On the Multi-Dimensional Augmentation of Fingerprint Data for Indoor Localization in a Large-Scale Building Complex Based on Multi-Output Gaussian Processes

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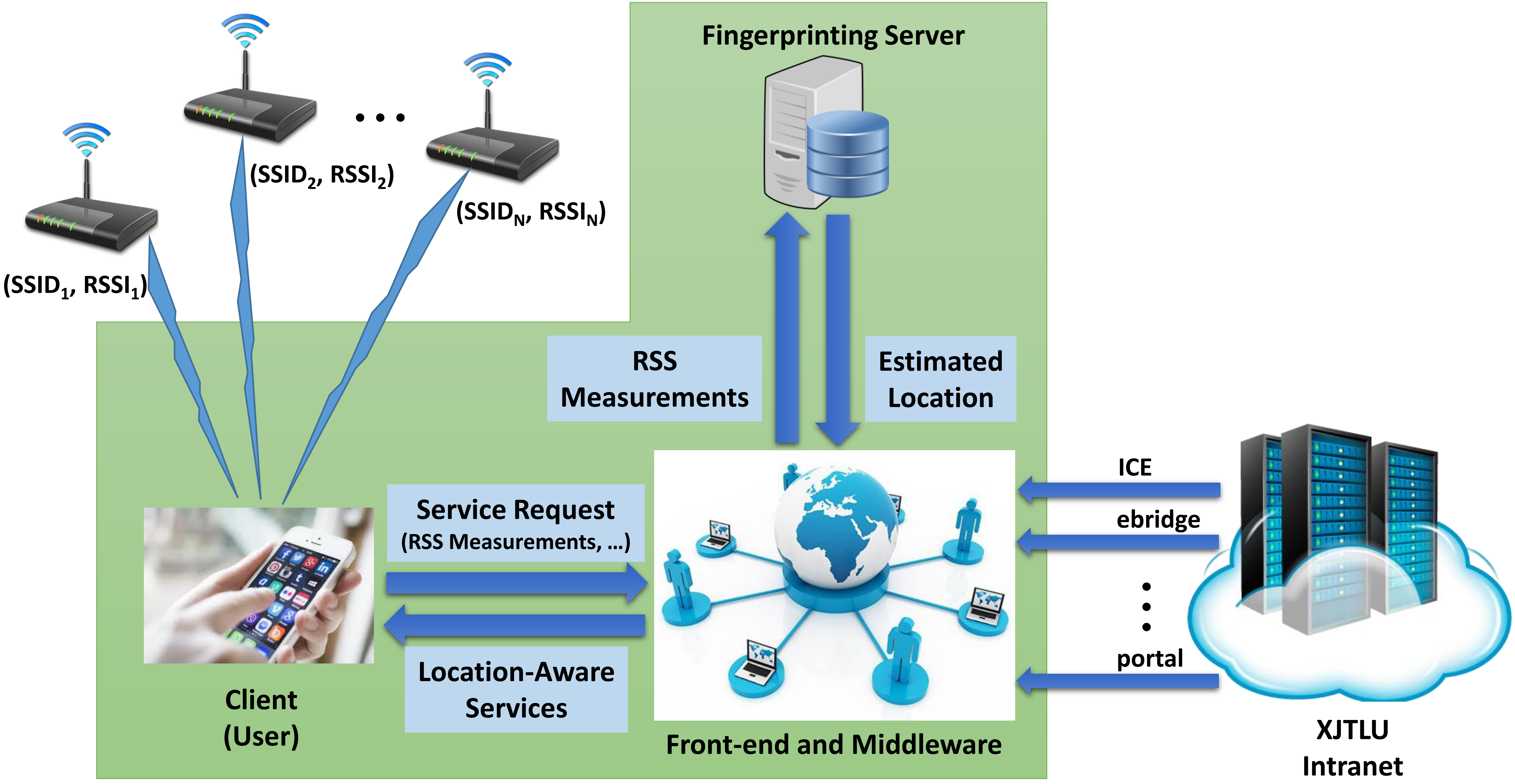
Outline

- Large-Scale Multi-Building Multi-Floor Indoor Localization
- Wi-Fi Fingerprinting
- Multi-Dimensional Fingerprint Data Augmentation Based on MOGP
- Experimental Results
- Conclusions and Future Work

