WIRELESS SYSTEMS FOR ROBOTICS AND IOT APPLICATIONS

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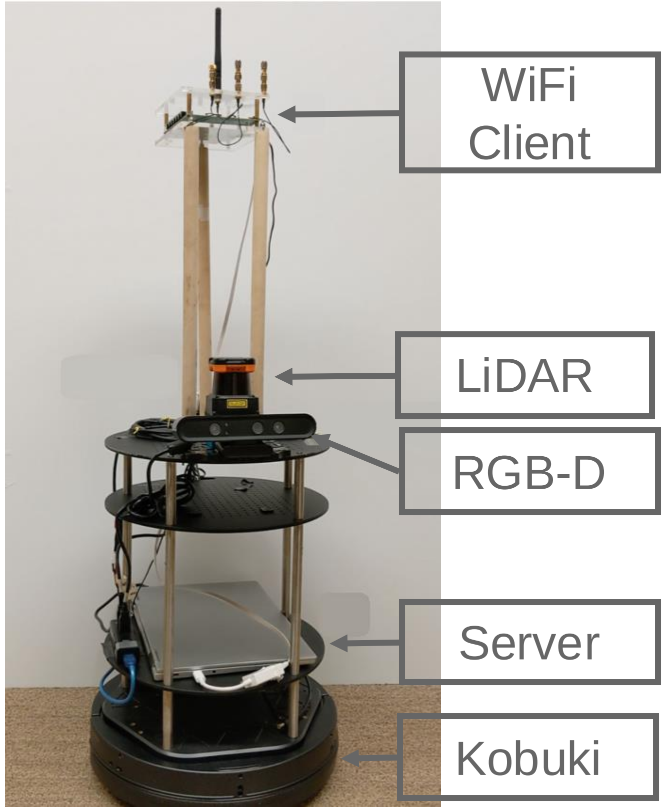
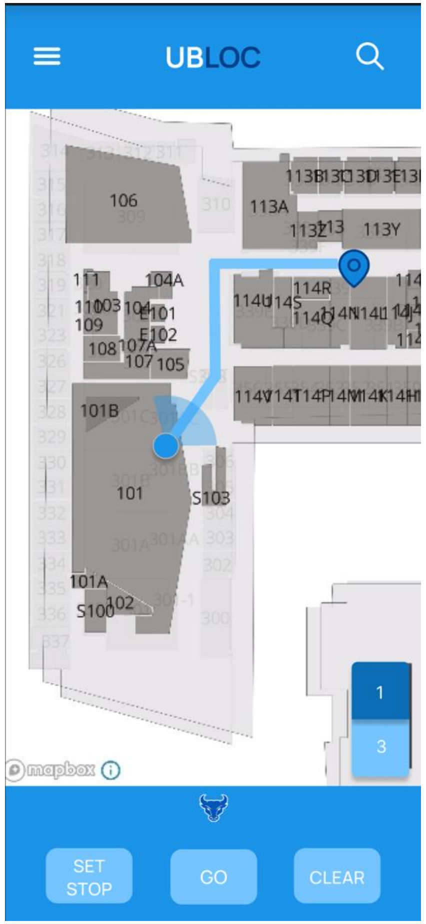
Wireless Systems @ UB

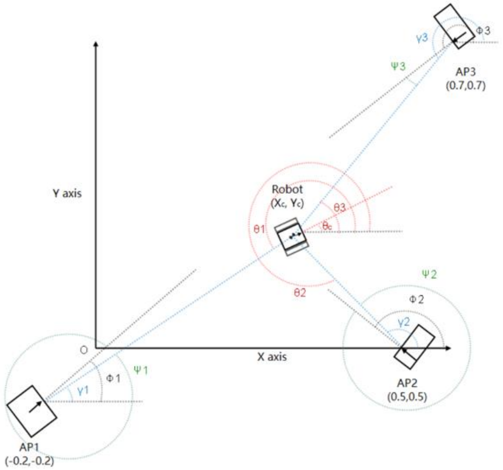
MapFind

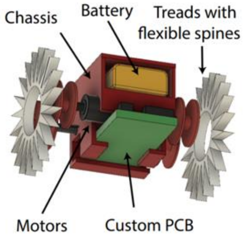


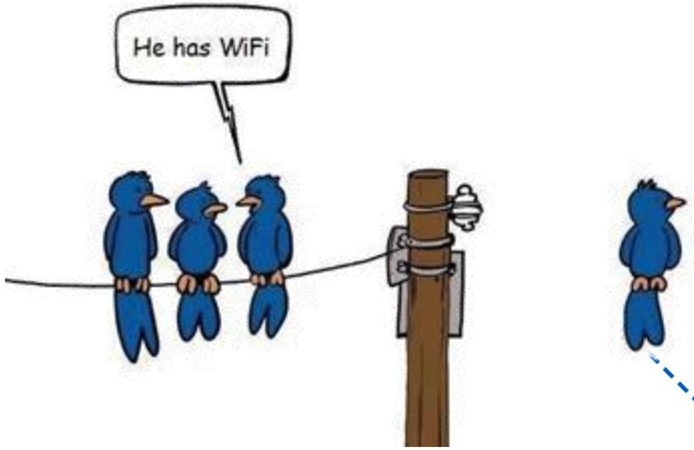
WLApp



WiConByte



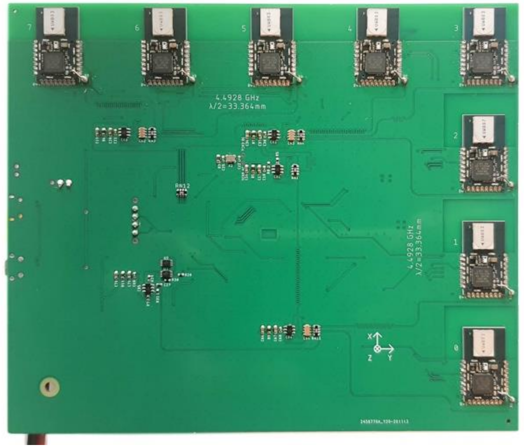




RF-Sensing for Robotics

Visual Sensors
- High Resolution
- Long Range
- Easily blocked by Obstacles

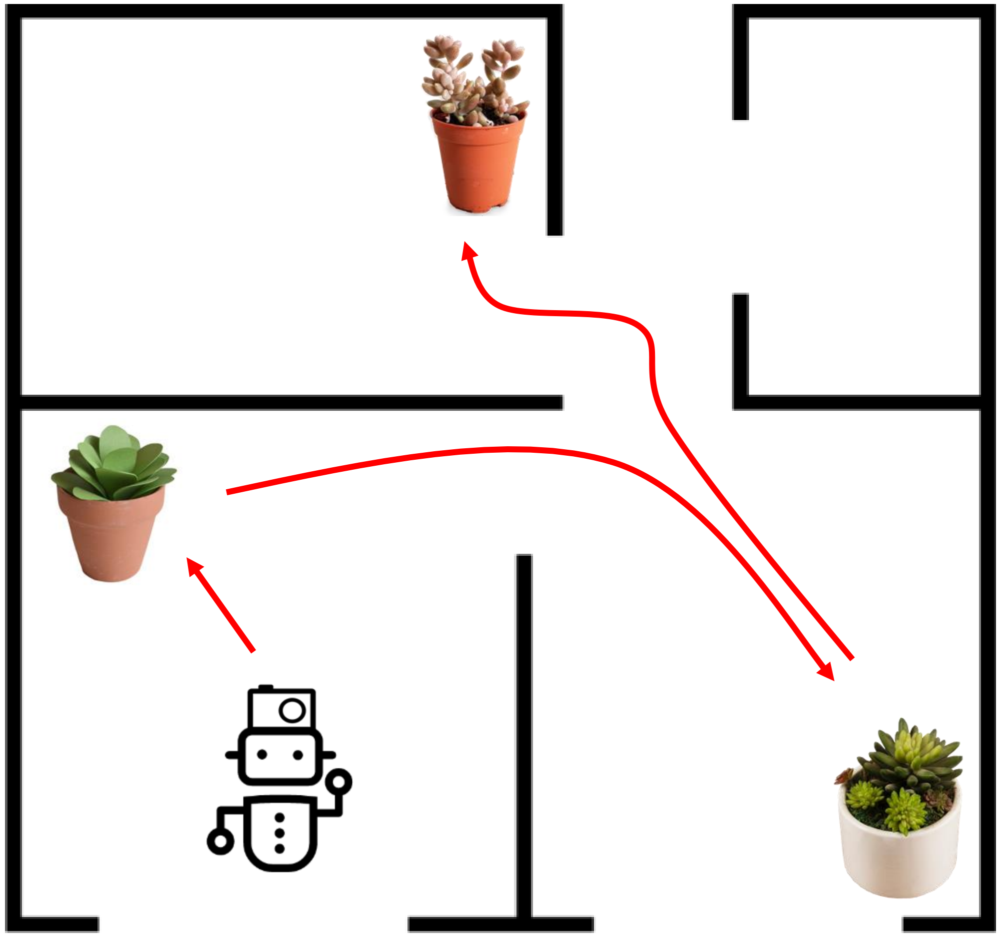
Acoustic Sensors
- High Resolution
- Short Range
- Robust to a few Obstacles

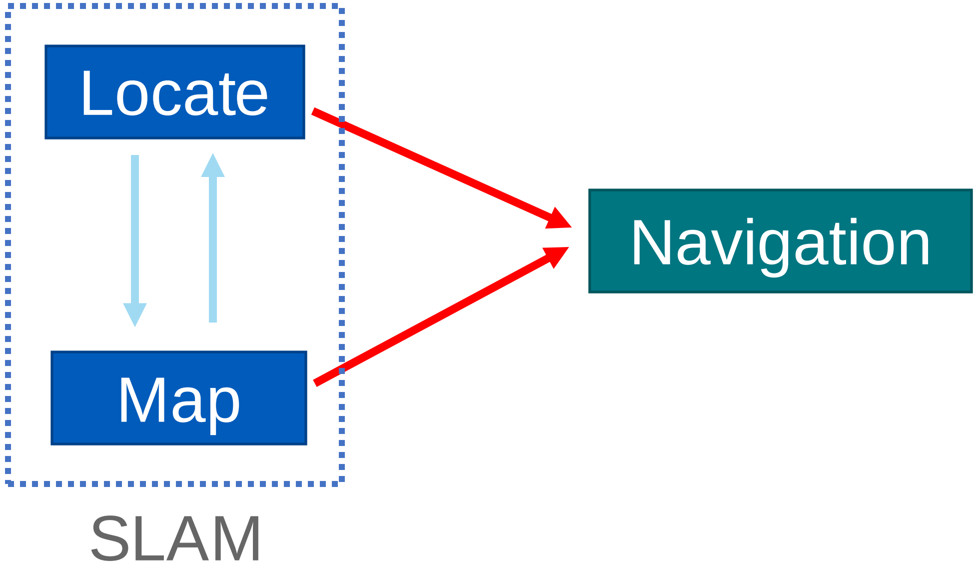


Wireless Sensors
- Poorer Resolution
- Long Range
- Robust to Obstacles

Multi-Modal Sensing

Task: **Autonomously** water all the plants in an **unknown** environment





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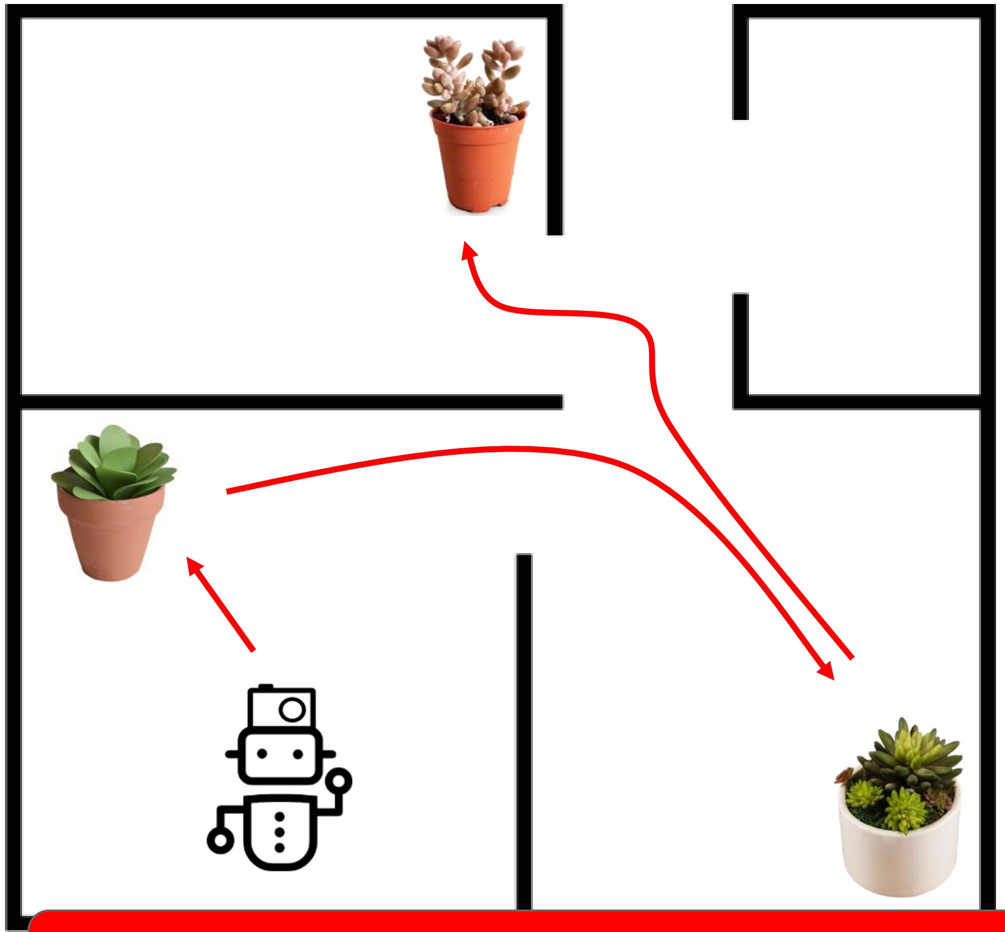
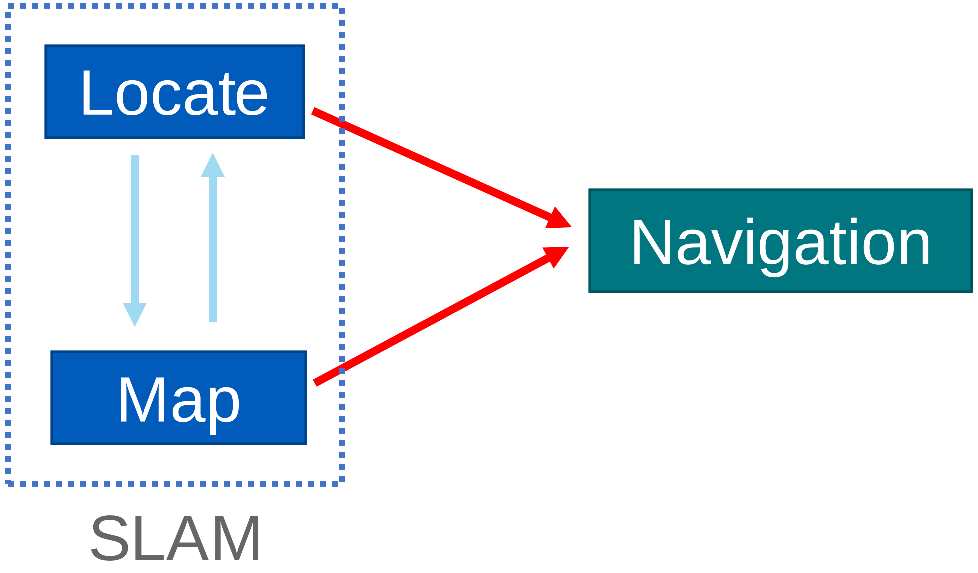
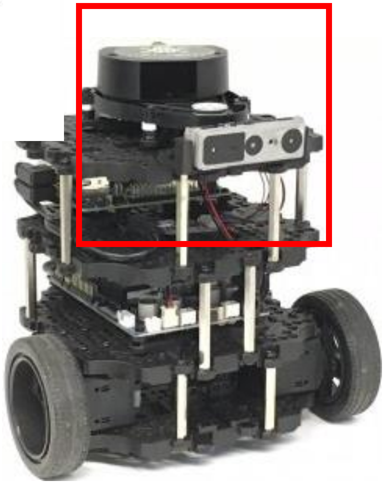




How does the robot localize itself in the environment

Robots use visual landmarks for SLAM and navigation



Images: https://onwardstate.com/2019/10/24/exploring-the-depths-of-the-mueller-althouse-tunnel/;
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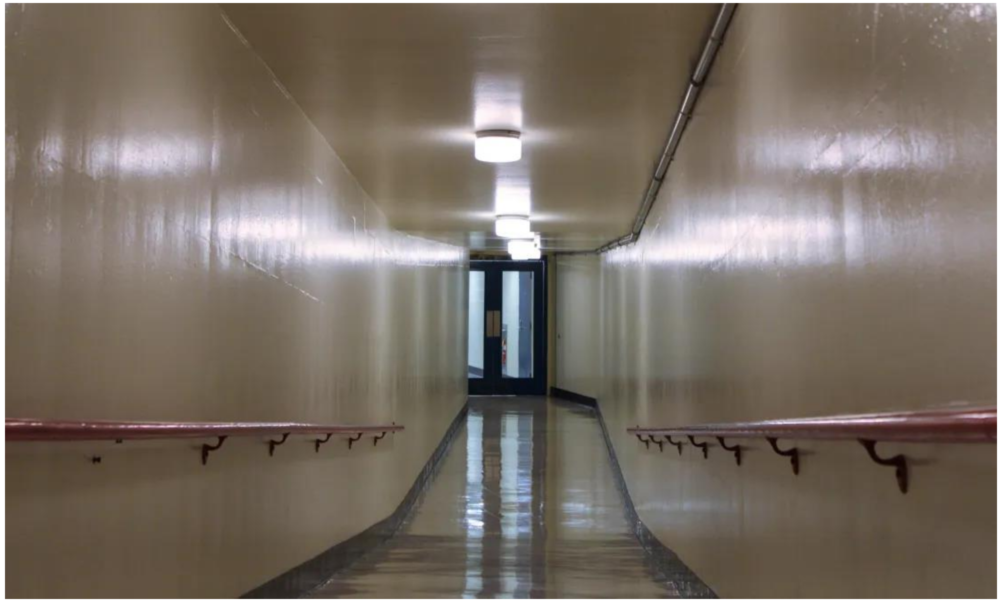

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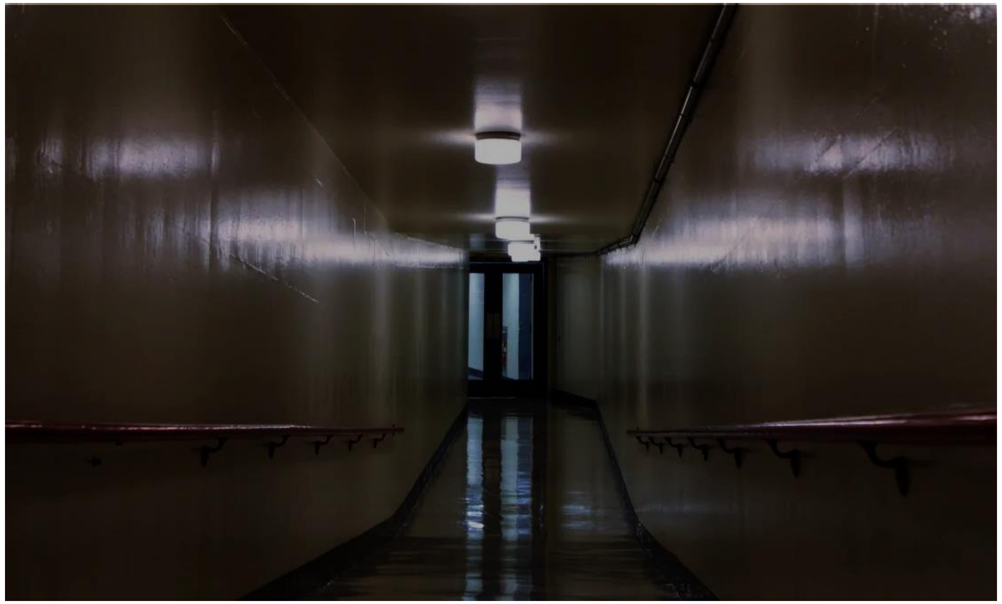

No strong visual landmarks to correct for robot drift

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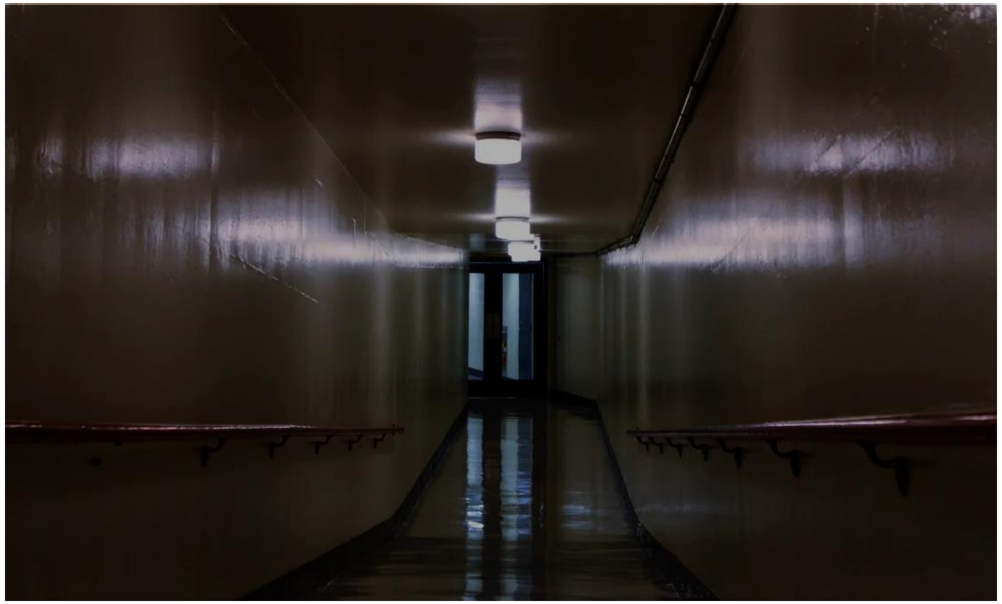
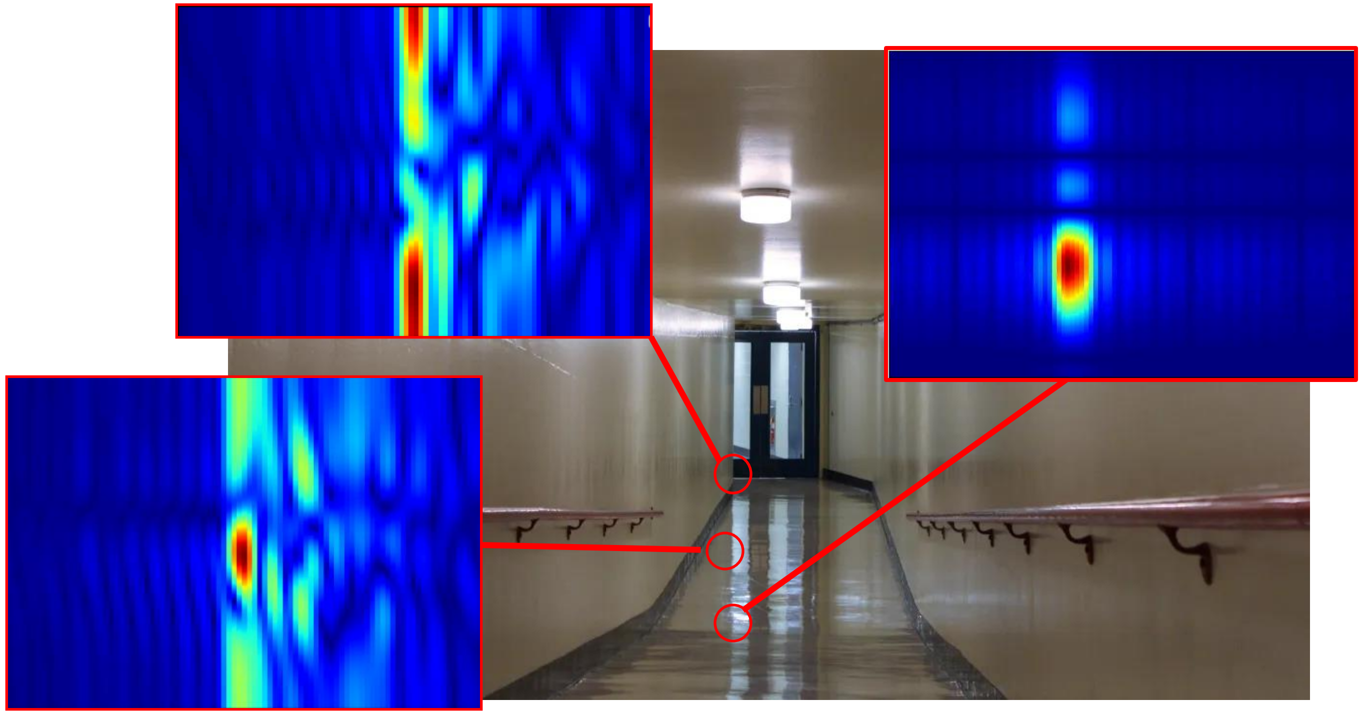


