The Tale of Location Determination Technologies

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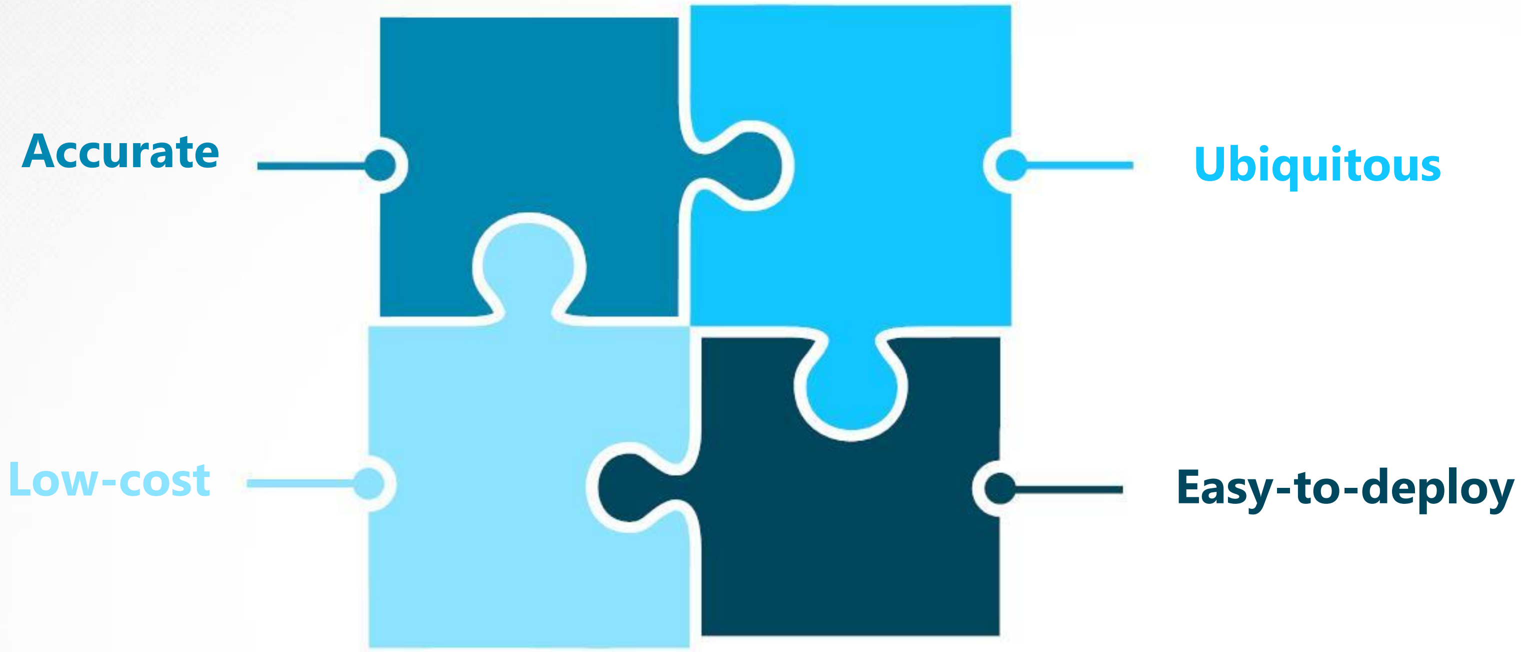
Motivation

- People spend 87% of their time indoors.
- Many services require localization system e.g. E911.

Objectives

- Many services require a localization system that is:



Technology

WiFi

WiFi Coverage

Depend on the installed WiFi infrastructure and coverage.

WiFi Support

Not all phones are equipped with WiFi chips.

Infrastructure changes

Removing access points requires recalibaration of the system

Sensor

Noise

These sensors (e.g. Acc, Gyro, and Compass) have high inherent noise.

Availability

These sensors are only available on the high-end phones.

Technology

Cellular

Widespread technology
Infrastructure everywhere

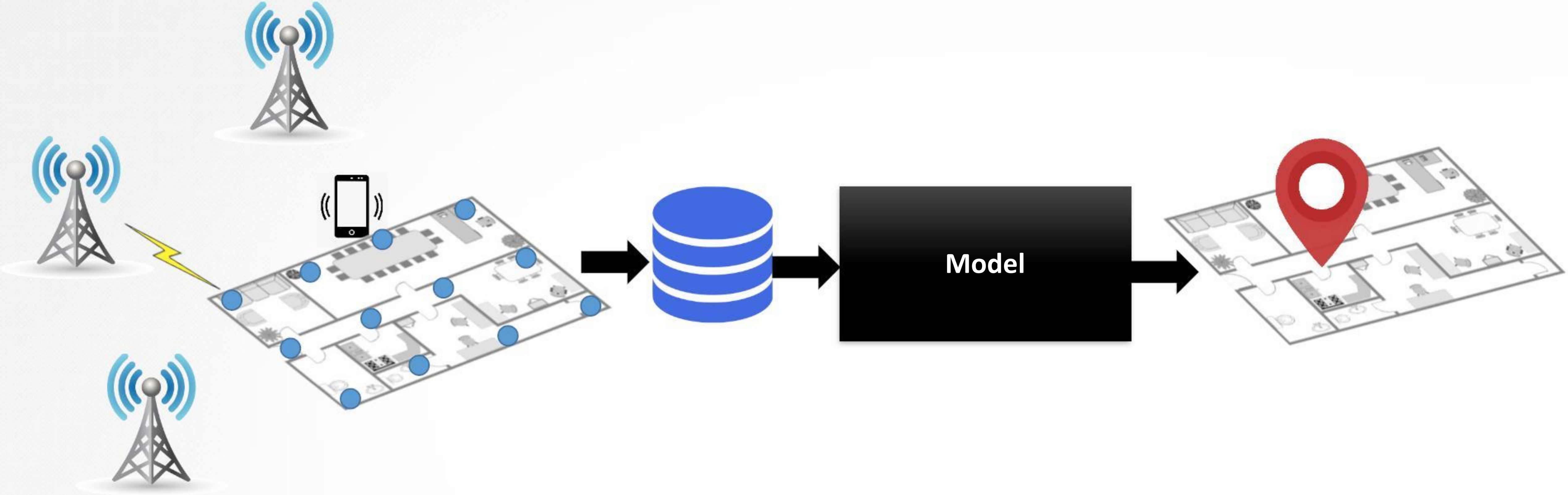
Supported by any cell phone
Low-end and high-end phones

Consumes zero extra energy
in addition to the phone operation

Rare infrastructure change
as changing the base stations is very expensive

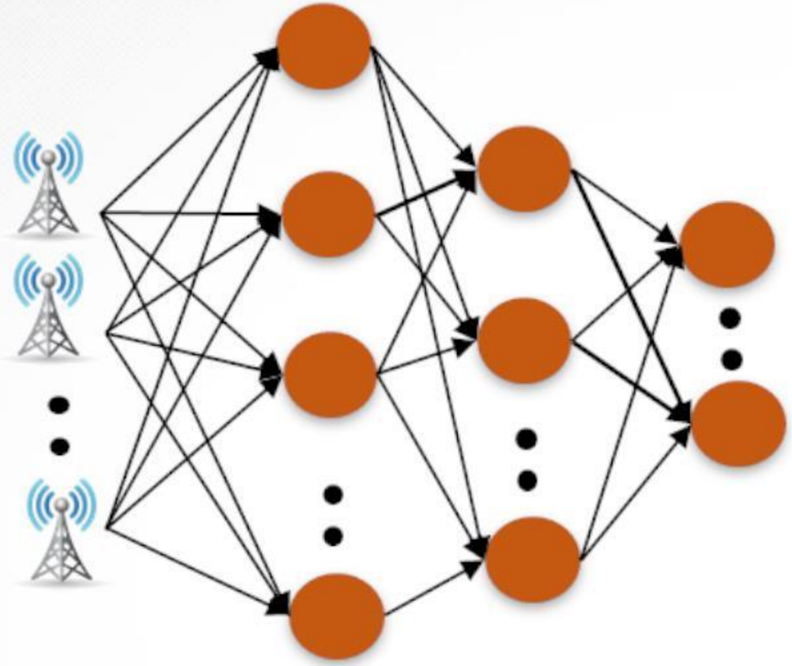
Tolerance for power failures
Base stations equipped with generators

The basic idea



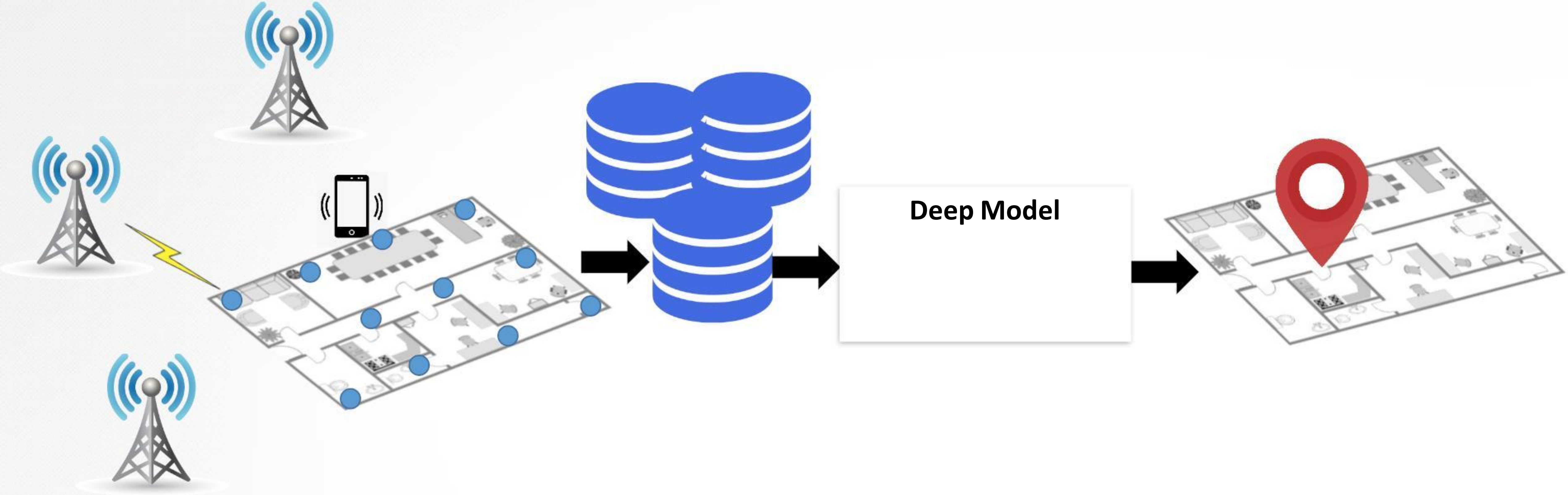
Model

- ❑ **The model is asked to learn a complex mapping function.**
- ❑ **Deep learning is adopted due to its distributed learning ability.**



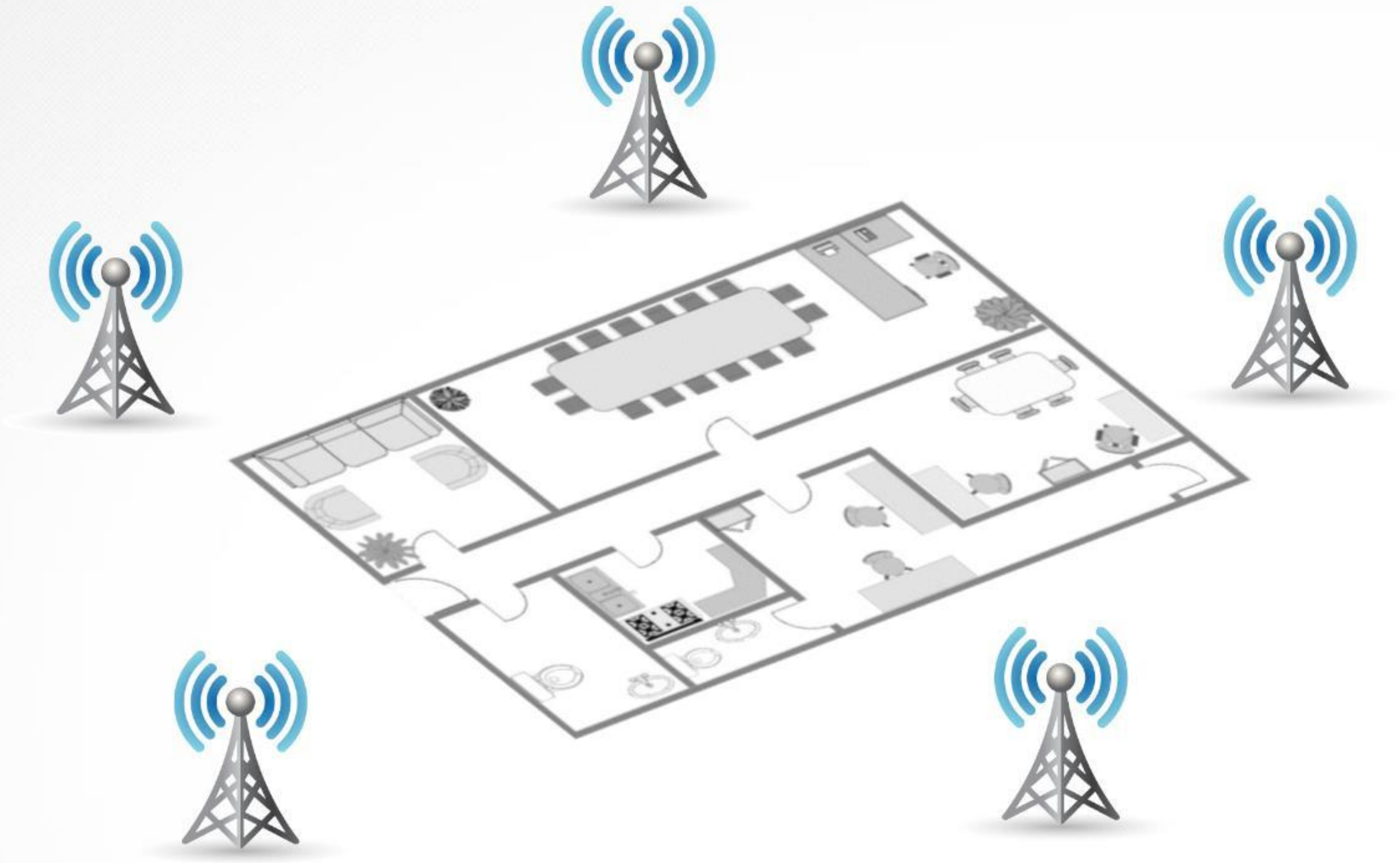
Challenges

The learning quality of deep networks depends on the amount of data used in training.