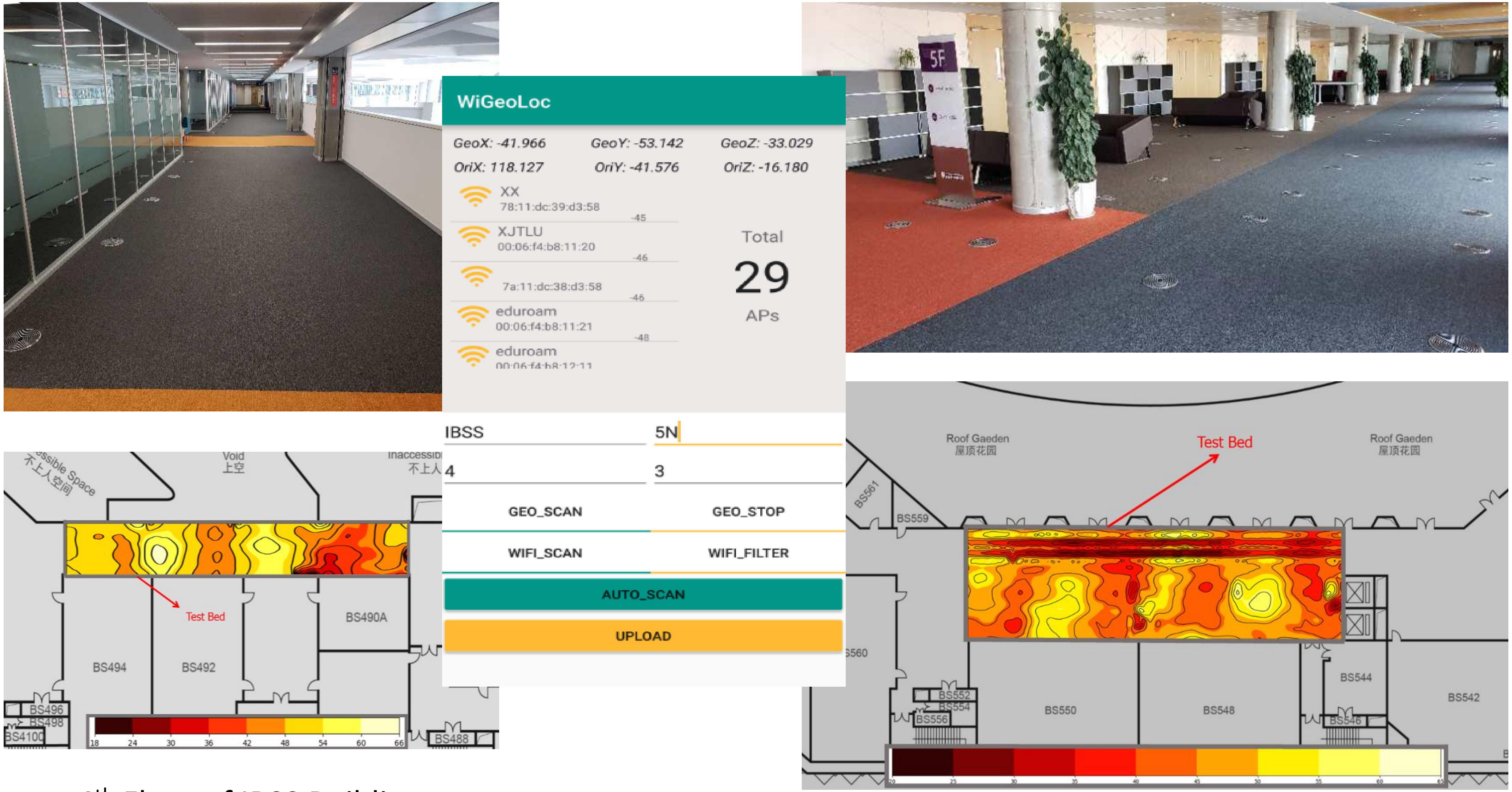
Large-Scale Multi-Building Multi-Floor Indoor Localization