No strong visual landmarks to correct for robot drift

Need a sensor providing **diverse** landmarks in **monotonous** environment

Images: htt
http://cogro

“WiFi-images” provide identifiable landmarks in the environment



“WiFi-images” provide diversity
even in monotonous environments

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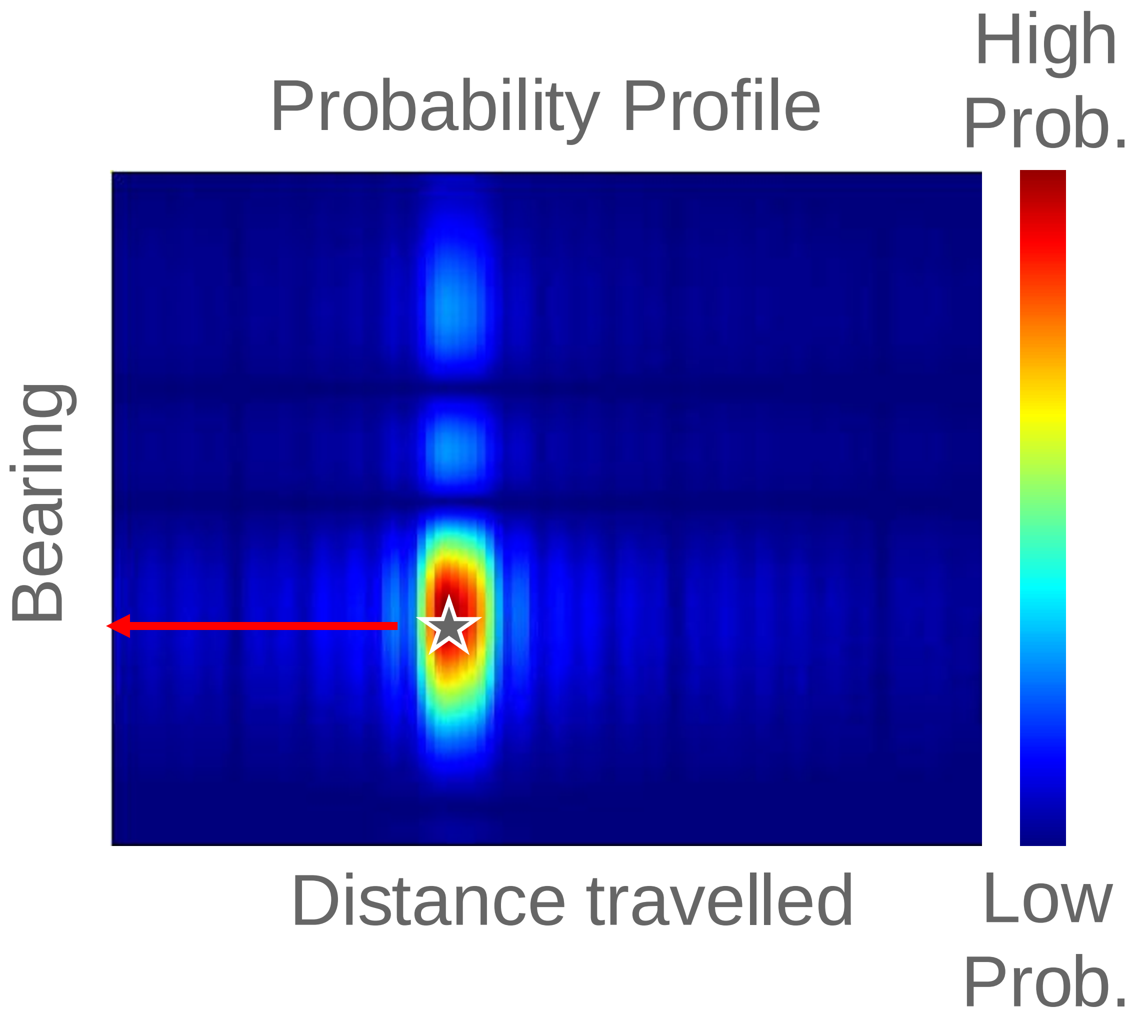
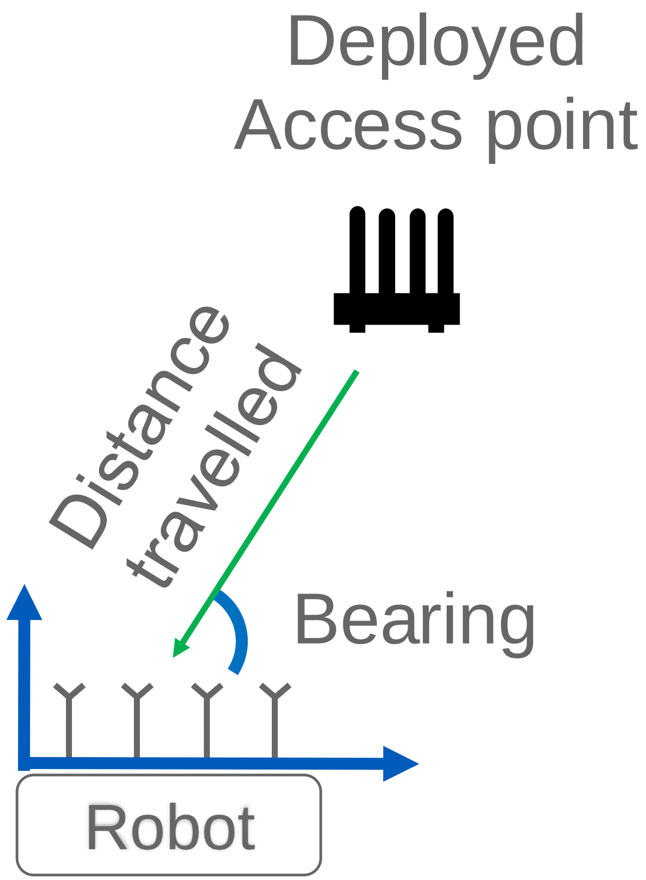
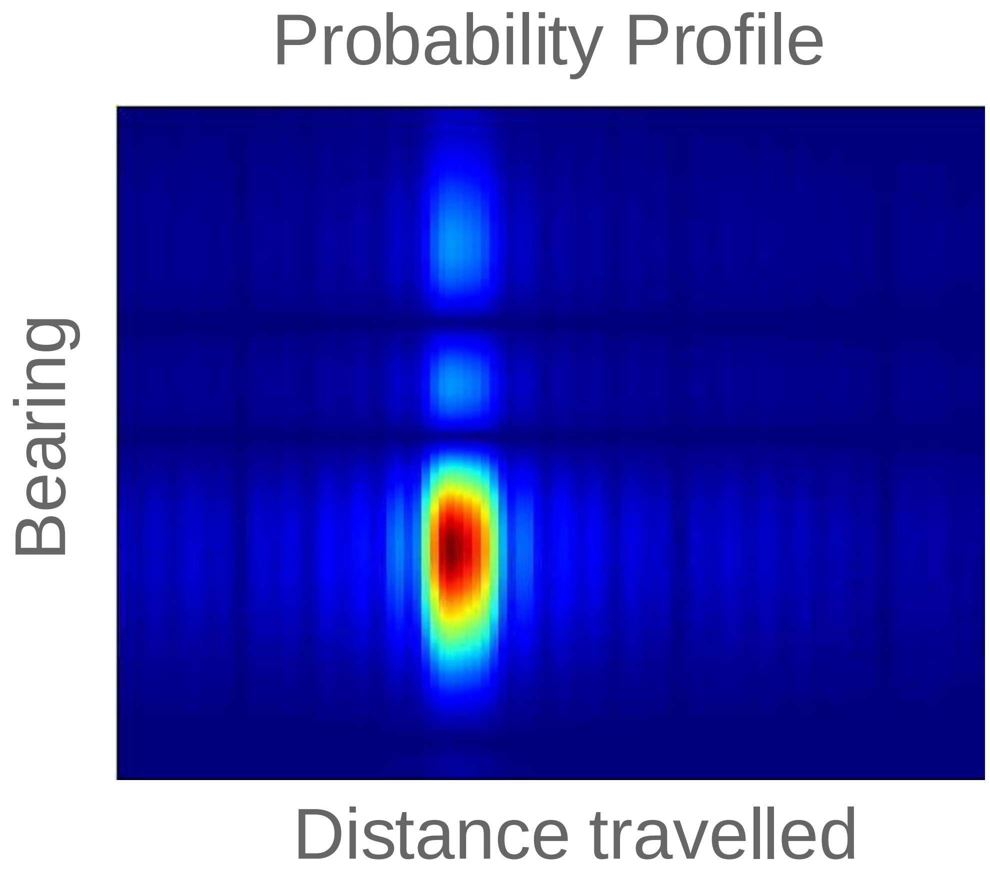
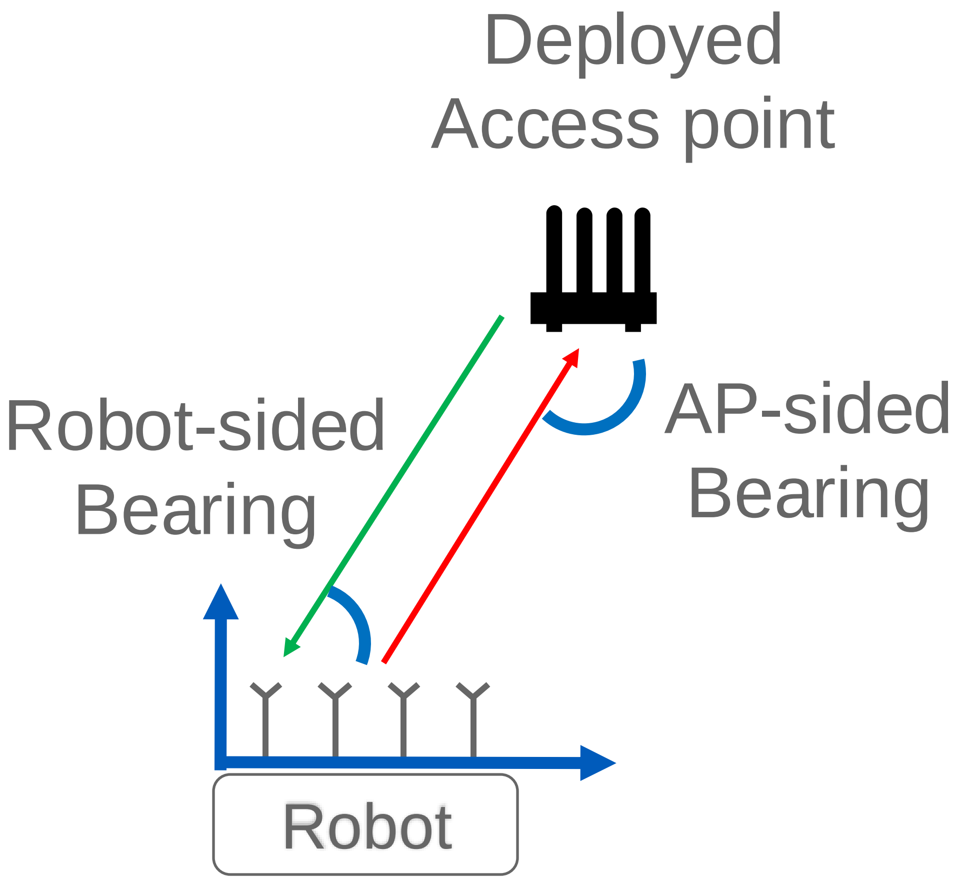
WiFi images are probability profiles encoding the angle of arrival of the signal





Via two-way packet exchange, bearings are measured on both ends





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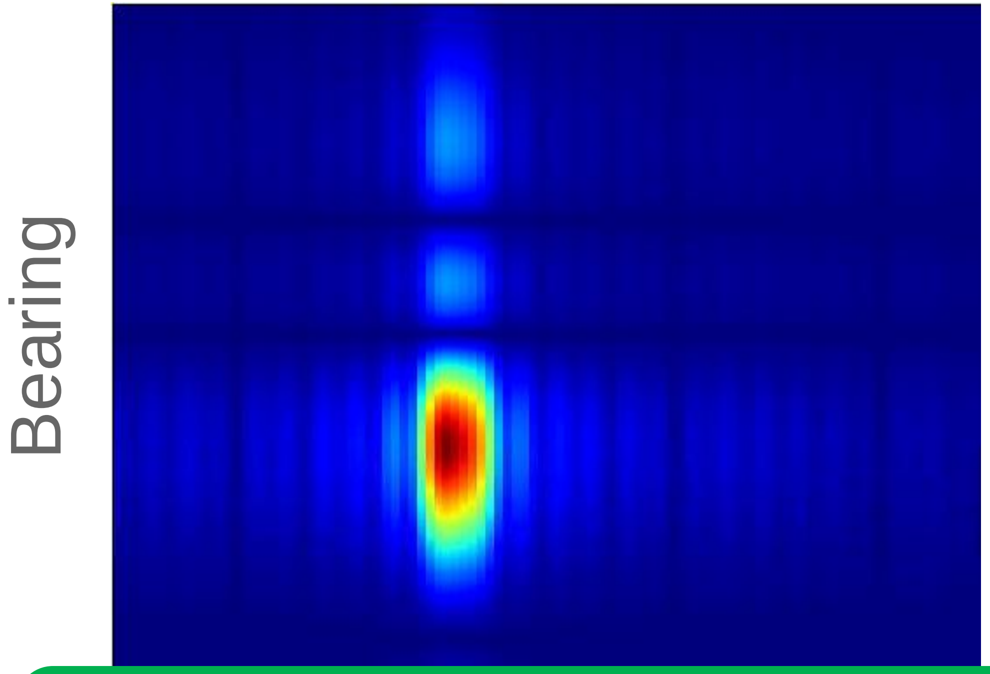
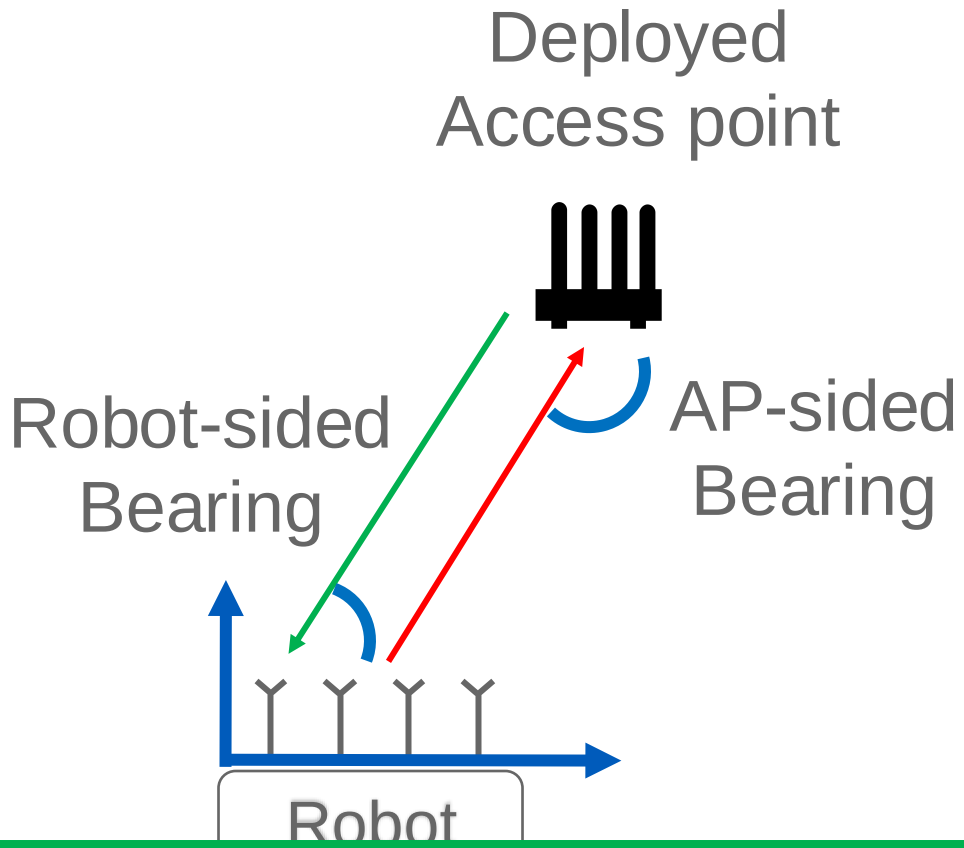
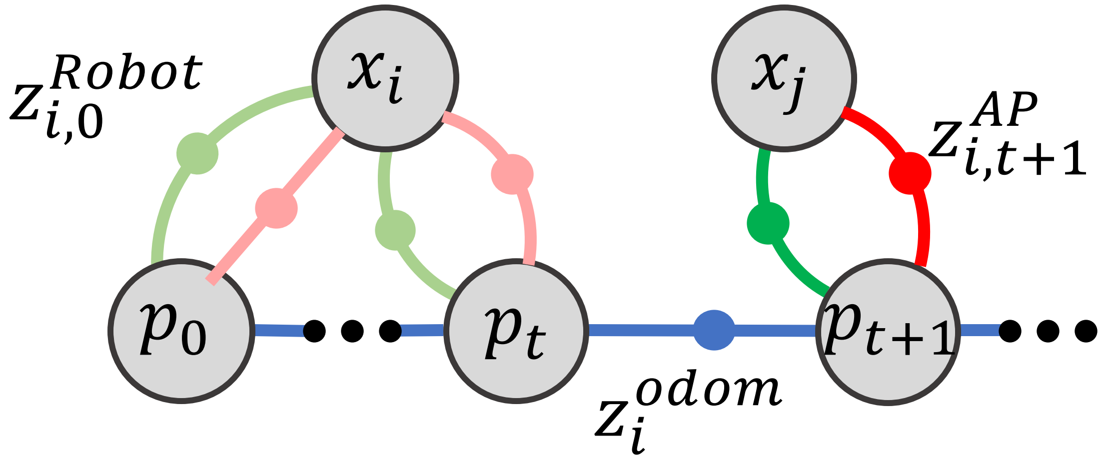
Probability Profile

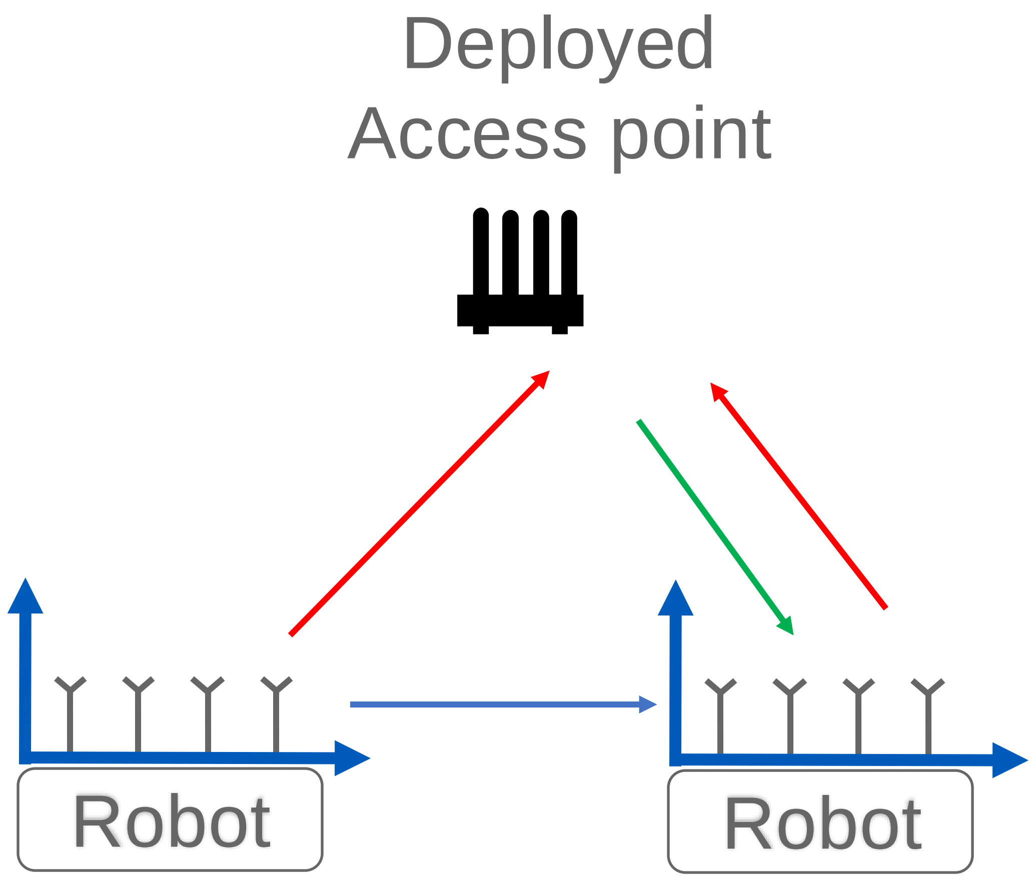




P2SLAM takes advantage of two-way bearings from ping and pong packets

Integrating two-sided bearing measurements within GTSAM's backend





p_t= Robot Positions and orientations at time t

x_i = Access point position and orientation

ICRA/RA-L'22

On-par with the state-of-the-art Visual SLAM

Building **consistent** maps is memory and compute intensive

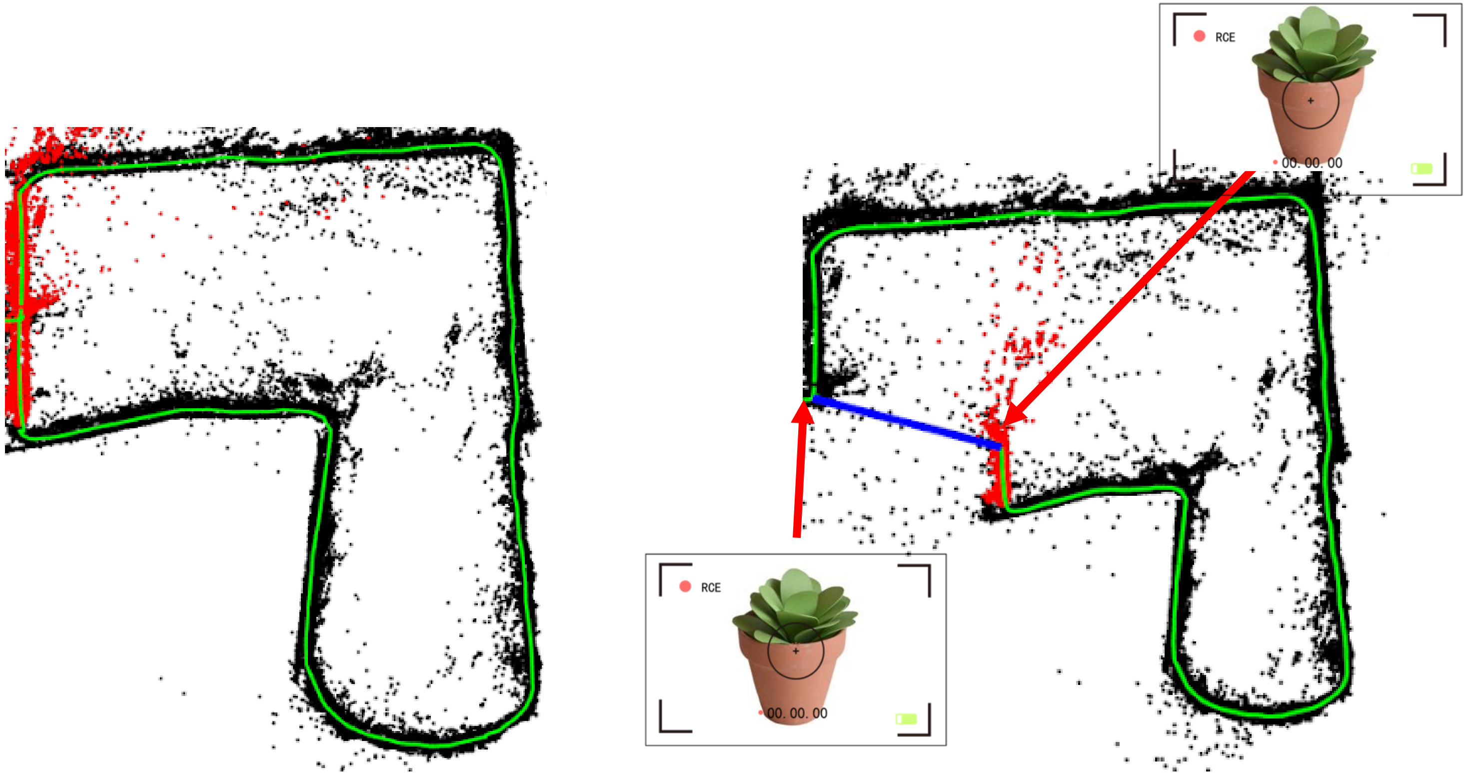


Image
Mur-Artal, R., Montiel, J. M. M., & Tardos, J. D. (2015). ORB-SLAM: a versatile and accurate monocular SLAM system. IEEE Transactions on Robotics, 31(5), 1147-1163
www.adequatetravel.com/blog/wp-content/uploads/2018/12/Colosseum-The-Most-Visited-Building-in-Rome.jpg

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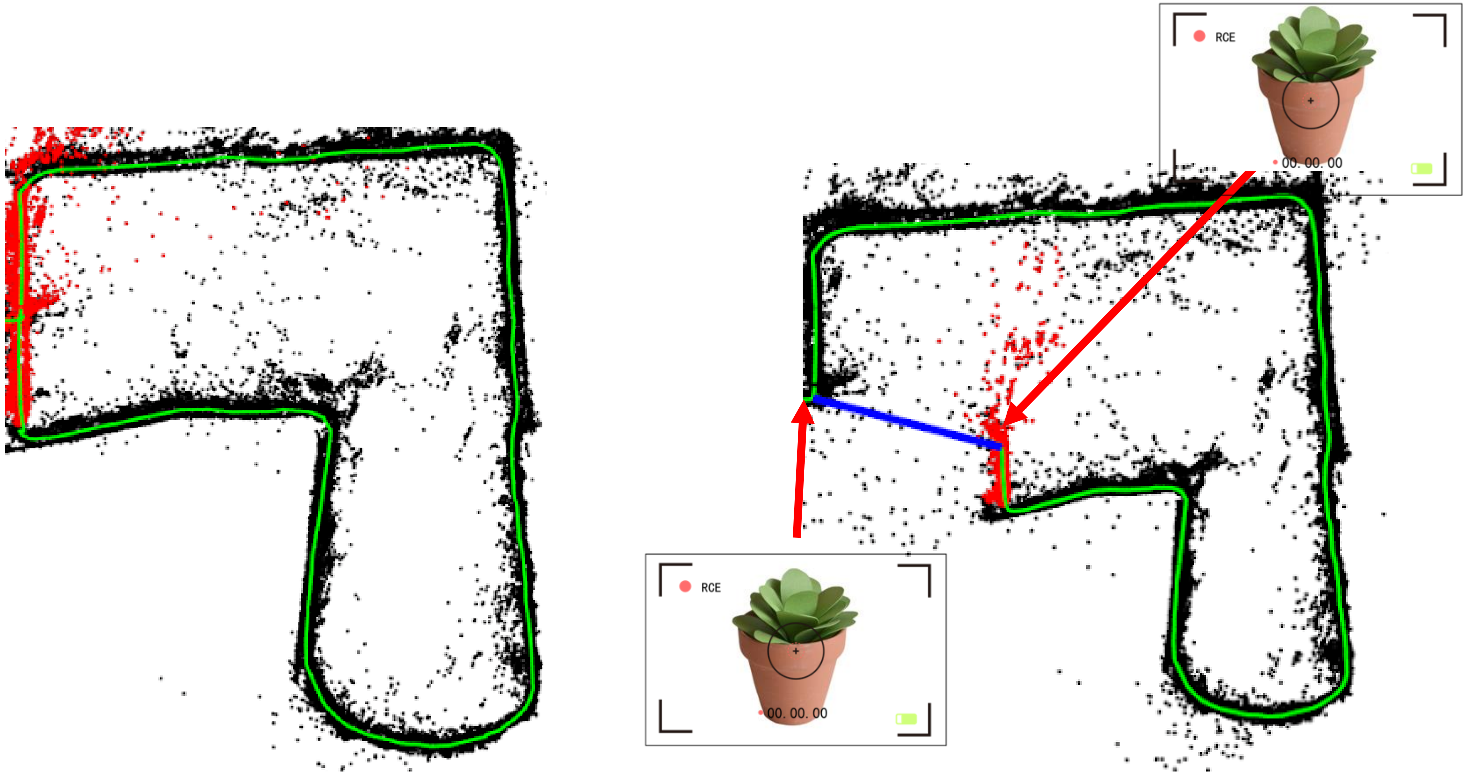

To **find** this loop closure match, **all** the previous observed landmarks need to be compared

Applying loop closures need **large** corrections to the trajectory and map

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Mur-Artal, R., Montiel, J. M. M., & Tardos, J. D. (2015). ORB-SLAM: a versatile and accurate monocular SLAM system. IEEE Transactions on Robotics, 31(5), 1147-1163
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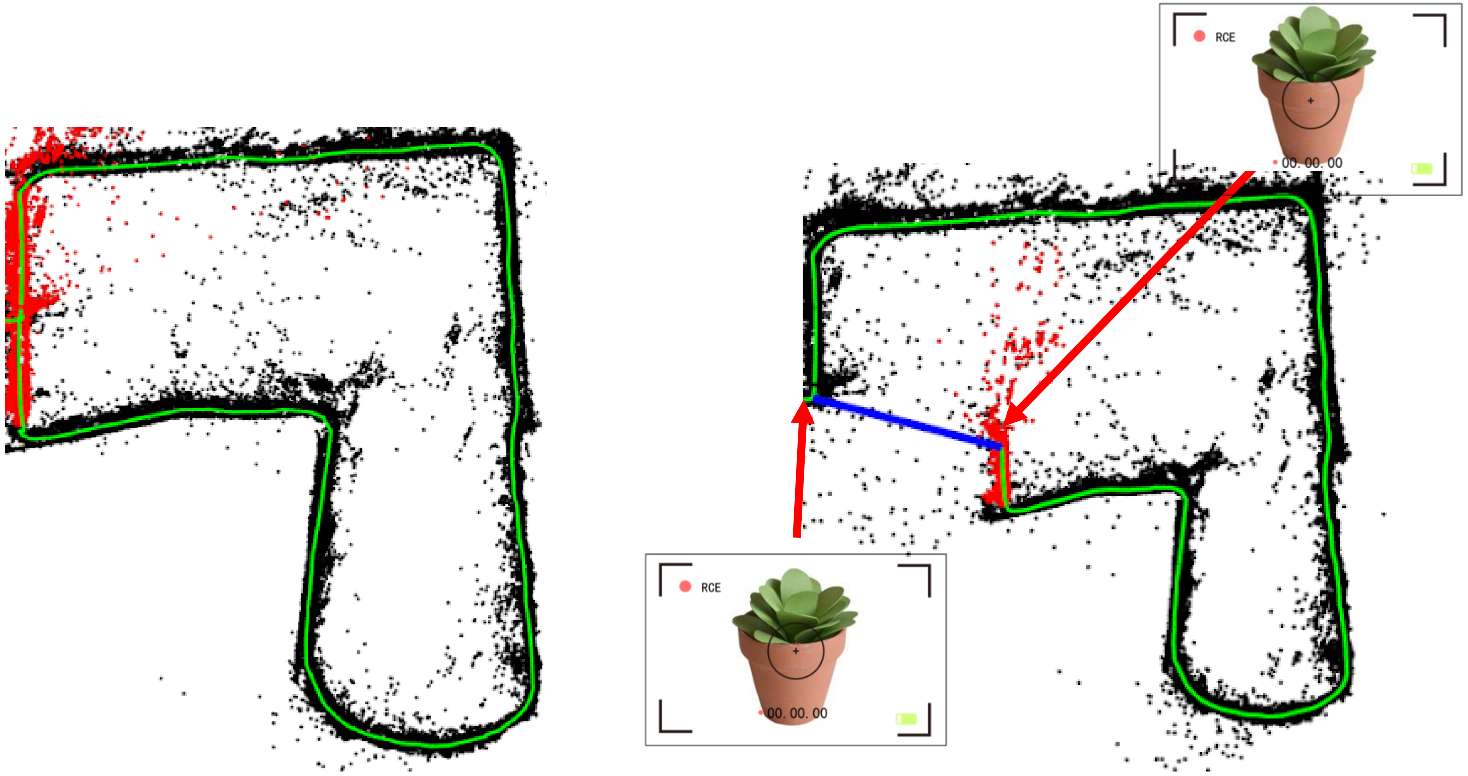