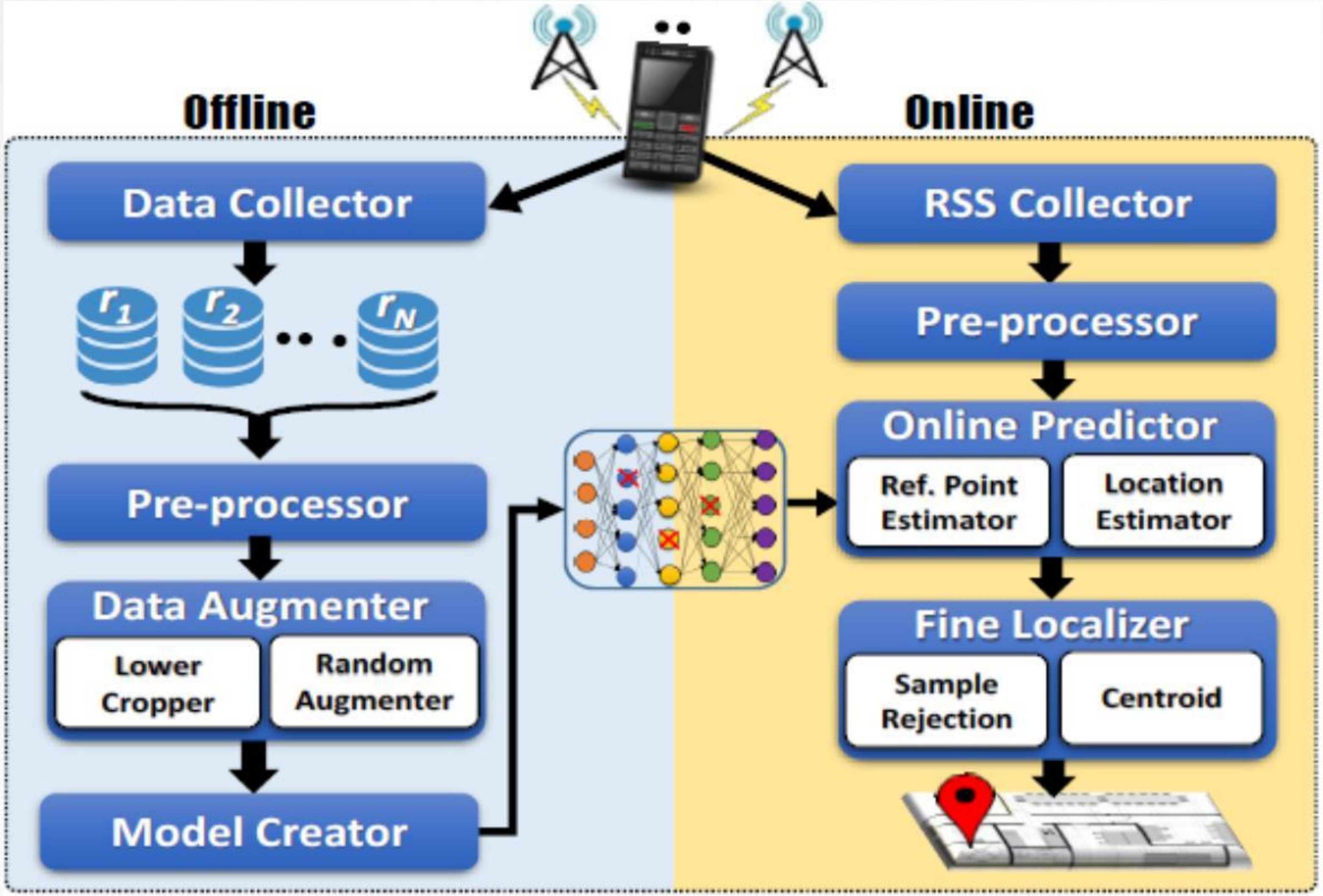


Challenges

- Instability



CellinDeep



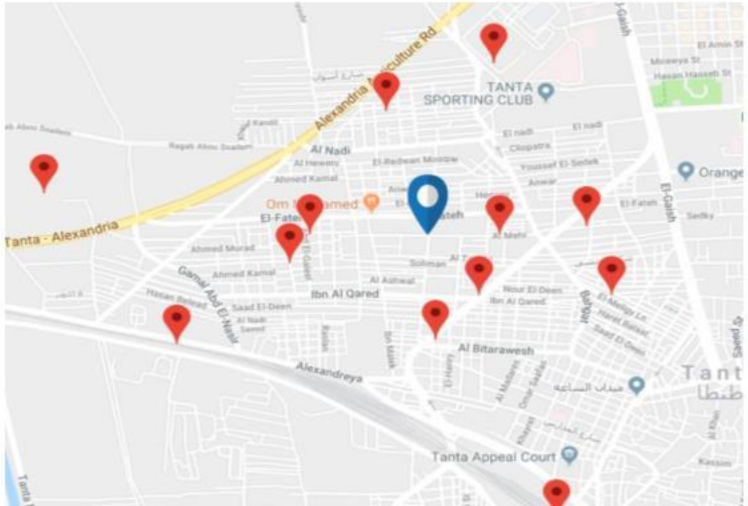
Offline
Online
Data Collector
r_1
r_2
r_N
Pre-processor
Data Augmenter
Lower Cropper
Random Augmenter
Model Creator
RSS Collector
Pre-processor
Online Predictor
Ref. Point Estimator
Location Estimator
Fine Localizer
Sample Rejection
Centroid

CellinDeep – Signature Collector

- To collect the training data, the cell phone scans for the cell towers heard in the area of interest.

- Each scan represents cell information from up to 7 cell towers (CID, RSS).

- Send to our server.



CellinDeep – Pre-processor

- Extends the input scan to the length of all detectable towers in the area of interest.
- Non-heard cell towers are assigned 0 ASU.

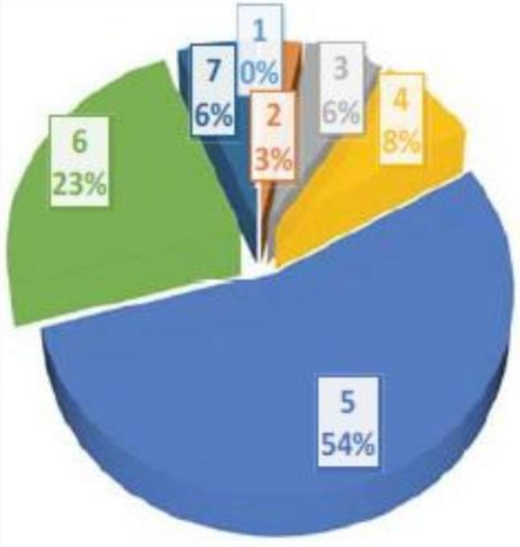
Scan 1	<CID_1,RSS_1> <CID_2,RSS_2> <CID_4,RSS_4>
Scan 2	<CID_1,RSS_1> <CID_2,RSS_2> <CID_3,RSS_3> <CID_4,RSS_4>

	CID_1	CID_2	CID_3	CID_4
Scan 1	RSS_1	RSS_2	0	RSS_4
Scan 2	RSS_1	RSS_2	RSS_3	RSS_4

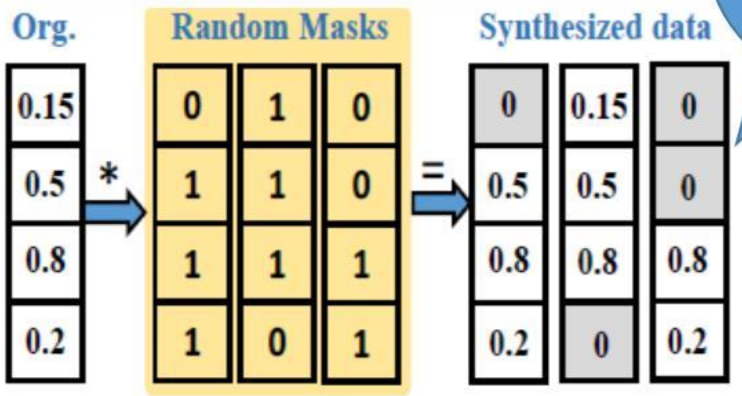
CellinDeep – Data Augmentation

Tower Dropping Techniques

The number of towers varies over different scans.



Random -based

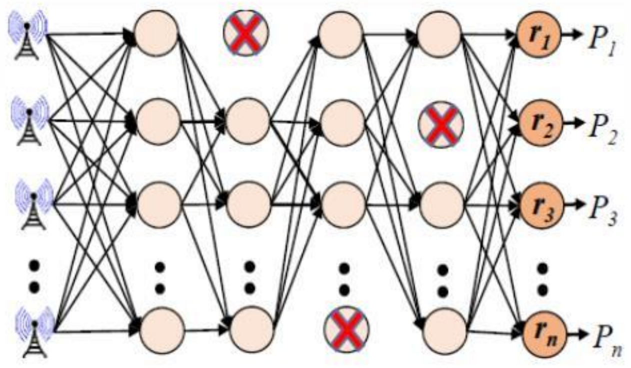


Threshold-based

CellinDeep - Model Creator

CellinDeep adopts a fully connected neural network.

The input layer
The signal strength detected from the towers in the area of interest.



Hidden layers
Four layers of ReLU function.

Output layer
A number of units corresponds the of reference points surveyed
A Softmax function is used that produce a probability of a scan belong to a point.

Preventing over-fitting

- ***Dropout*** neurons are randomly removed from the deep neural network during the training phase.
- ***Early stopping*** training would halt once the performance improvements are no longer obtained.

CellinDeep - Online Predictor

Aims to track the user in the continuous space

Spatial Averaging

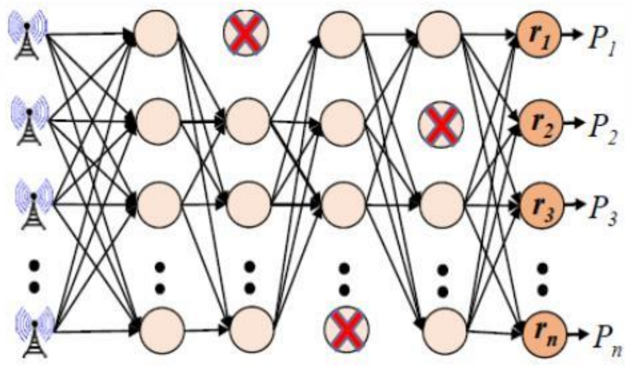
Estimating the user location as the center of mass of the reference points.

Sample rejection

Removes the anomalous location that may be estimated due to the noisy wireless channel.

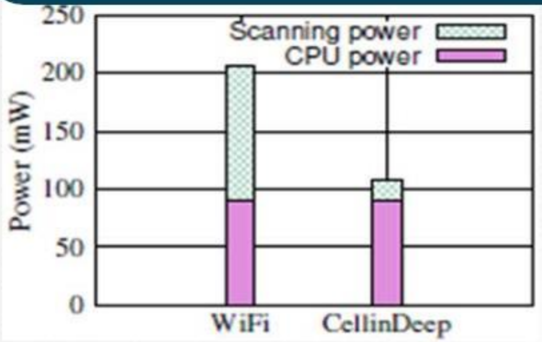
Temporal averaging

The average of a sequence of locations is calculated and reported.



CellinDeep - Evaluation

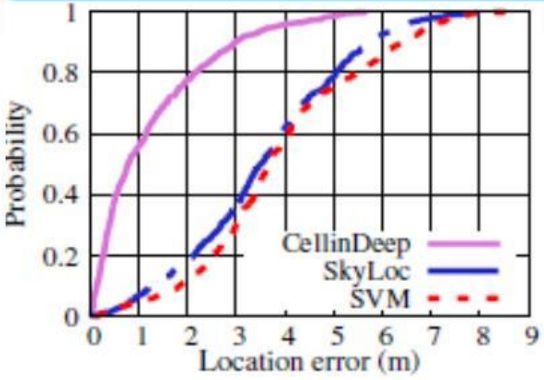
Power consumption.



93.4%

Power savings

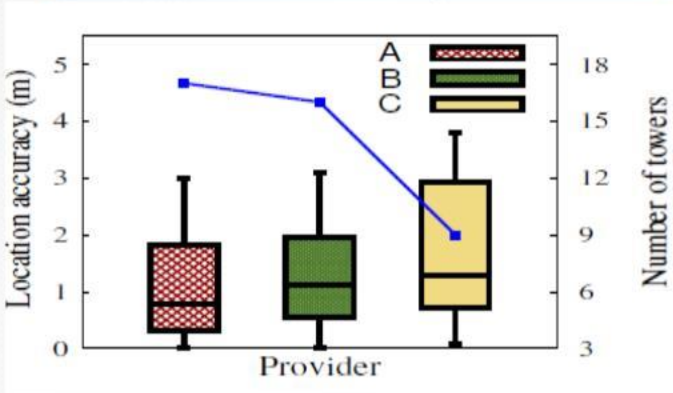
CDF of the localization error.



