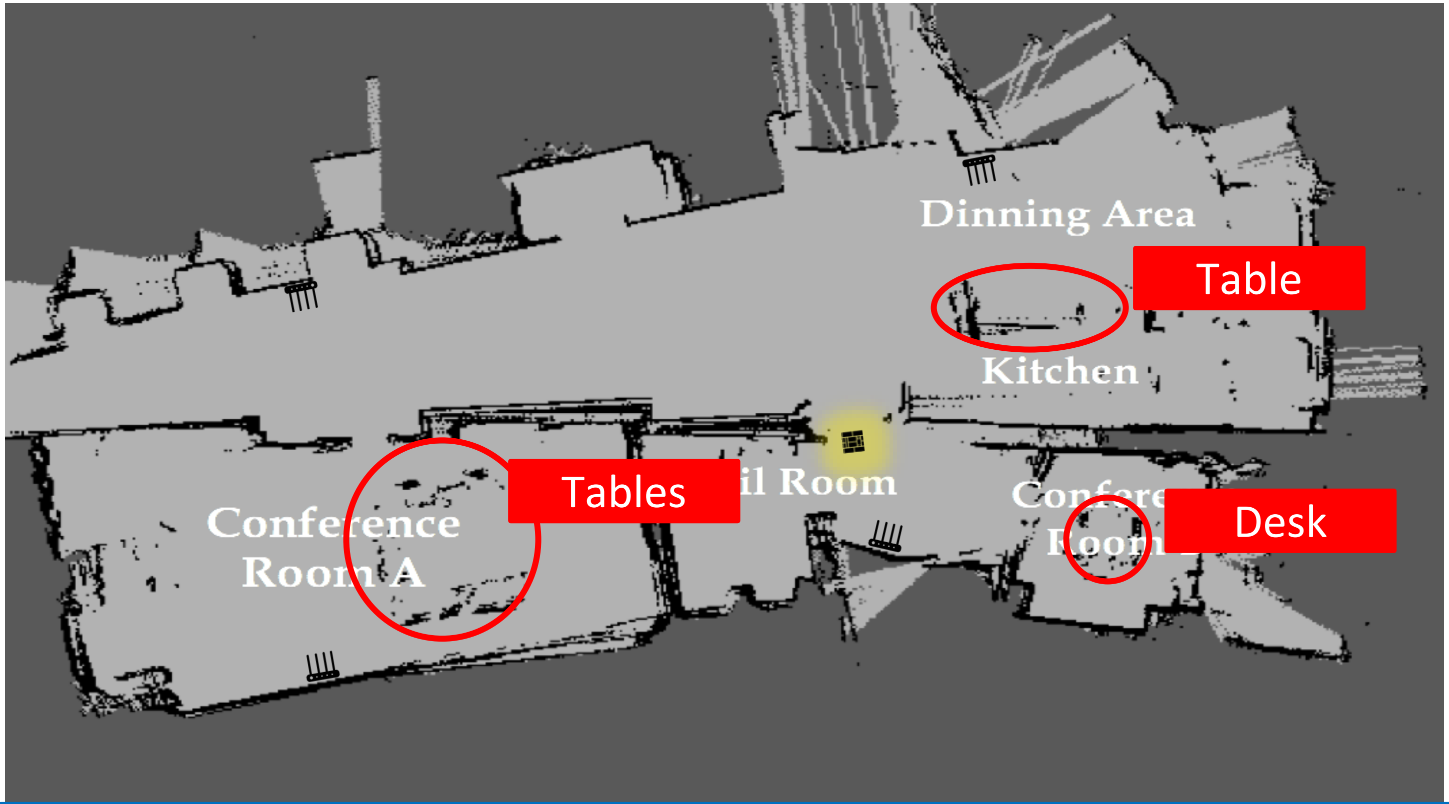


How much data is needed?