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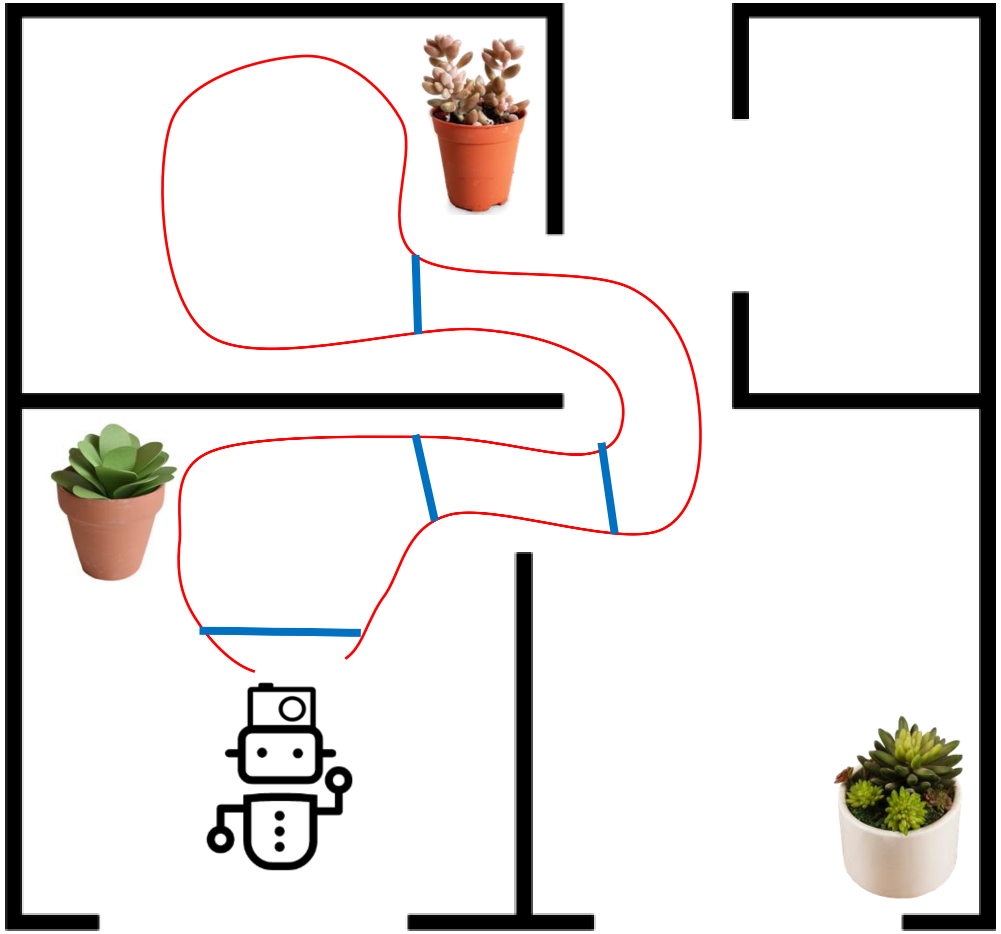
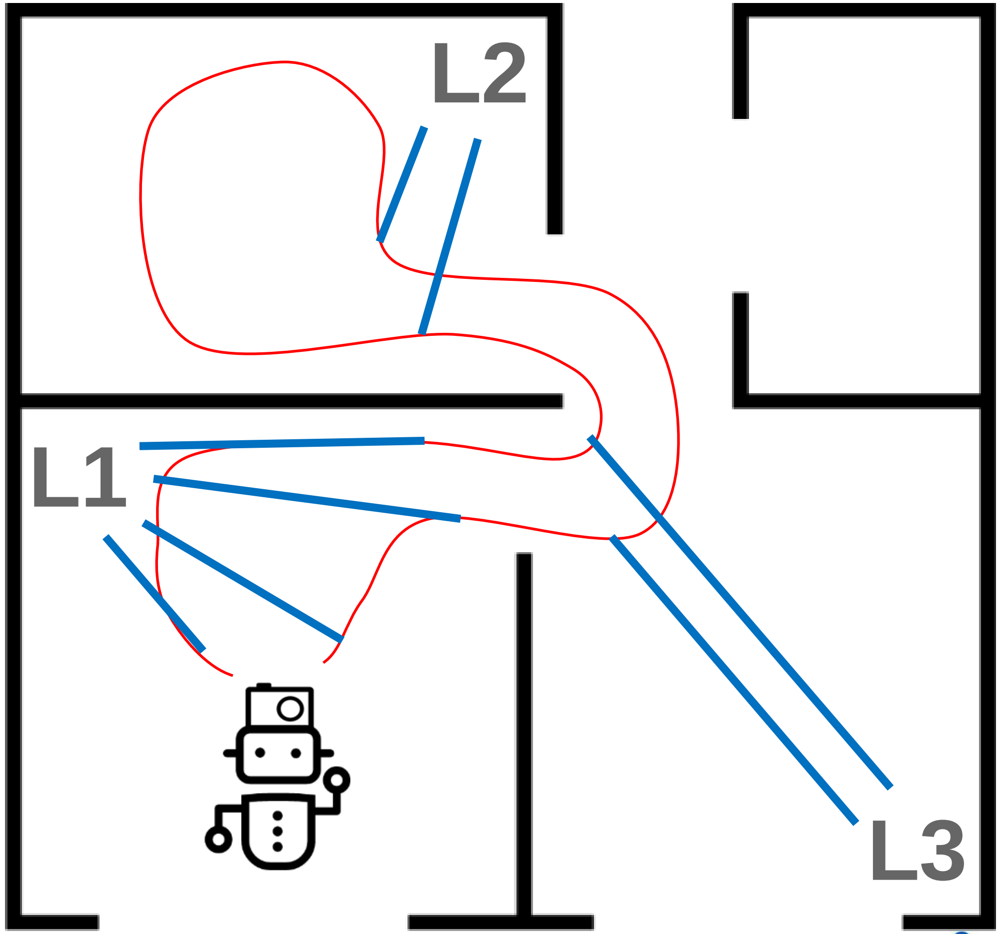
Loop closures are a necessary evil in a visual SLAM system

Loop closures detections avoided if landmarks can uniquely identify themselves





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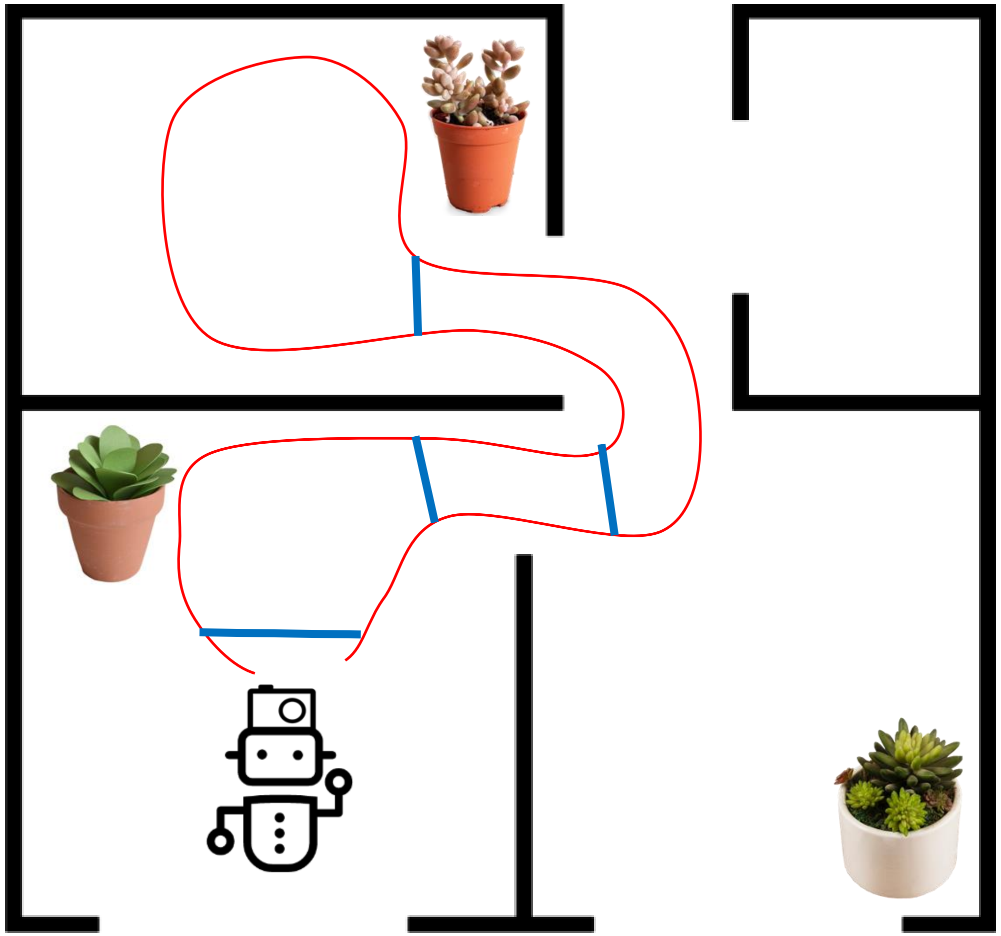
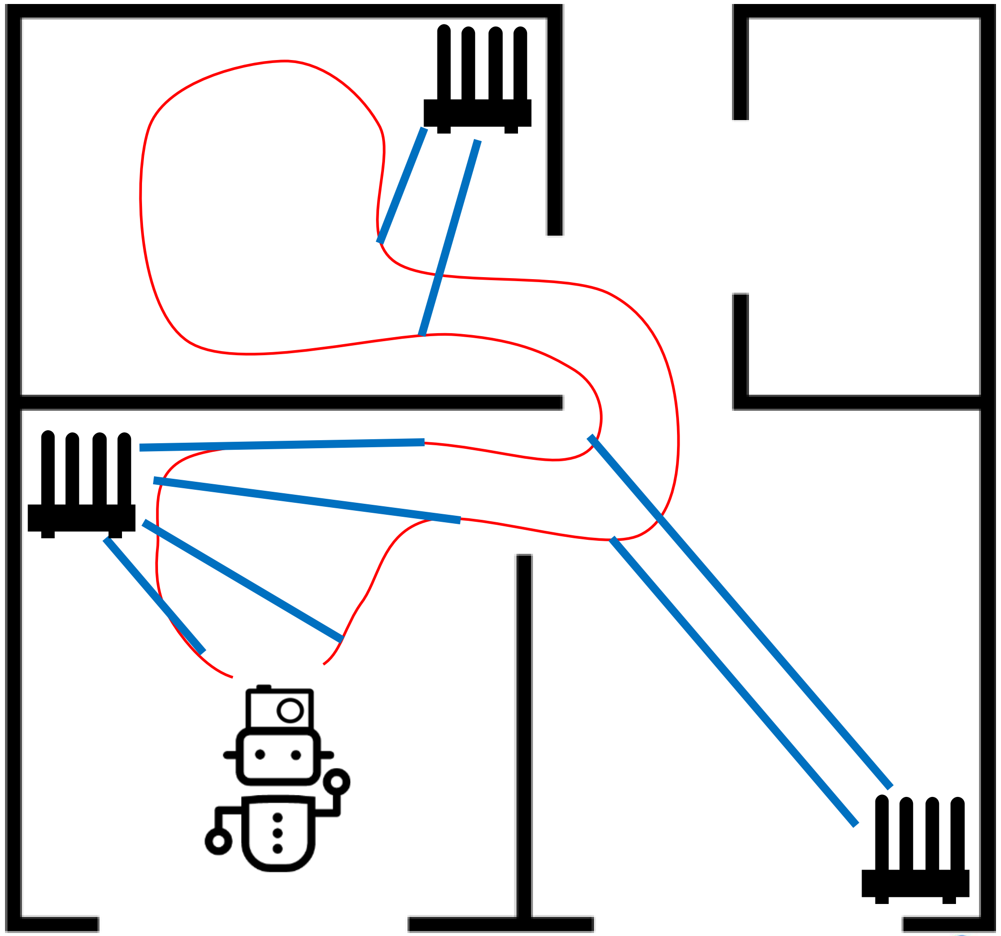
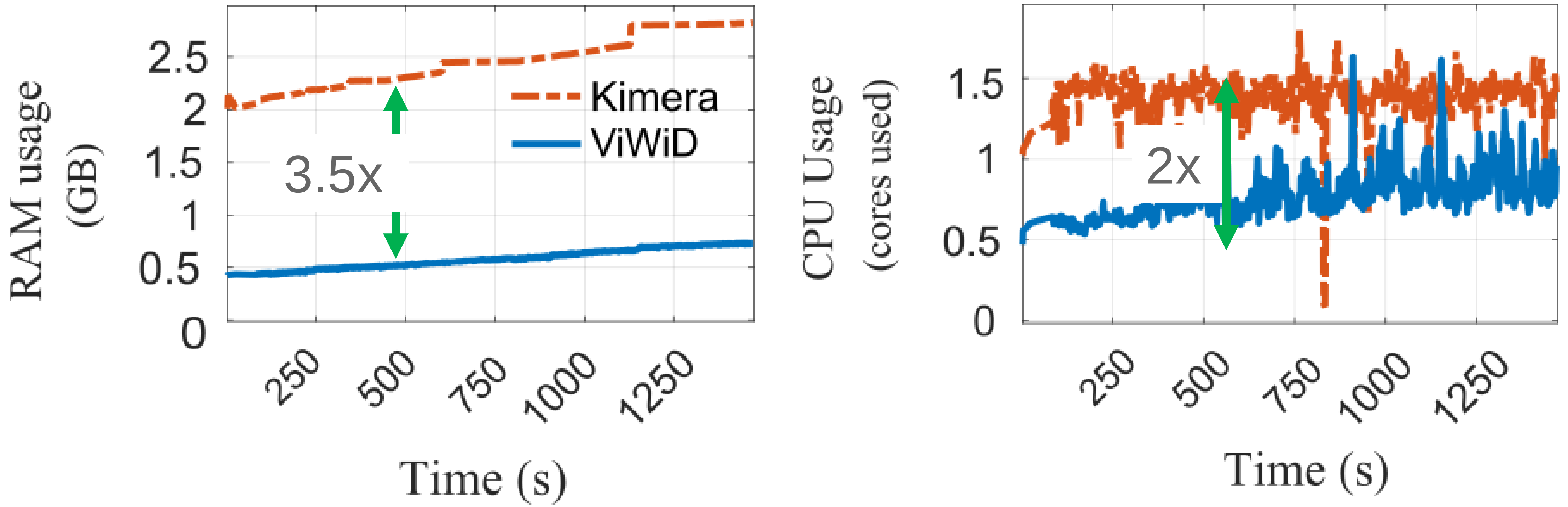


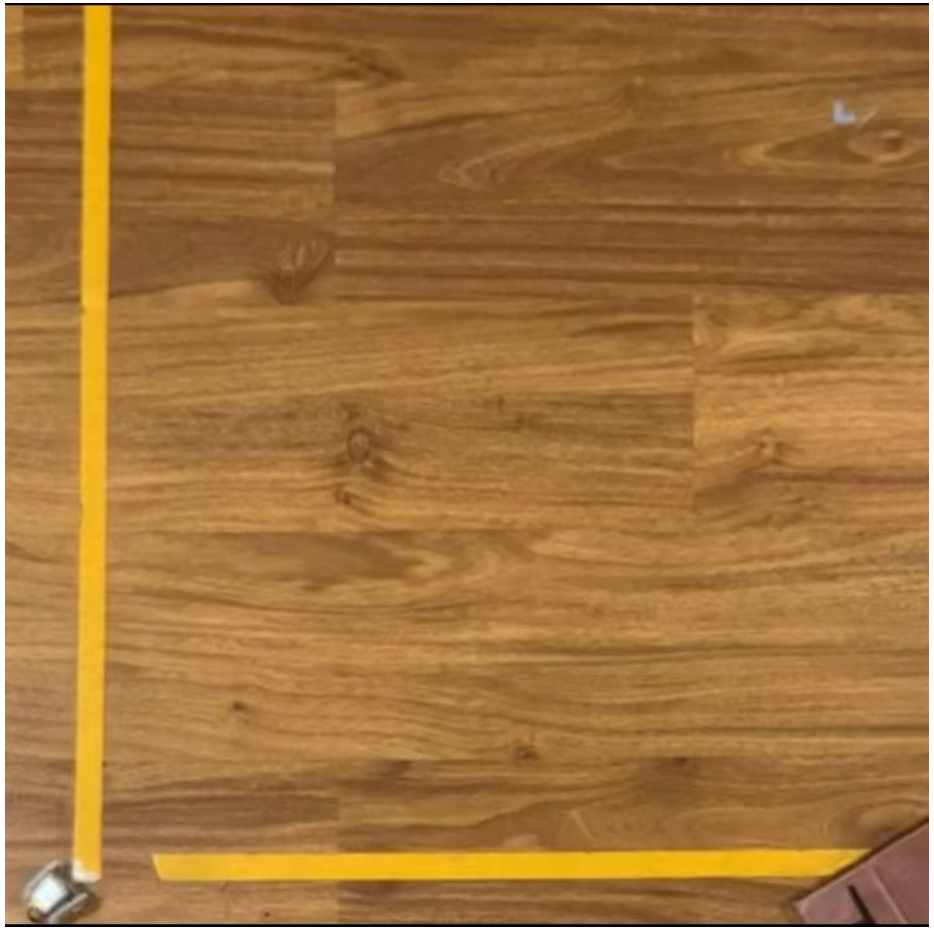


ViWiD – Wi-Fi integrated into Visual SLAM



Wi-Fi makes SLAM efficient

Wi-Fi based Navigation for Tiny Robots



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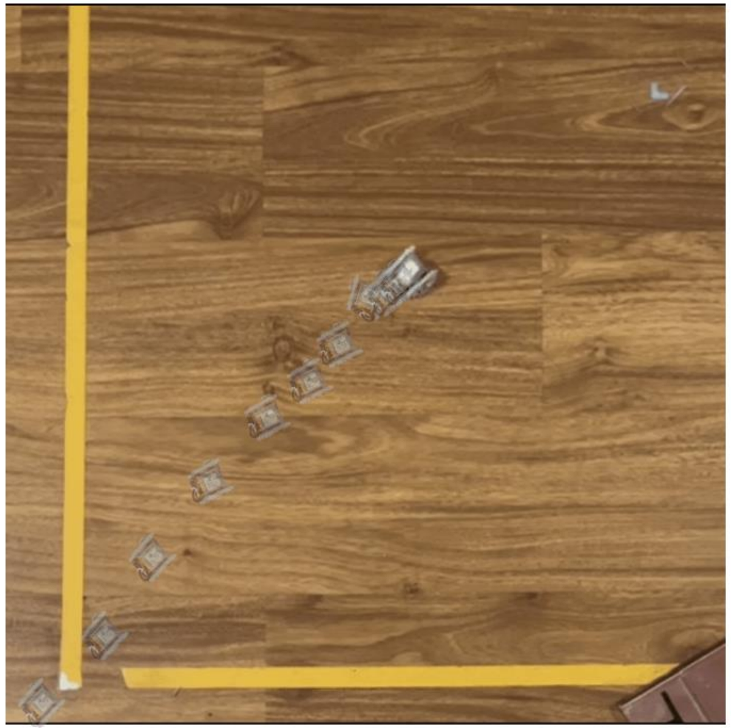
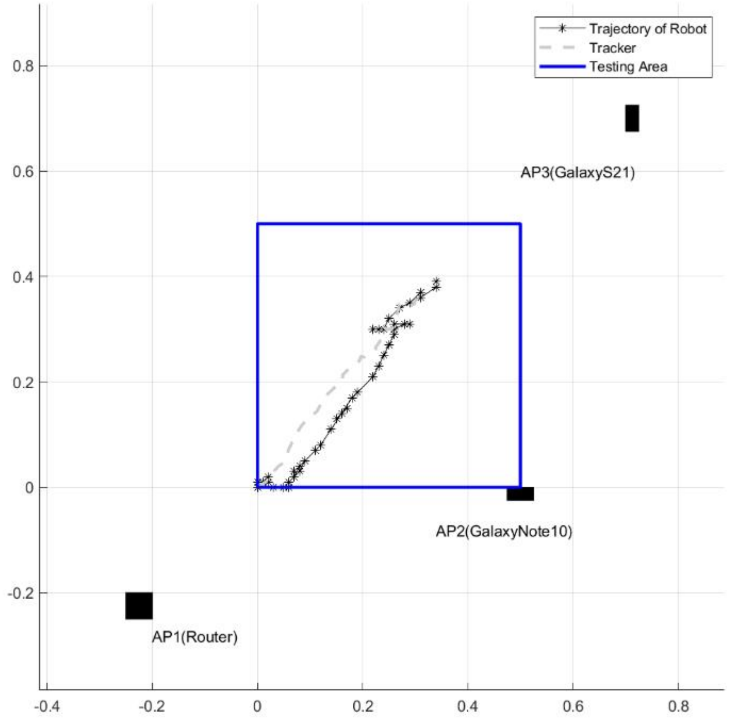
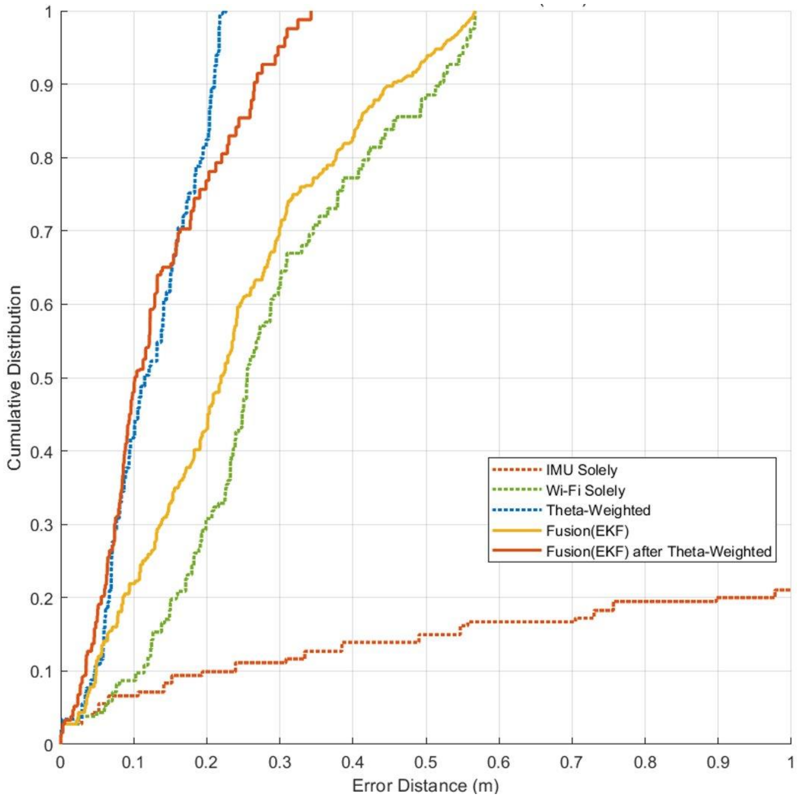


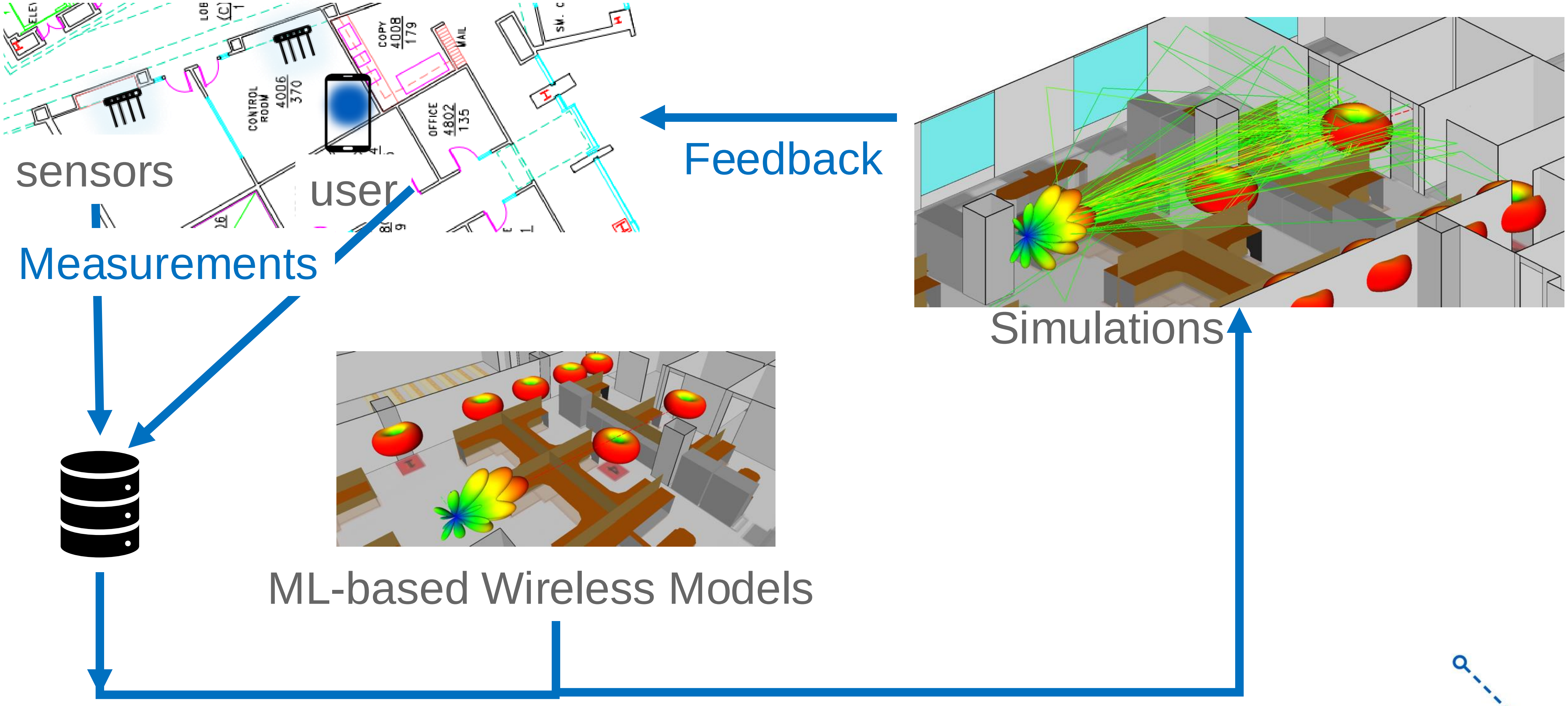
(a) Real Trajectory



(b) Localization result



Physics based ML Simulators for Wireless Sensors



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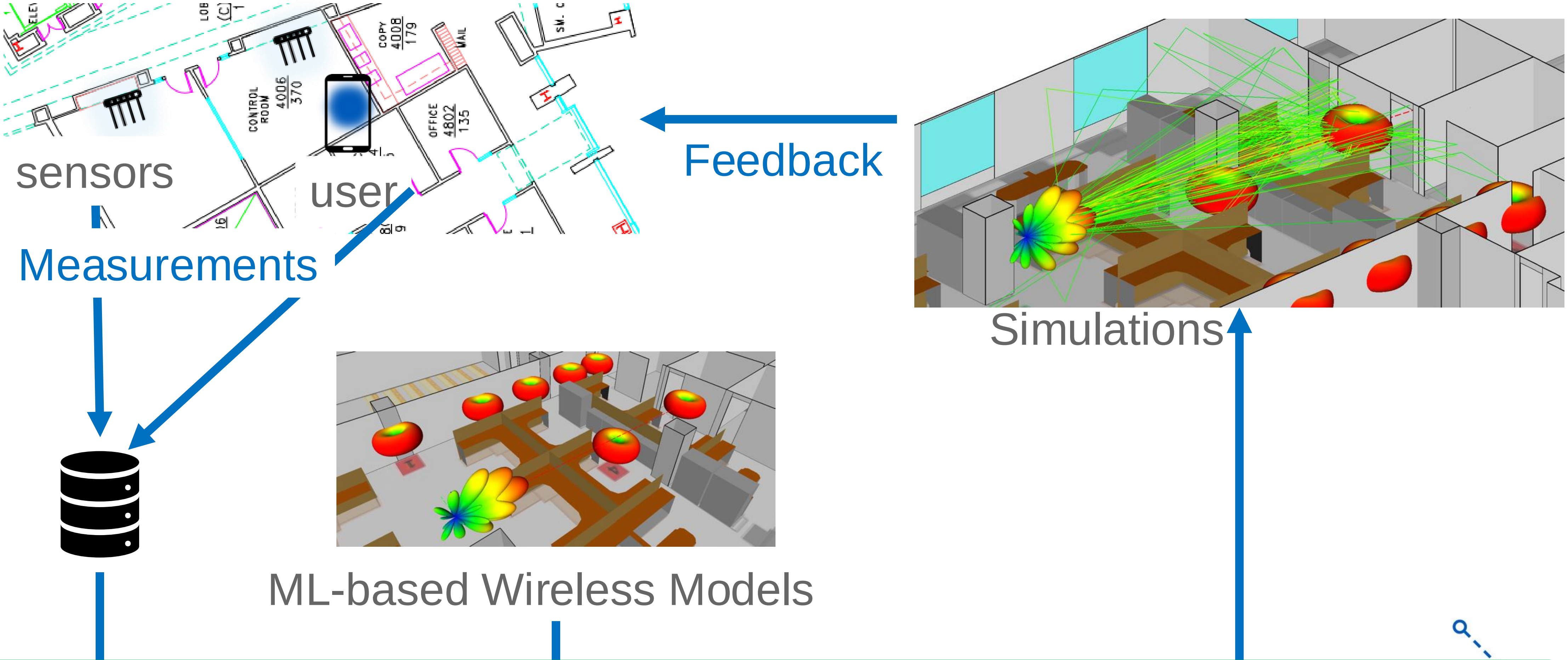


Needs real-time map updates and Environment Updates

Real-time and Autonomous Map updates for Dynamic Environments

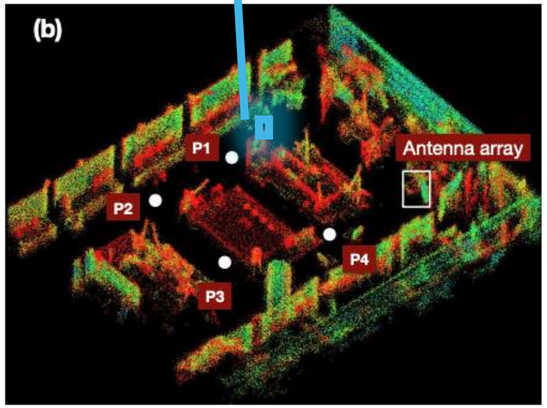
Dynamic environments like a vast construction sites need updated maps in real-time.

How can we *automate* these in *real-time* mapping updates using everyday Wi-Fi signals?