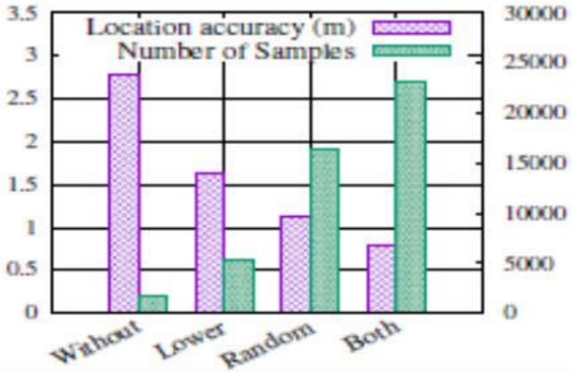
350 %

Better Accuracy

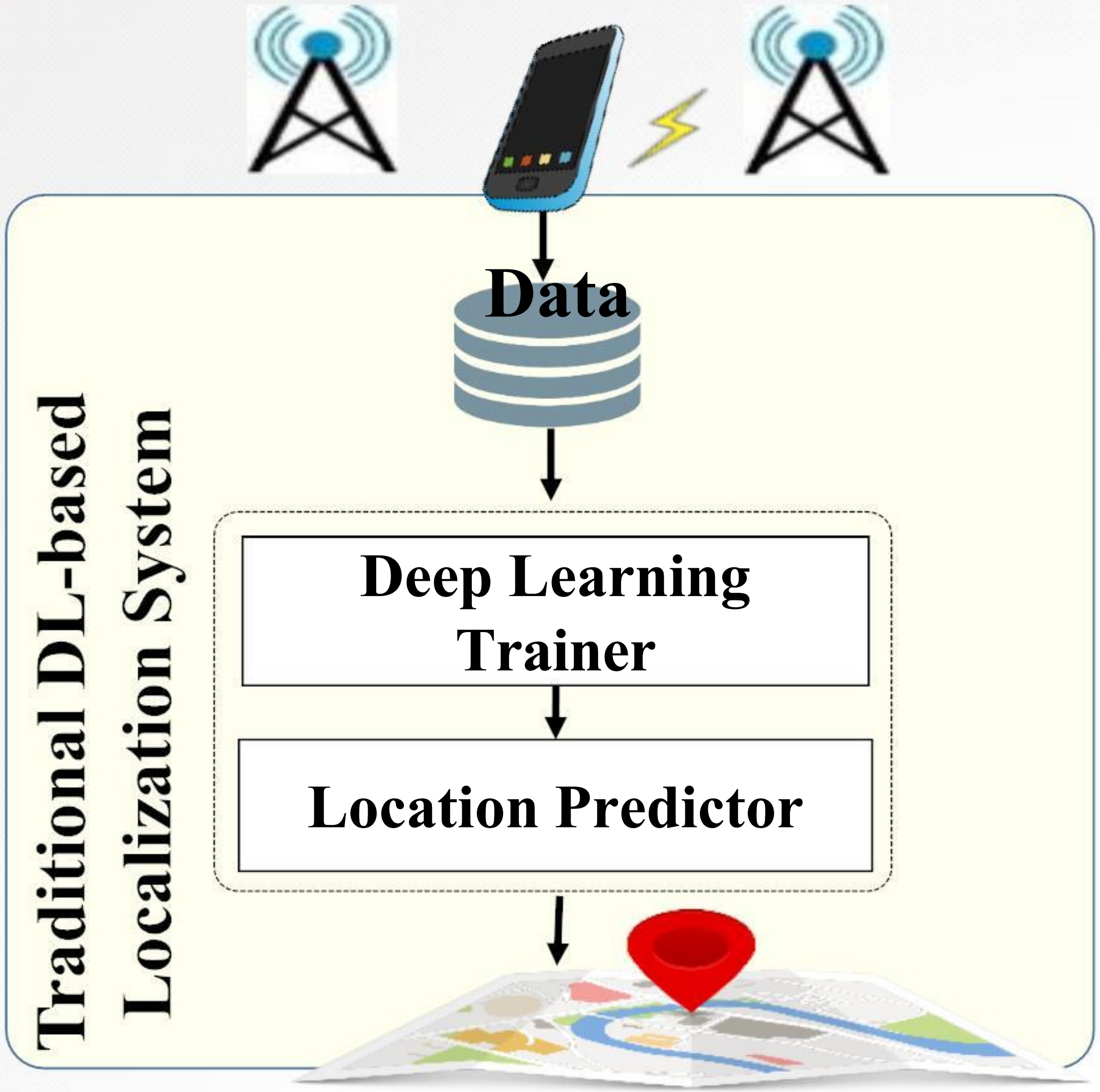
Effect of cellular providers on accuracy.



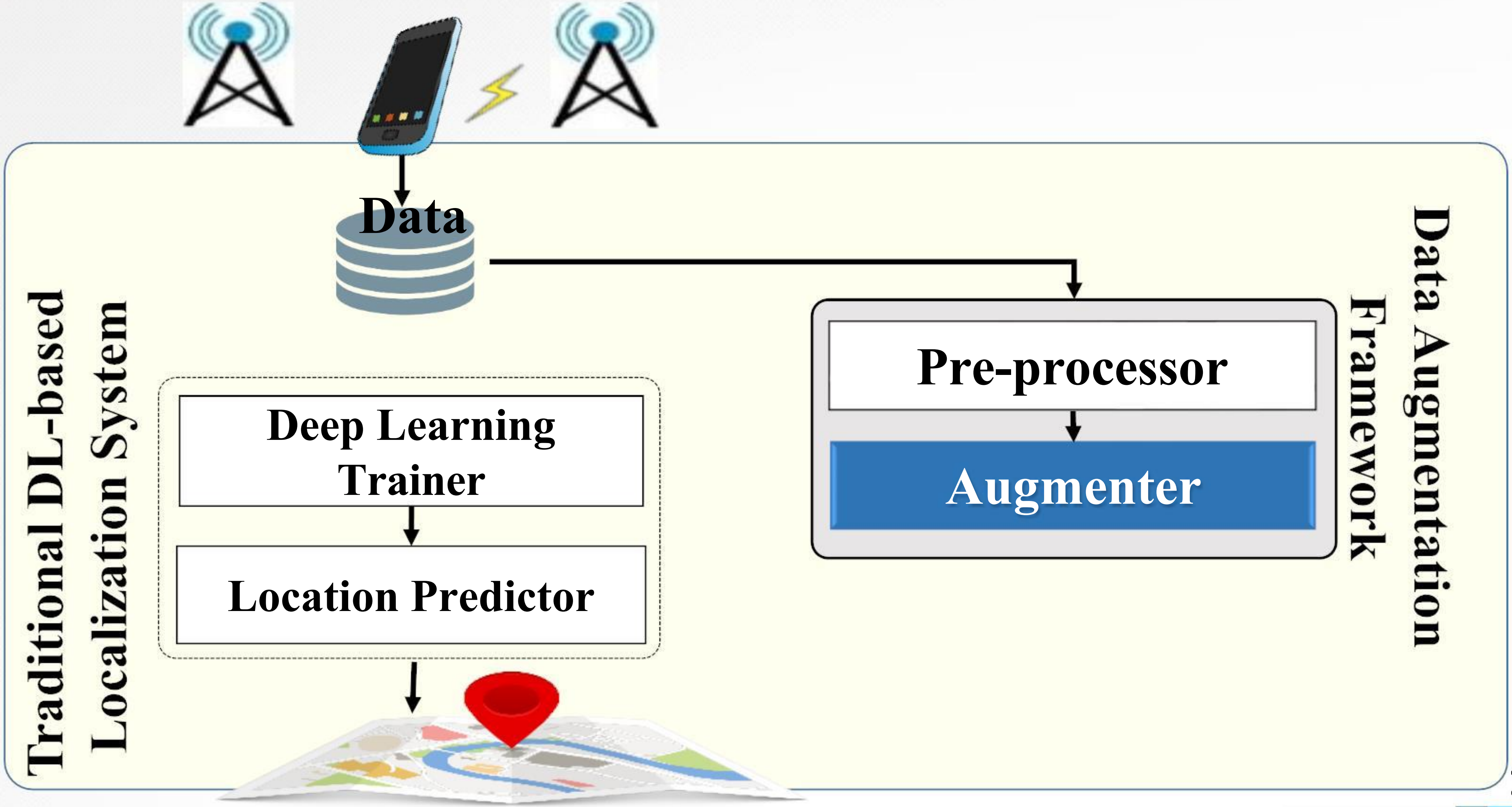
data augmentation methods on accuracy.



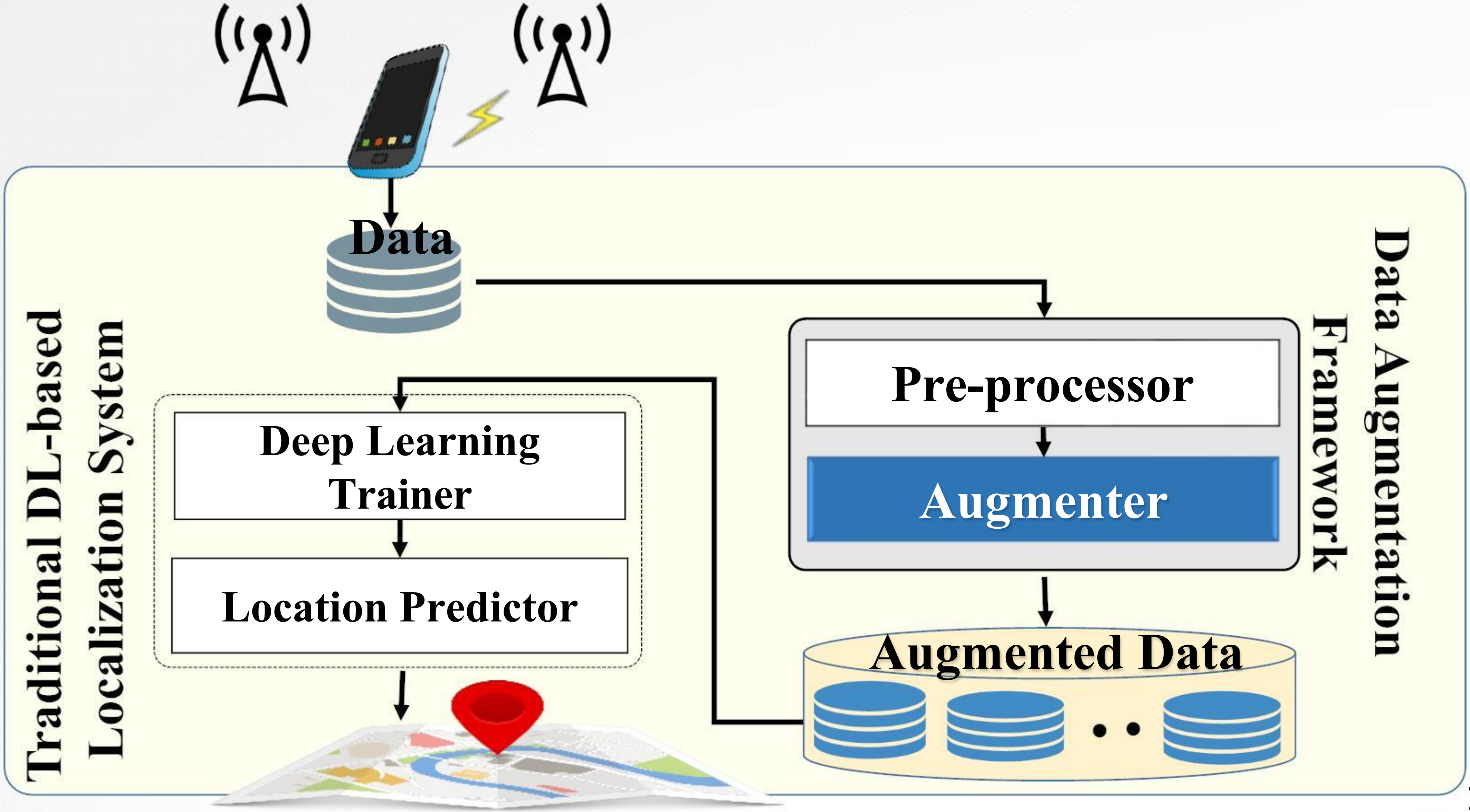
Data Augmentation Framework



Data Augmentation Framework



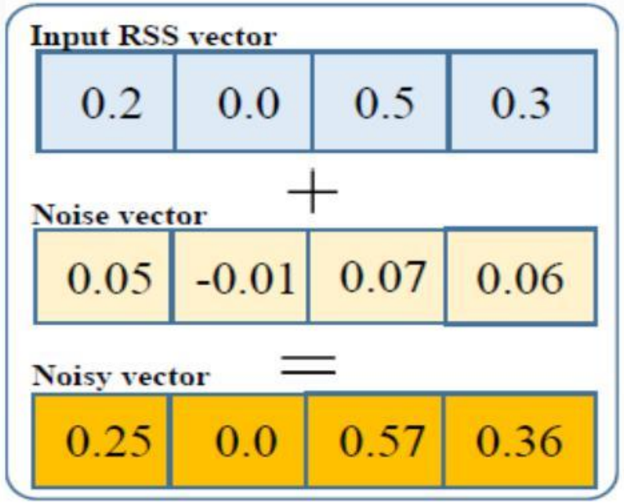
Data Augmentation Framework



Data Augmentation Framework

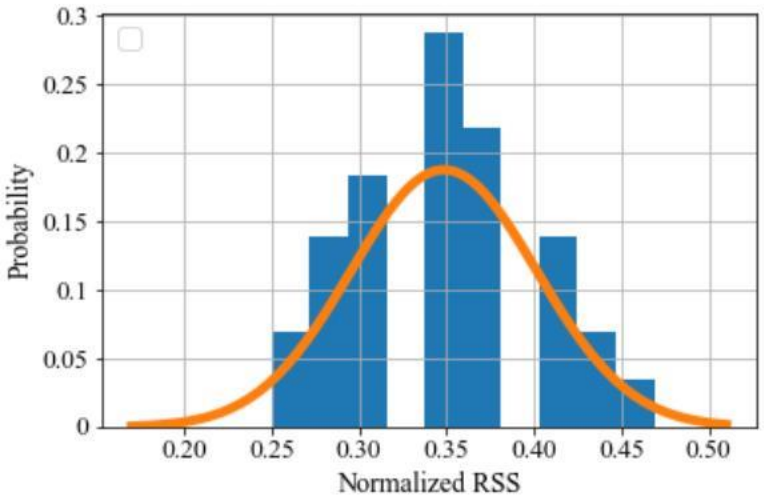
1. Additive Noise Technique

- A white Gaussian noise is added to RSS from each tower.