XJTLU Camus Information and Visitor Service System

Examples: Indoor Navigation and Location-Aware Service

Multi-Floor Indoor Localization with RSSI/Geomagnetic Field*

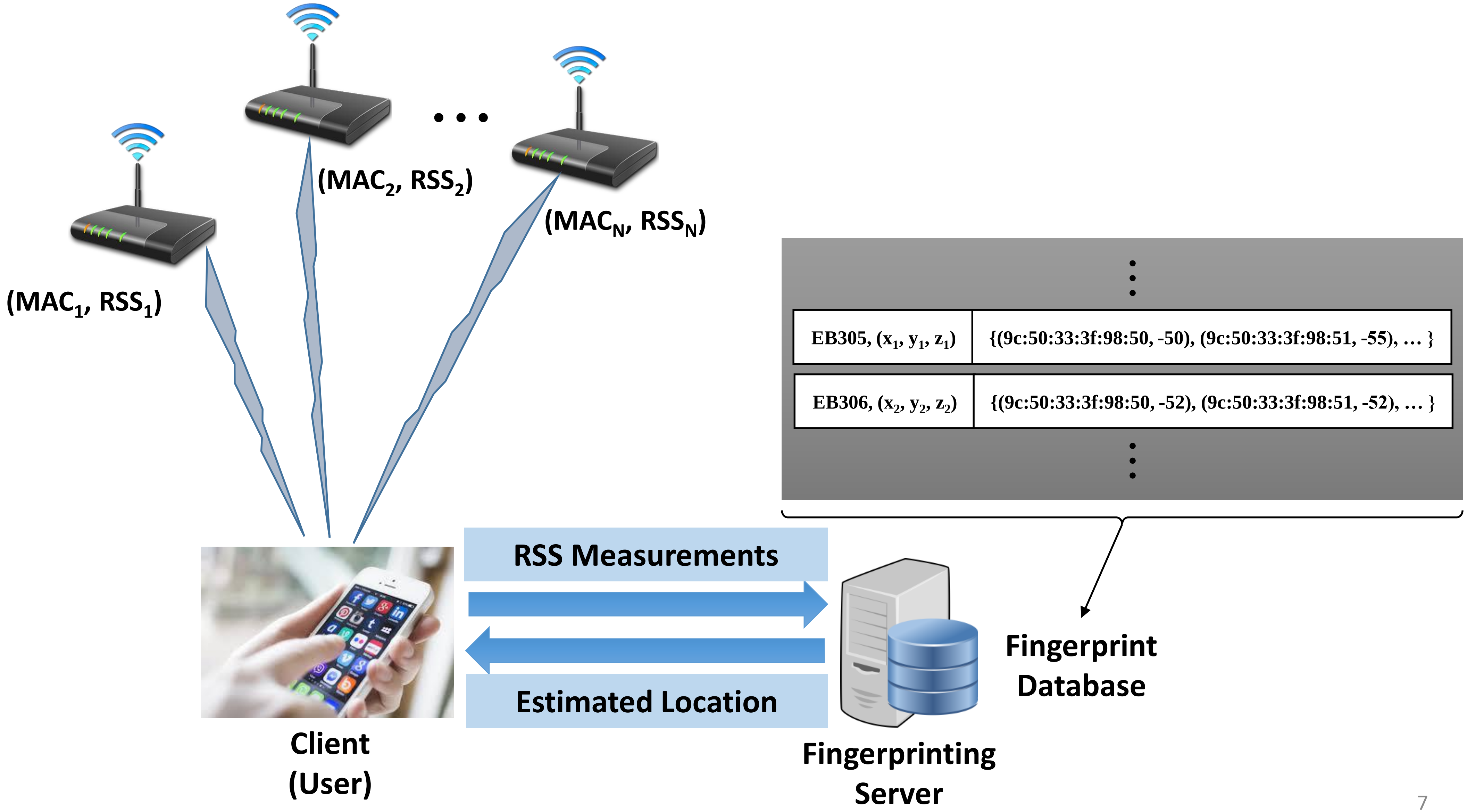


4th Floor of IBSS Building

5th Floor of IBSS Building

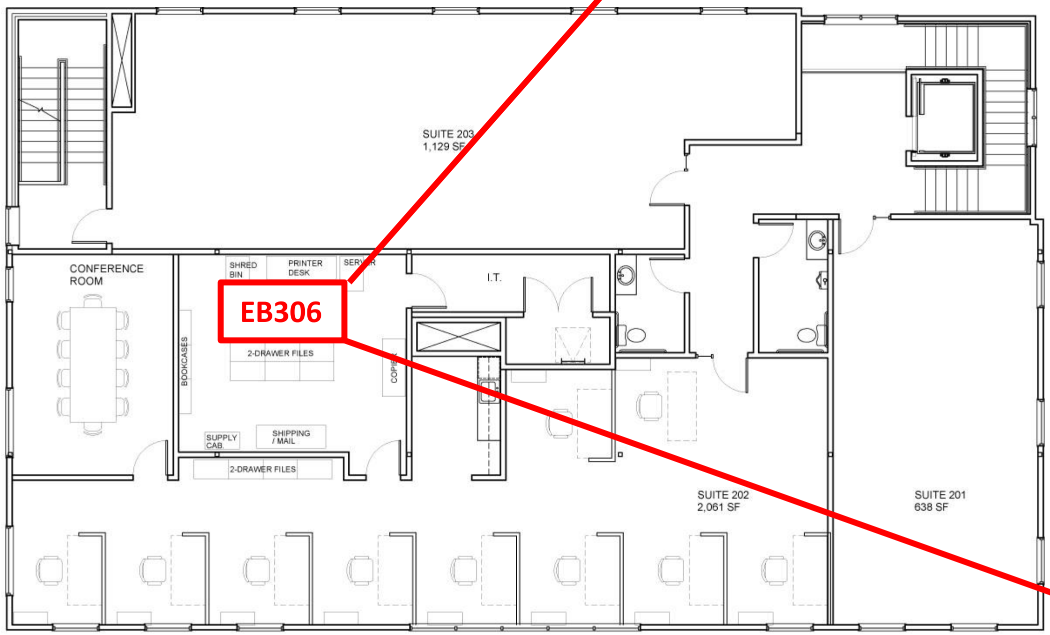
* Z. Zhong et al., "[XJTLUIndoorLoc: A new fingerprinting database for indoor localization and trajectory estimation based on Wi-Fi RSS and geomagnetic field]," Proc. 2018 CANDAR, Takayama, Japan, Nov. 27–30, 2018.