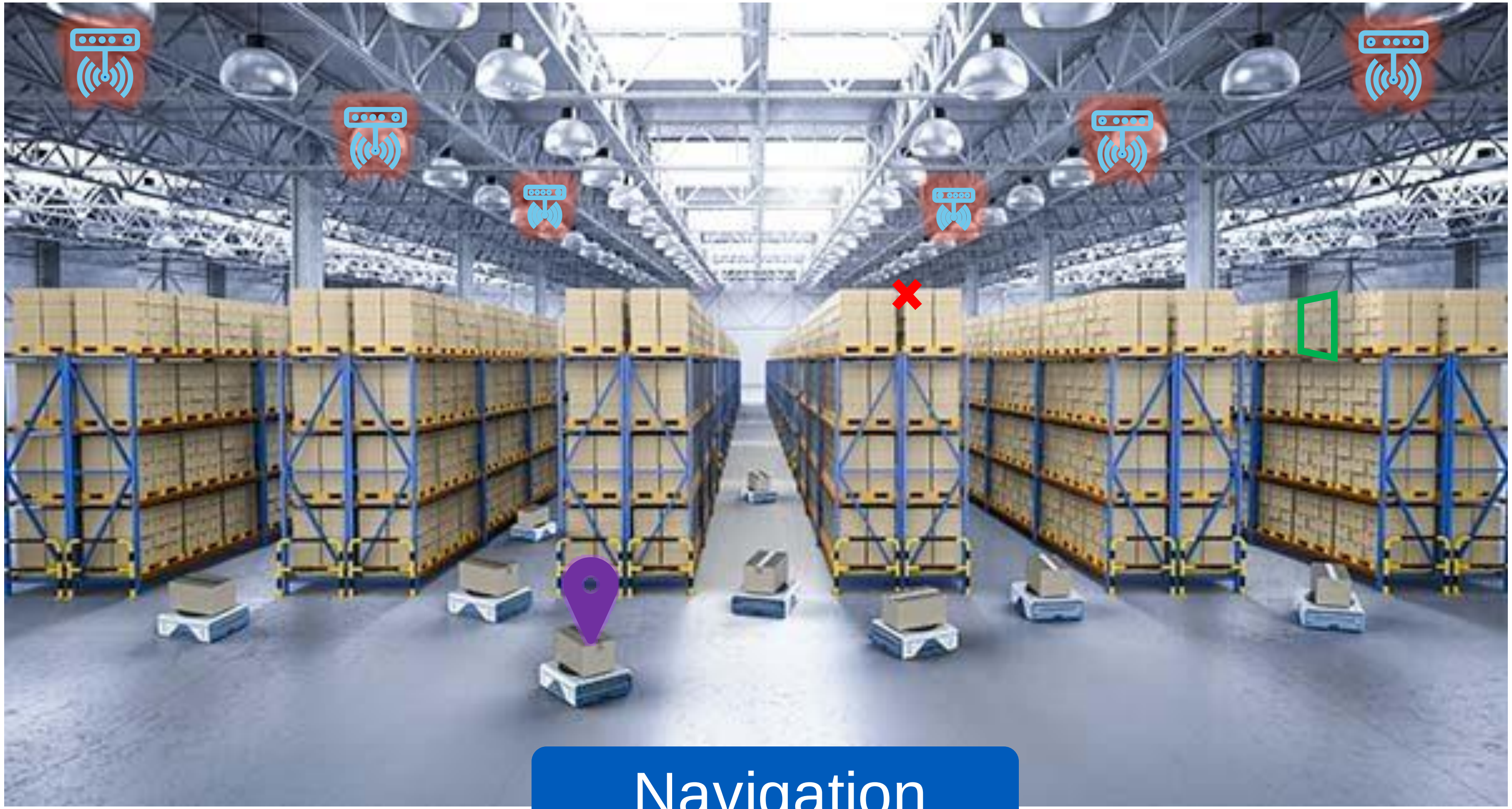
Using mmWave Radars for Perception

RGB/CMY: color
D: depth

ε_r: relative permittivity
Γ_r: reflection co-efficient



RF-Sensing for Localization and Navigation



Navigation

Accurate and Reliable Location Deterrents

Navigation

Multipath and Non Line of Sight

Two Decades of RF based localization

MonoLoco MobiSys'18

Chronos NSDI'16

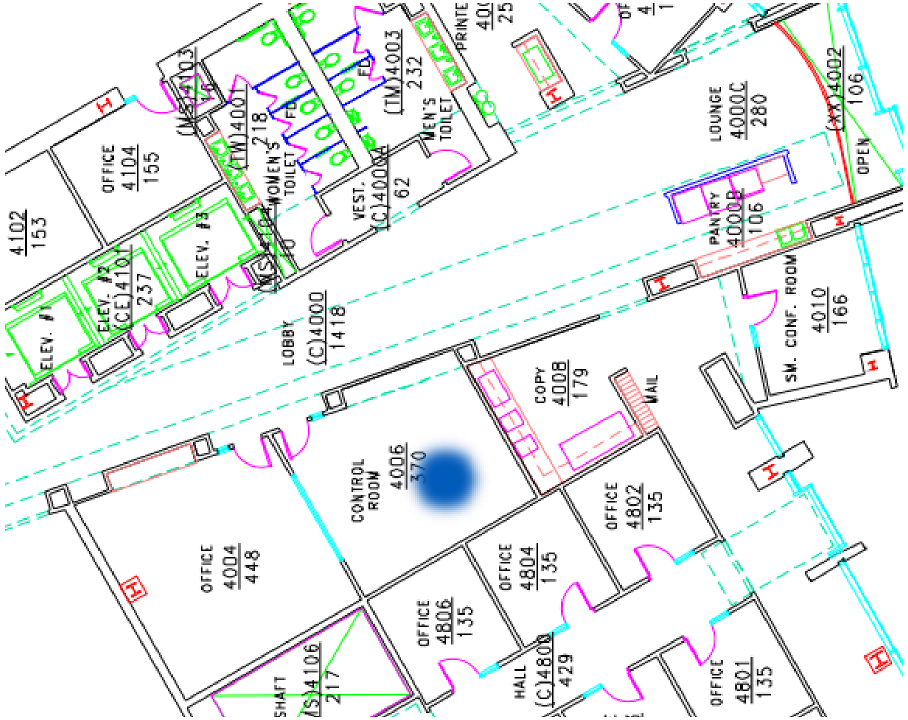
ToneTrack Mobicom'15

SpotFi Sigcomm'15

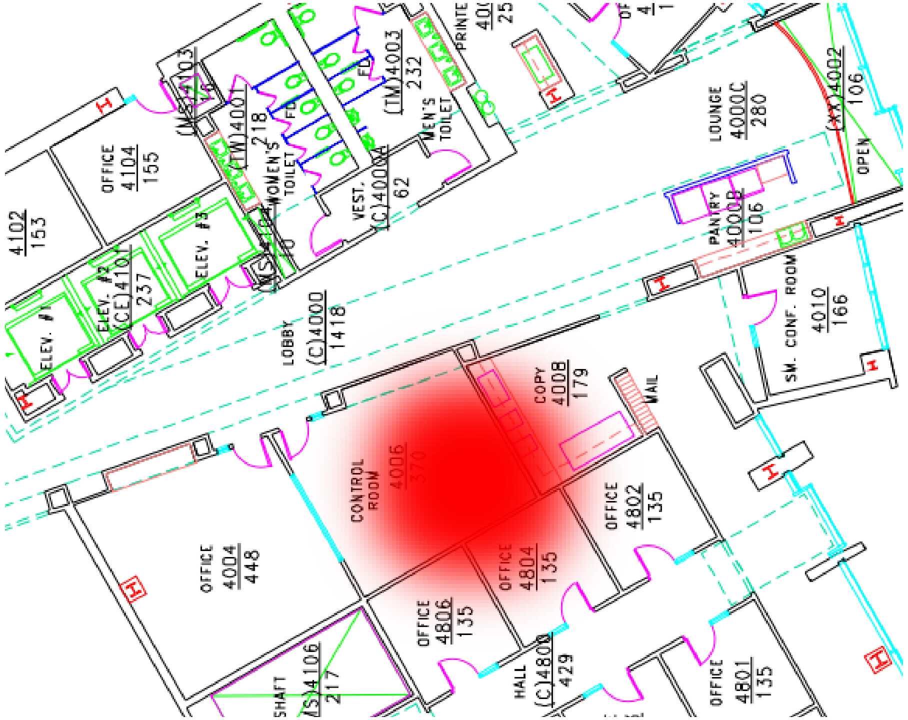
ArrayTrack NSDI'13

EZ Mobicom'10

RADAR Infocom'00

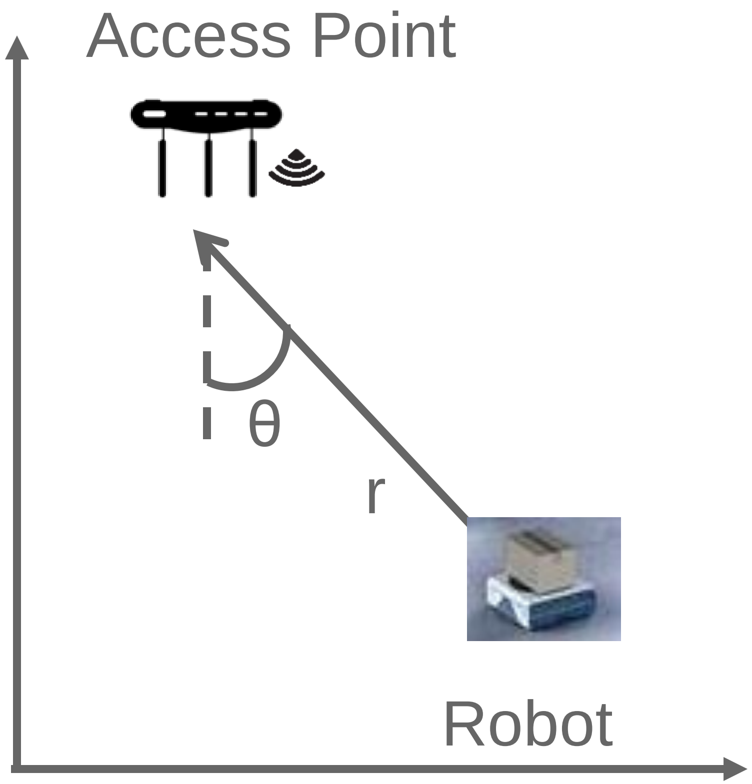


Median: few decimeters

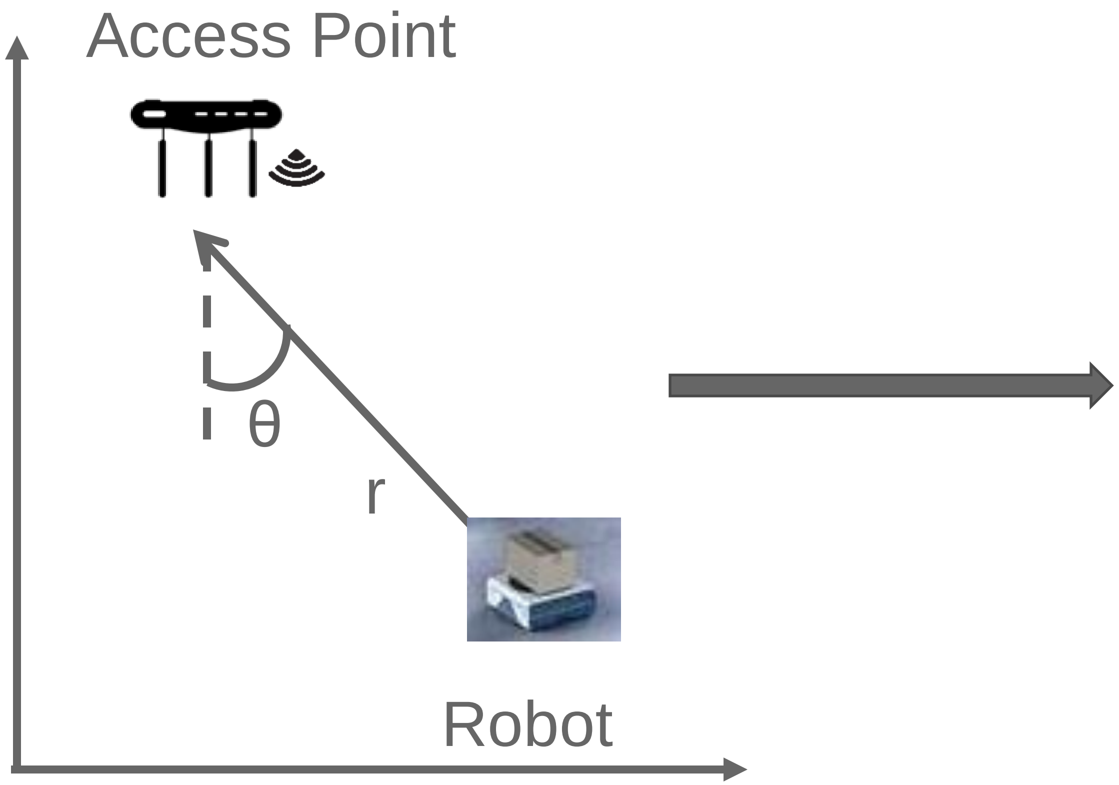


>10% of cases: few meters

Input Representation: AoA-ToF images



Input Representation: AoA-ToF images



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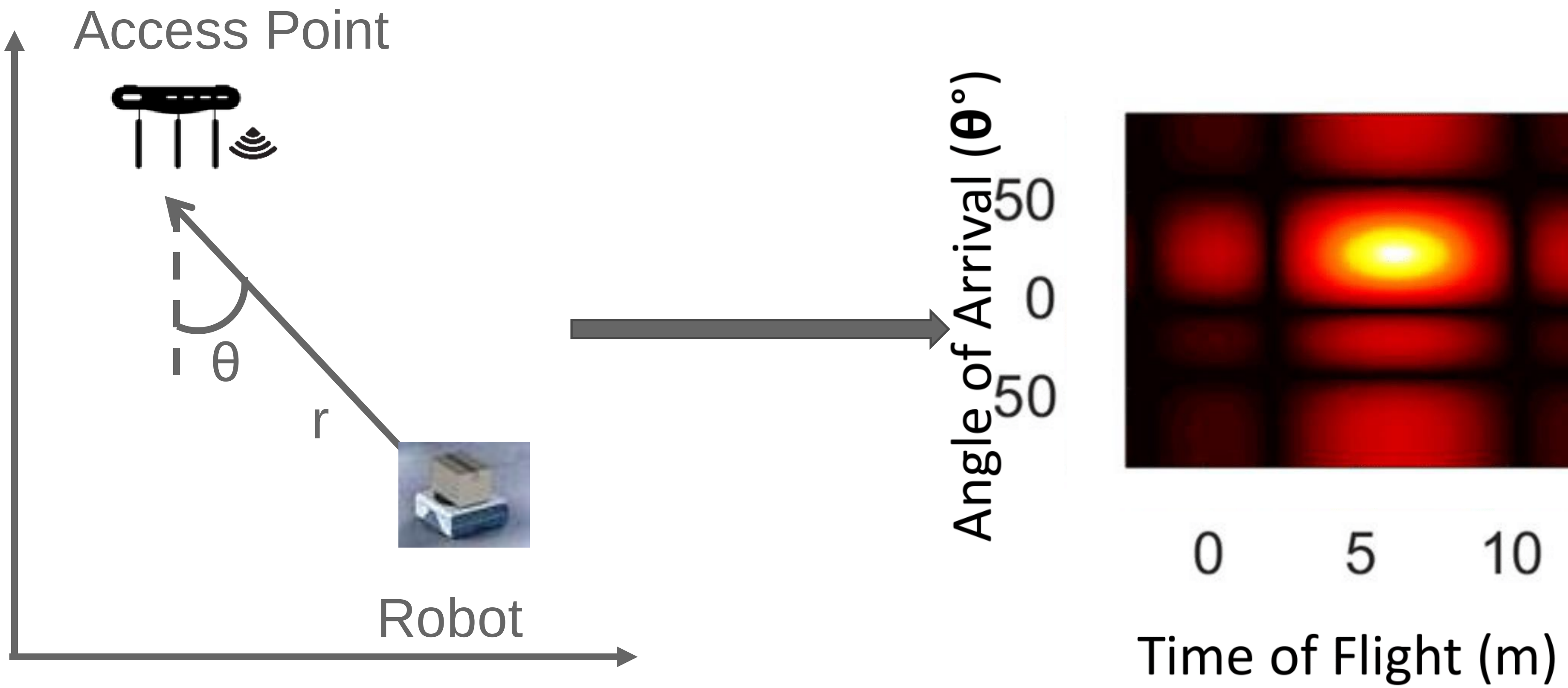

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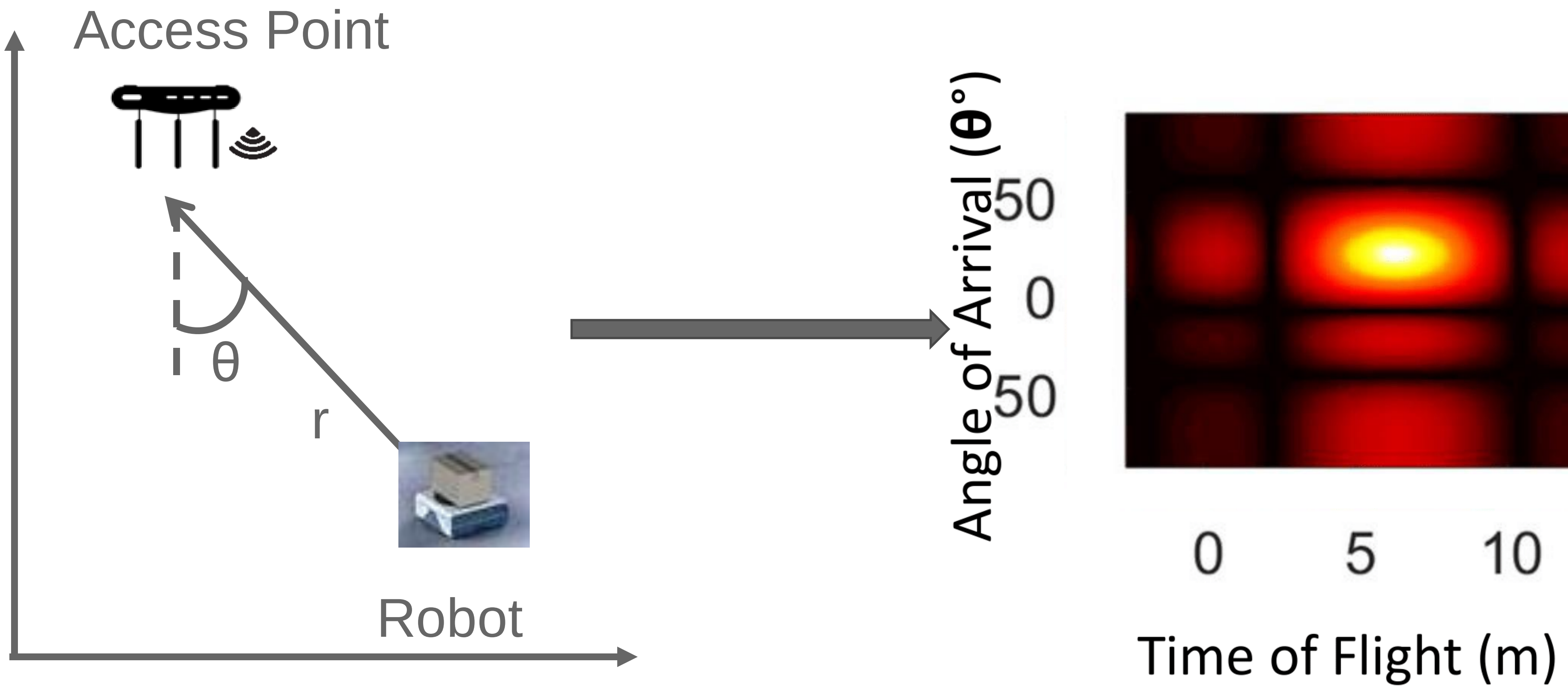

Does not have context of Space and AP locations

Input Representation: XY images

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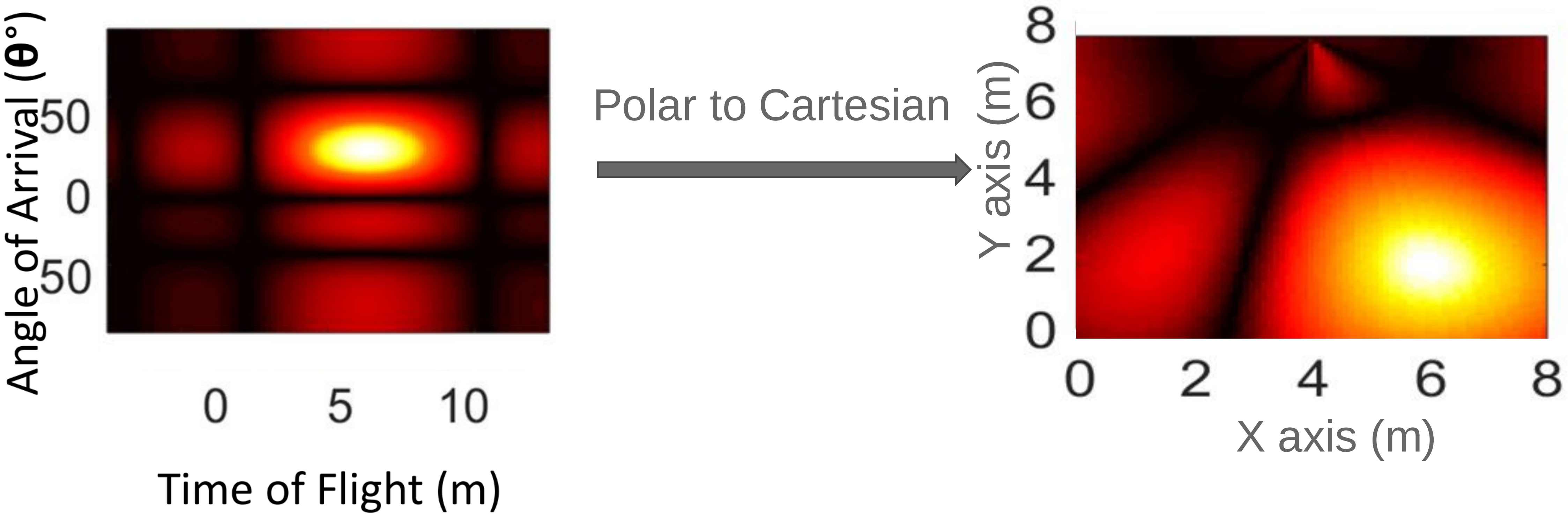

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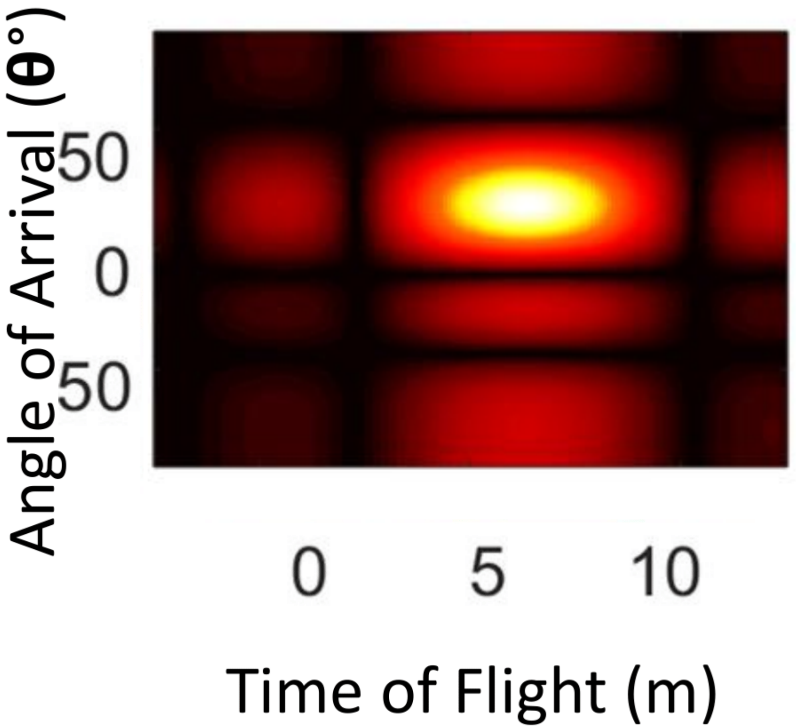
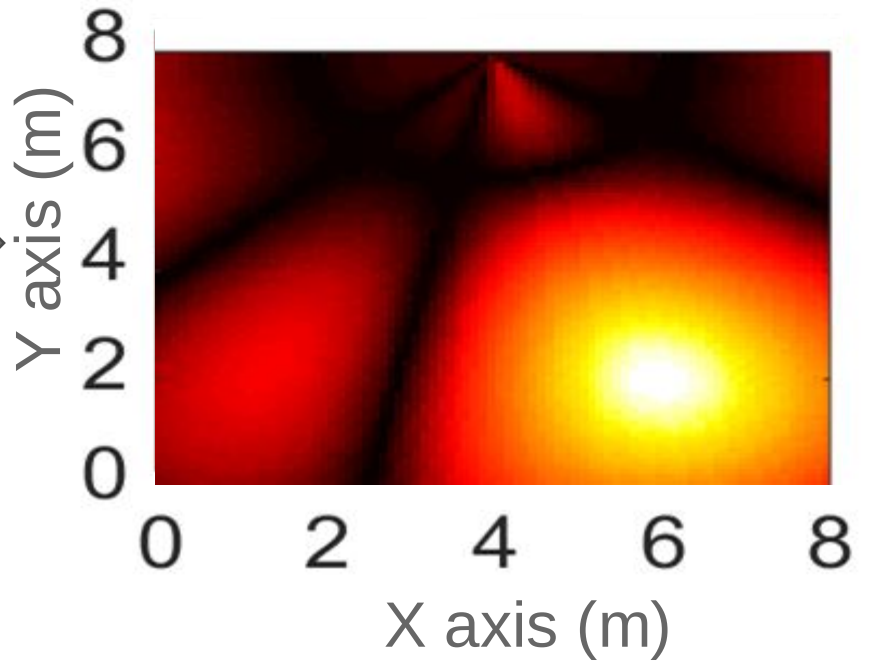