2. Sampling Technique

- Constructs the RSS distribution.
- Generates synthetic data by sampling.



Data Augmentation Framework

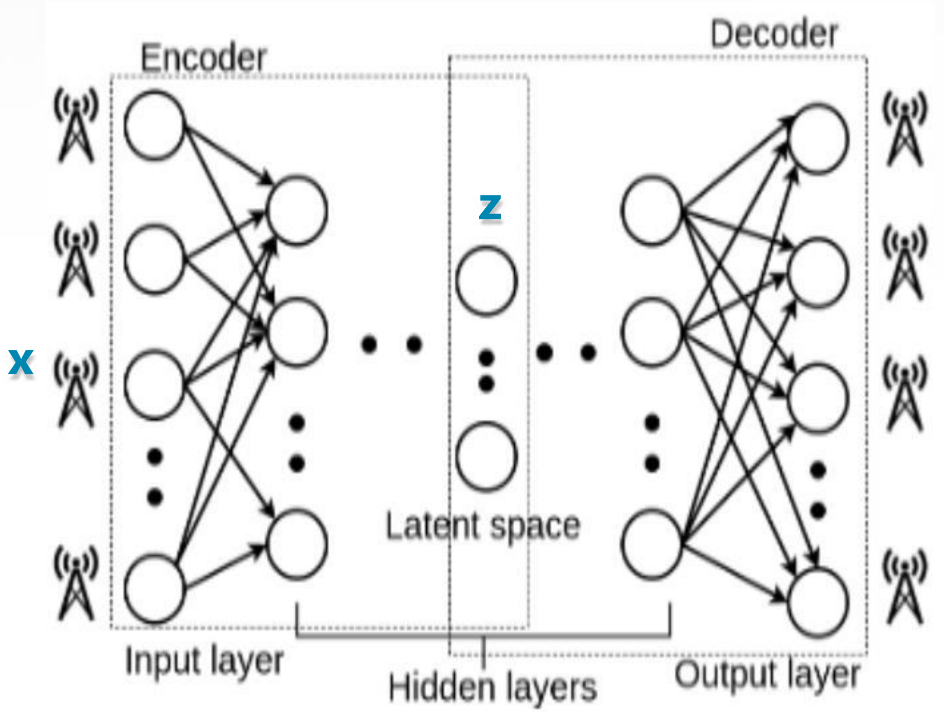
3. Deep generative technique (VAE)

- **VAE network has two parts**
  - **Encoder :** encode the samples **x** to smaller space bottleneck **z.**
  - **Decoder** : reconstruct the sample**.**

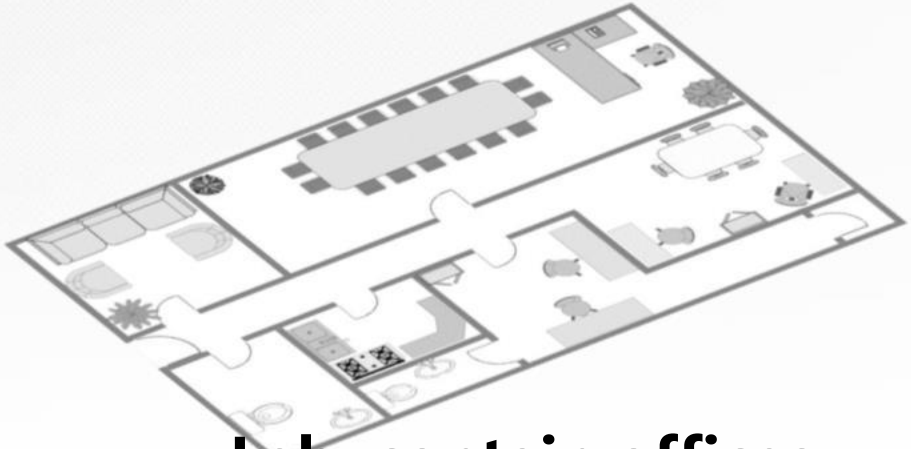
- **Loss consists of two parts**
  - **Reconstruction loss :** forces the decoder to reconstruct the sample **x** from **z.**
  - **Regularizer :** forces the bottleneck **z** to follow a predefined distribution **p(z).**

- **By sampling z from the p(z) distribution and feeding z to the decode network, we can get new samples x.**

- **VAE learns the joint distribution of the different cell towers.**



Evaluation



Lab: contain offices, meeting
Room and corridor.

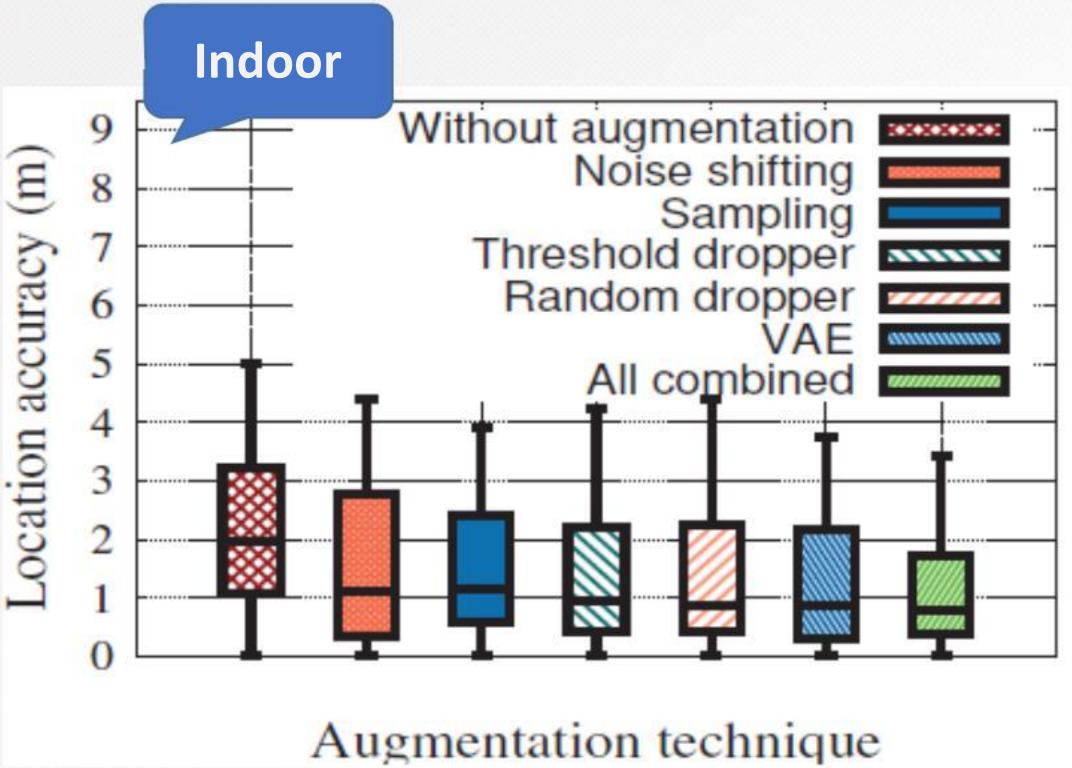
Urban Area
Alexandria, Egypt.

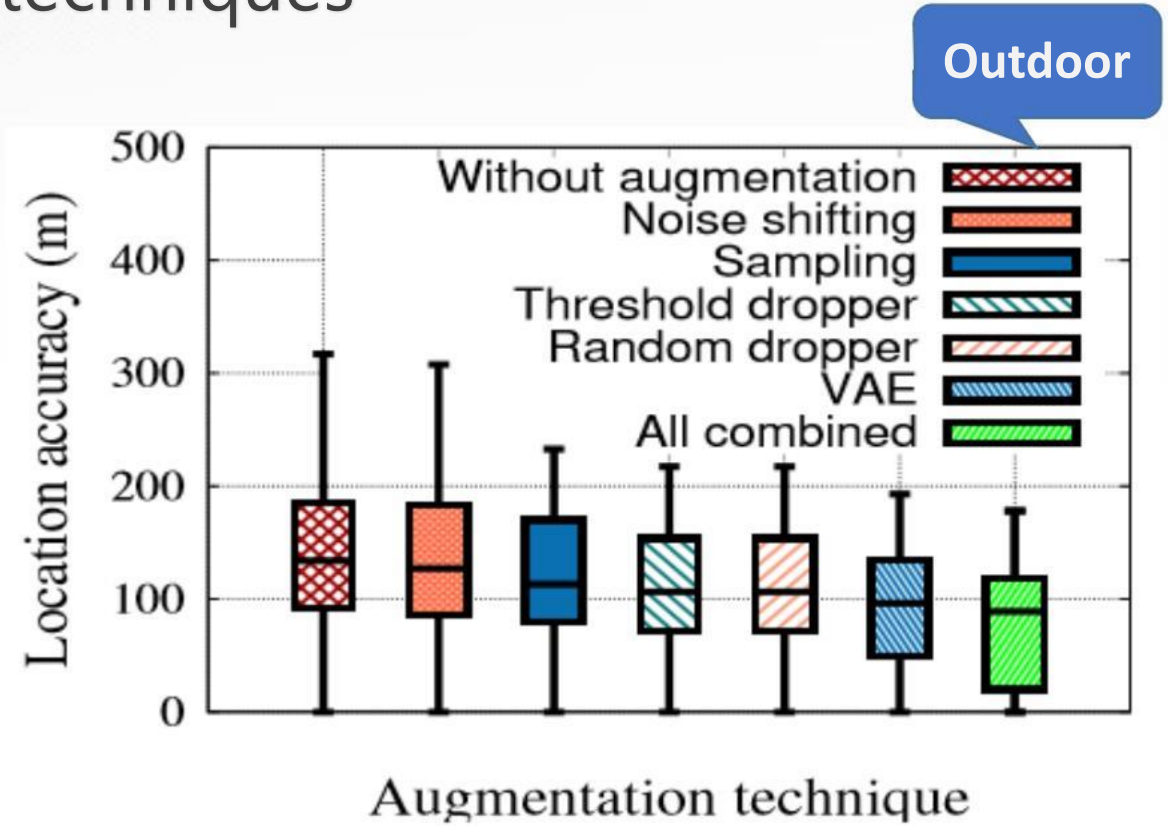
Testbed parameters

Testbed	Indoor	outdoor
Area	11x12 m^2	400x500 m^2
Grid cell length (m)	1 m	100 m
Number of cell towers	17	37
Sampling rate (scan/sec)	1	1

Evaluation – Results

Effect of different data augmentation techniques





157% **Better accuracy**

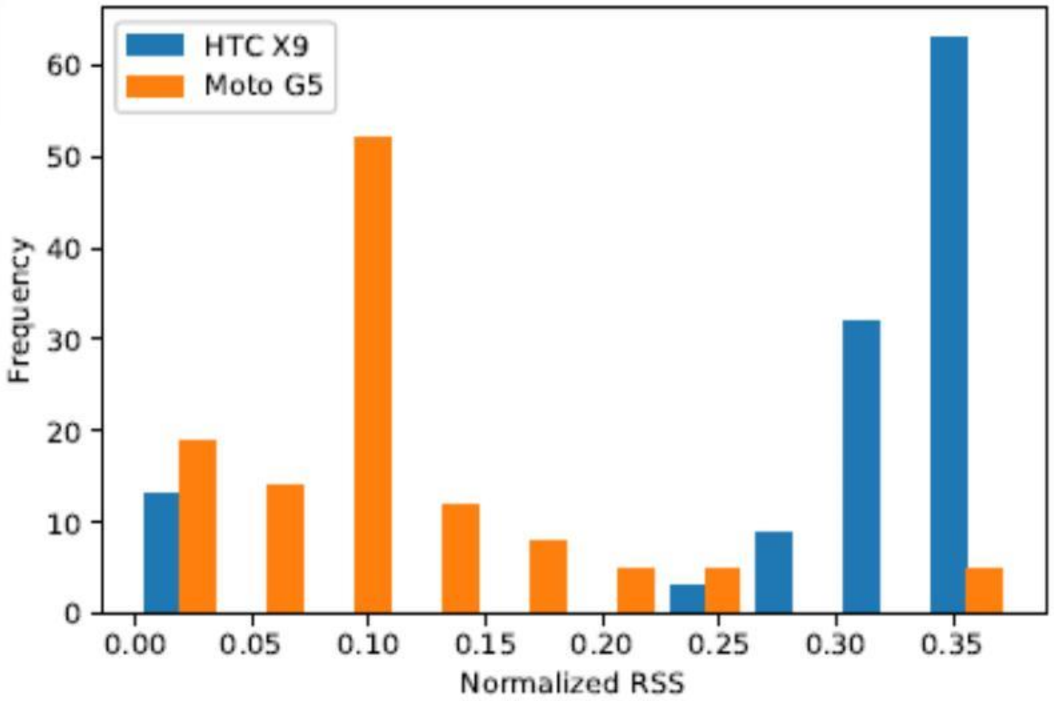
50.5% **Better accuracy**

- **Applying all augmentation techniques together leads to the best accuracy.**

OmniCells: Cross-Device Cellular-based Indoor Location Tracking Using Deep Neural Networks