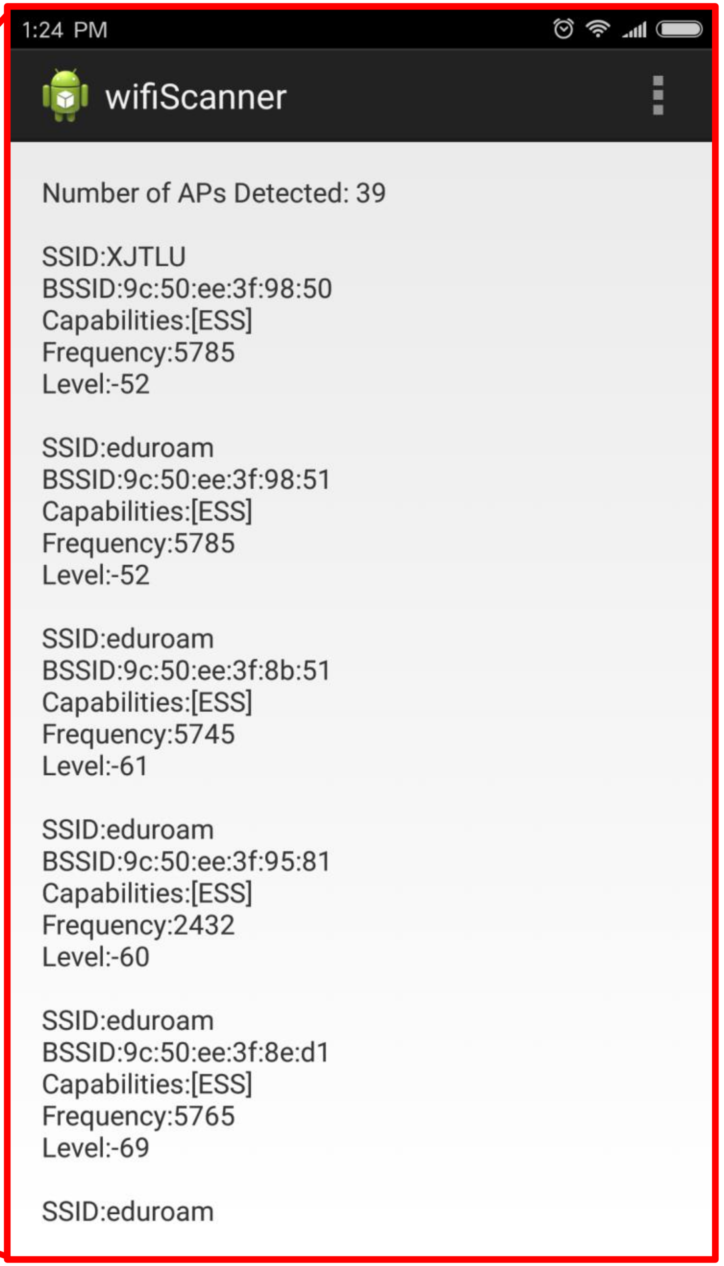
Indoor Localization based on Wi-Fi Fingerprinting



Location Fingerprint

- A tuple of $(\mathcal{L}, \mathcal{F})$
  - $\mathcal{L}$: Location information
    - Geographic coordinates or a label (e.g., “EB306”)
  - $\mathcal{F}$: Vector/function of *received signal strength Indicators (RSSIs)*
    - e.g., $(\rho_1, \cdots, \rho_N)^T$ where ρ_i is the RSSI from i_{th} access point (AP_i).