Path Planning

Path Planning

Maximize coverage

Minimize traversal length

Path Planning

Maximize coverage

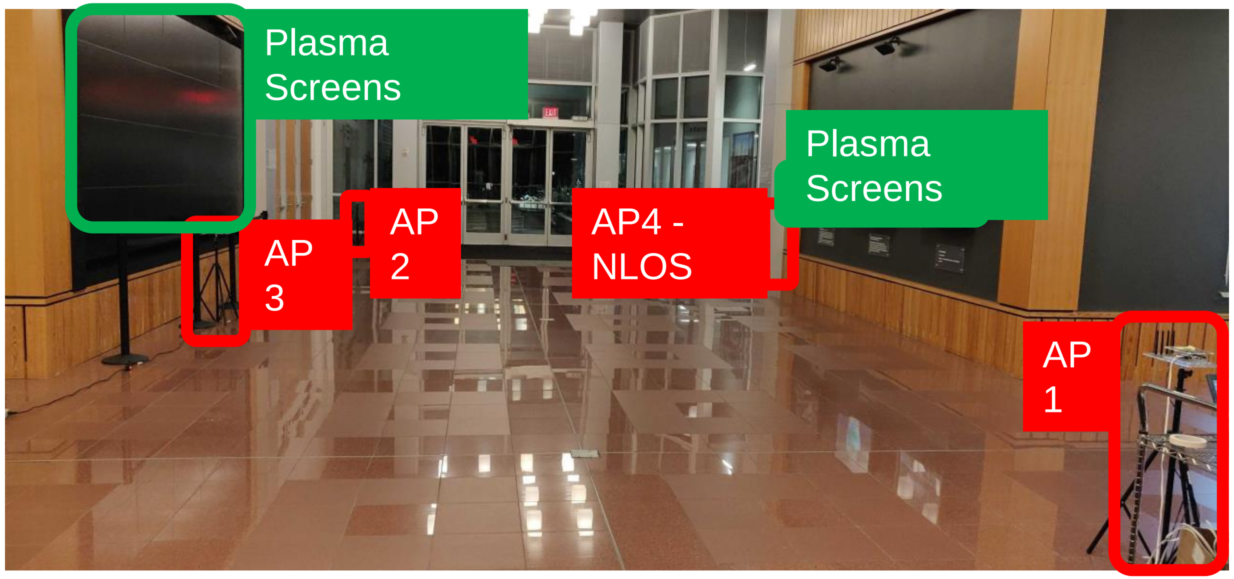
Minimize traversal length

Context Enabled Accurate Indoor Localization

Results

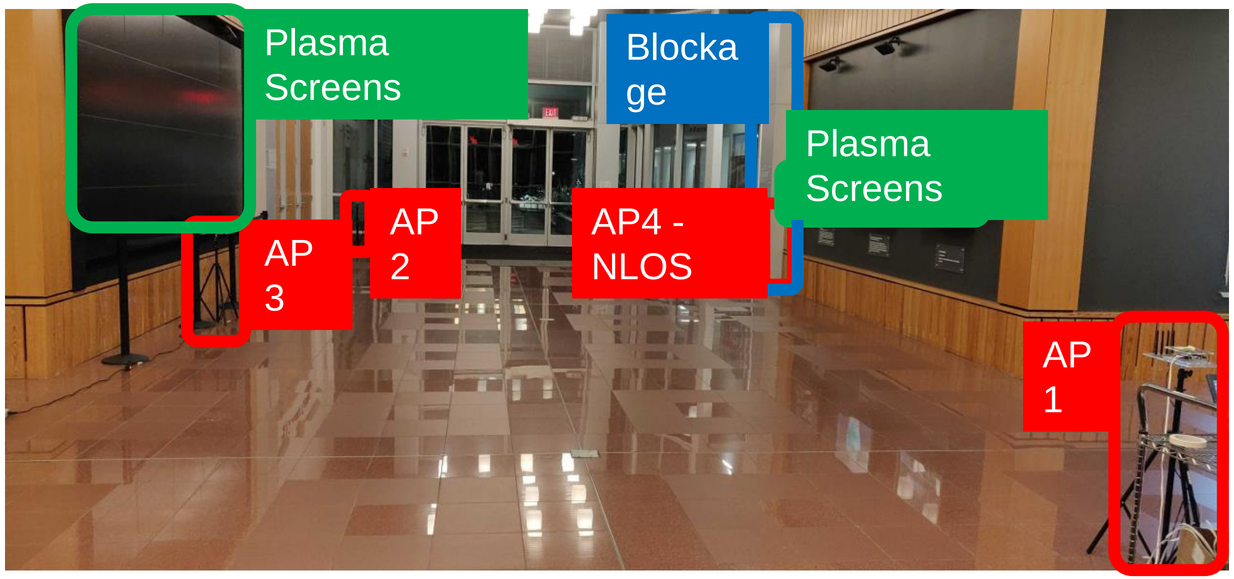
Setup

Setup



Complex High-multipath and NLOS environment (1500 sq. ft.)