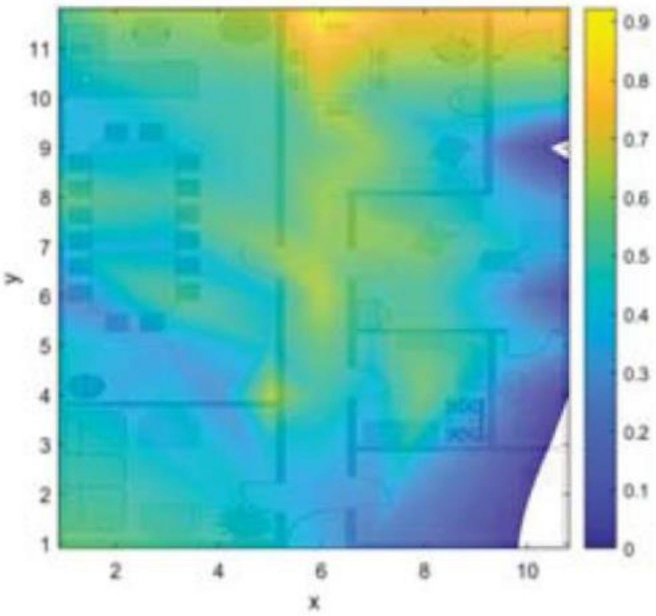
Challenges

- **Different mobile phones have different sensing capability.**

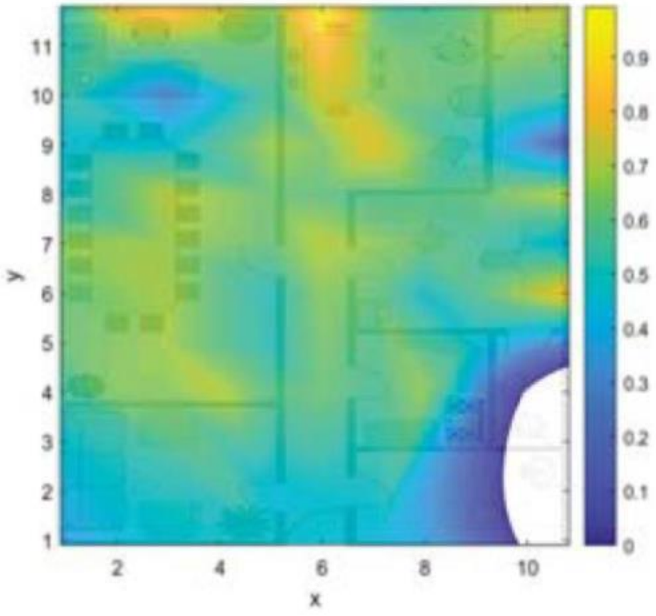


IDEA

Challenge: Device Heterogeneity



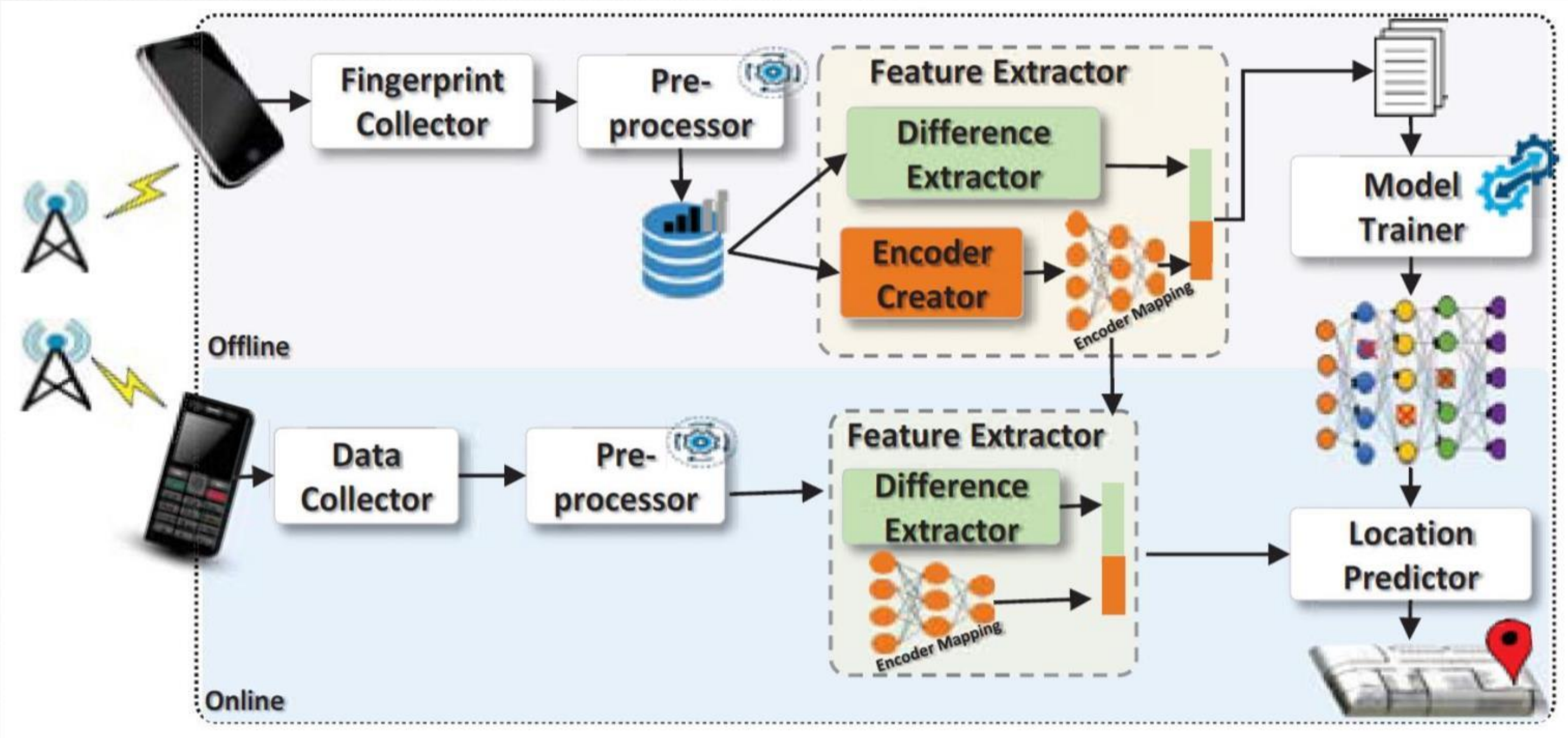
(a) HTC One X9 phone.



(b) Motorola Moto G5 phone.

Fig. 1. Heatmaps of the normalized RSS received by different phones from an arbitrary cell tower in the area of interest.

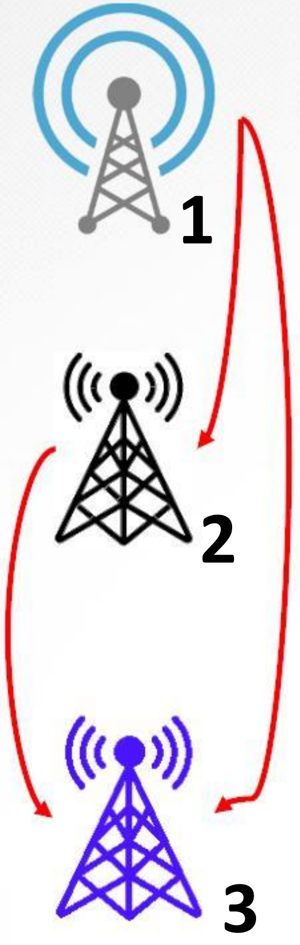
OmniCells



Fingerprint Collector
Pre-processor
Feature Extractor
Difference Extractor
Encoder Creator
Encoder Mapping
Model Trainer
Offline
Data Collector
Pre-processor
Feature Extractor
Difference Extractor
Encoder Mapping
Location Predictor
Online

The Proposed System – Feature Extractor

- Difference



5	9
7	11
12	16

$\Delta_{12} = 2$

$\Delta_{13} = 7$

$\Delta_{23} = 5$

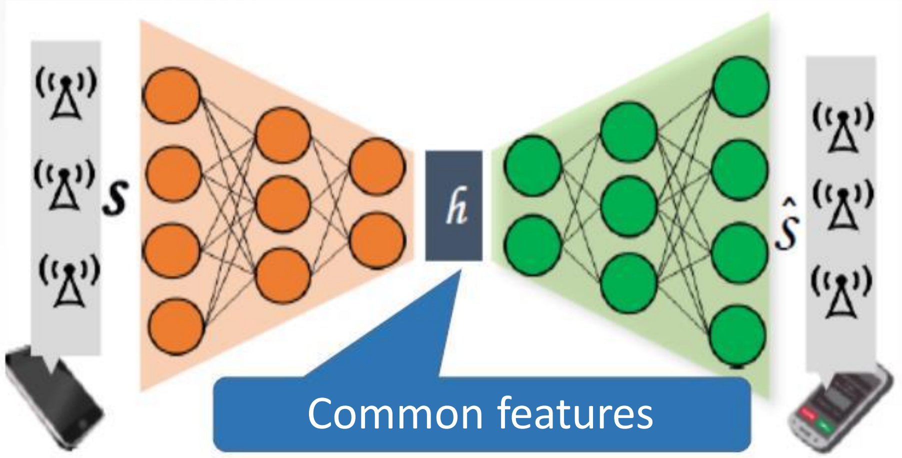
OmniCells – Feature Extractor

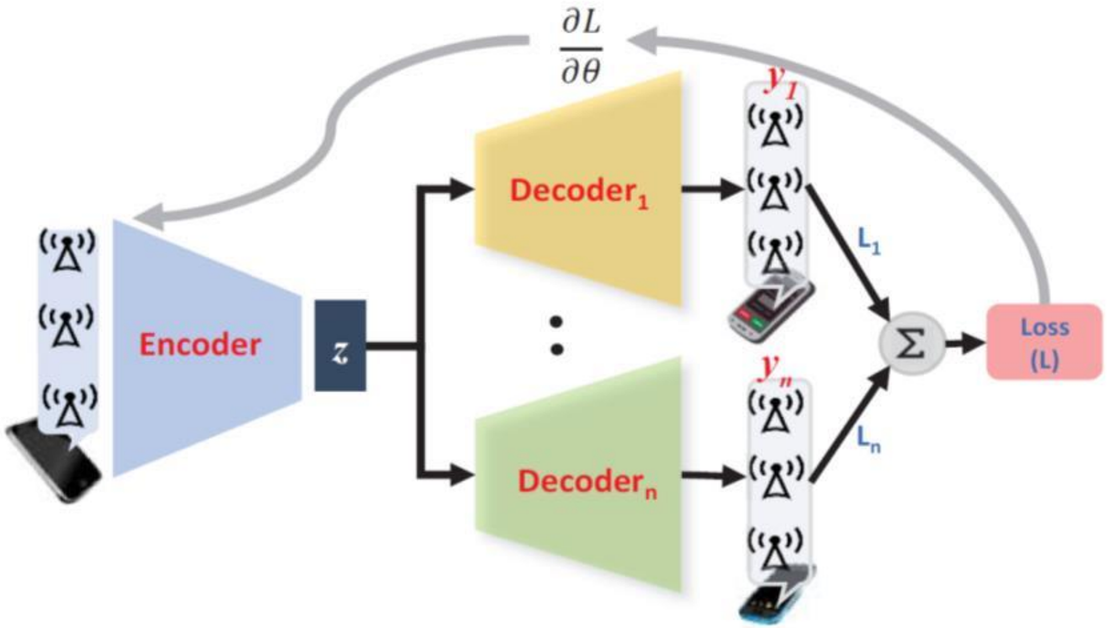
❑ Encoder-Decoder Model is used.

- **Encoder:** encodes the RSS input vector.
- **Decoder:** reconstruct the input.