Challenges

Scalability

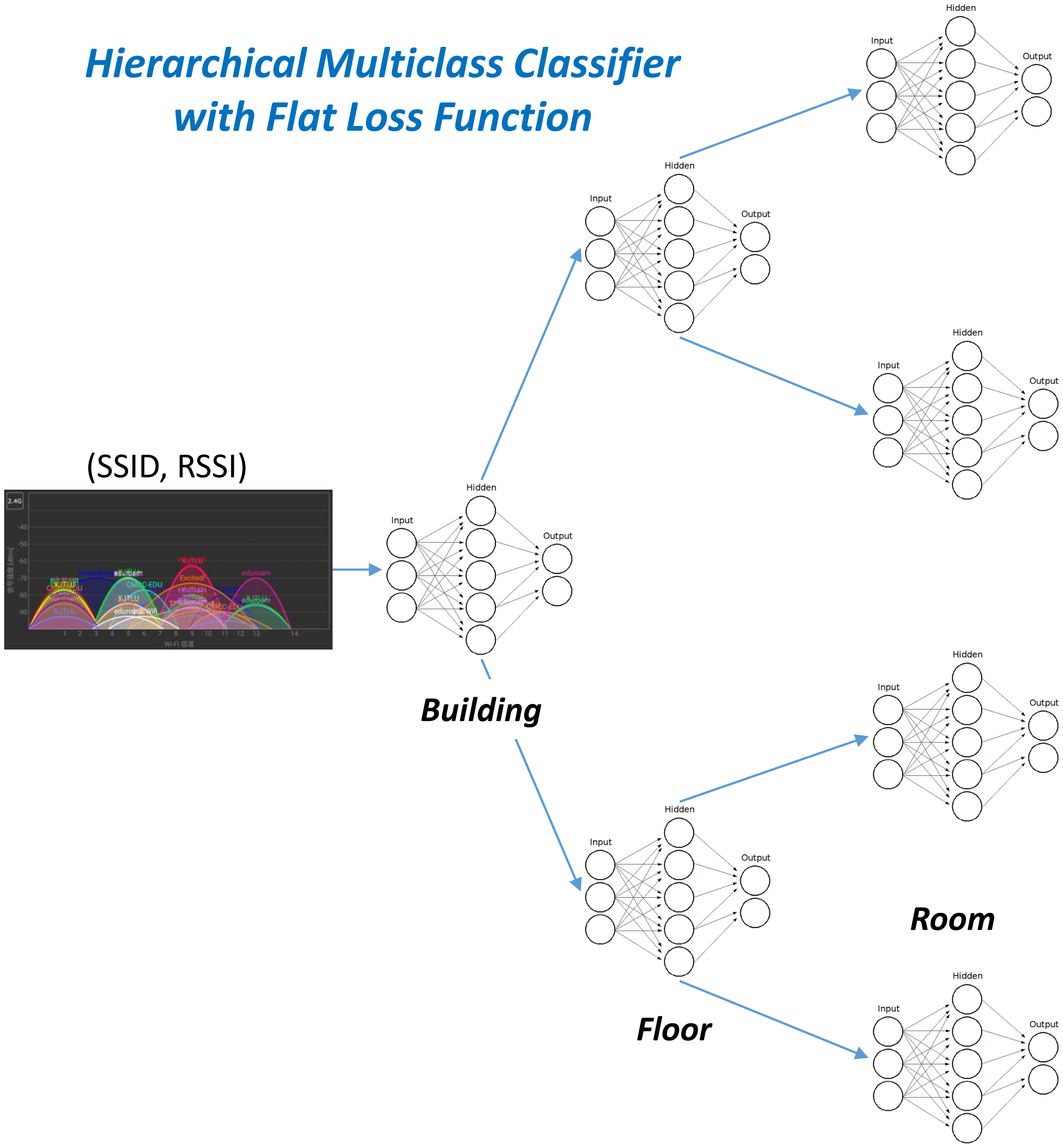
Long-Term Service

Major Challenges in Large-Scale Implementation

- ***Scalability***
  - Localization models
  - Fingerprint DB construction
- ***Localization accuracy***
- ***Non-stationarity*** of location fingerprints
  - Incremental/online learning algorithms with pruning/forgetting mechanisms*
- Passive vs. active location estimation
- Integration with other services