Setup



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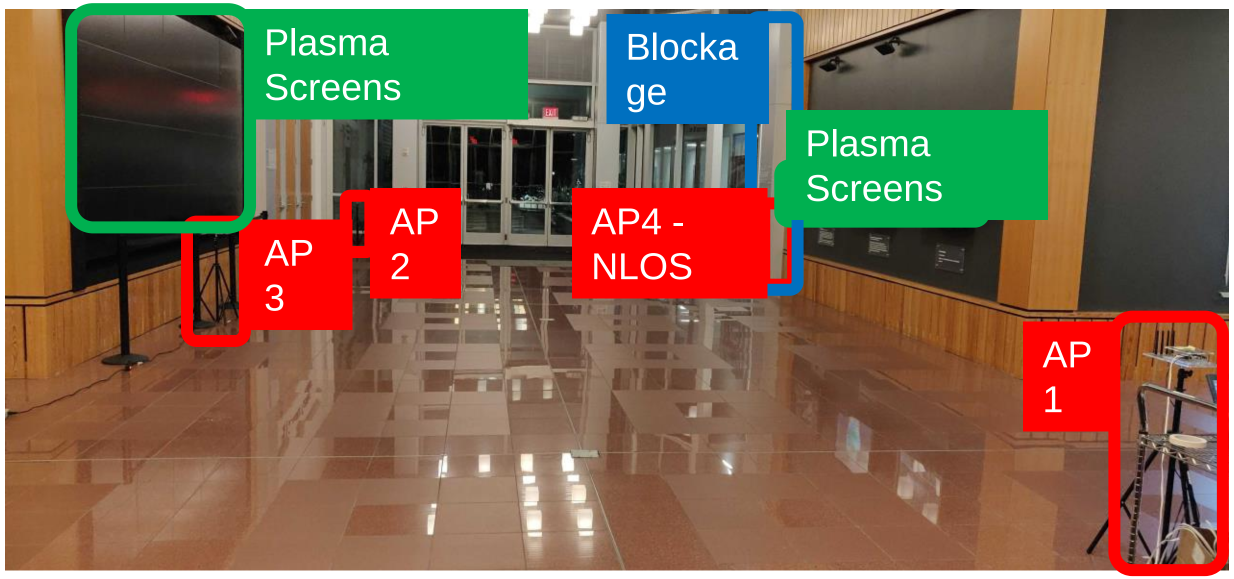
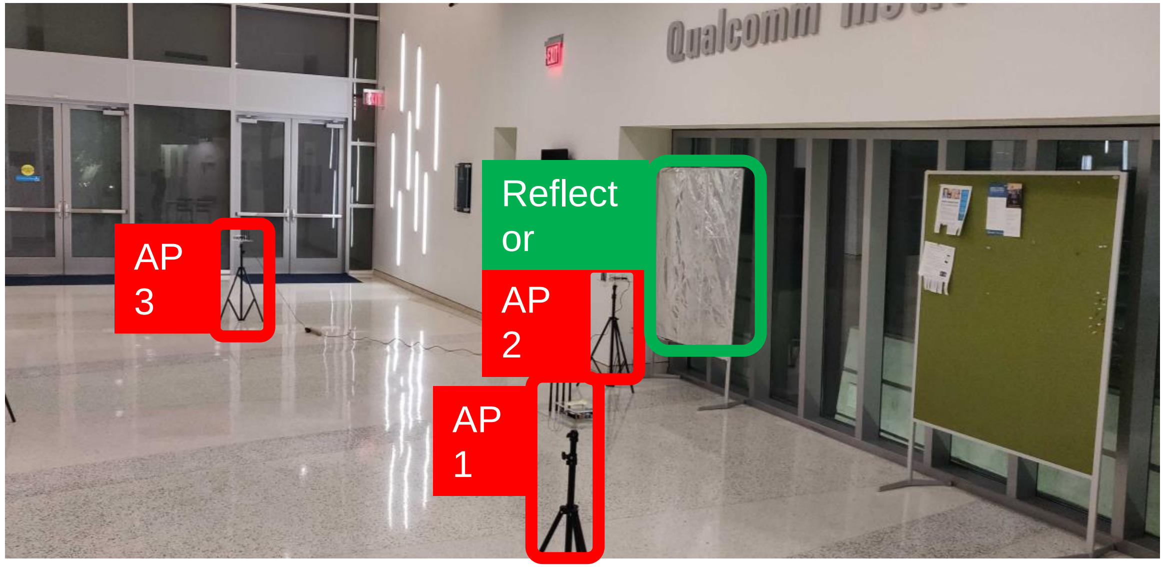