Polar to Cartesian



Context embedded Input Representation

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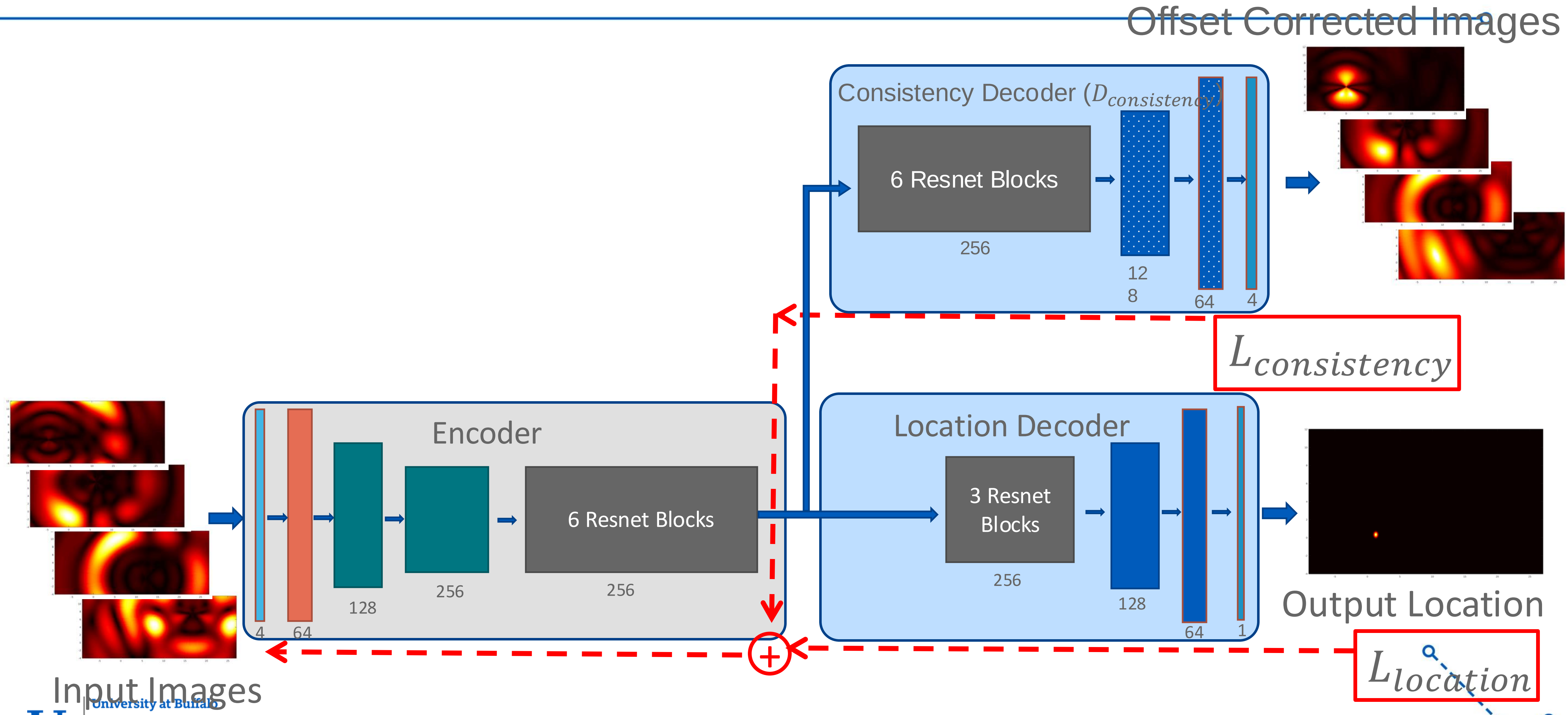
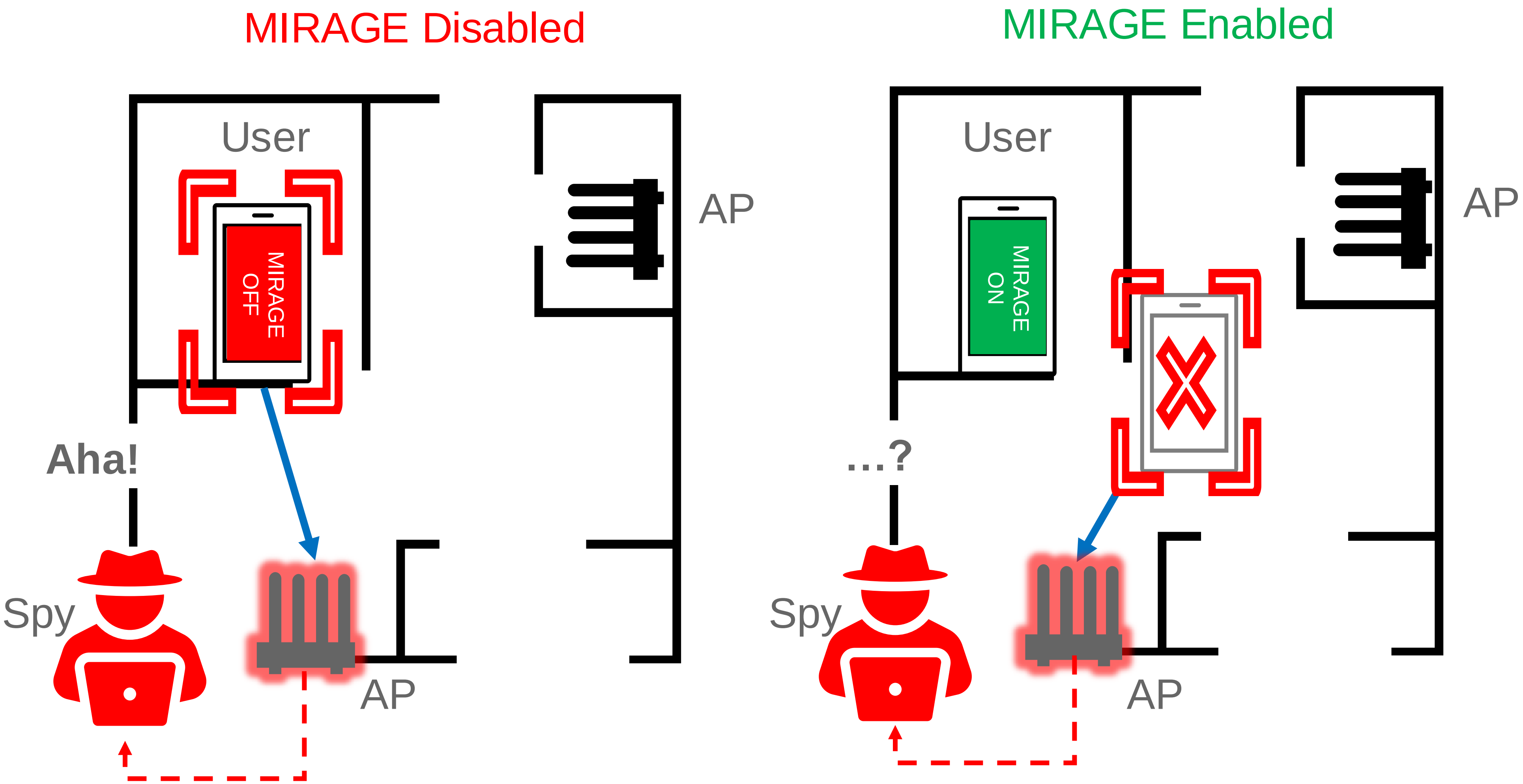
DLoc: Network Architecture



Data Collection: MapFind

MIRAGE – Enabling Location Privacy



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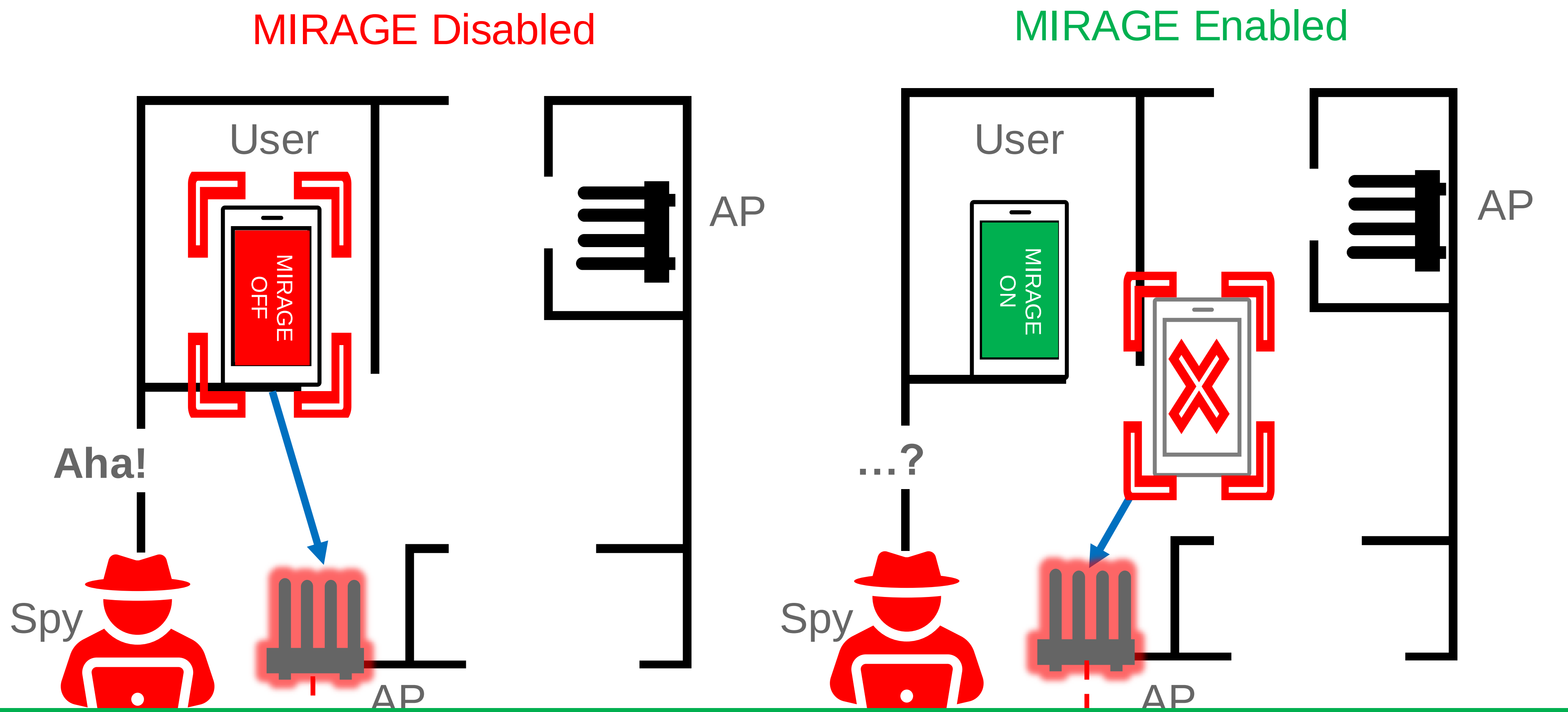
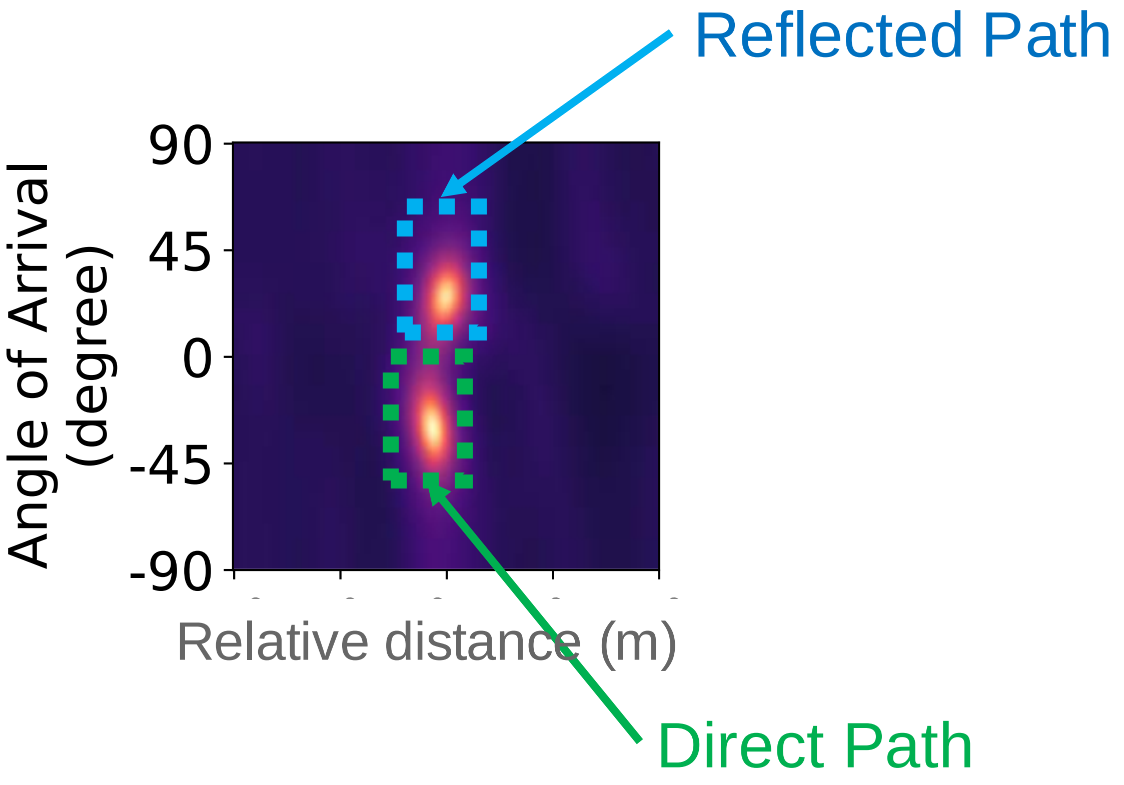
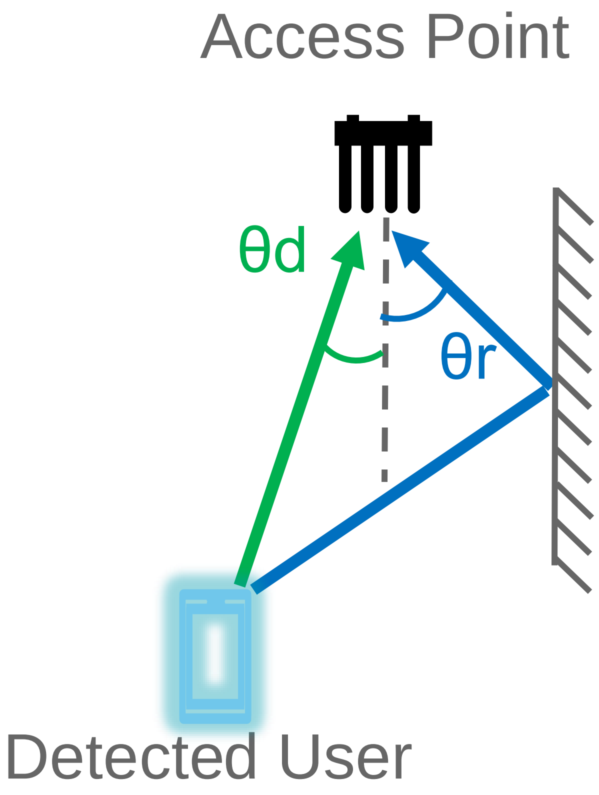


Direct Path – No more least travelled path

Direct Path – Least Traveled Path





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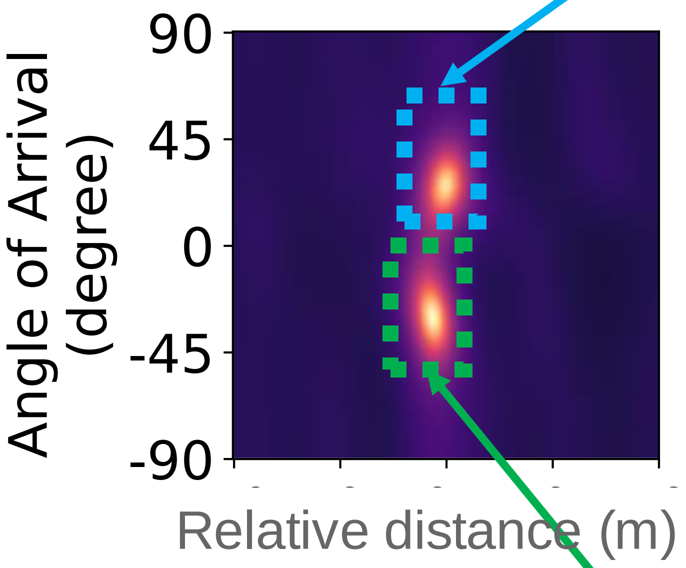
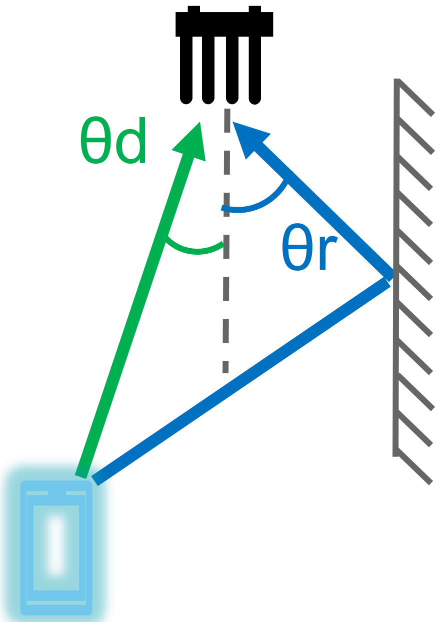
Direct Path – Least Traveled Path

Reflected Path



Direct Path

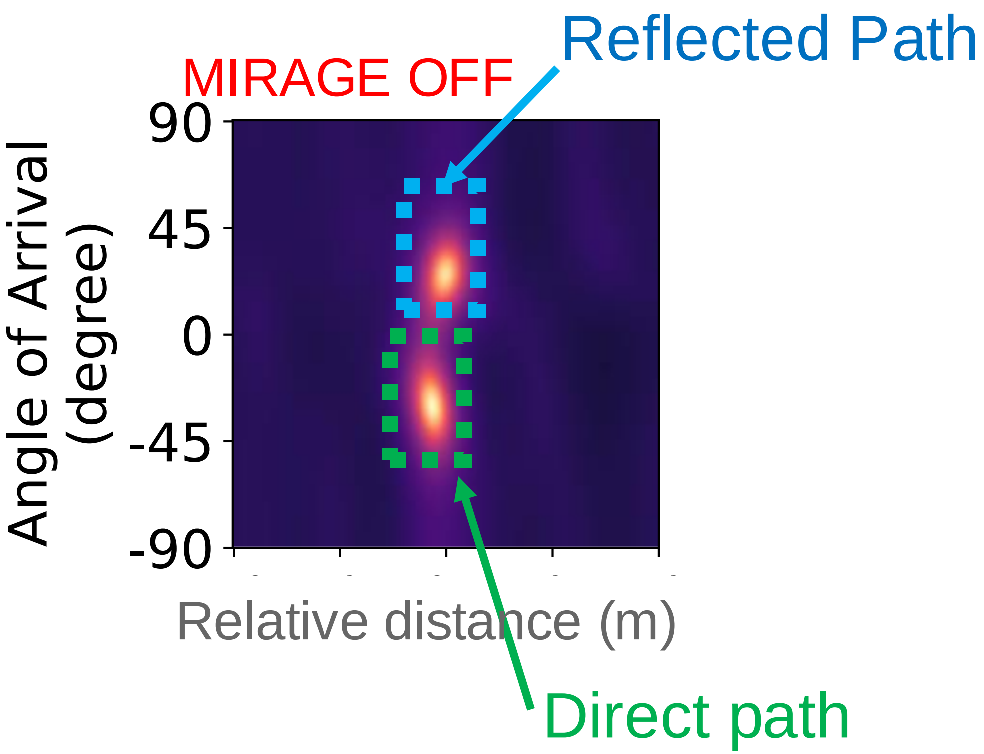
Access Point

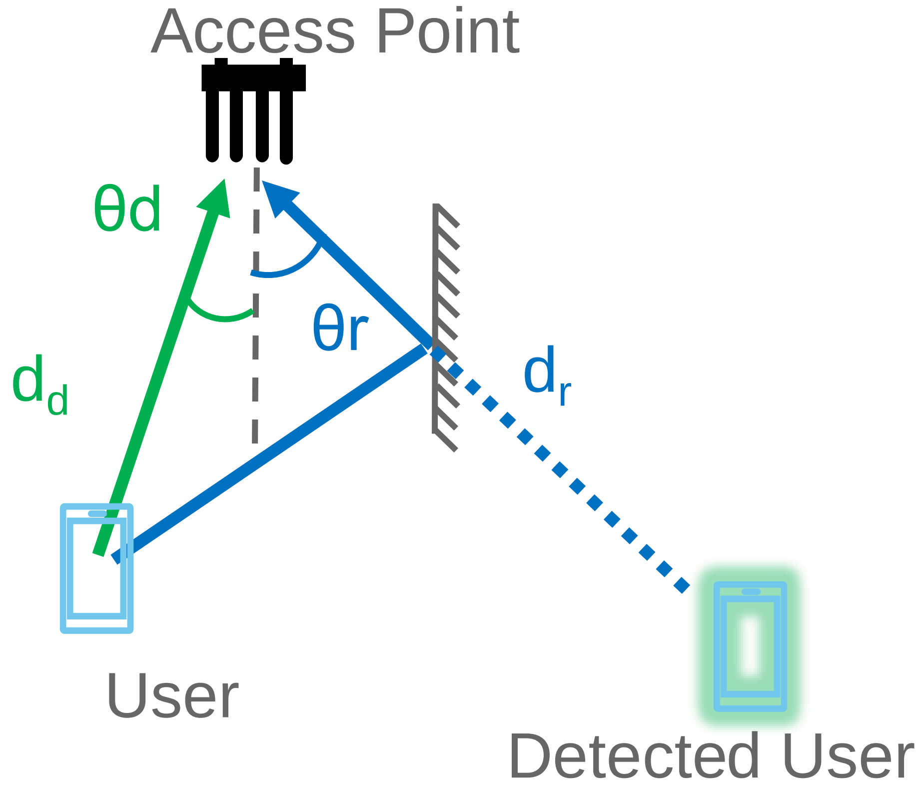


Detected User

How can we ensure Attacker does not know Direct Path?

Obfuscate the Direct Path





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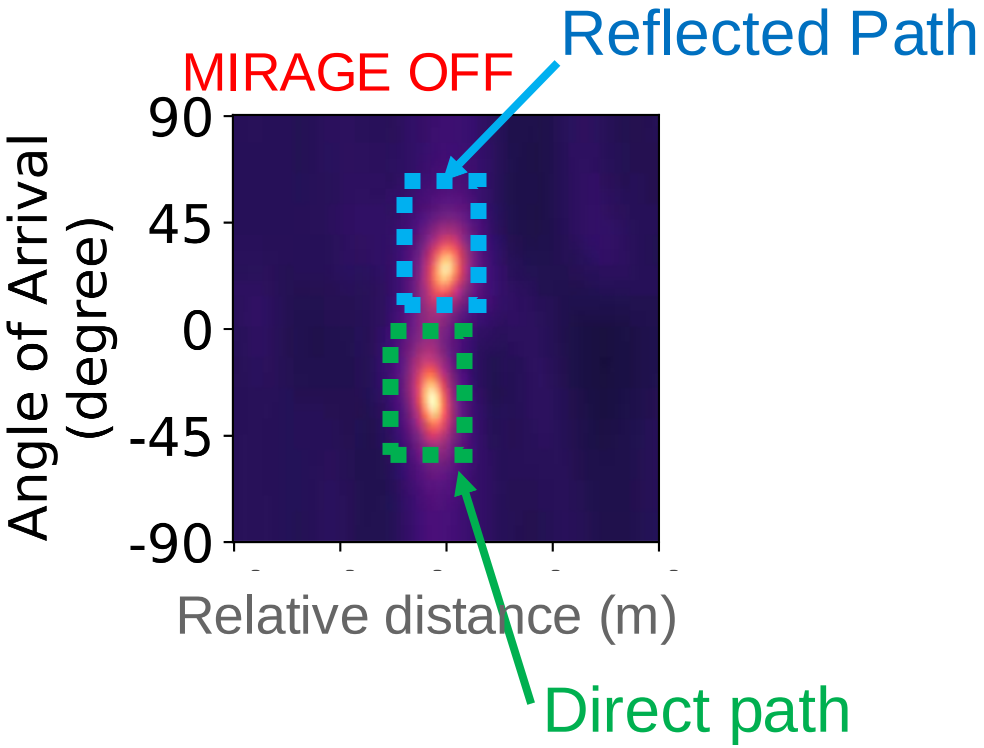
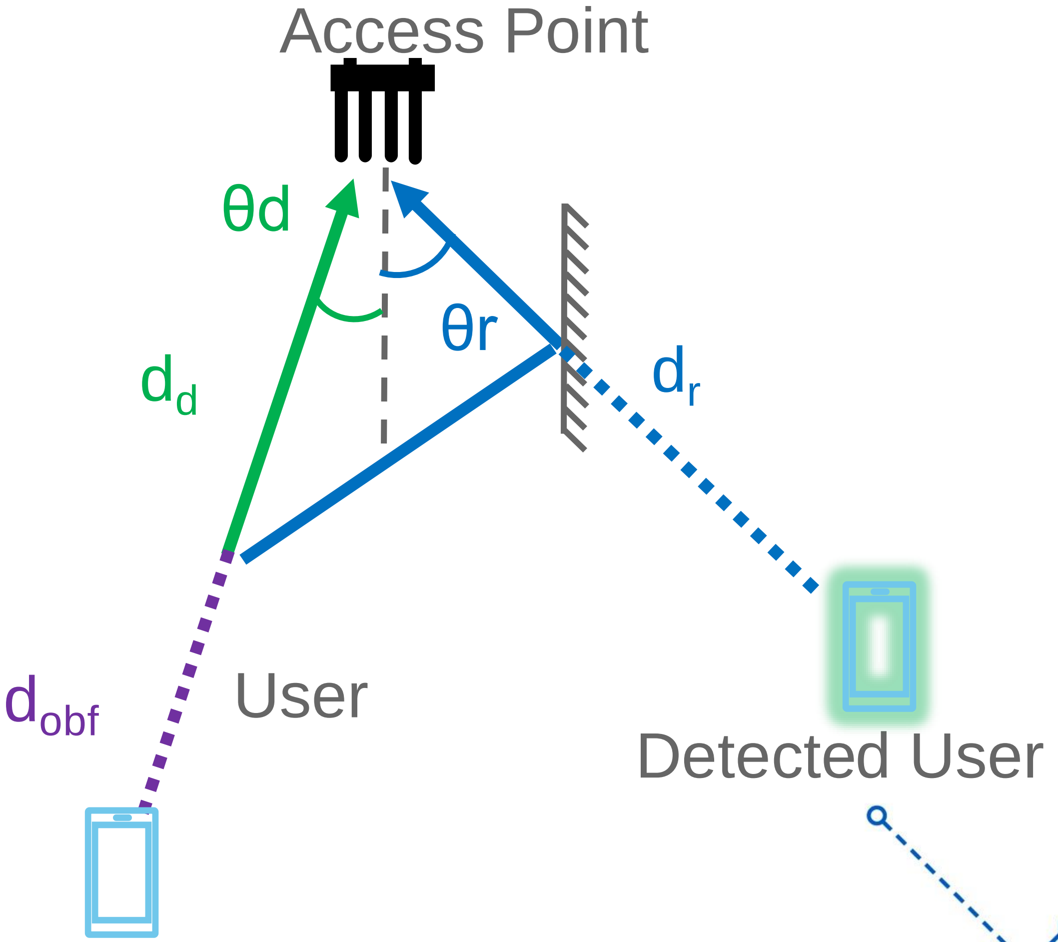
Obfuscate the Direct Path





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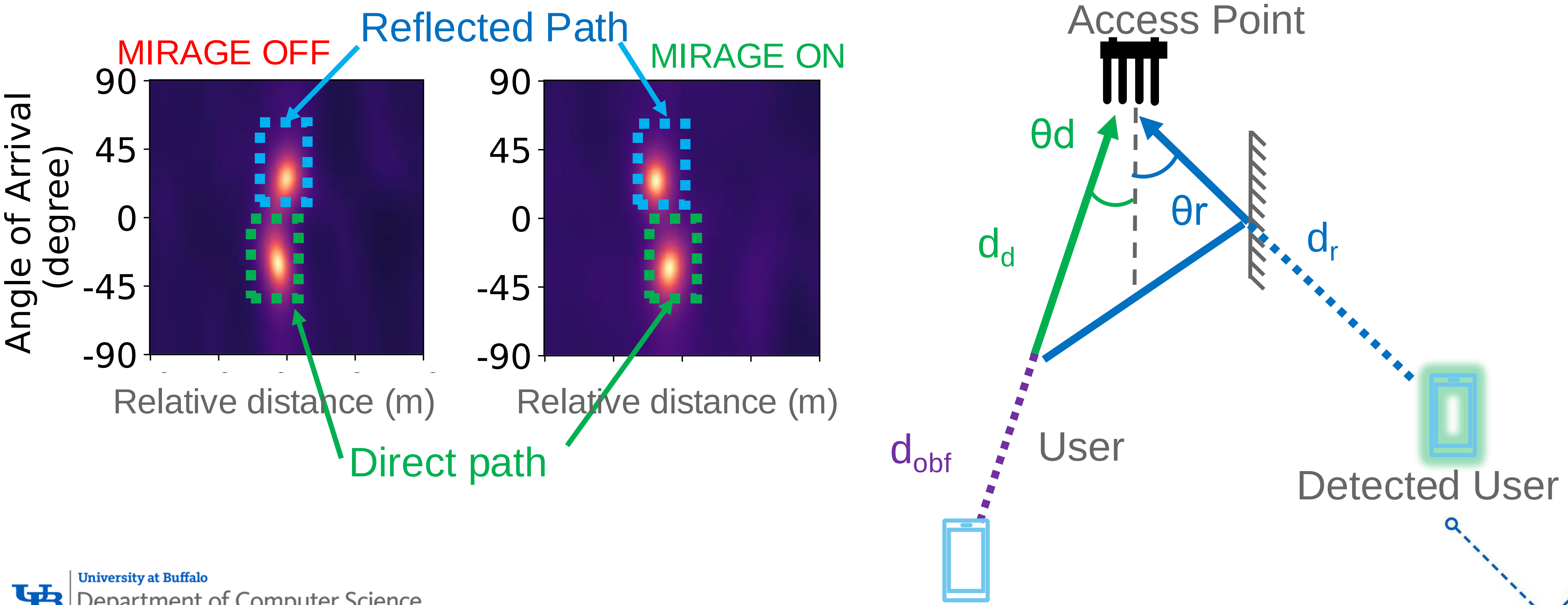