- The sensed RSS $s = x + \epsilon$

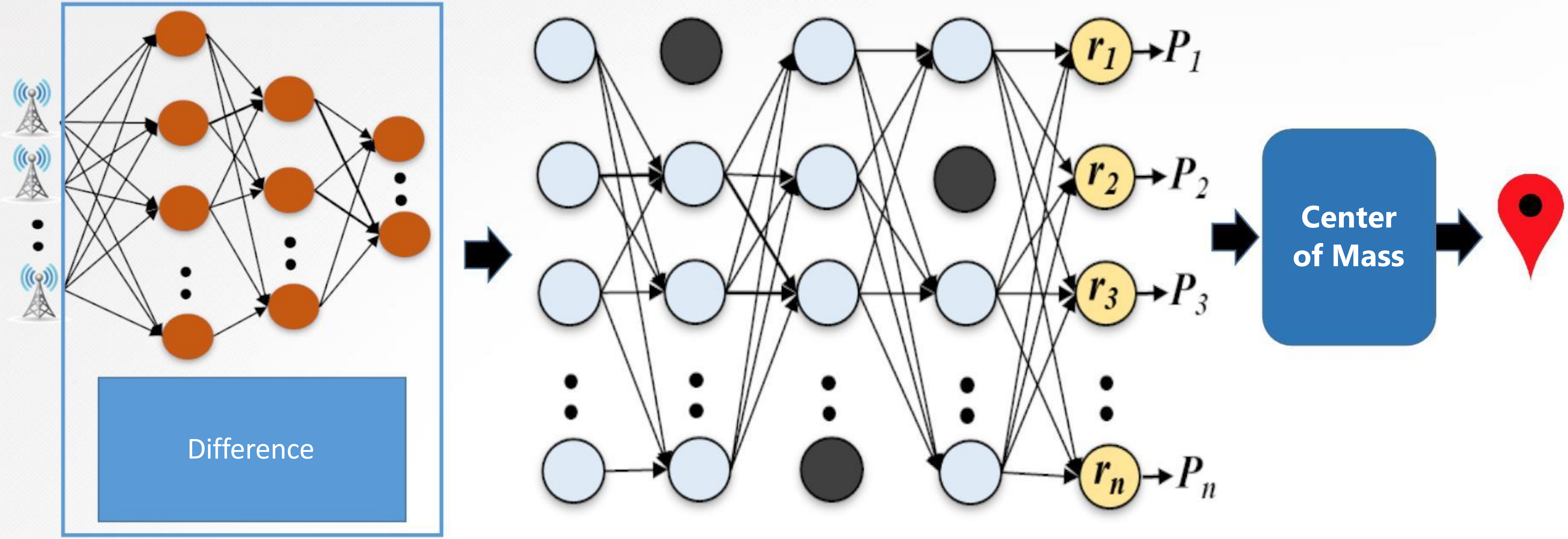
- **Training:** using different target phone.





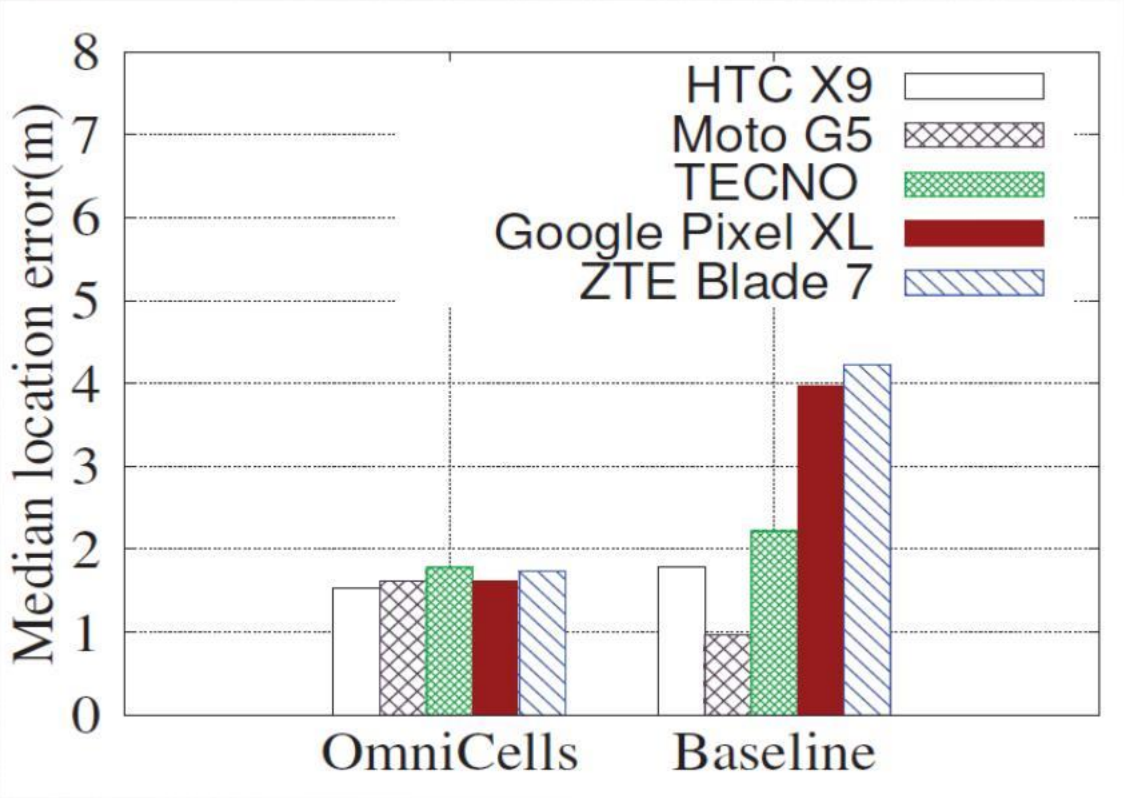
OmniCells – Online Predictor

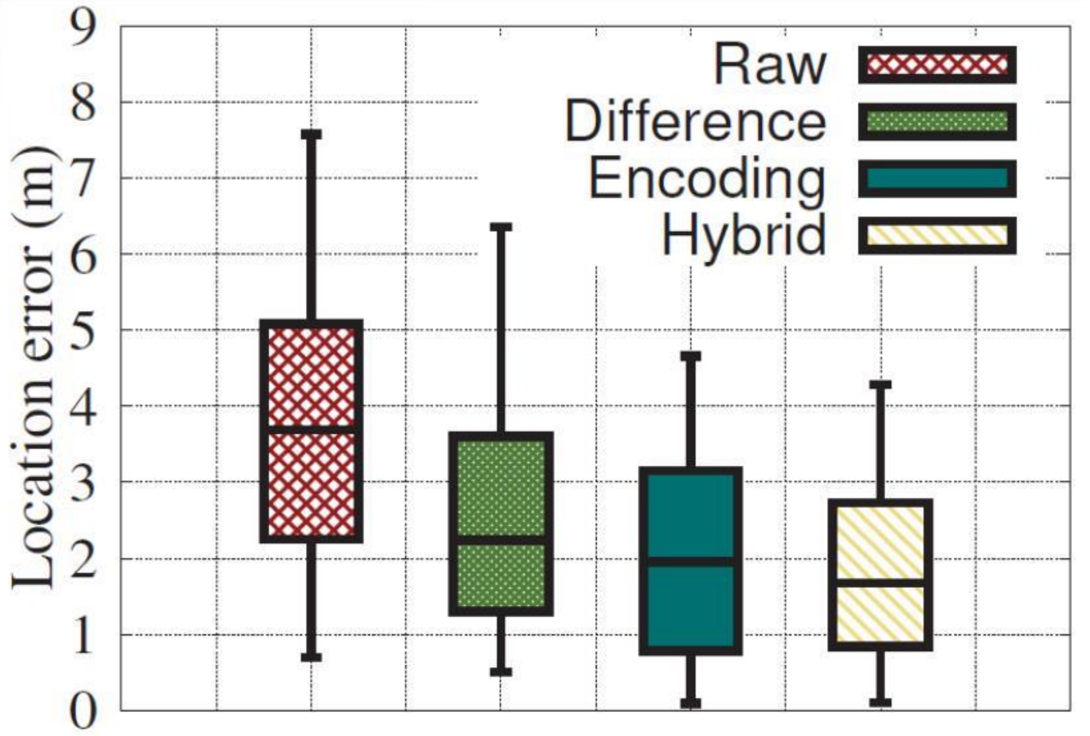
Aims to track the user in continuous space.



The accuracy is then enhanced by performing Map-matching

Evaluations

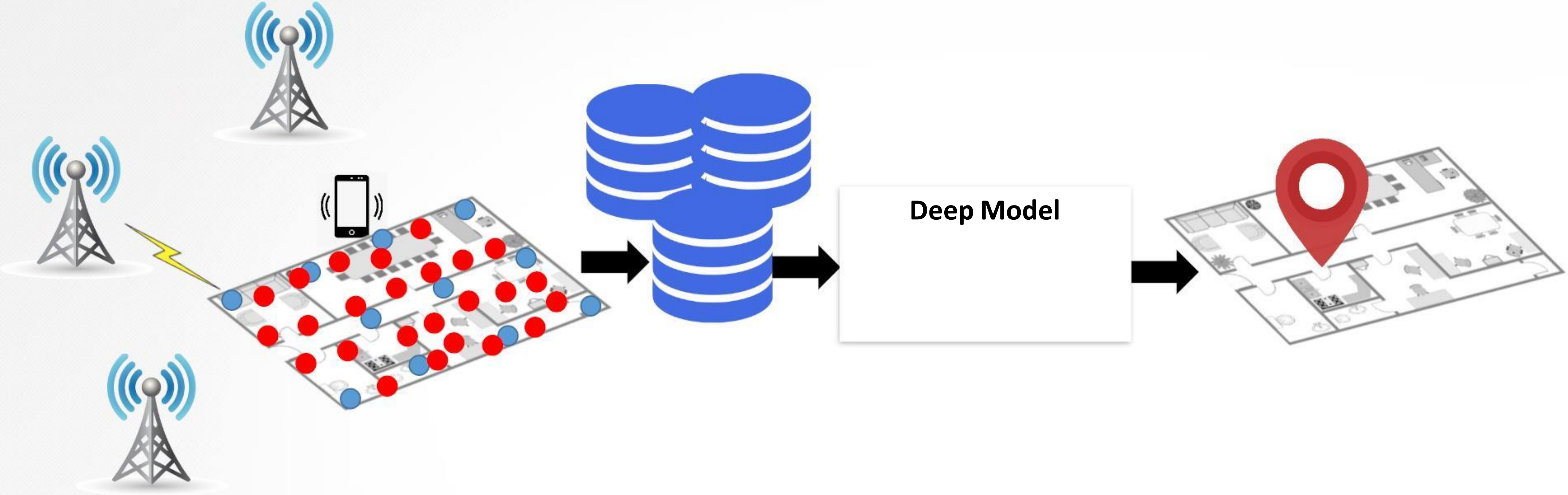




MonoDCell: A Ubiquitous and Low-Overhead Deep Learning-based Indoor Localization with Limited Cellular Information

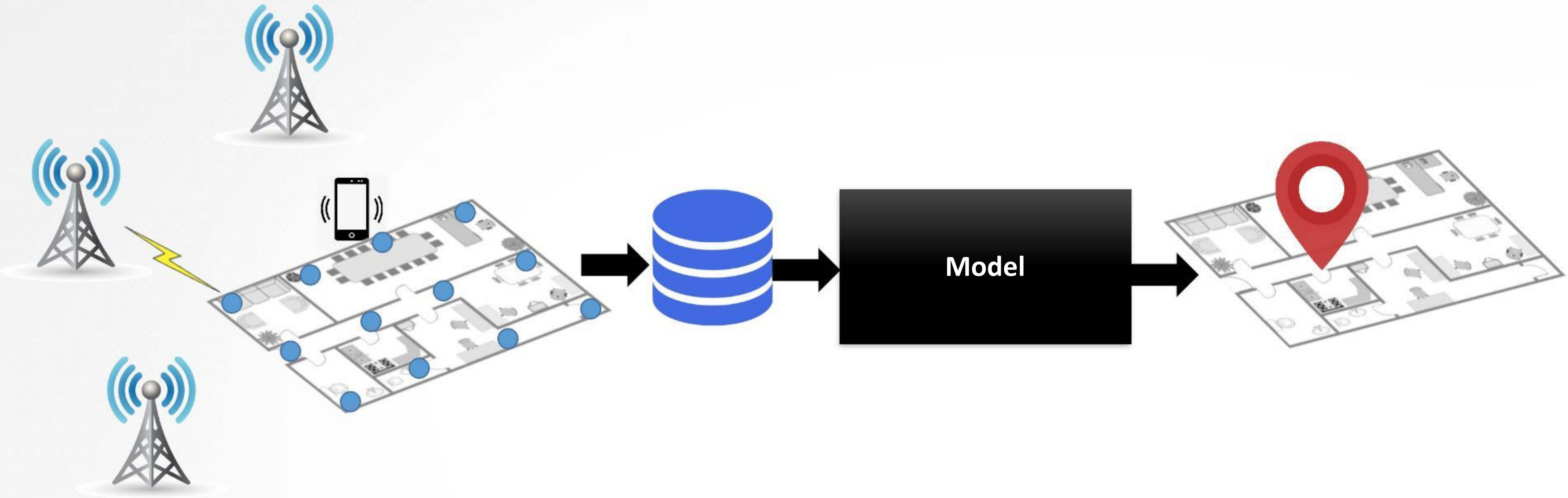
Challenges

- Dense fingerprinting usually enhances the performance.
- This may negatively affect the deployment at scale.