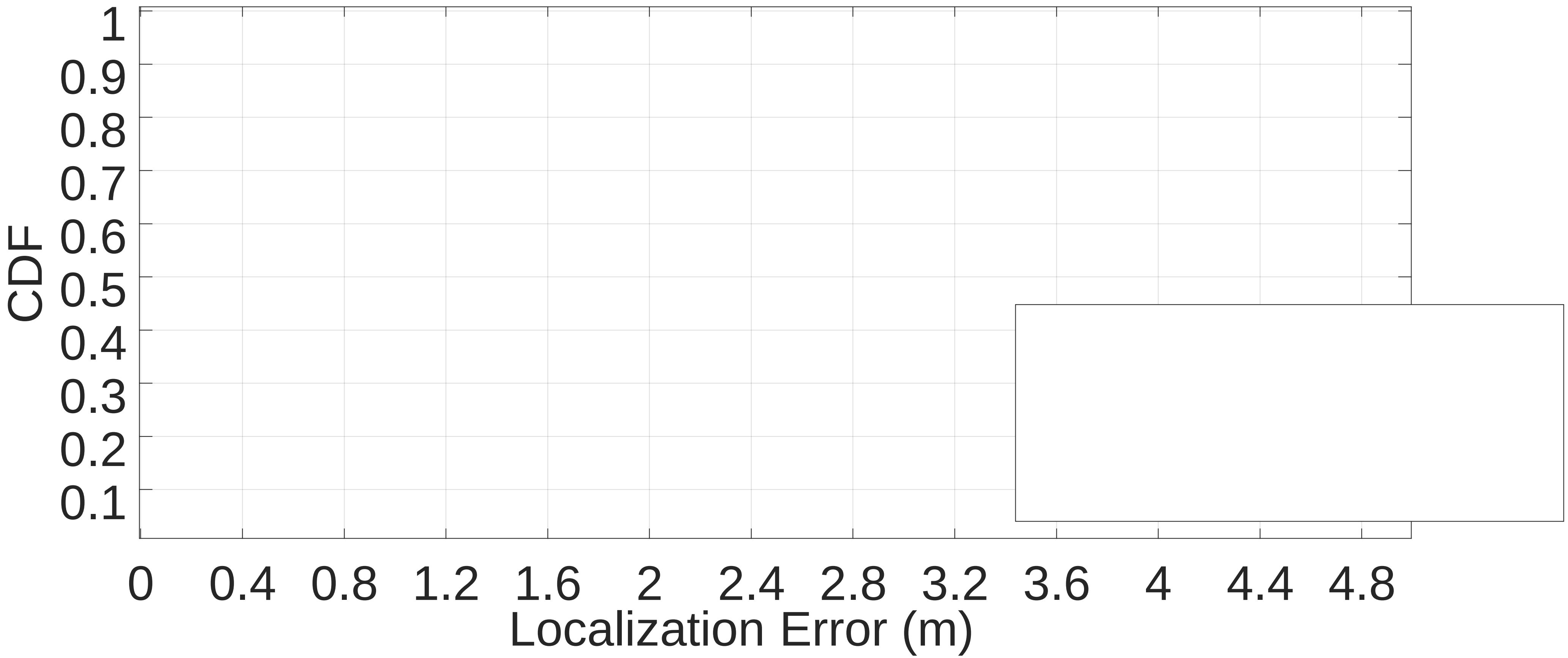




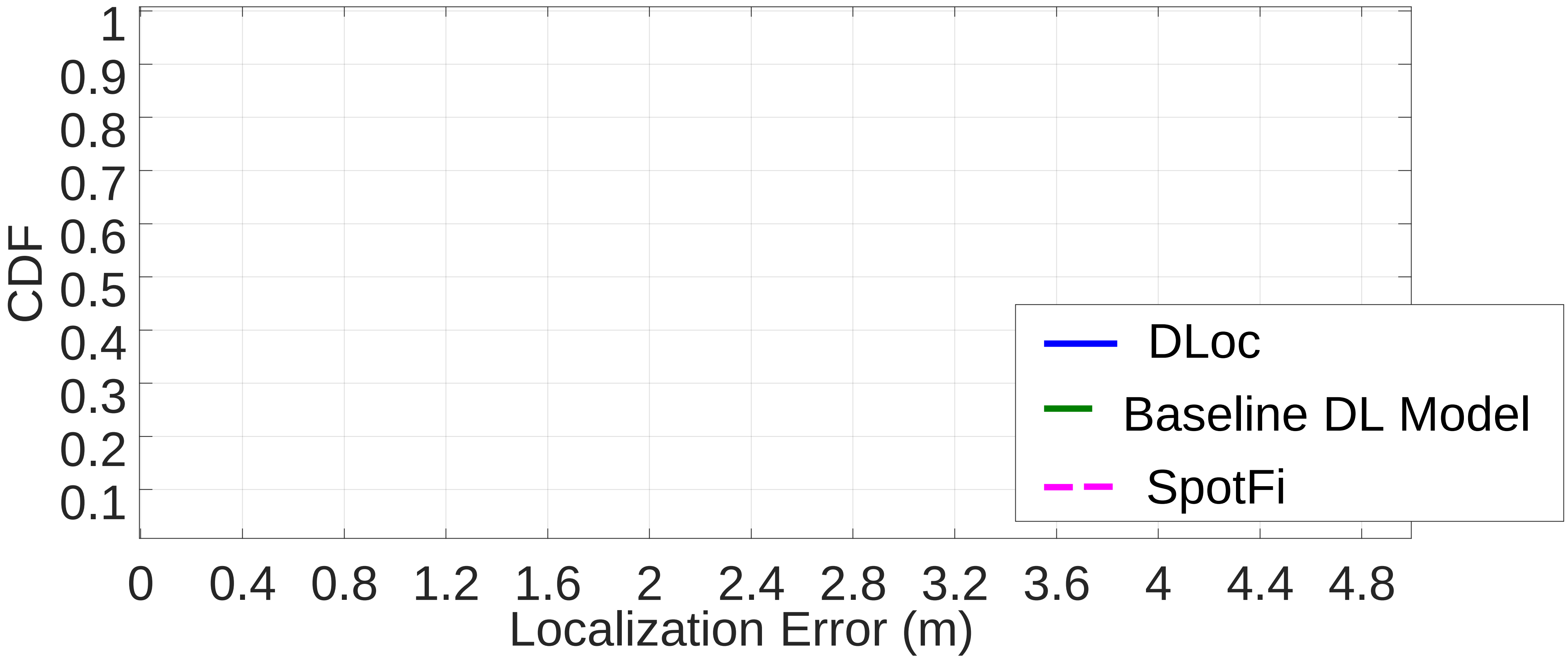
Complex High-multipath and NLOS environment (1500 sq. ft.)