- Security/privacy issues

** R. Elwell and R. Polikar, "Incremental learning in nonstationary environments with controlled forgetting," Proc. IJCNN'09.*

Hierarchical Multiclass Classifier with Flat Loss Function



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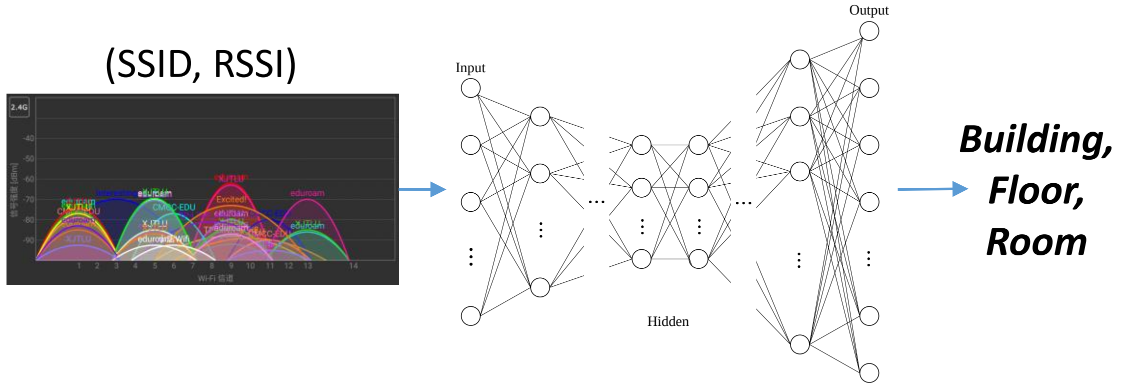
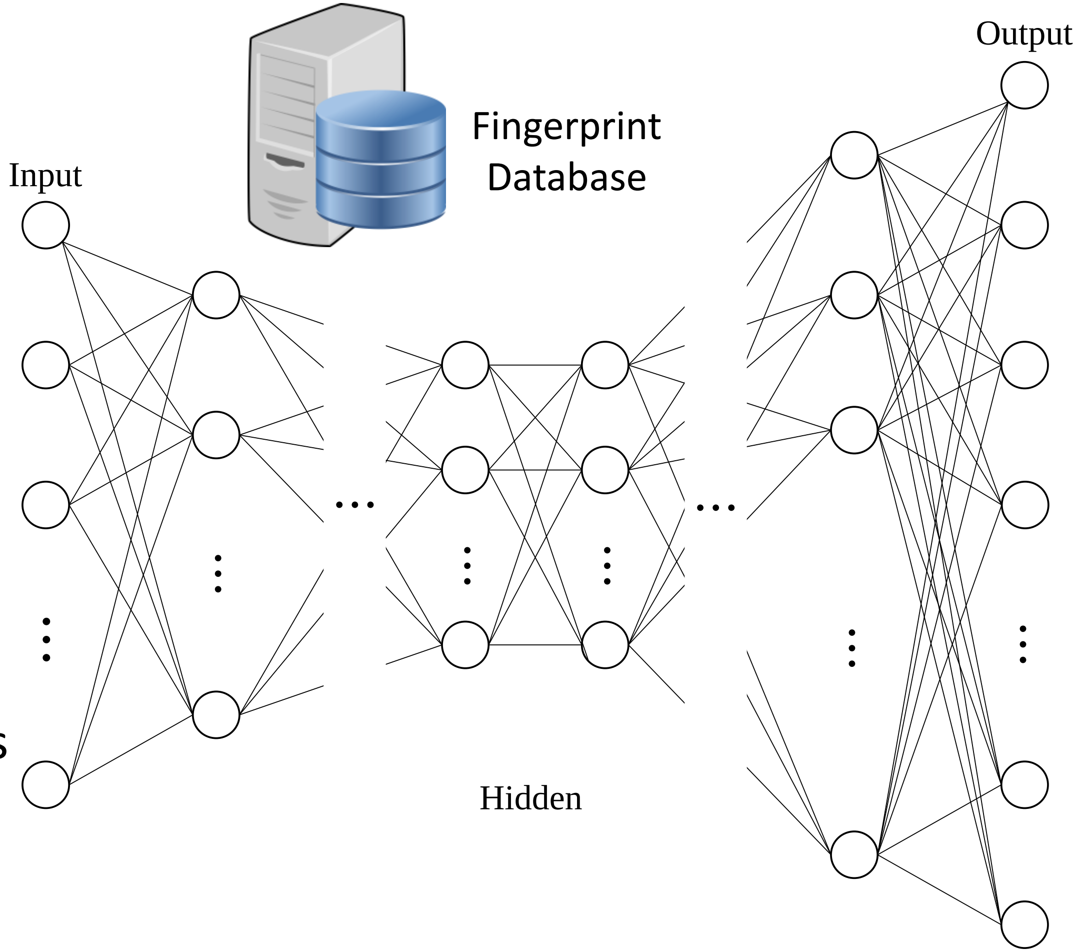
Flat Multiclass Classifier with Hierarchical Loss Function