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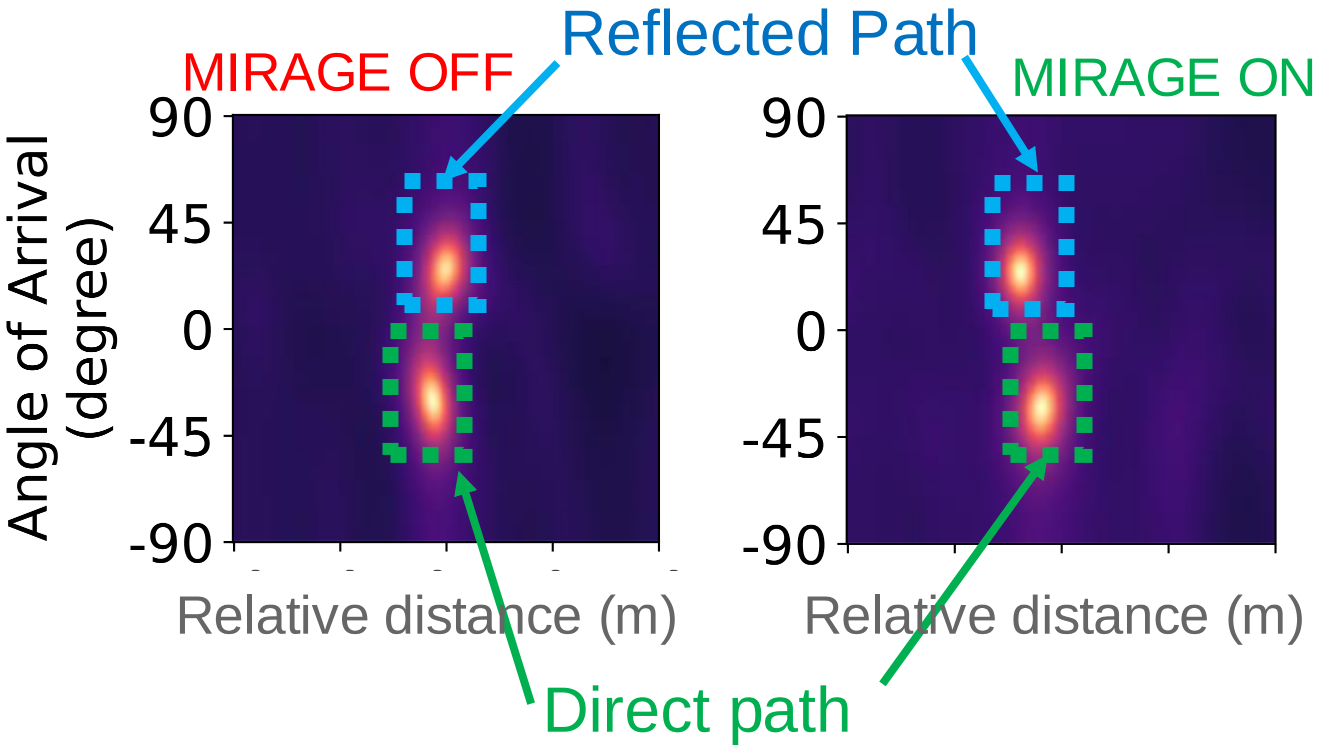
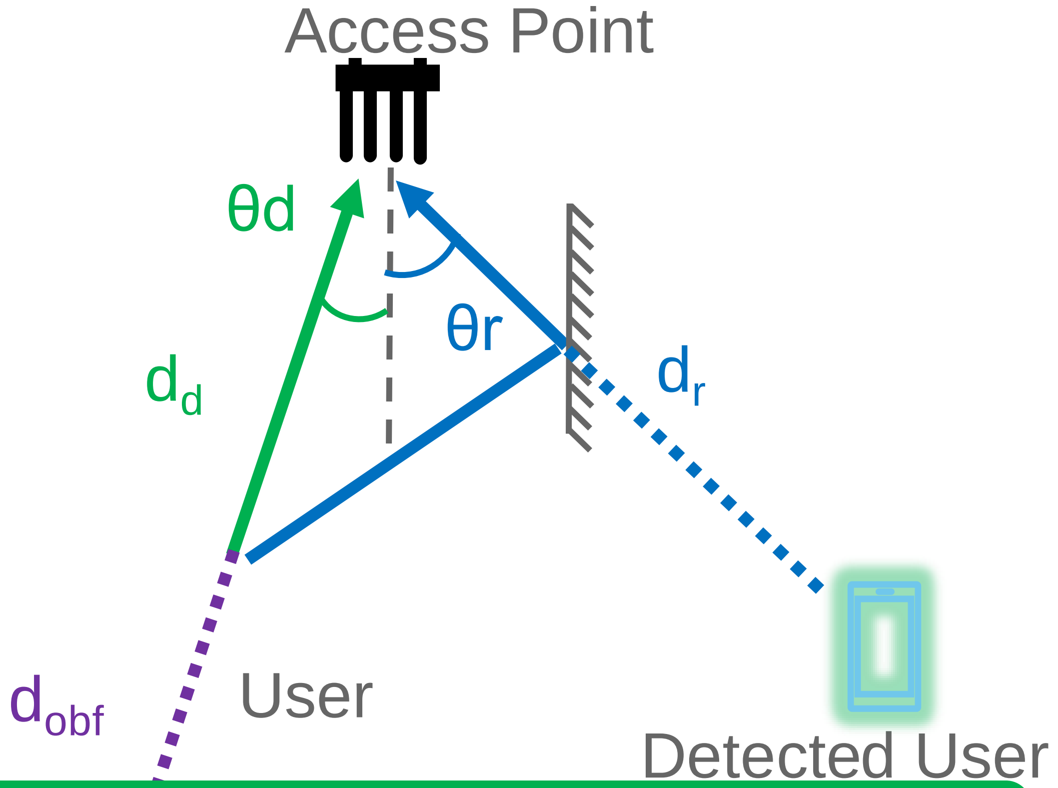
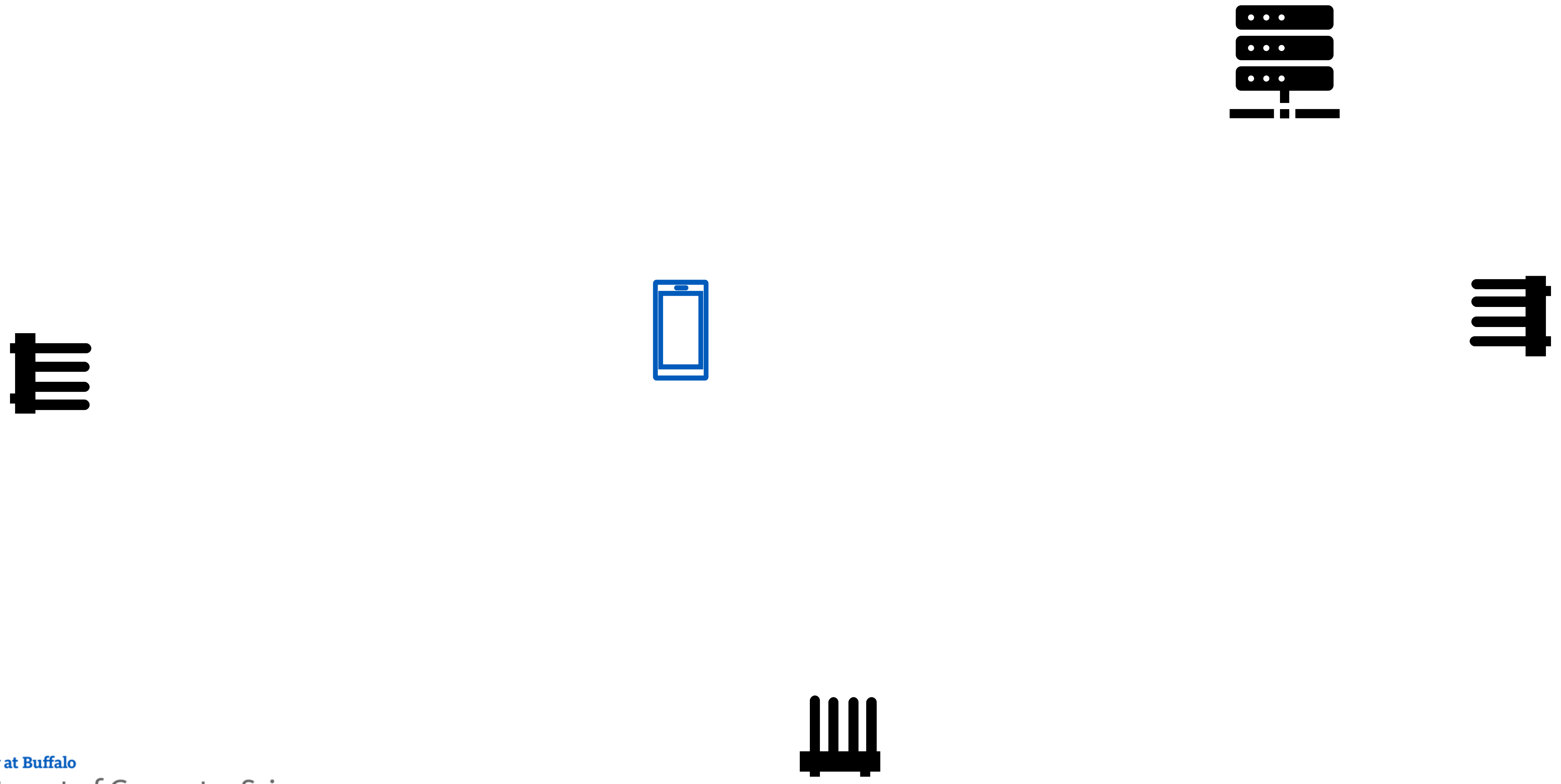
Obfuscate the Direct Path