Simple LOS based environment (500 sq. ft.)

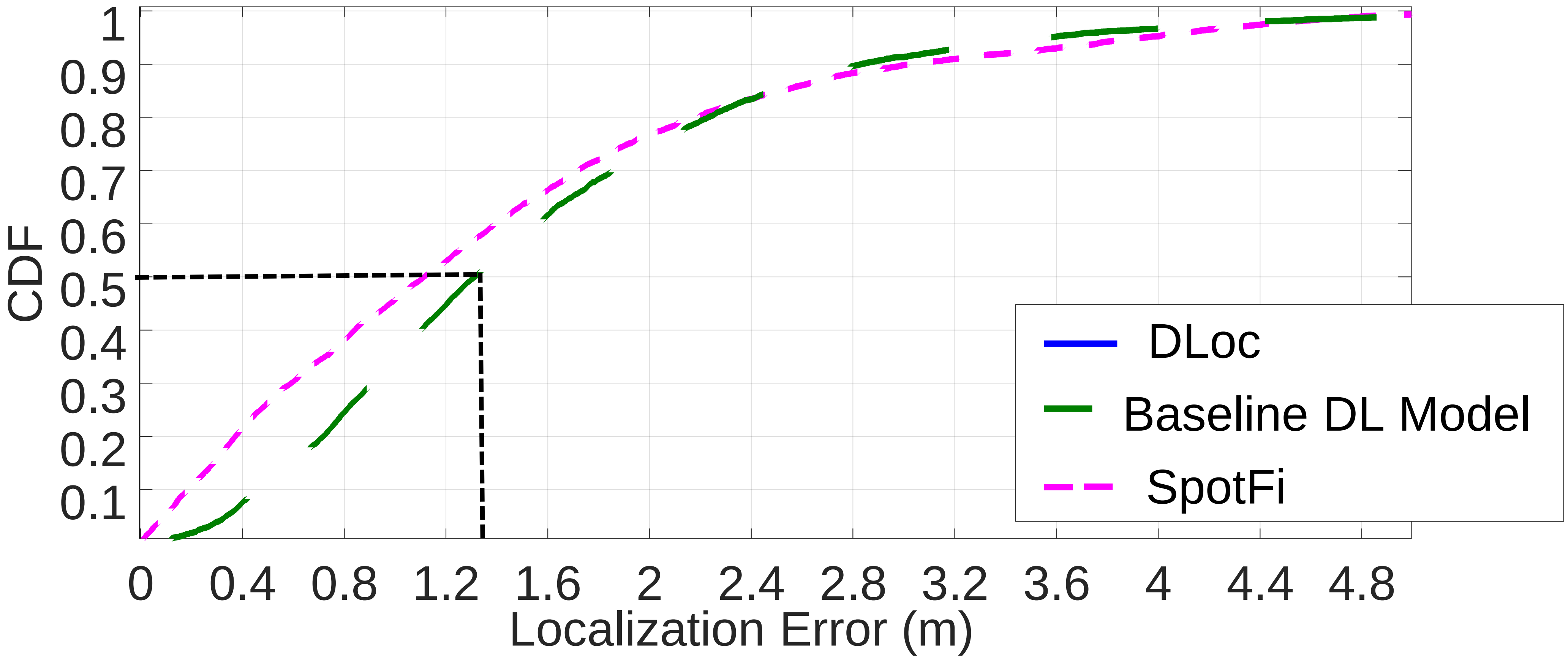
DLoc Result – Complex Environment



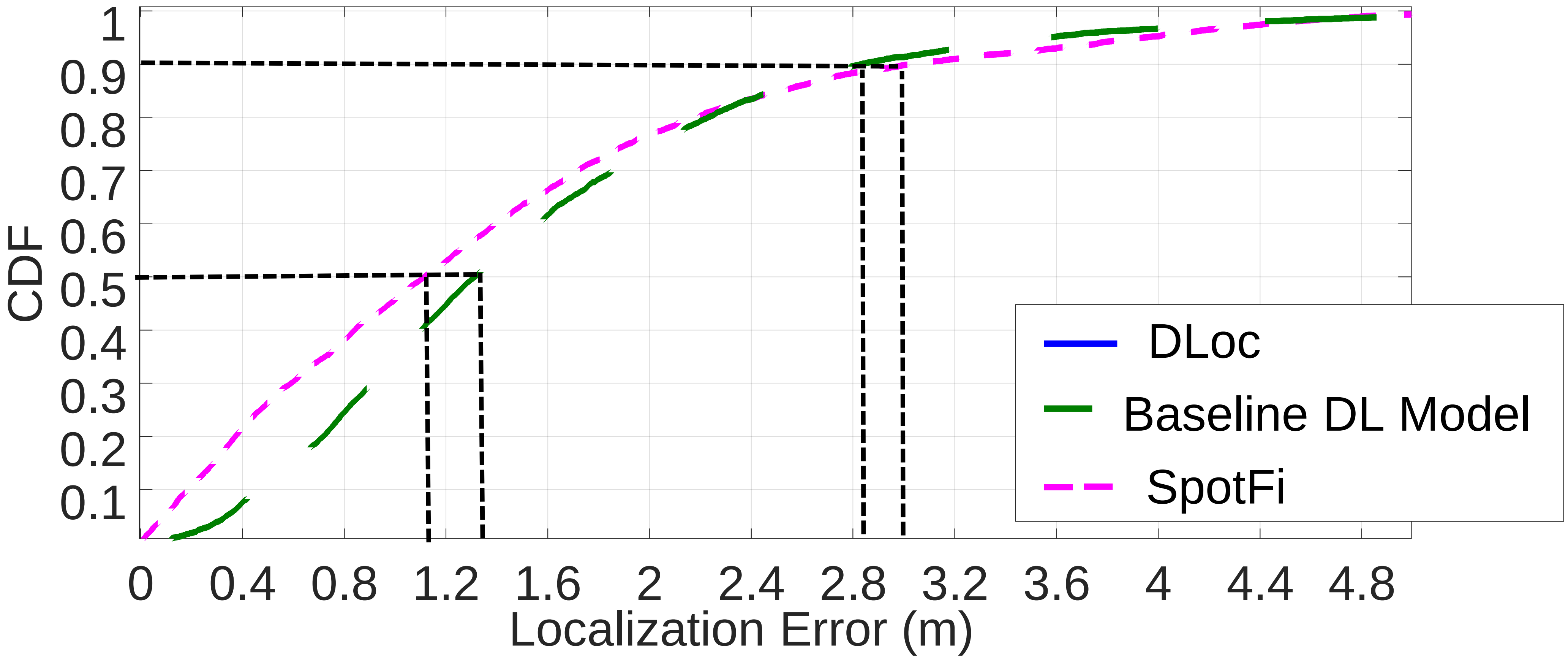
DLoc Result – Complex Environment



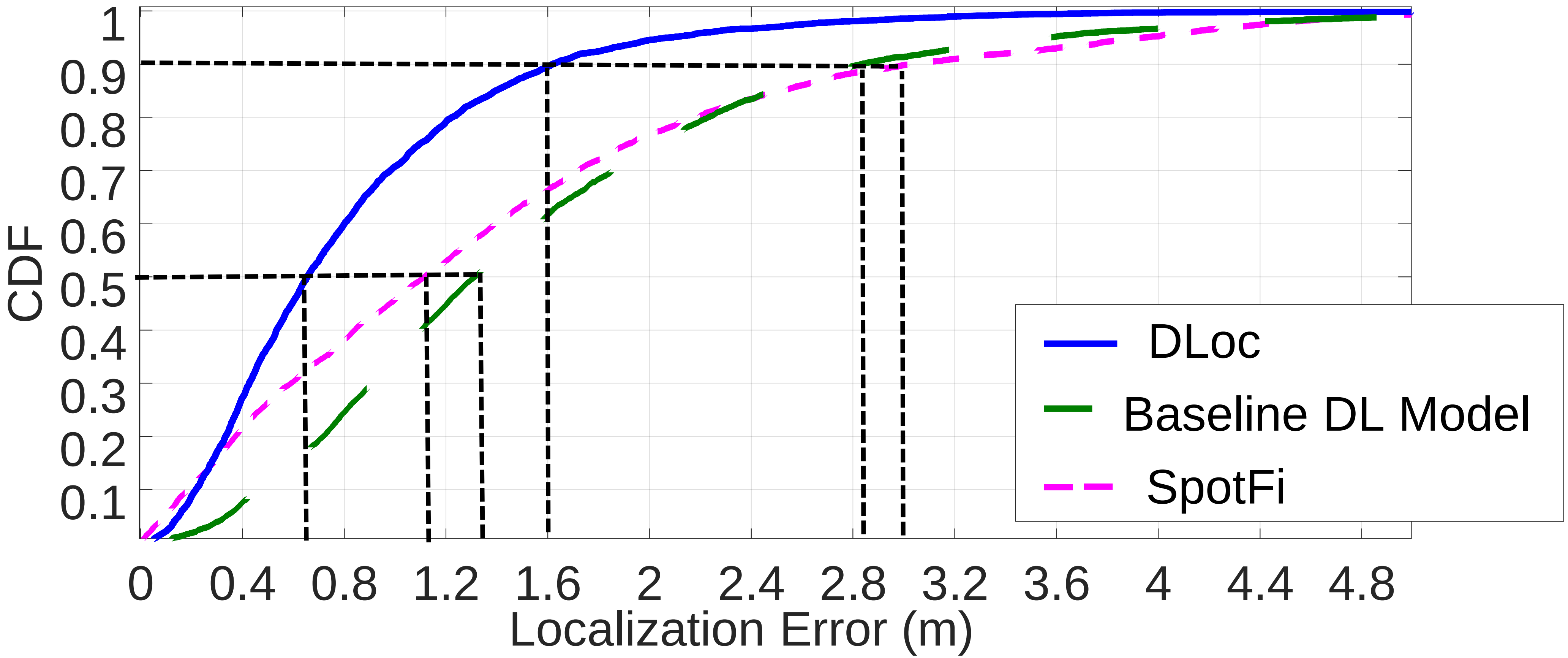
DLoc Result – Complex Environment



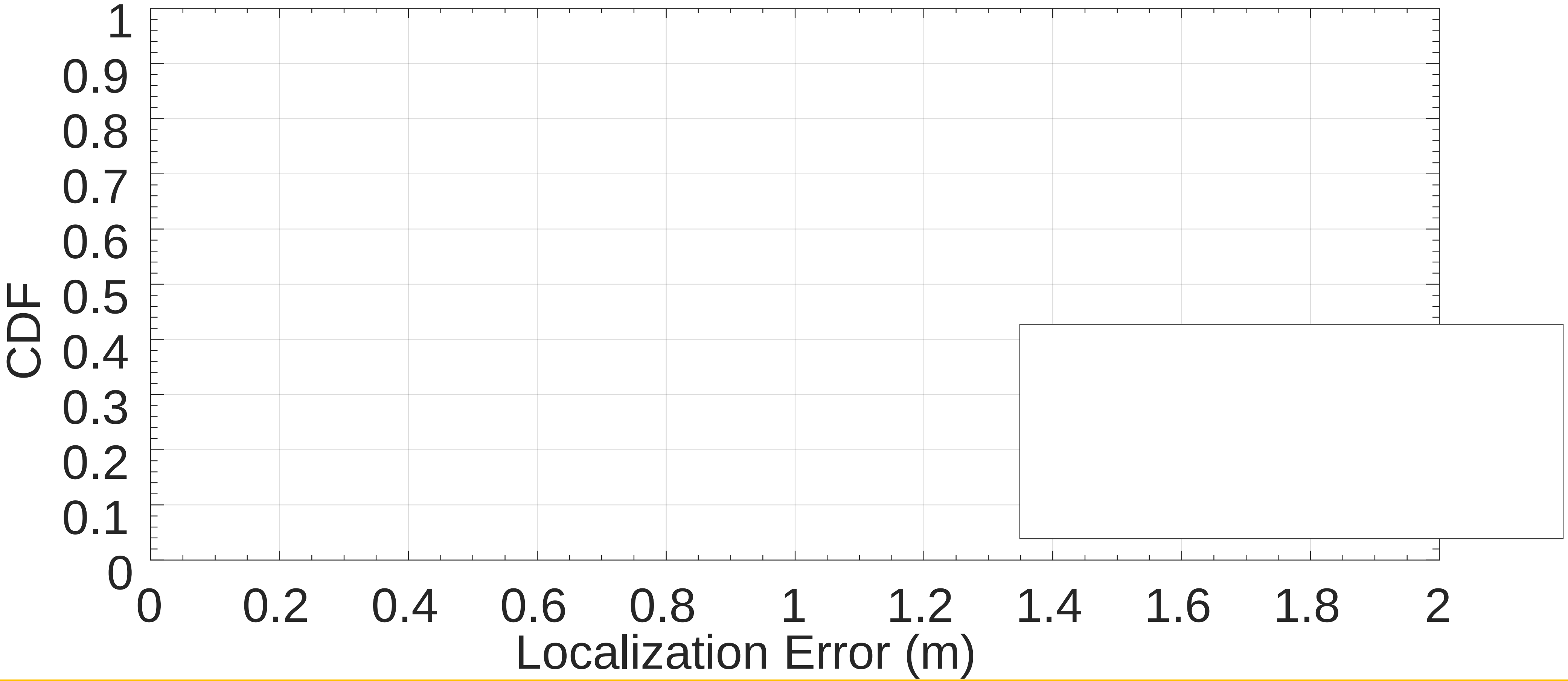
DLoc Result – Complex Environment



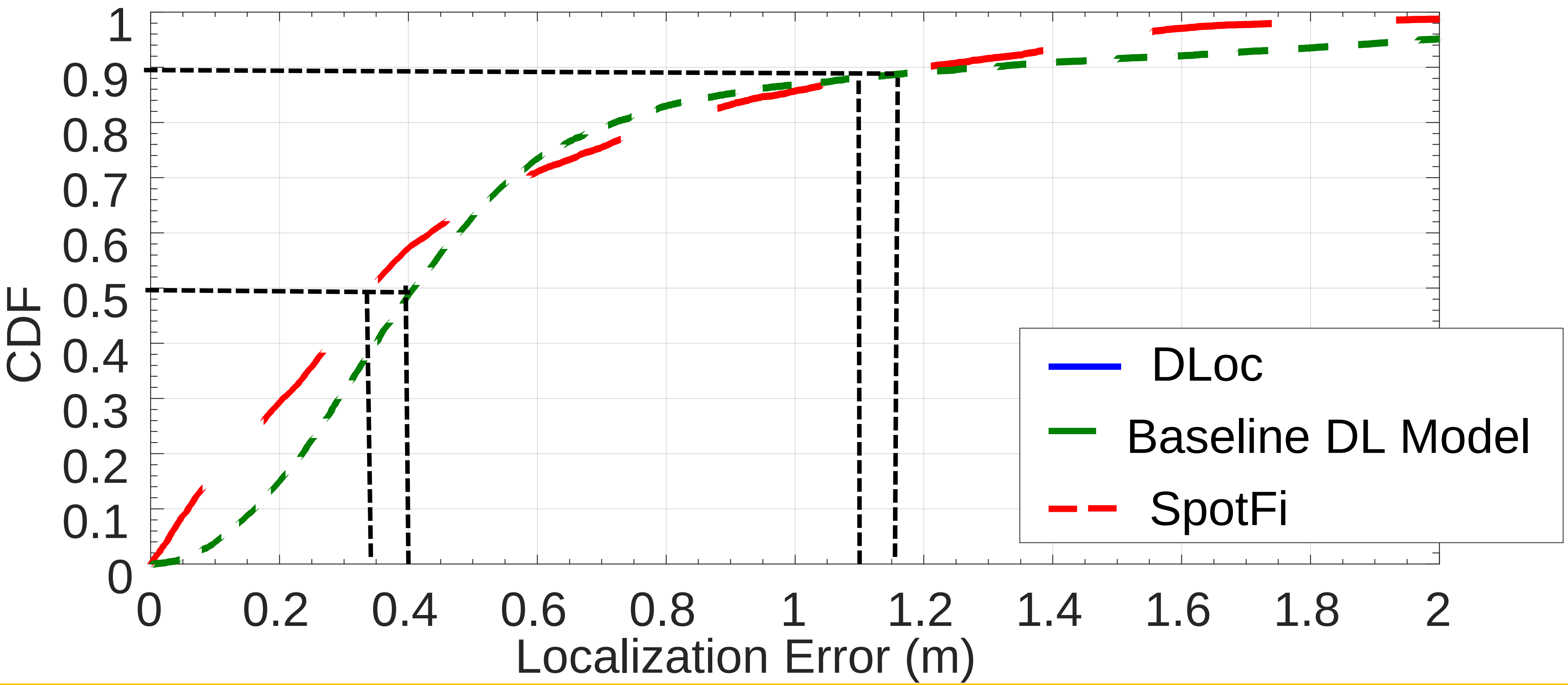
DLoc Result – Complex Environment



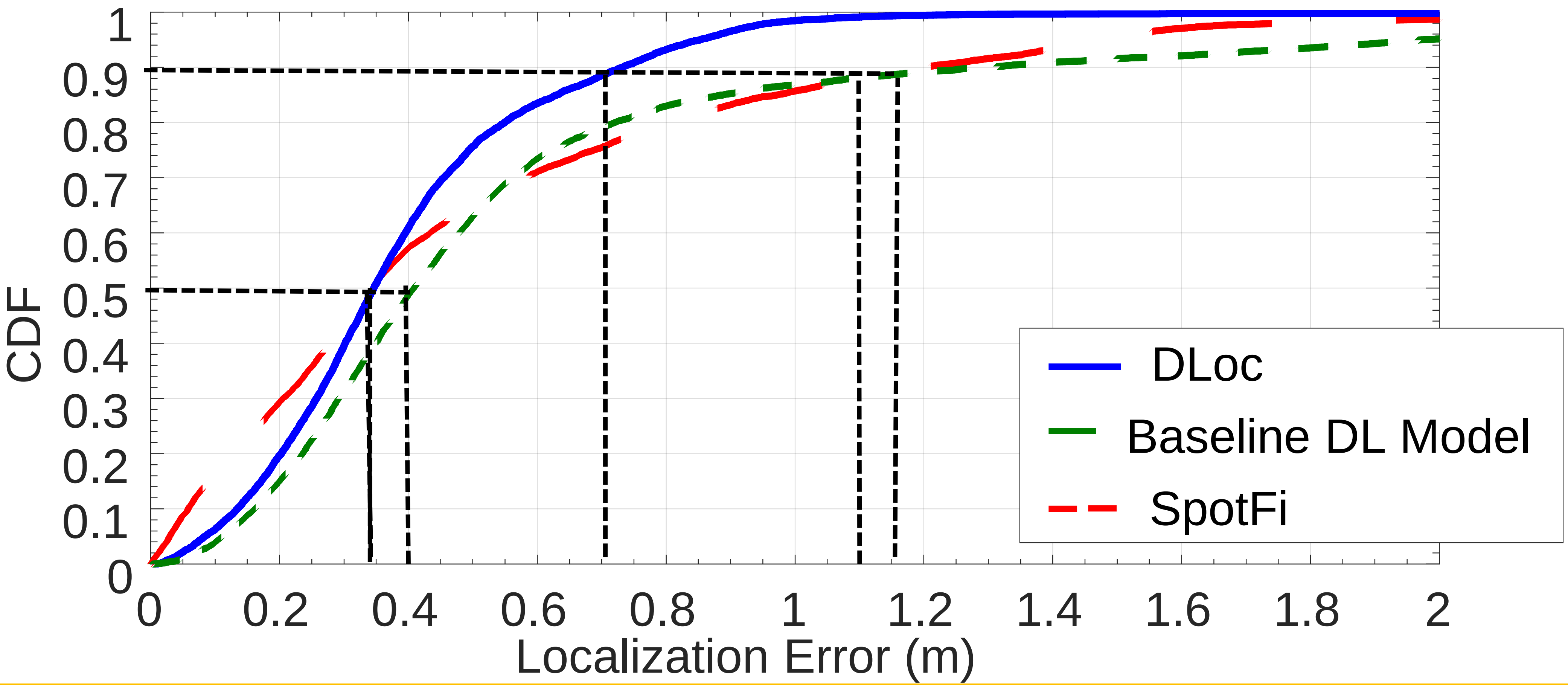
DLoc Result – Simple Environment



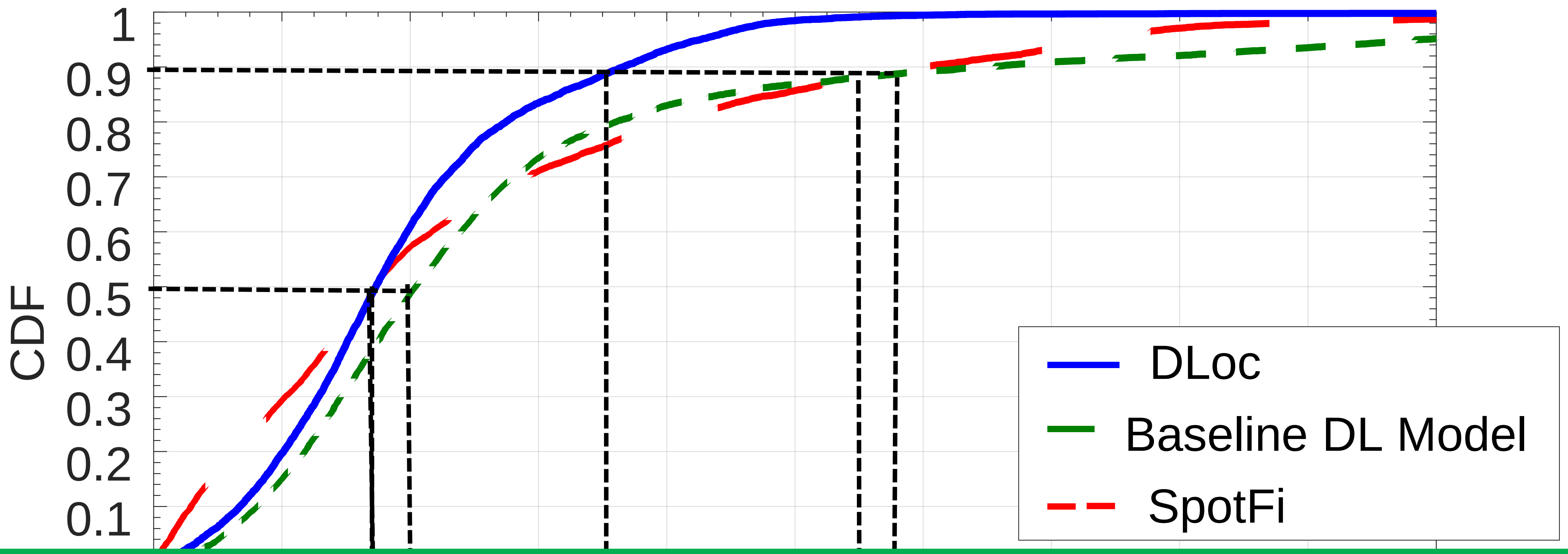
DLoc Result – Simple Environment



DLoc Result – Simple Environment



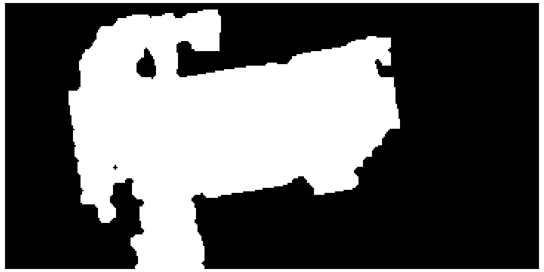
DLoc Result – Simple Environment



Accurate Indoor Localization

Generalization across multiple setups