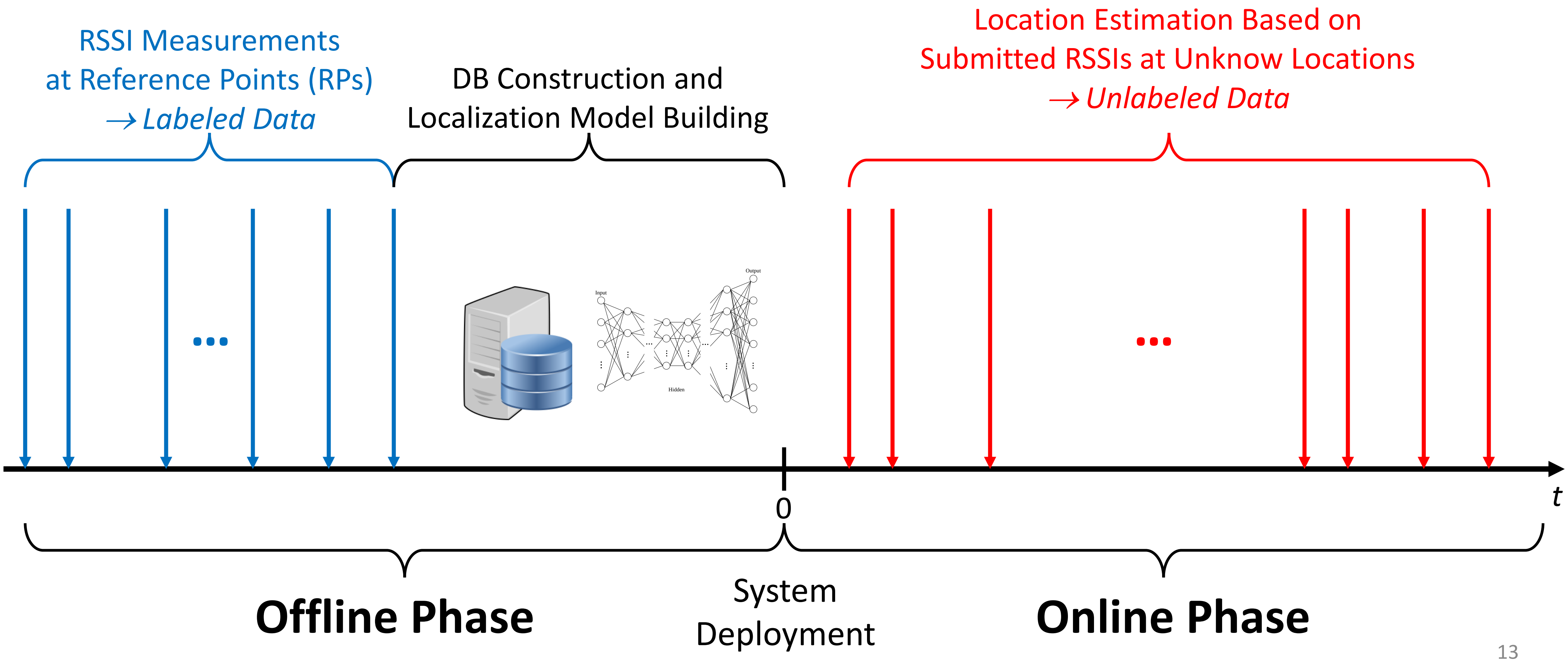


Scalability

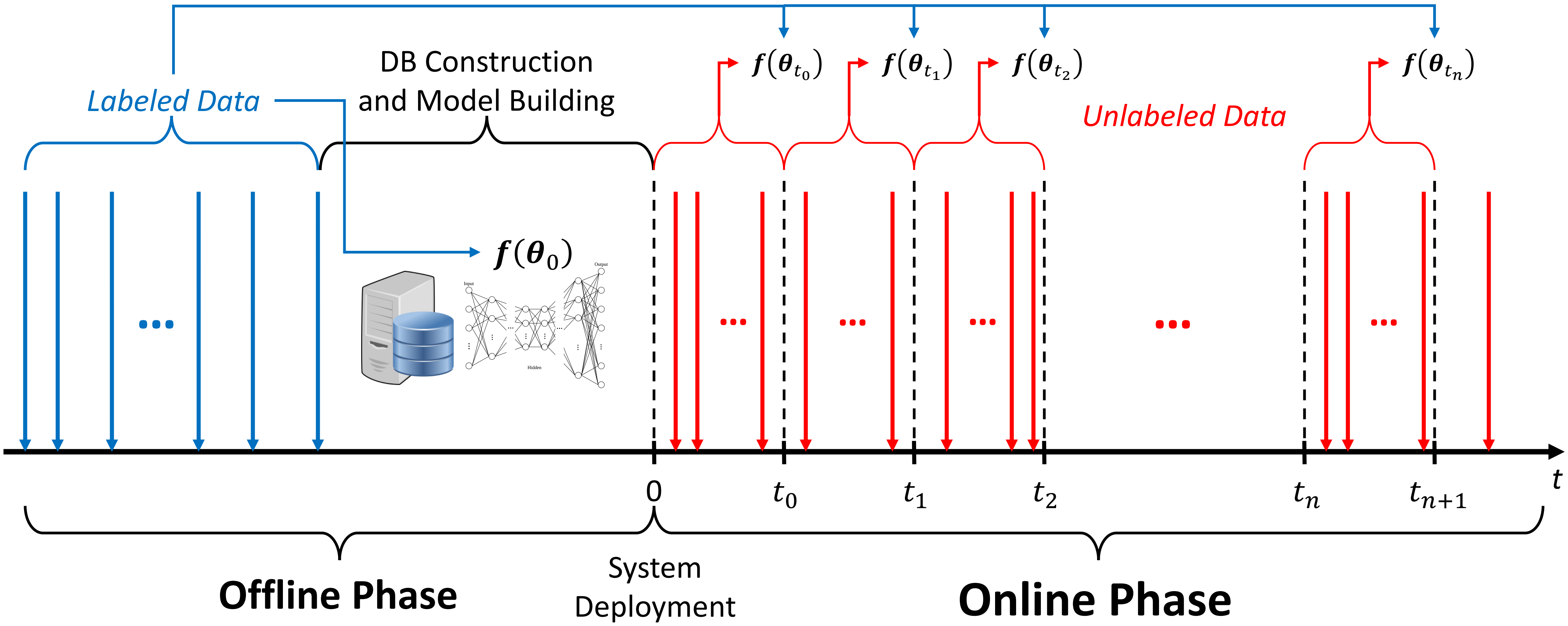
- **Output scalability**
  - The number of RPs, which is related to the number of output nodes and the number of trainable parameters of NN models.
- **Data scalability**
  - A large amount of manpower is required for the construction of a large-scale fingerprint database.
    - Even much larger under the current pandemic situations.
- **Input scalability**
  - The dimension of input data (e.g., RSS vector), which is related to the number of input nodes and, again, the number of trainable parameters of NN models.



Long-Term Service



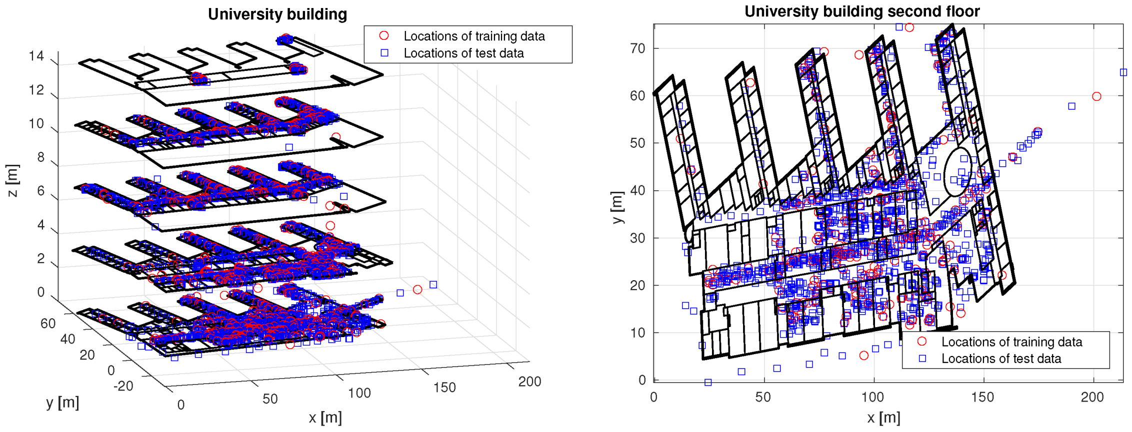
Investigation of Time Variability of RSSI Fingerprints: Exploiting Unlabeled Data During Online Phase