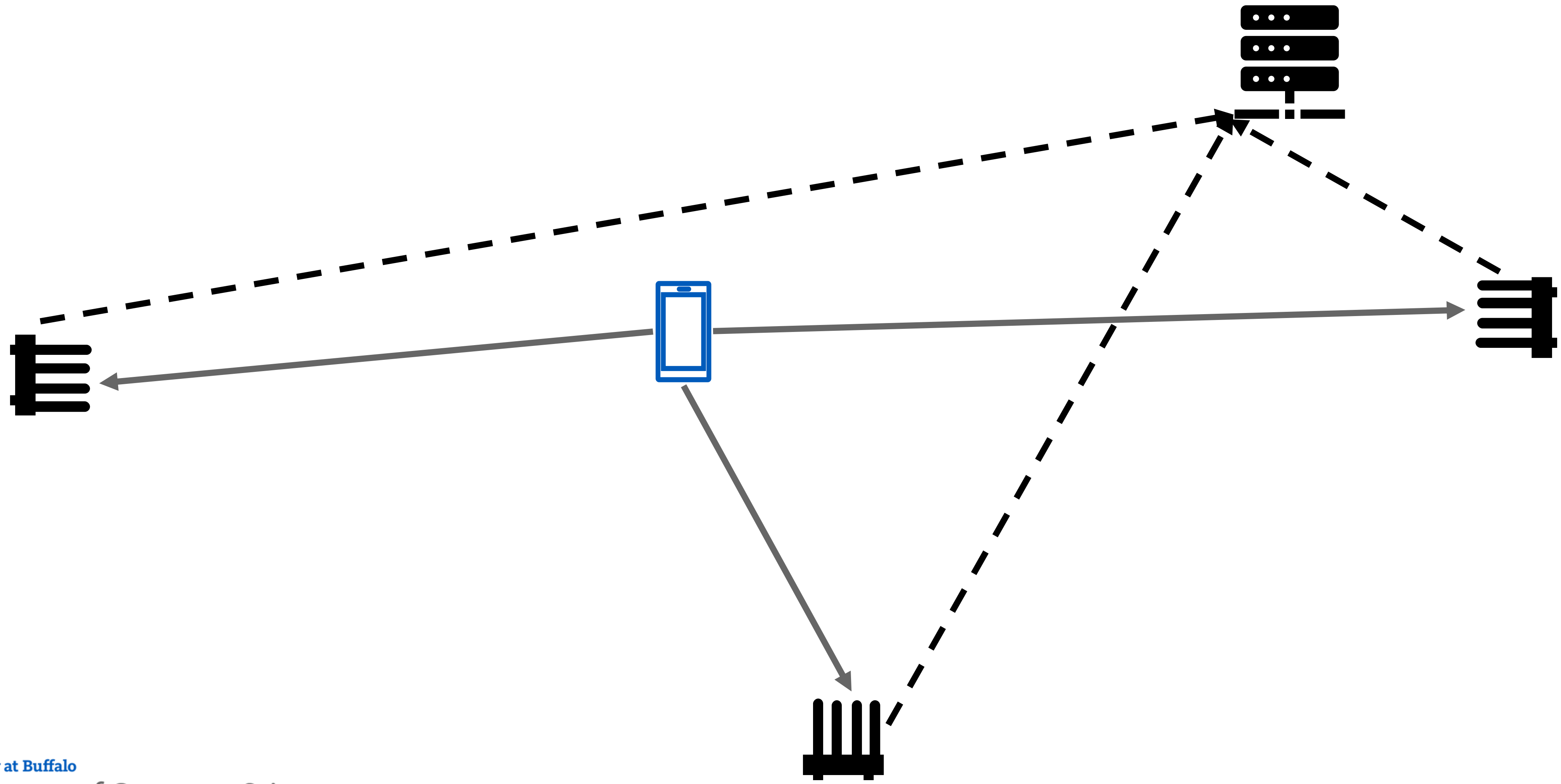


Direct Path – No more least travelled path

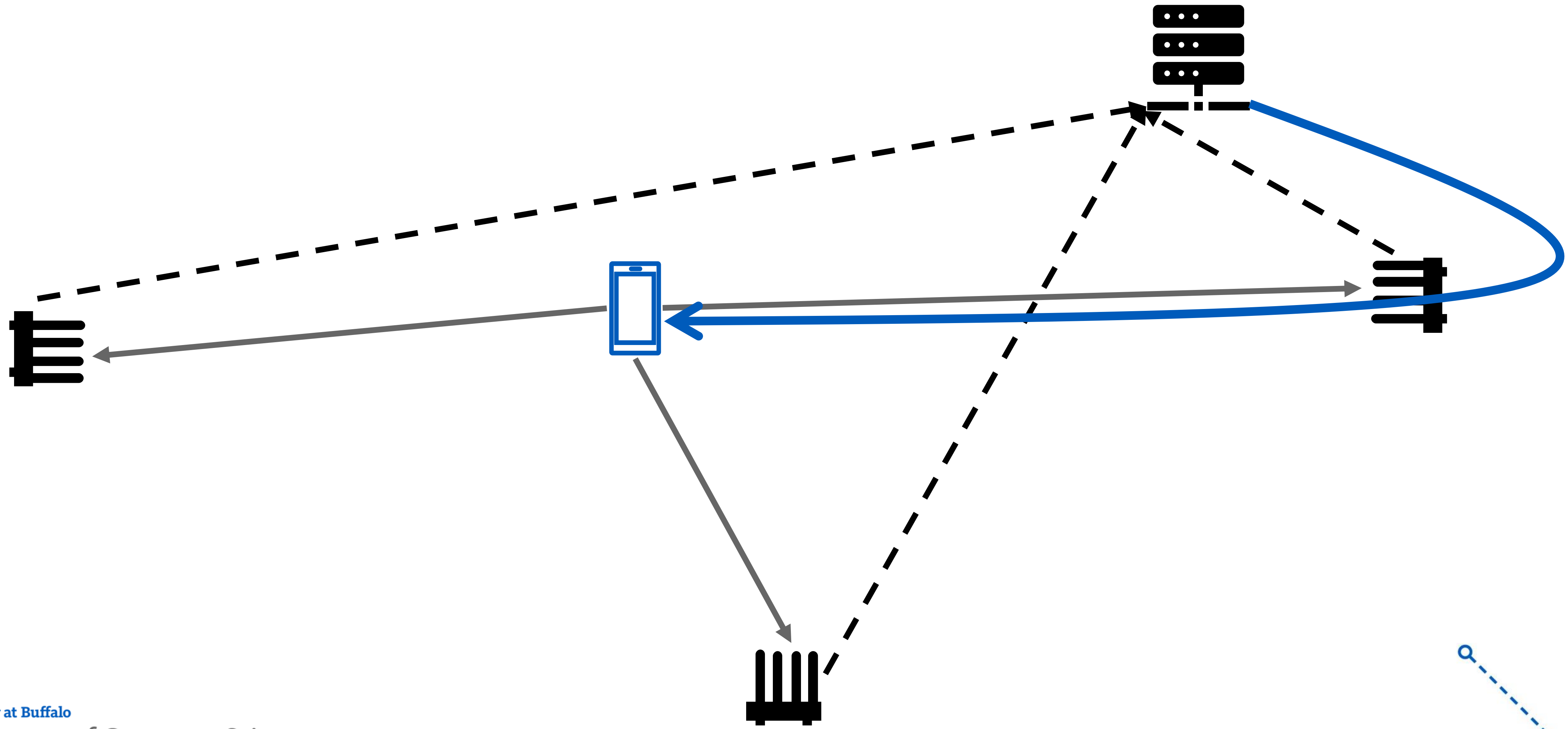
Deployable Localization and Navigation



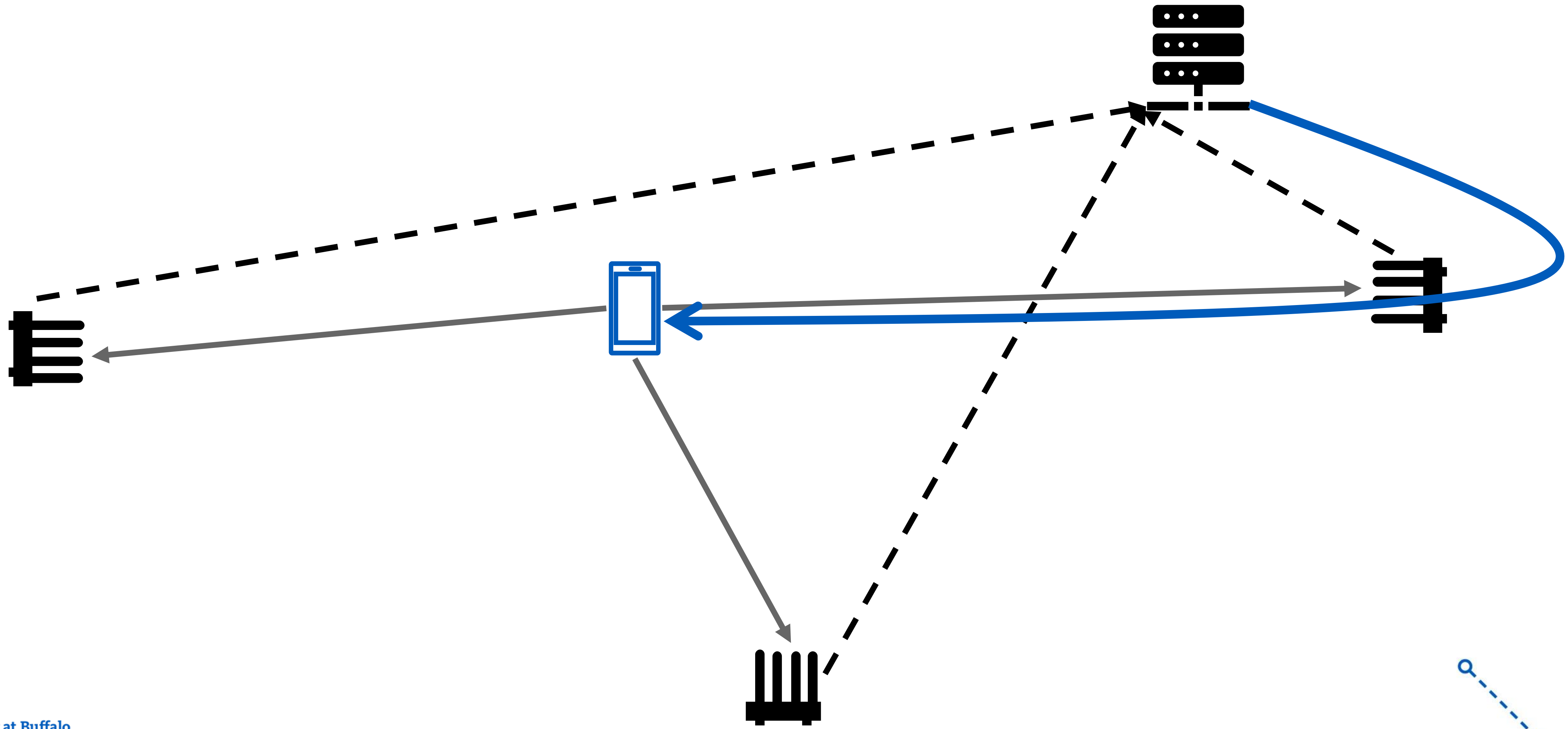
Deployable Localization and Navigation



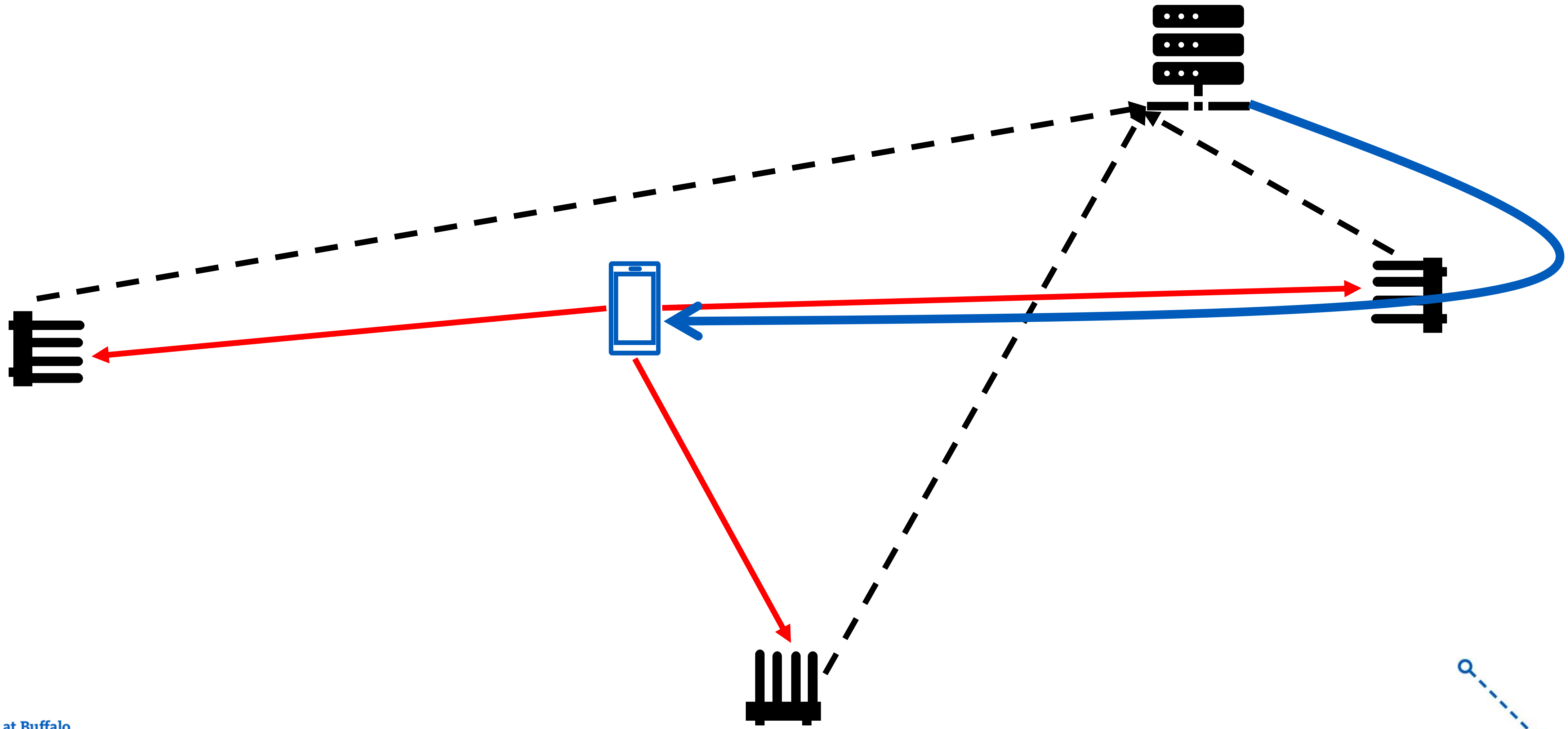
Deployable Localization and Navigation



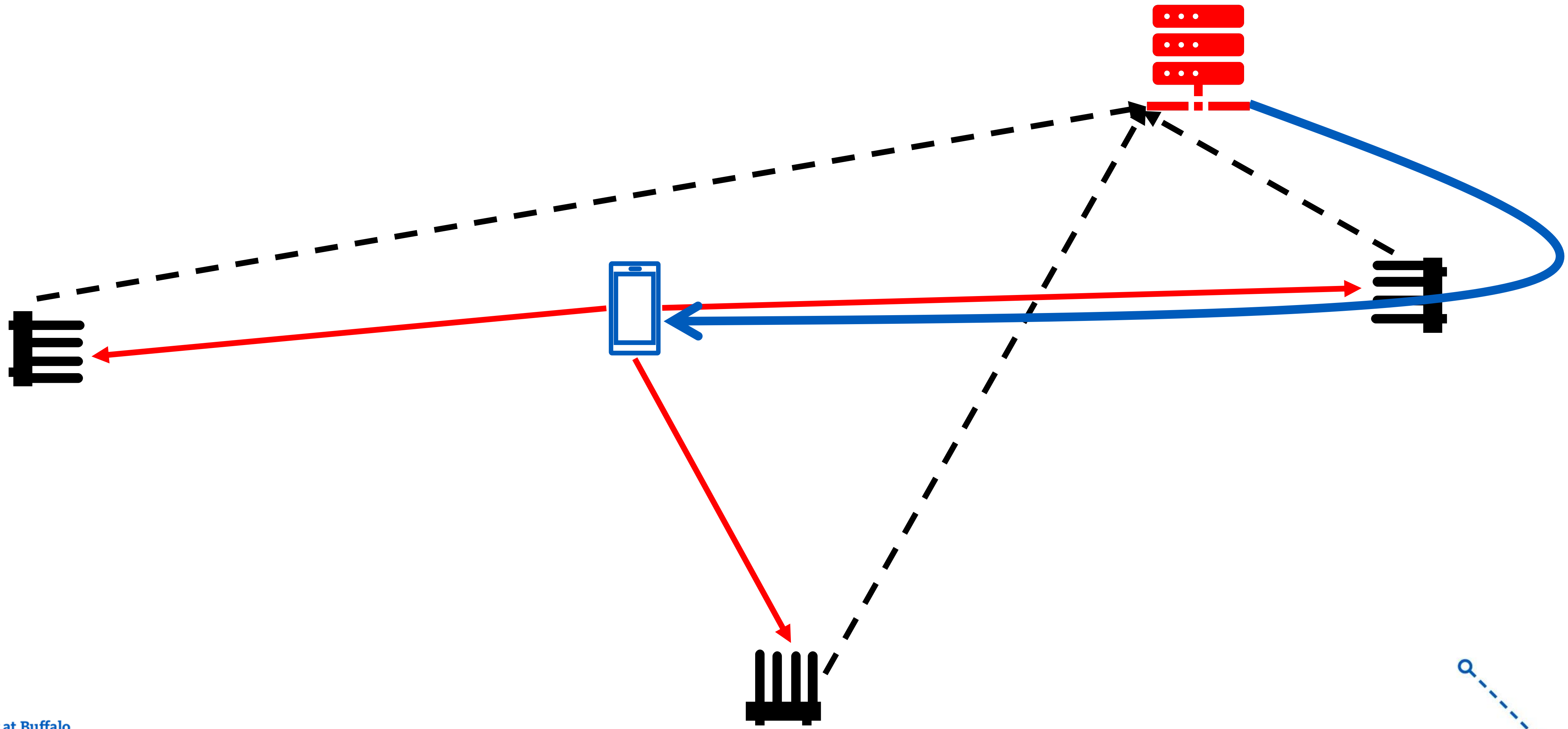
Privacy of User's Location



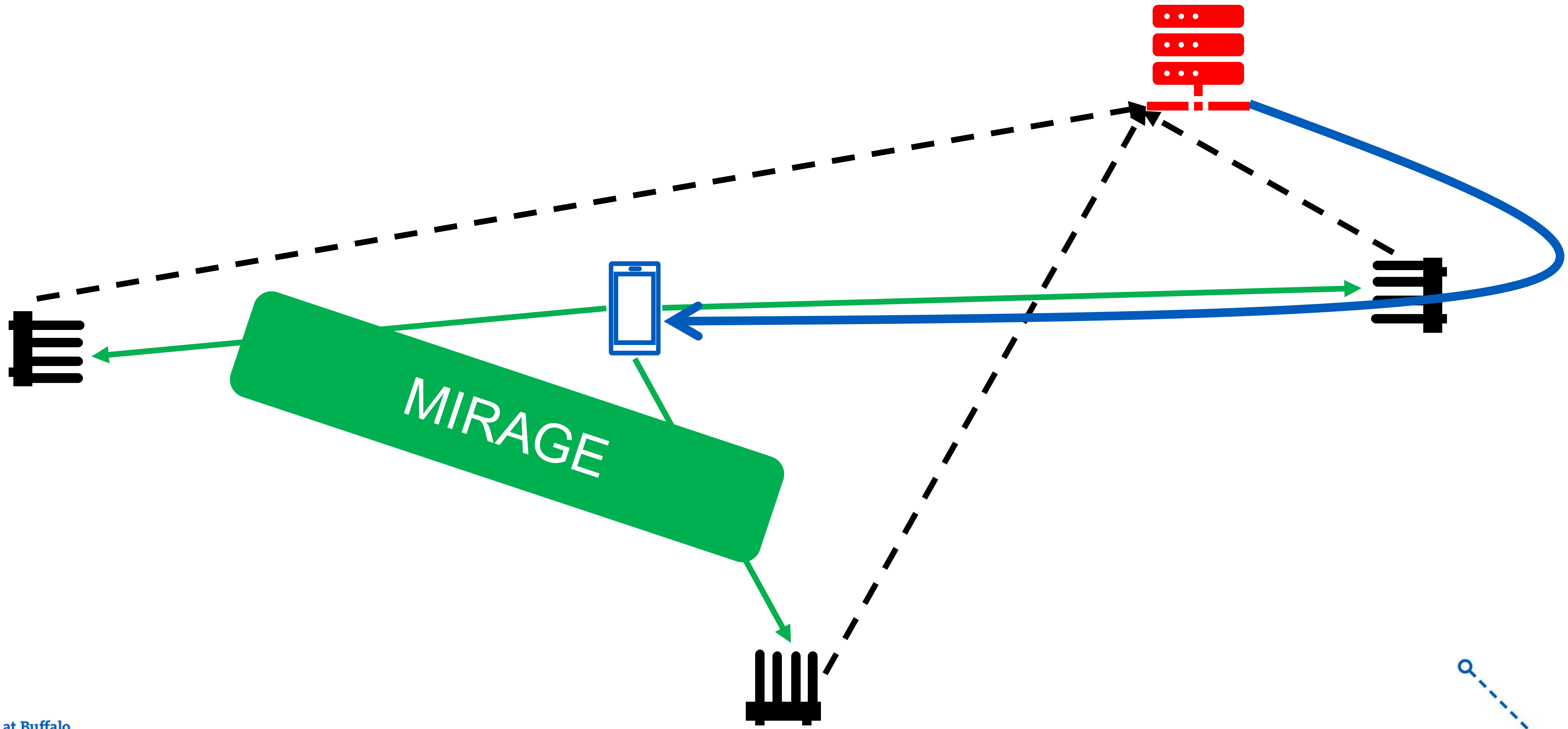
Privacy of User's Location



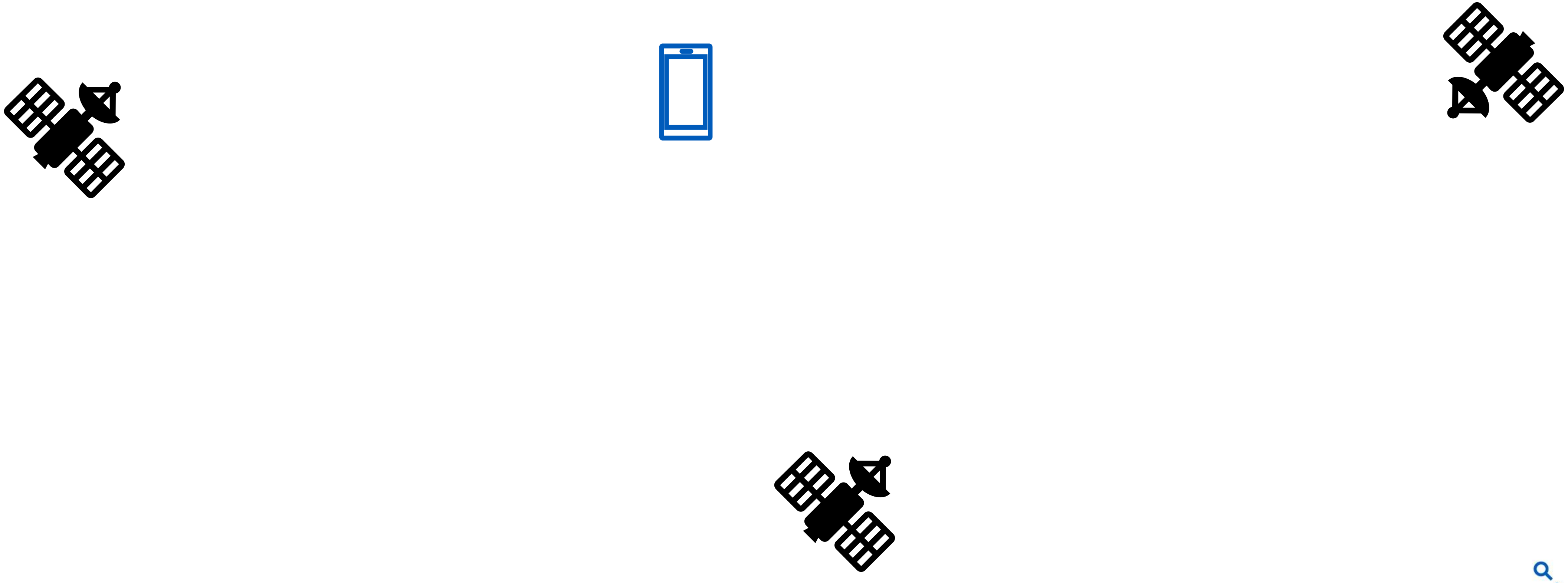
Privacy of User's Location



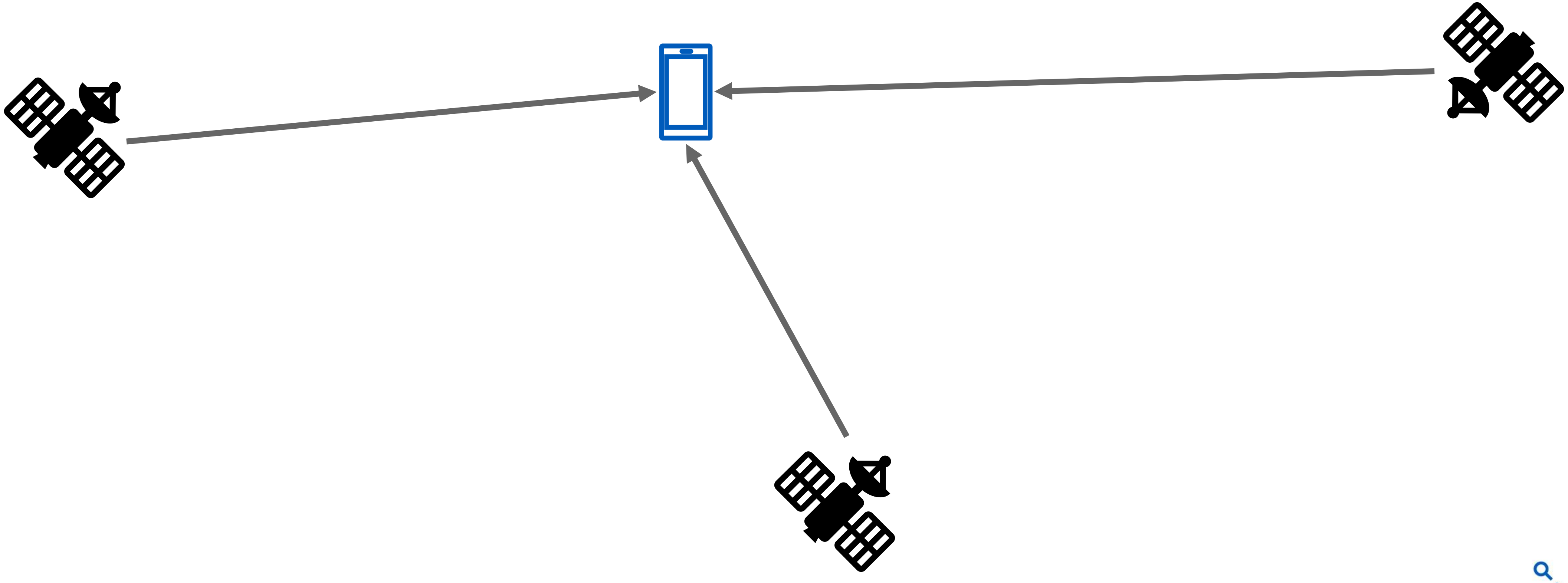
Privacy of User's Location



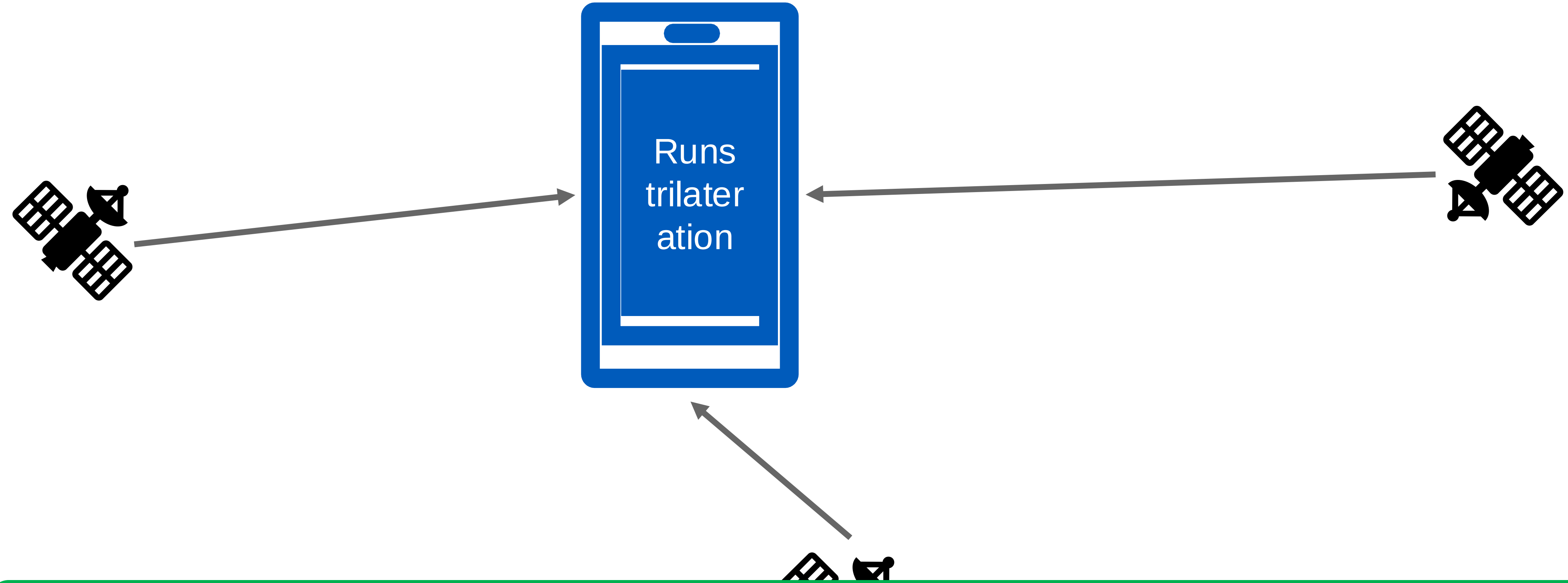
How does GPS do it?



How does GPS do it?

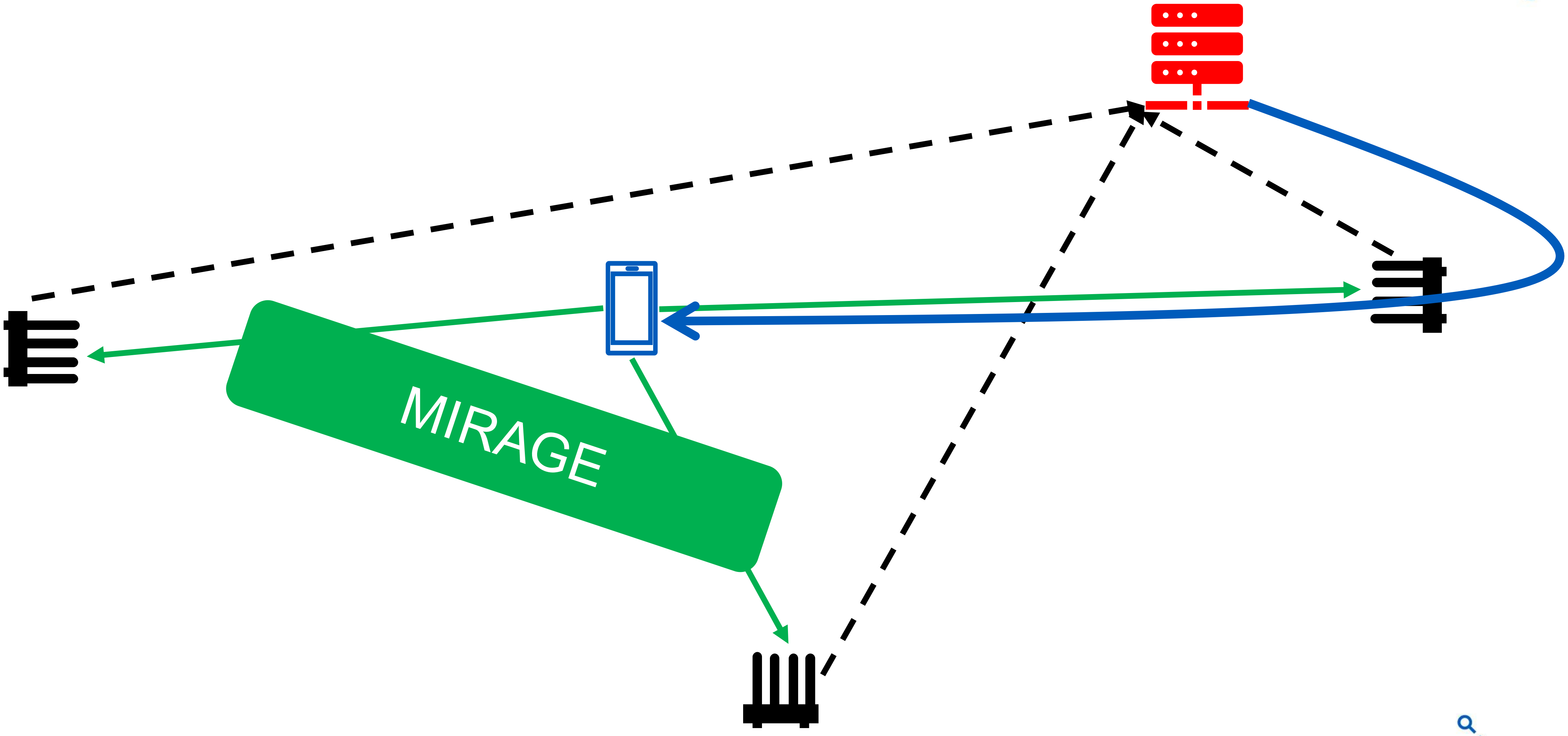


How does GPS do it?

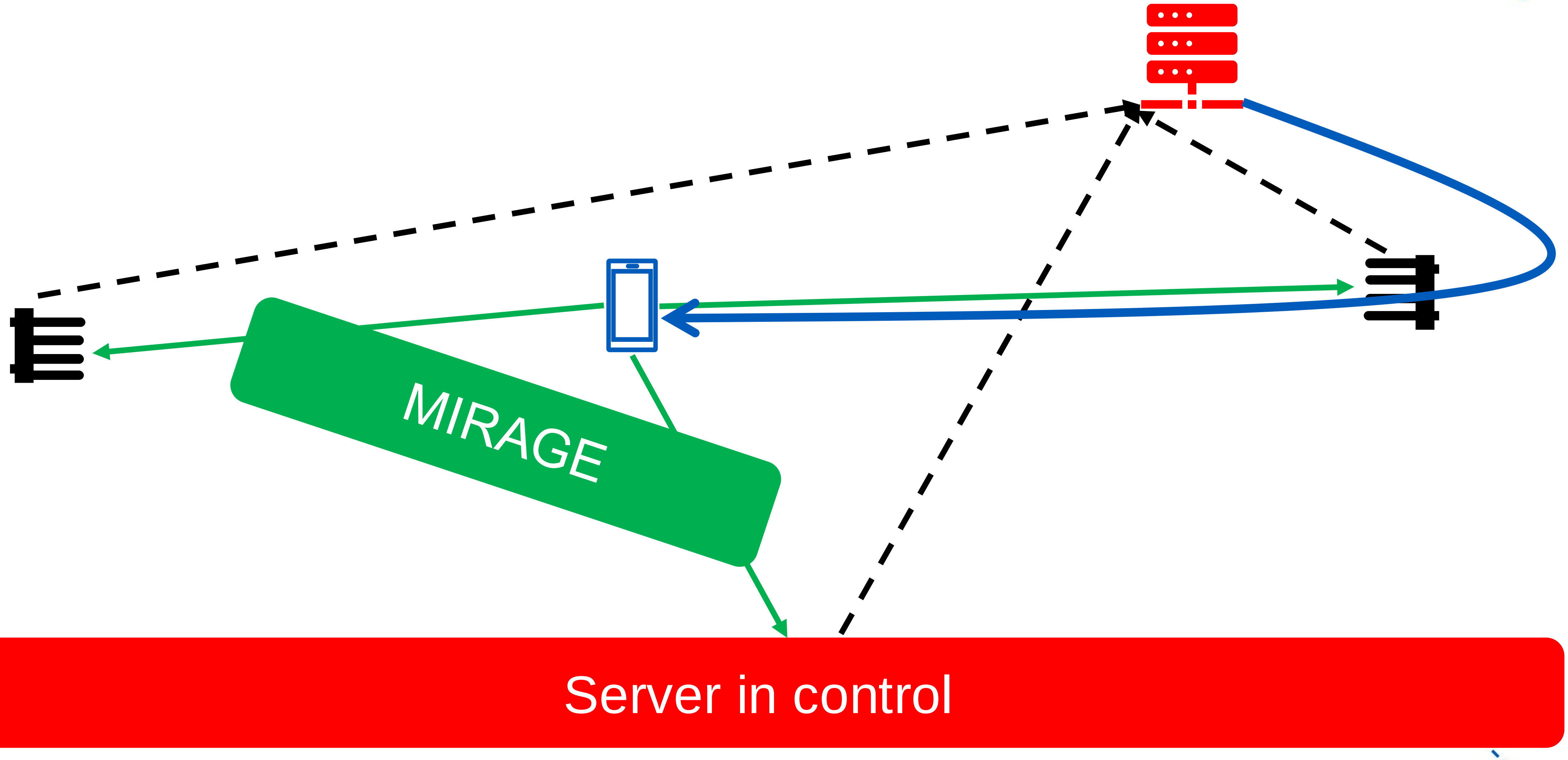


Phone estimates its own Location – User in Control

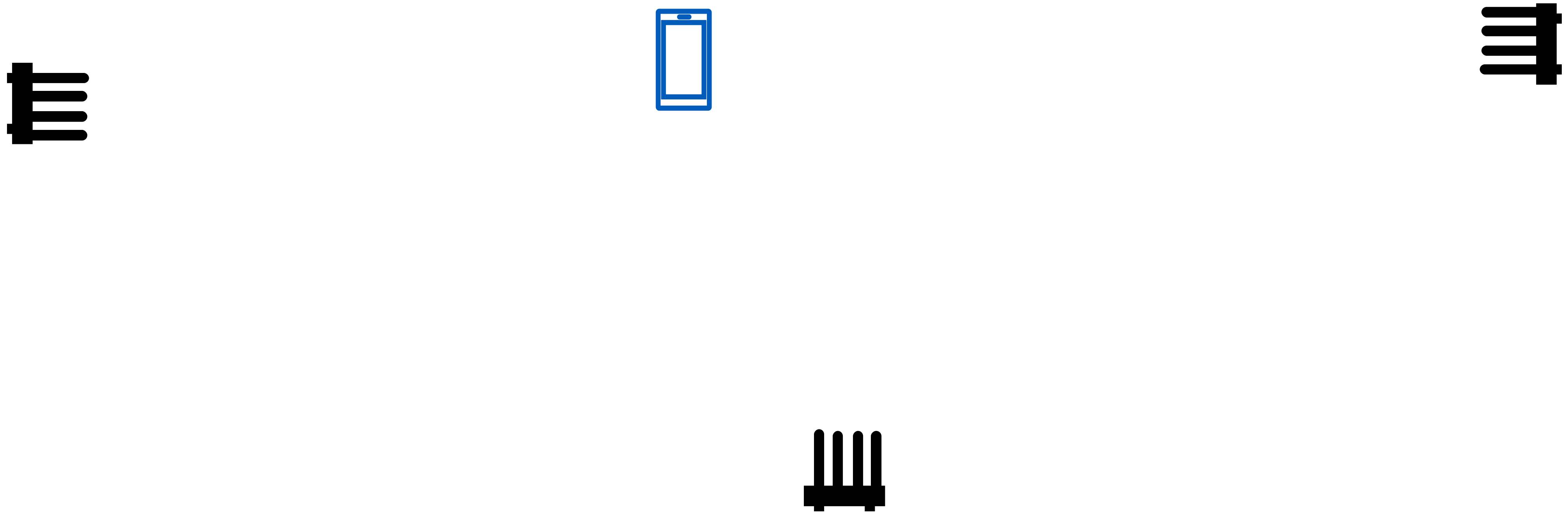
Compromised Server



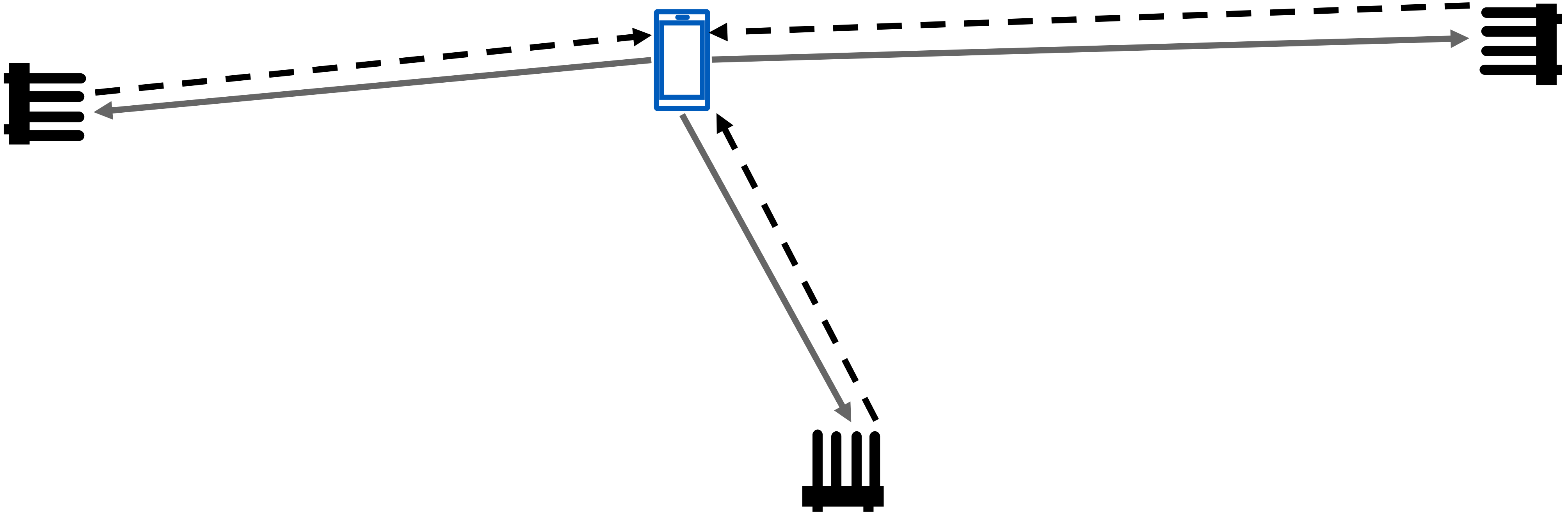
Compromised Server



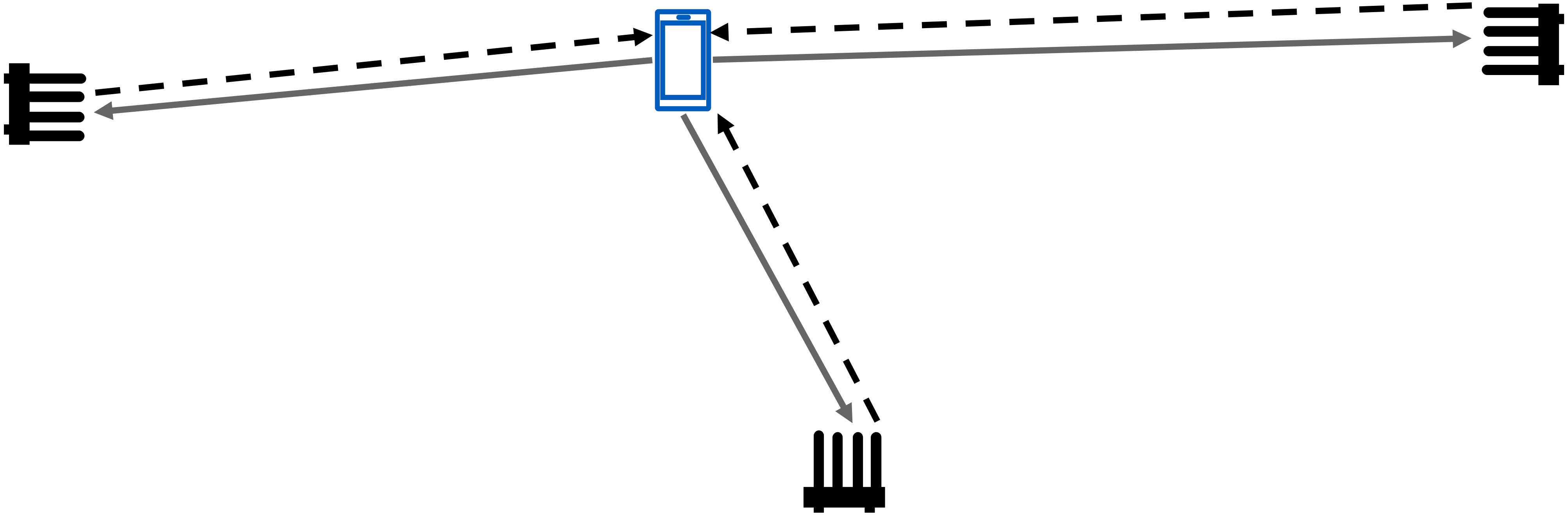
Federated DLoc



Federated DLoc

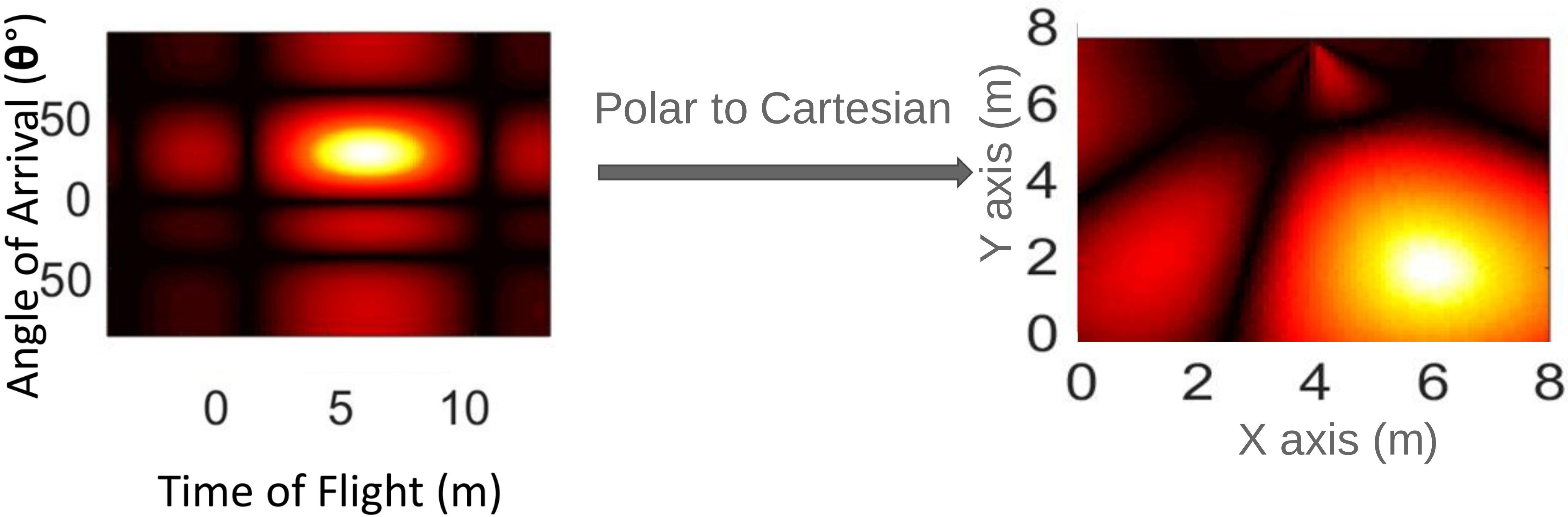


Federated DLoc

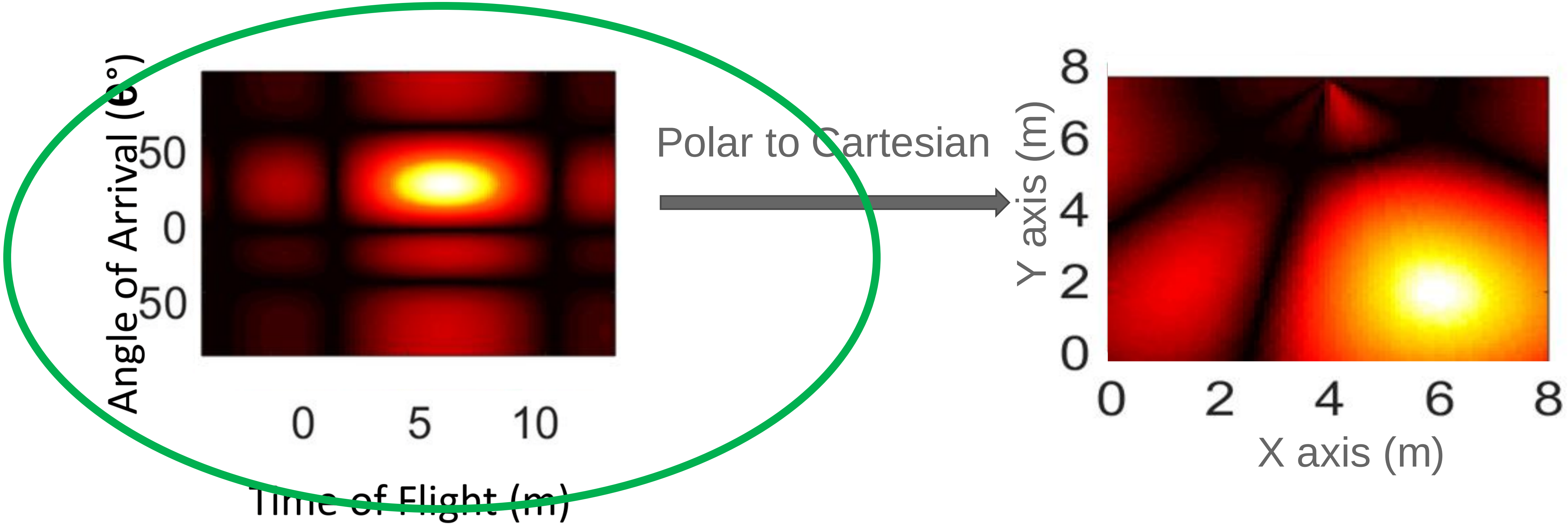


Phone estimates its own Location – User in Control

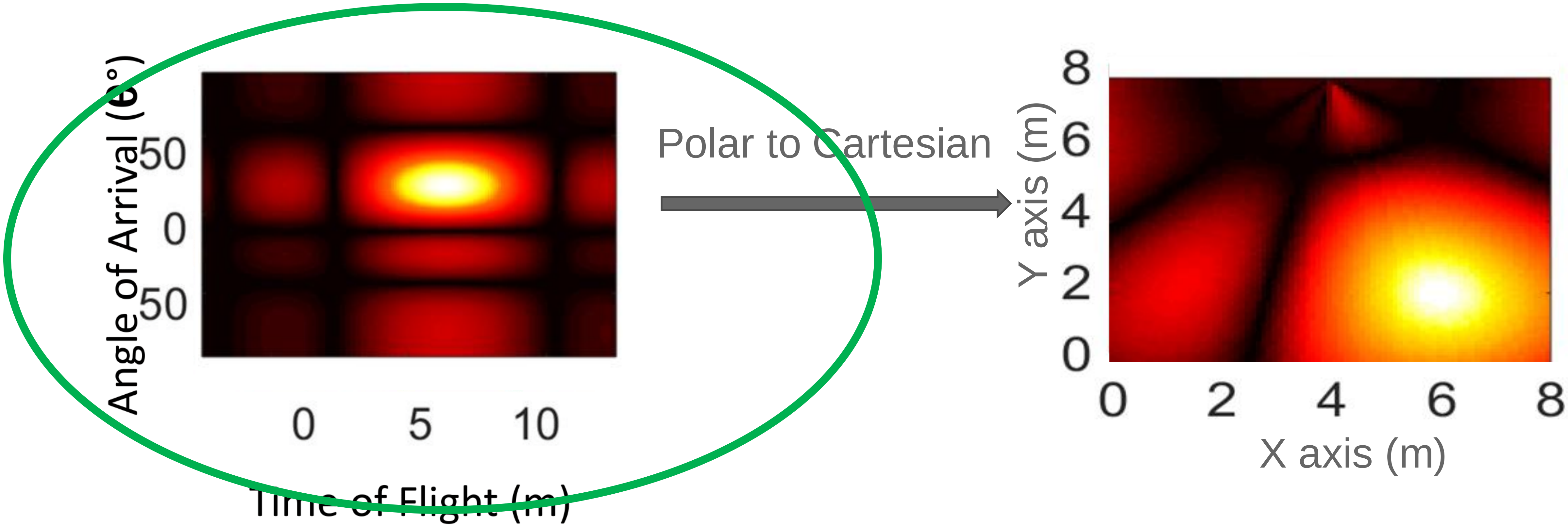
Input Representation – AoA-ToF: easy to scale



Input Representation – AoA-ToF: easy to scale

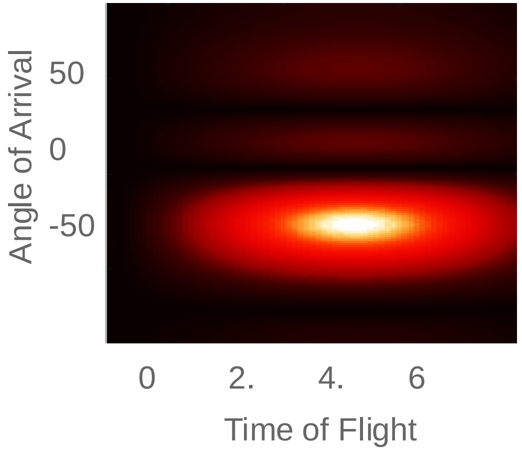


Input Representation – AoA-ToF: easy to scale



How to bring in AP's location context?