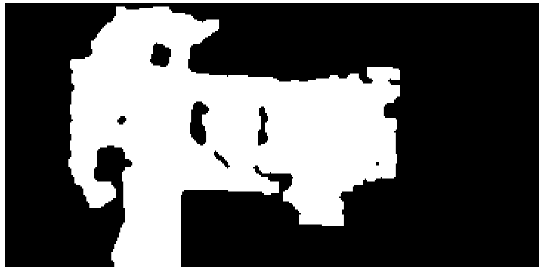
Generalization across multiple setups



Setup-1

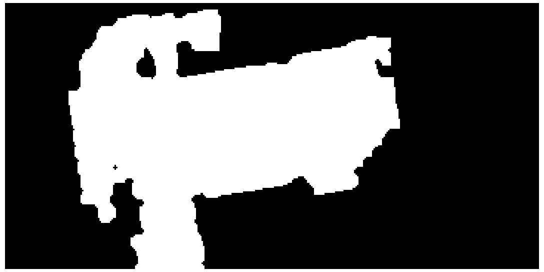
Setup-2

Setup-3



Setup-4

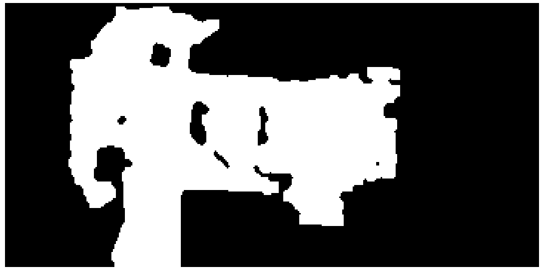
Generalization across multiple setups



Setup-1

Setup-2

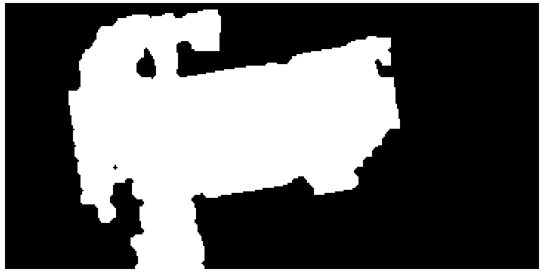
Setup-3



Setup-4

Trained on Setup	Tested on Setup	Median Error (cm)		90th Percentile Error (cm)	
		DLoc	SpotFi	DLoc	SpotFi
1,3,4	2				
1,2,4	3				
1,2,3	4				

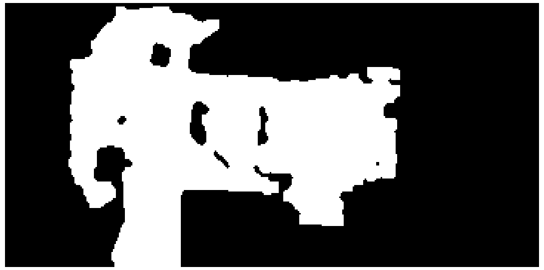
Generalization across multiple setups



Setup-1

Setup-2

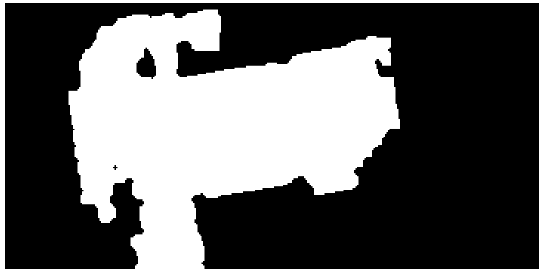
Setup-3



Setup-4

Trained on Setup	Tested on Setup	Median Error (cm)		90th Percentile Error (cm)	
		DLoc	SpotFi	DLoc	SpotFi
1,3,4	2		198		420
1,2,4	3		154		380
1,2,3	4		161		455