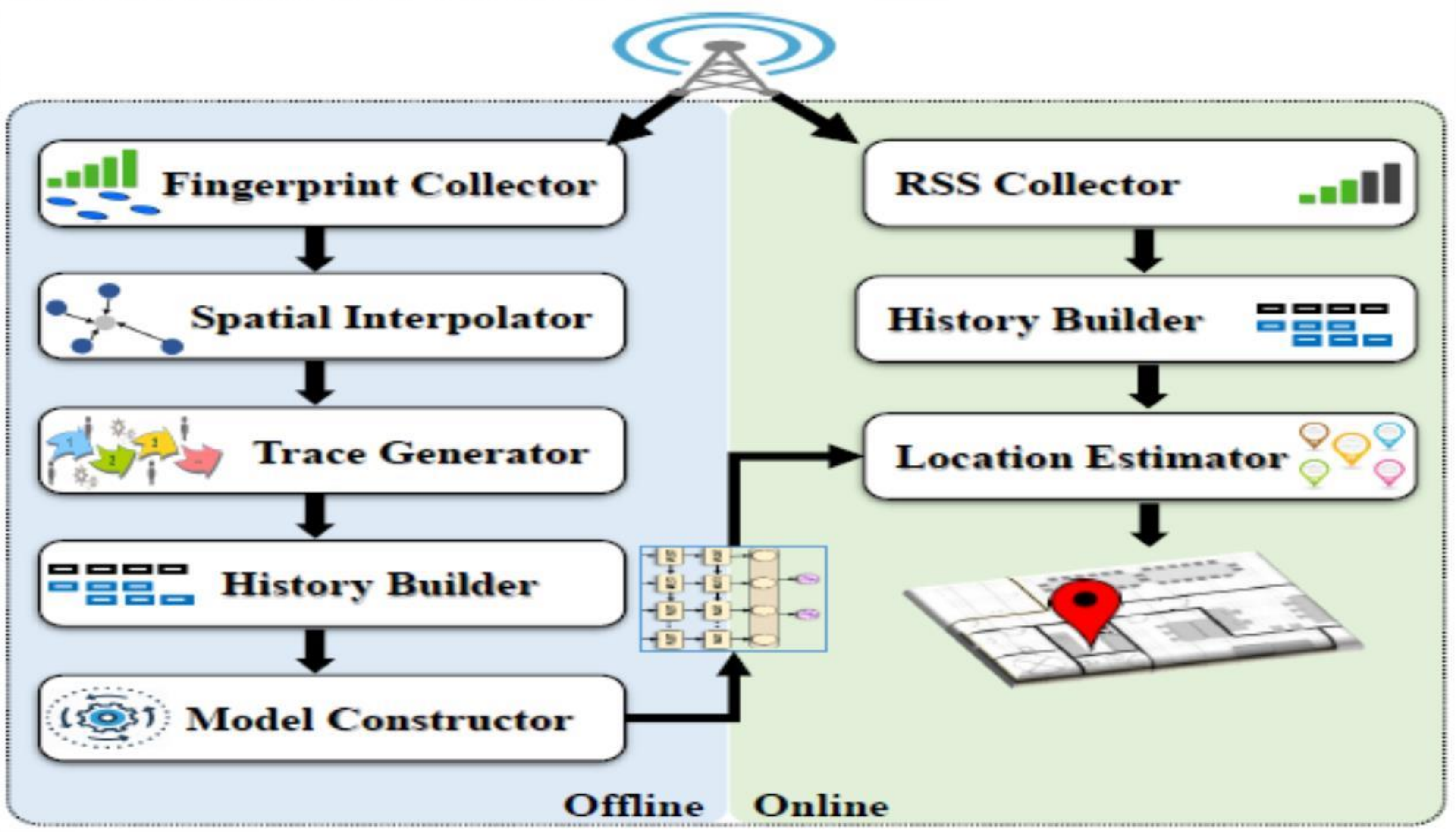


Challenge

Majority of cell phones usually report only the associated cell tower information.



MonoDCell



Fingerprint Collector
Spatial Interpolator
Trace Generator
History Builder
Model Constructor
RSS Collector
History Builder
Location Estimator
Offline
Online

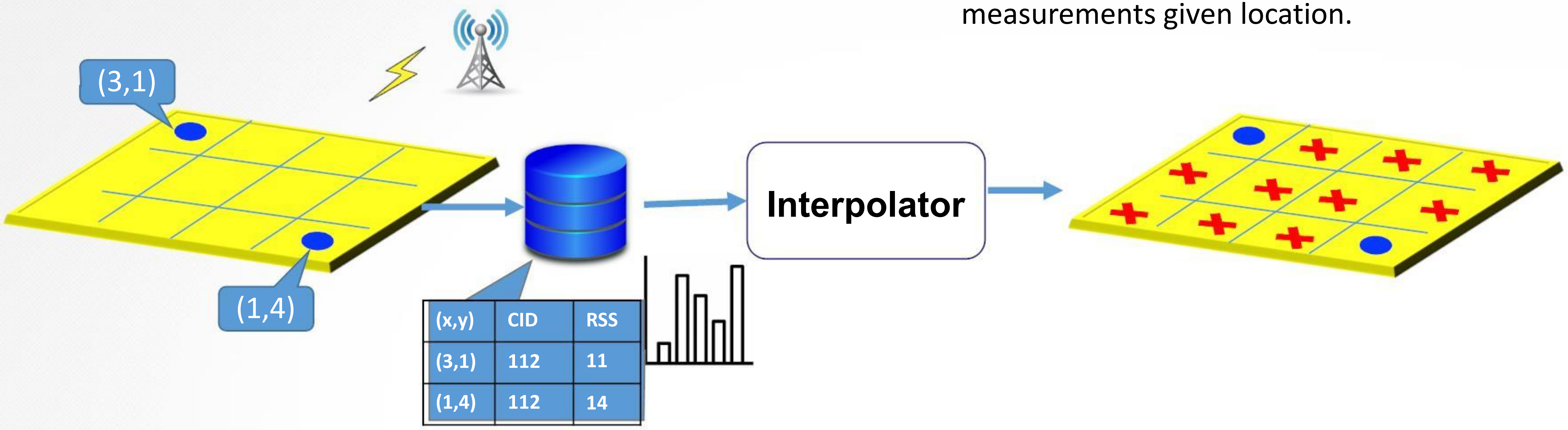
MonoDCell

1 Fingerprinting at few points

- Using a sensing App to record (CID,RSS) .

2 Spatial Augmentation

- KNN regressor is leveraged to produce cell measurements given location.



(x,y)	CID	RSS
(3,1)	112	11
(1,4)	112	14

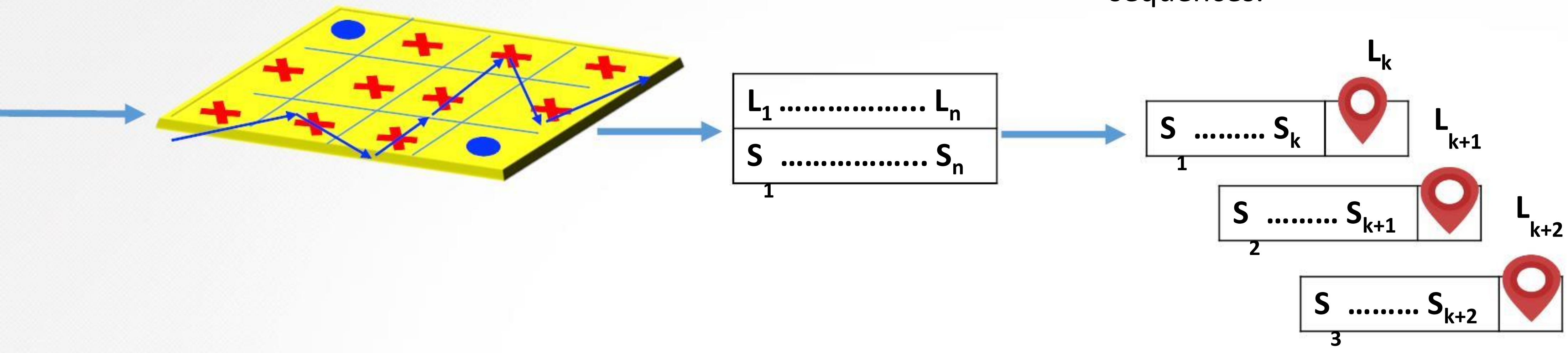
MonoDCell

3 Trace Construction

- Using Markov Model.

4 Sequence Formation

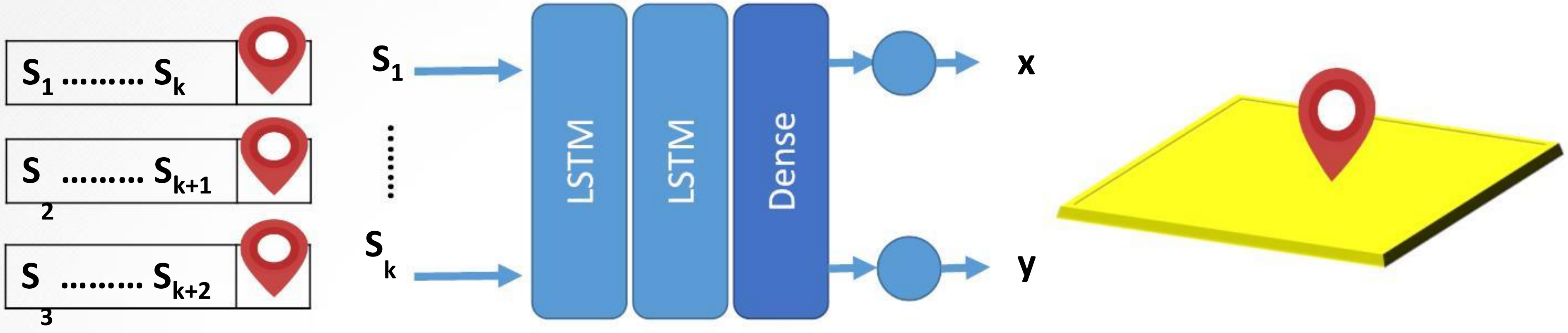
- Segmenting the trace into k-length sequences.



MonoDCell

5 Model Trainer

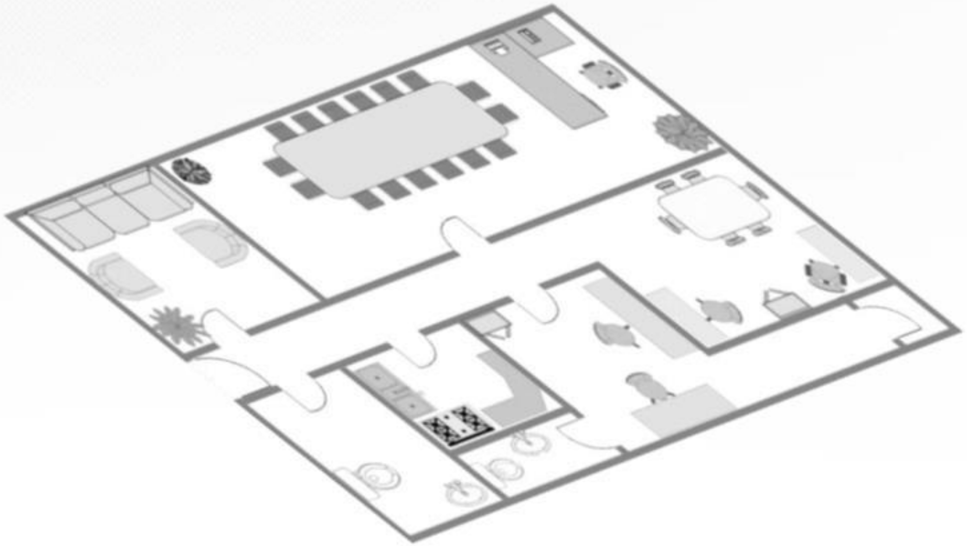
- RNN characterize the sequential nature of the input data.
- The input data is the historical RSS from the associated cell towers.



History of the cellular information **RNN**

Evaluation

Method	Precision
Area	132m^2
Num. of points	55
Num. of training samples / point	3000
Testing	30% unseen
Num. of participants	4
Num. of the considered phones	5

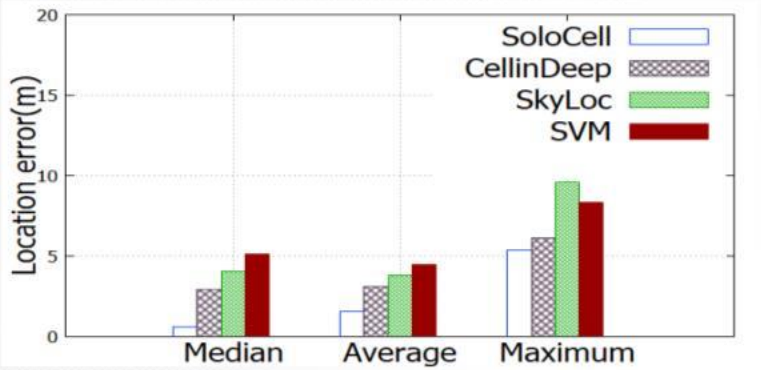


HTC ZTE

Tecno Pixel Moto

Evaluation

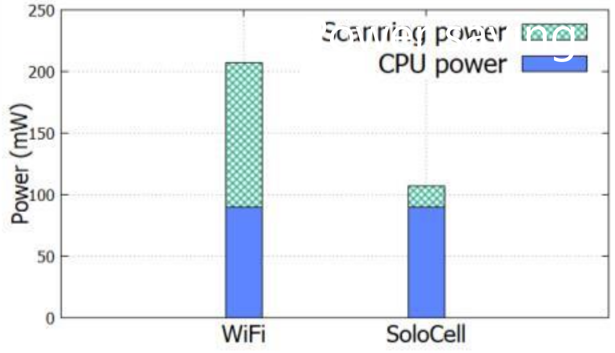
202% better median localization accuracy.