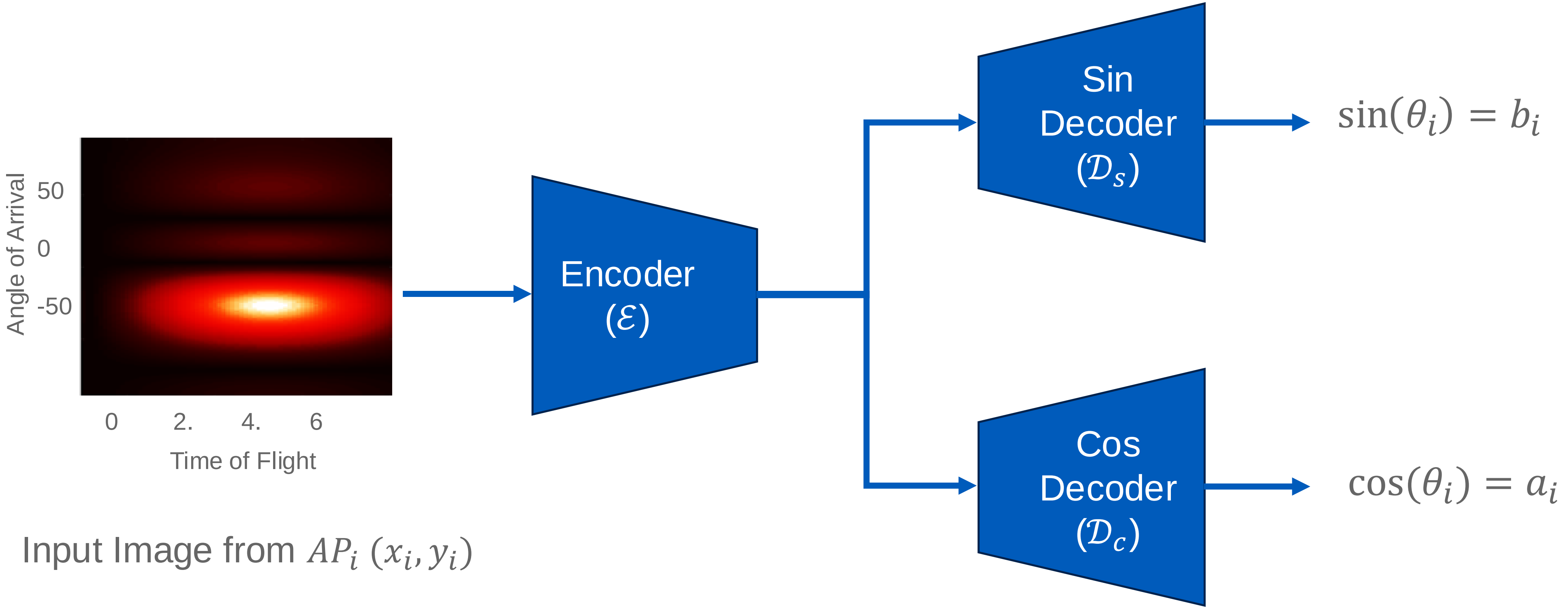
Offline Training – Predicting AoA for each AP



Input Image from $AP_i\ (x_i, y_i)$

$$\mathcal{L} = \sum_{i=1}^{N_{ap}} \mathcal{L}_{abs,i} + \mathcal{L}_{loc}$$

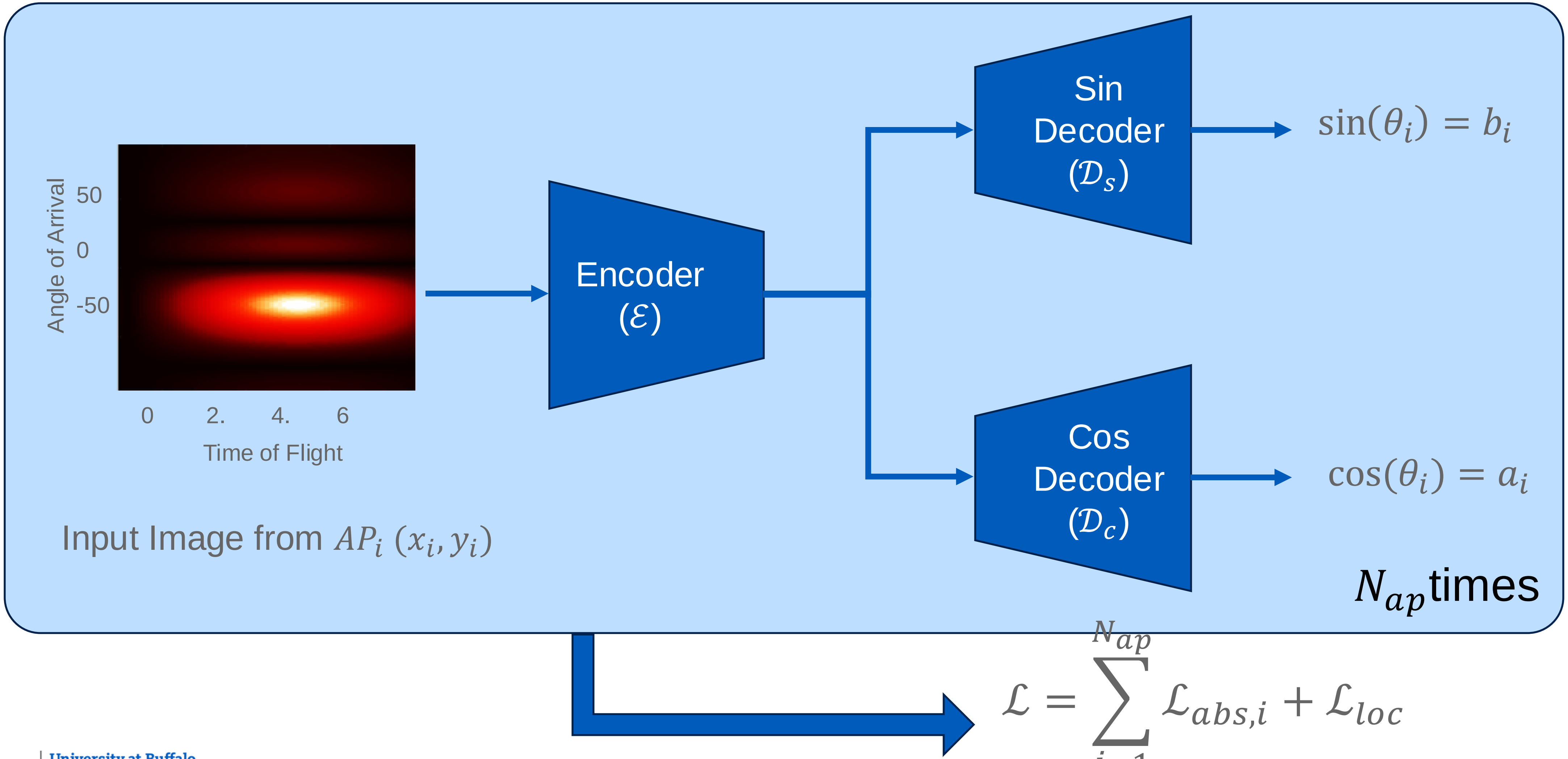
Offline Training – Predicting AoA for each AP



Input Image from $AP_i\ (x_i, y_i)$

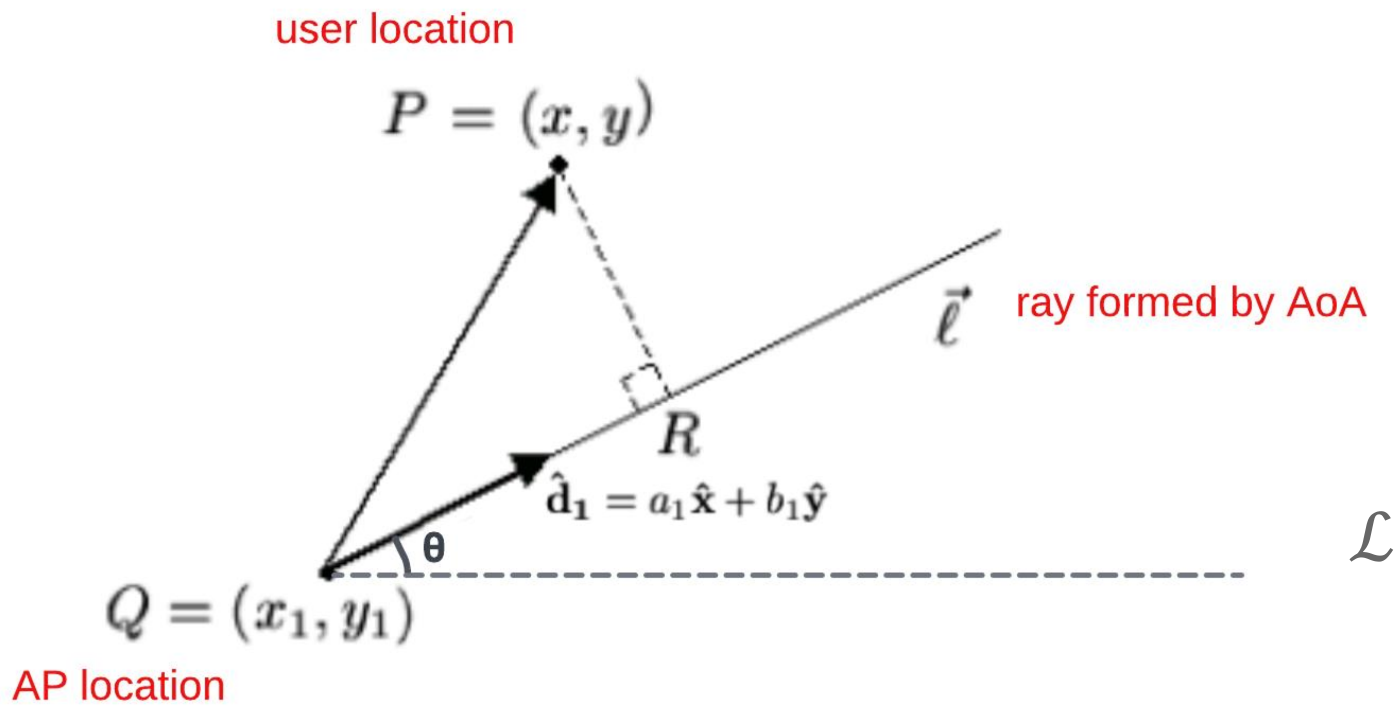
$$\mathcal{L} = \sum_{i=1}^{N_{ap}} \mathcal{L}_{abs,i} + \mathcal{L}_{loc}$$

Offline Training – Predicting AoA for each AP



$$\mathcal{L} = \sum_{i=1}^{N_{ap}} \mathcal{L}_{abs,i} + \mathcal{L}_{loc}$$

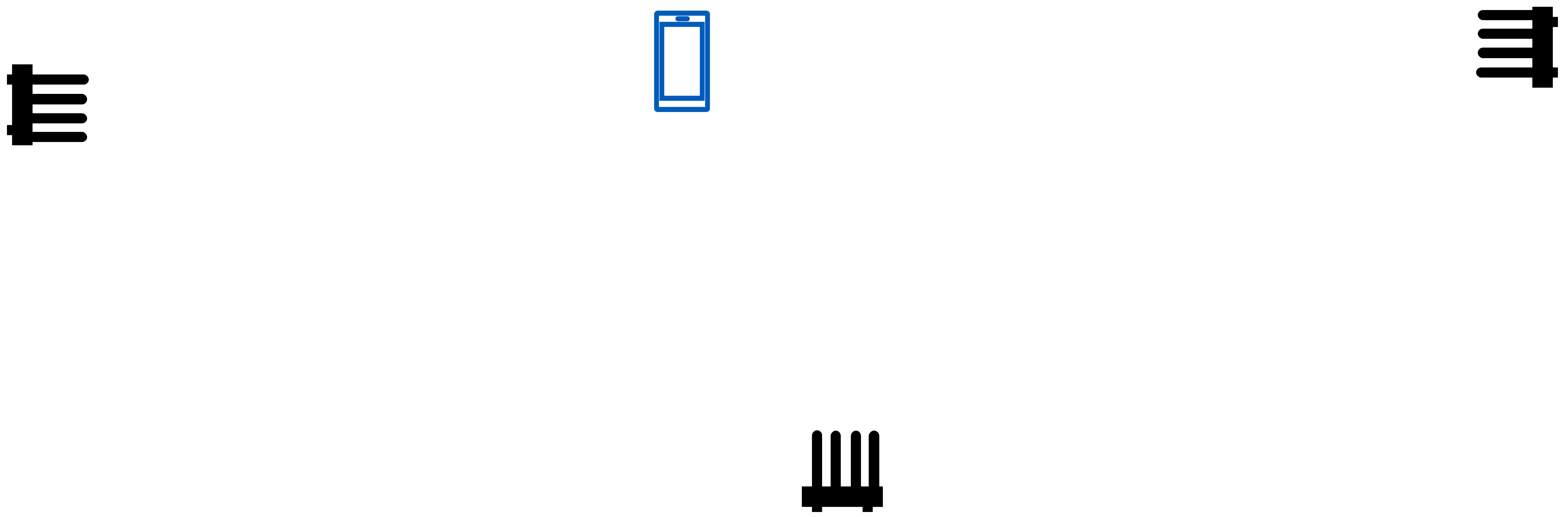
Minimize the distance from the line



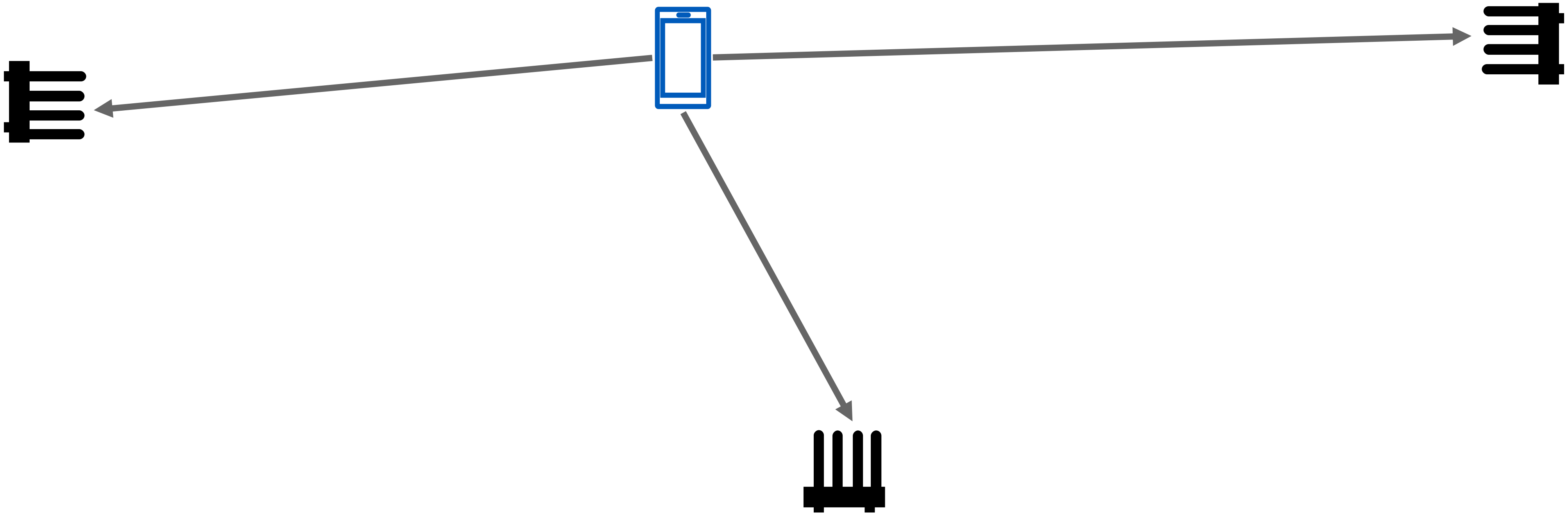
$$\mathcal{L}_{loc} = \left|(x_p - x_t), (y_p - y_t)\right|_2$$

$$[x_p, y_p] = \min \sum_{i=1}^{N_{ap}} [(x - x_i)^2 + (y - y_i)^2 \ - a_i(x - x_i)^2 - b_i(y - y_i)^2]$$

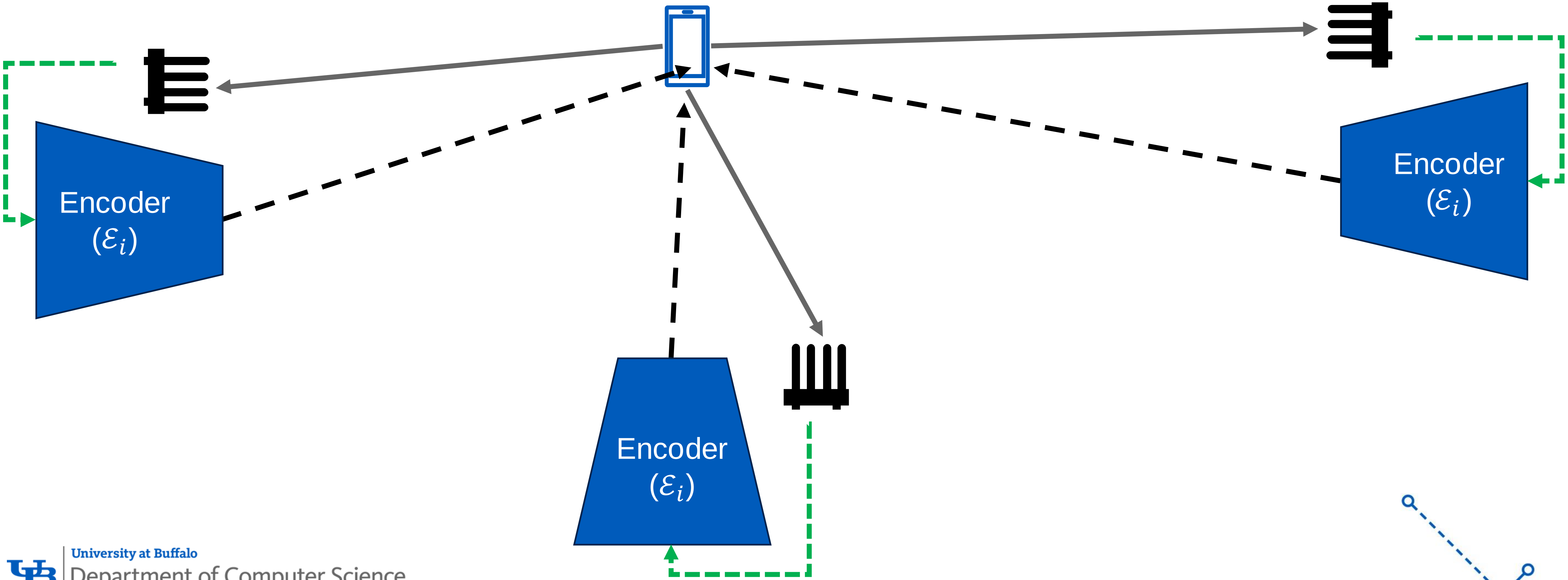
Deployment



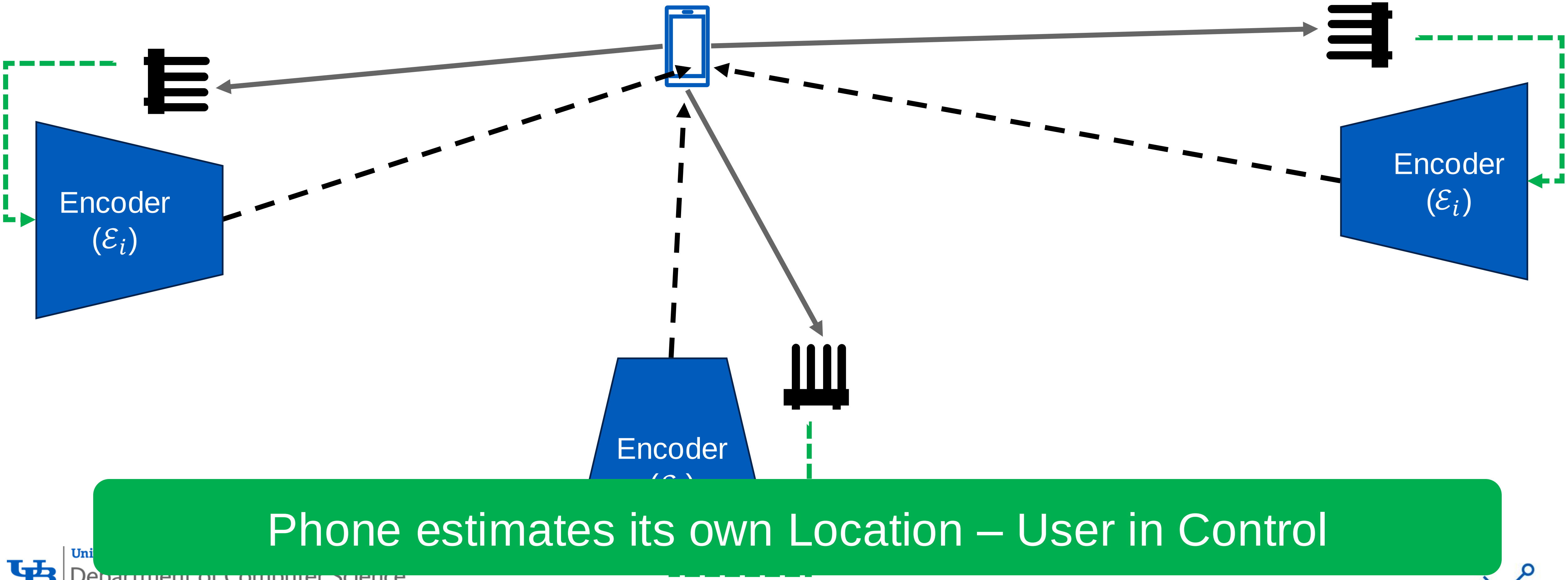
Deployment



Deployment

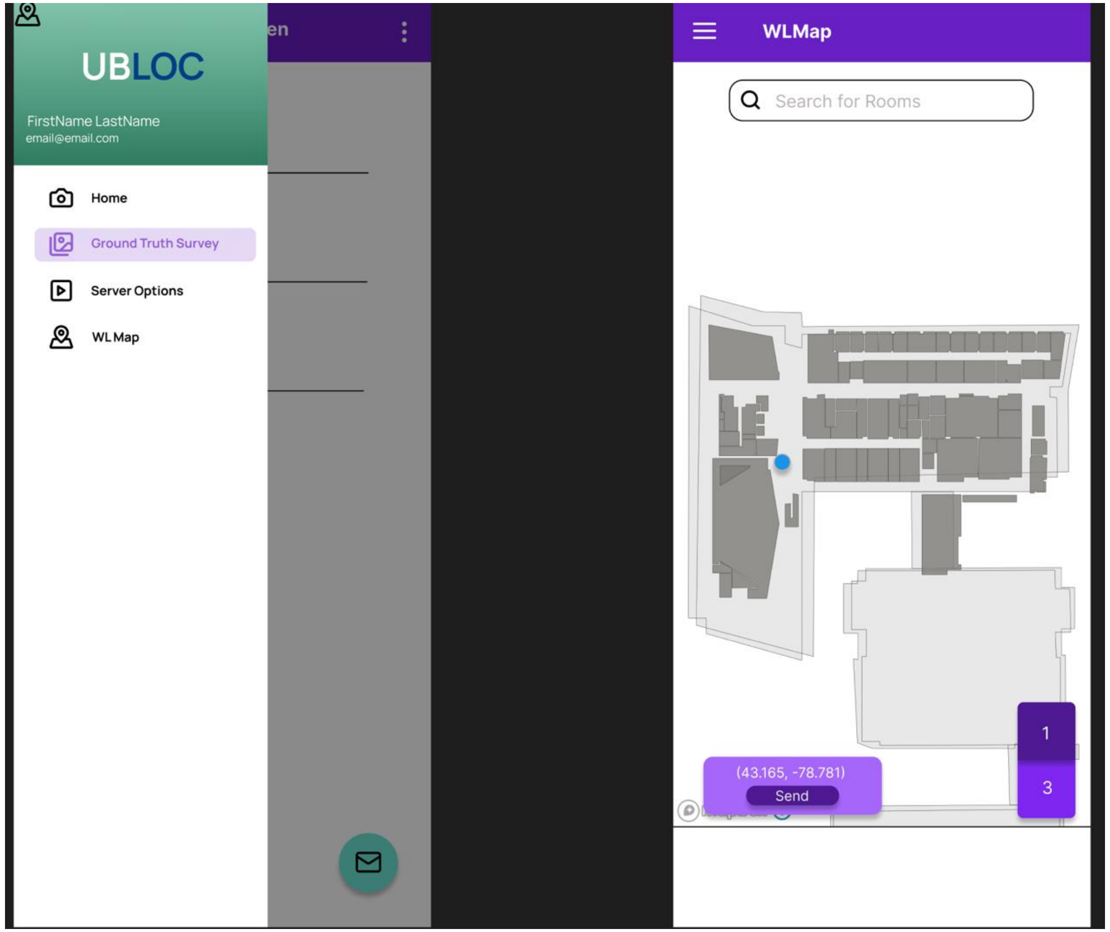


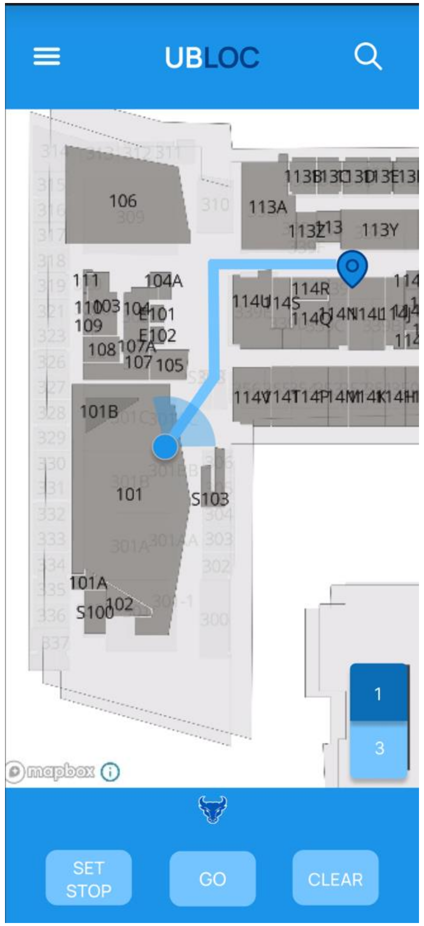
Deployment



Phone estimates its own Location – User in Control

App – For data collection and navigation





Thank you

Questions?