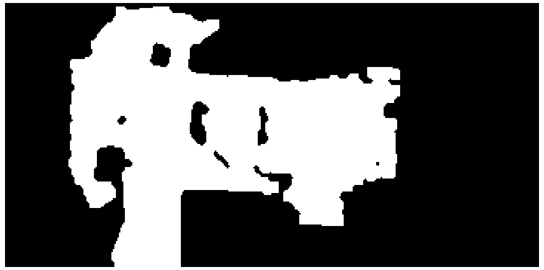
Generalization across multiple setups



Setup-1

Setup-2

Setup-3



Setup-4

Trained on Setup	Tested on Setup	Median Error (cm)		90th Percentile Error (cm)	
		DLoc	SpotFi	DLoc	SpotFi
1,3,4	2	71	198	171	420
1,2,4	3	82	154	252	380
1,2,3	4	105	161	277	455

Open-Sourced Dataset

Open-Sourced Dataset

- Enabling Baseline comparison for all algorithms

Open-Sourced Dataset

- Enabling Baseline comparison for all algorithms
- Pushing Indoor Localization to realization

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Open-Sourced Dataset

https://wcsng.ucsd.edu/wild/

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SCAN ME

Labelled WiFi CSI data (WILD-v1)

8 different setups

4 different days

108K datapoints

2 different environments

Open-Sourced Dataset

https://wcsng.ucsd.edu/wild/

SCAN ME

- Enabling Baseline comparison for all algorithms
- Pushing Indoor Localization to realization
- Pushing towards a competition similar to ImageNet program

Labelled WiFi CSI data (WILD-v1)

8 different setups

4 different days

108K datapoints

2 different environments

WILD-v2 Coming Soon

- 20 different setups
- 10 different days
- 1 million datapoints
- 8 different environments
- 20 different AP locations

Conclusion and Future Work

- Novel Deep Learning based algorithm with 85% incremental performance compared to state-of-the-art.
- MapFind we have collected over 108k datapoints (and expanding) that is open-sourced.
- Enabling large scale and autonomous indoor navigation

https://wcsng.ucsd.edu/dloc/

SCAN ME