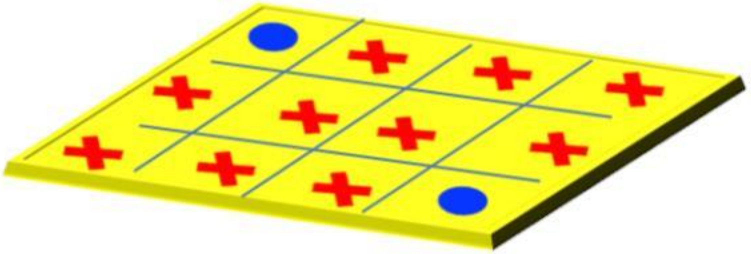
Technique	*Median*	*Average*	*Maximum*
SoloCell	**0.95**	**1.58**	**5.39**
CellinDeep [5]	2.95 (-210%)	3.08 (-95%)	6.14 (-7.7%)
SkyLoc [2]	4.03 (-324%)	3.84 (-143%)	9.61 (-69%)
SVM [7]	5.13 (-440%)	4.49 (-184%)	8.35 (-46%)

MonoDCell

93%

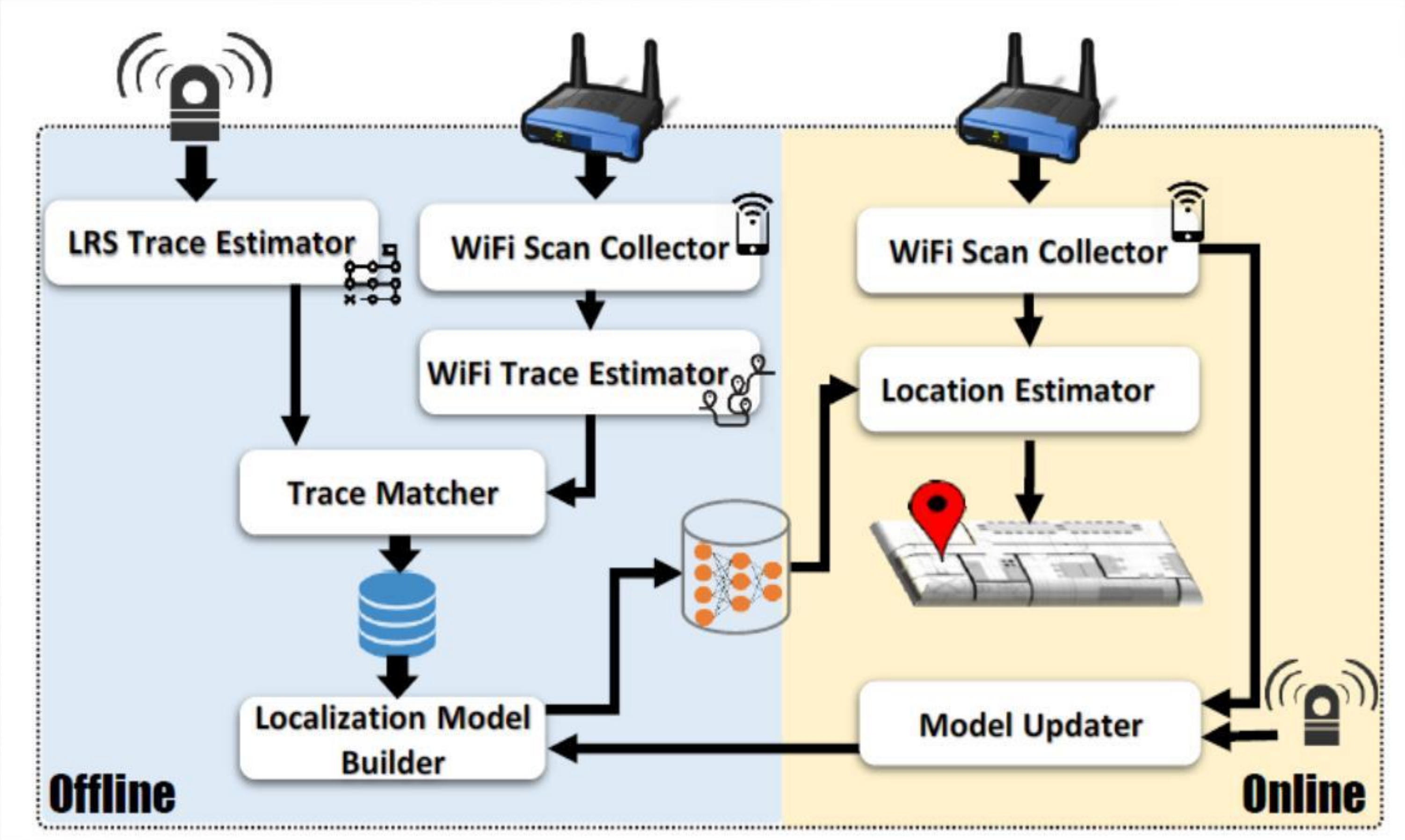


30% Saving of the fingerprinting time.

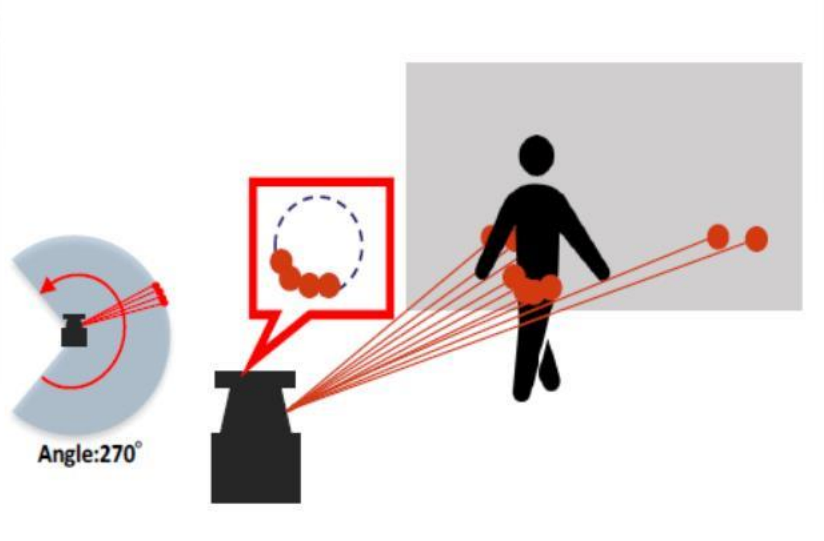


Gain Without Pain: Enabling Fingerprinting-based Indoor Localization using Tracking Scanners

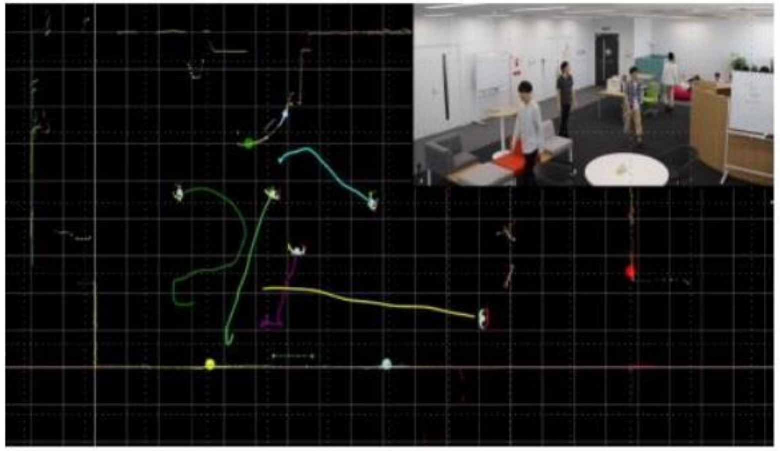
LiPhi



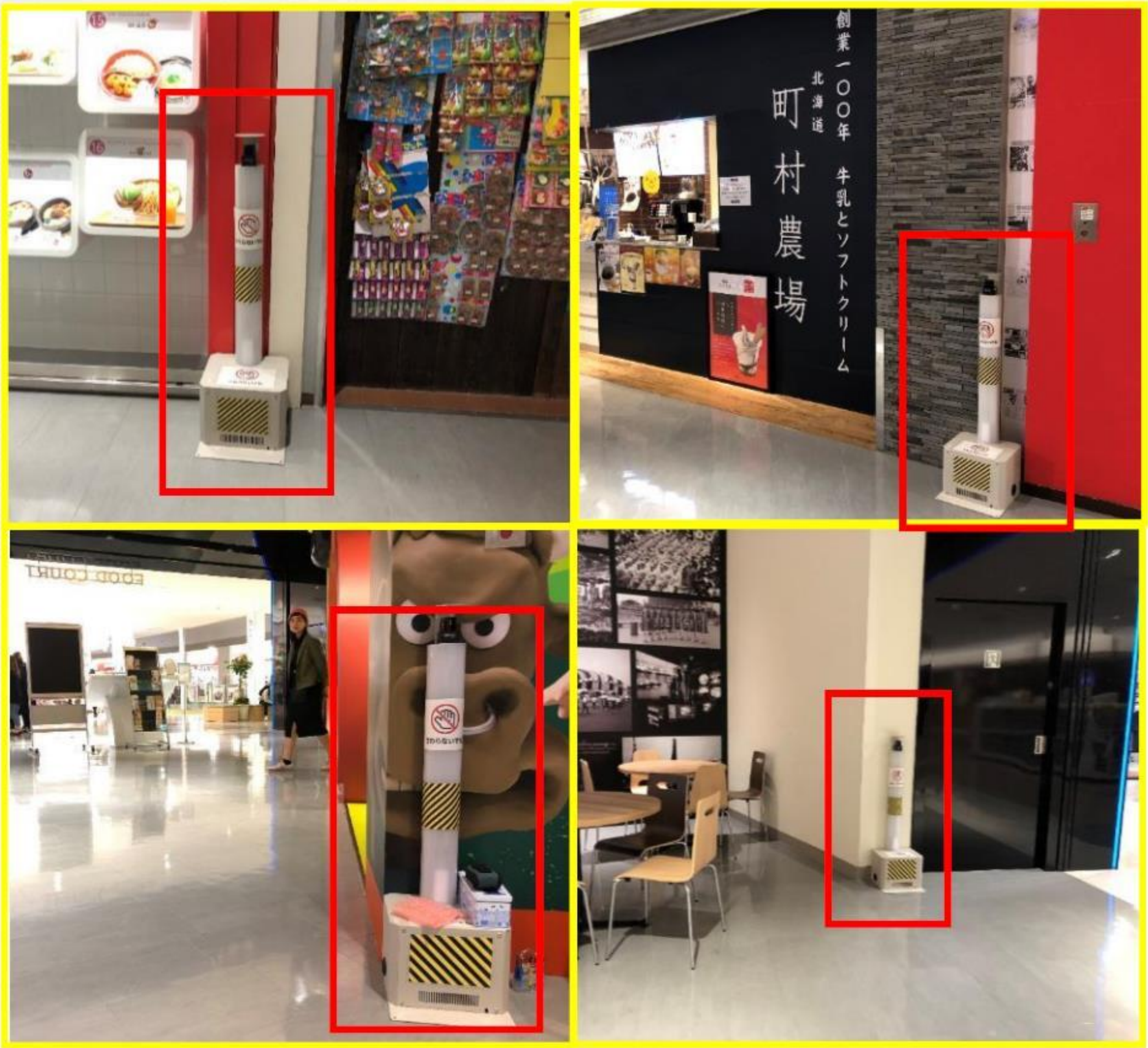
LRS Trace Estimator
WiFi Scan Collector
WiFi Trace Estimator
Trace Matcher
Localization Model Builder
Offline
WiFi Scan Collector
Location Estimator
Model Updater
Online

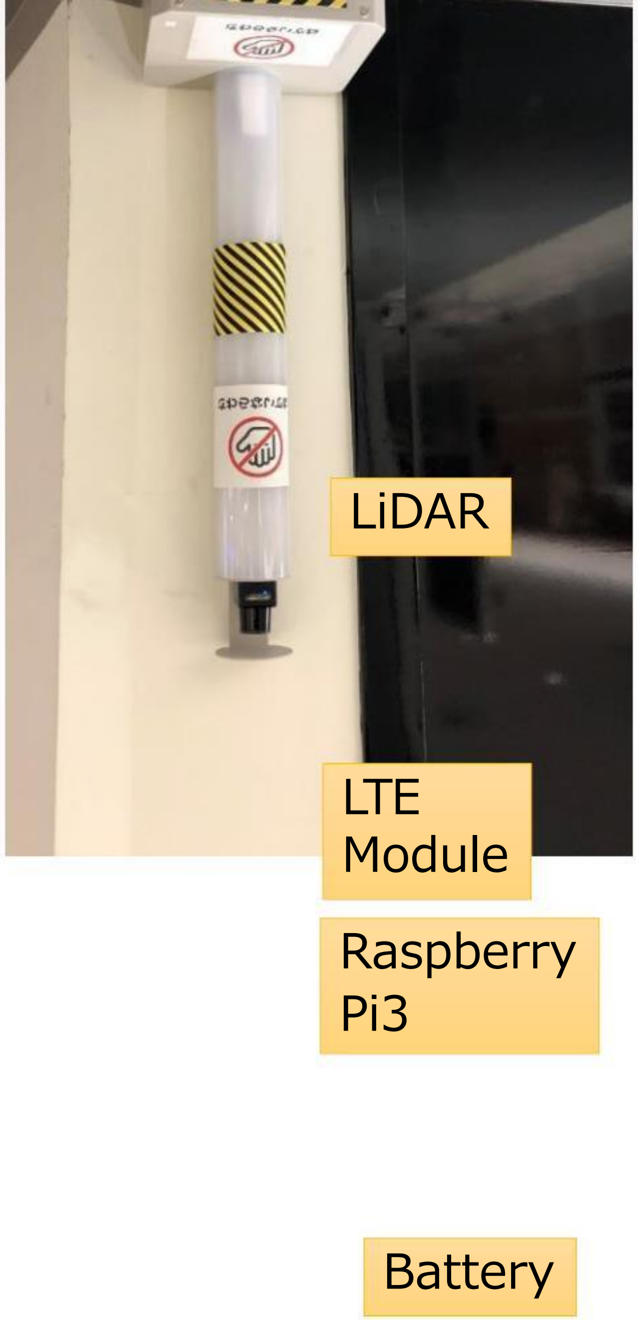


Angle:270°



LiPh for Smart Mall





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