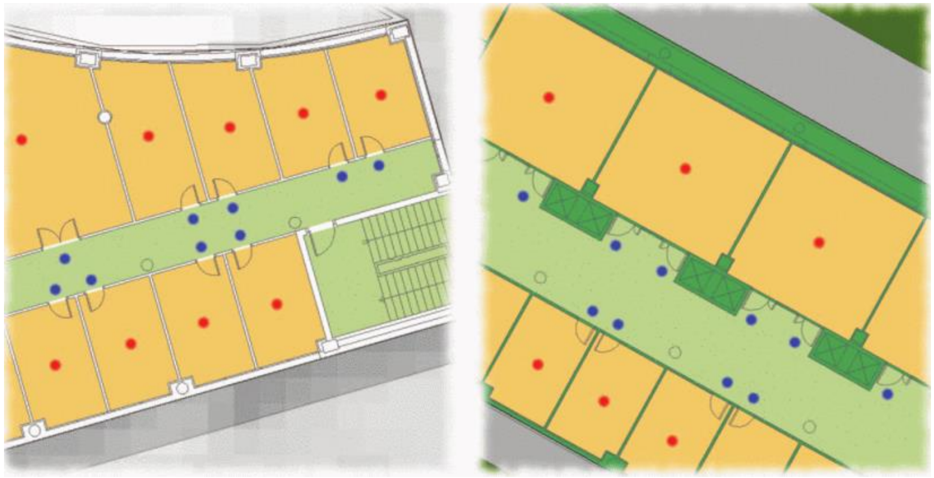
Multi-Dimensional Fingerprint Data Augmentation Based on MOGP

Reasons for Fingerprint Data Augmentation*

- Uneven spatial distributions of RPs.
  - These could lead to a large difference in positioning accuracy among different buildings and floors.
- Areas that cannot be accessible for measurements.
  - e.g., personal offices, Labs requiring authorization for access.
- High cost of data collection.



(a) (b)



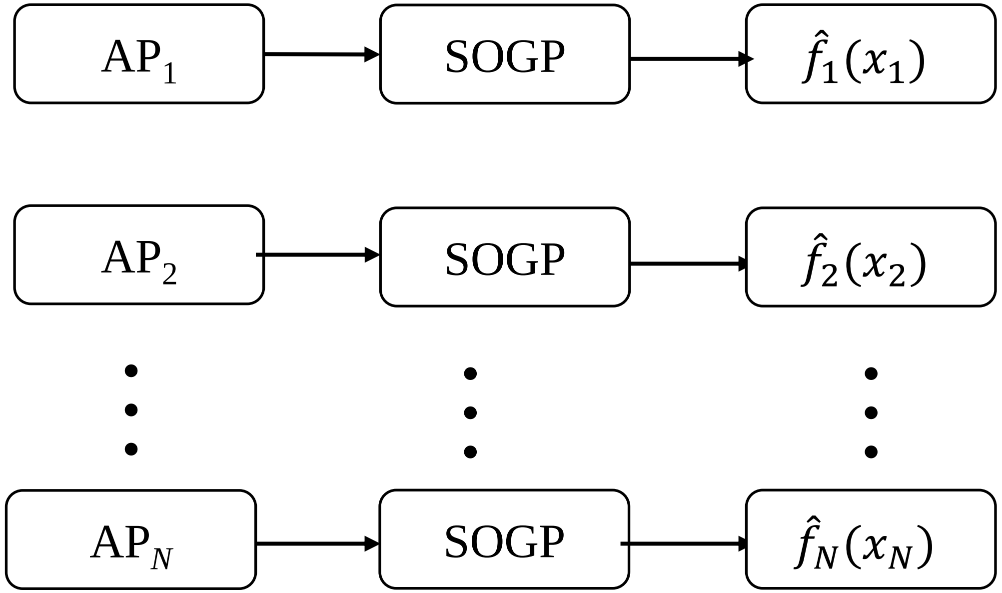
* Z. Tang, S. Li, K. S. Kim, and J. Smith, "[Multi-output Gaussian process-based data augmentation for multi-building and multi-floor indoor localization](#)," Proc. 2022 ICC Workshops, pp. 361-366, May 2022.

Neural Network (NN) vs. Gaussian Process (GP)

- NNs use adaptive basis functions or hidden units to learn hidden features of a problem.
- NNs, however, are not so easy to apply in practice due to many decisions like
  - Network architectures,
  - Activation functions,
  - Learning rate, and so on.
- There is the lack of a principled framework to answer these questions, too.

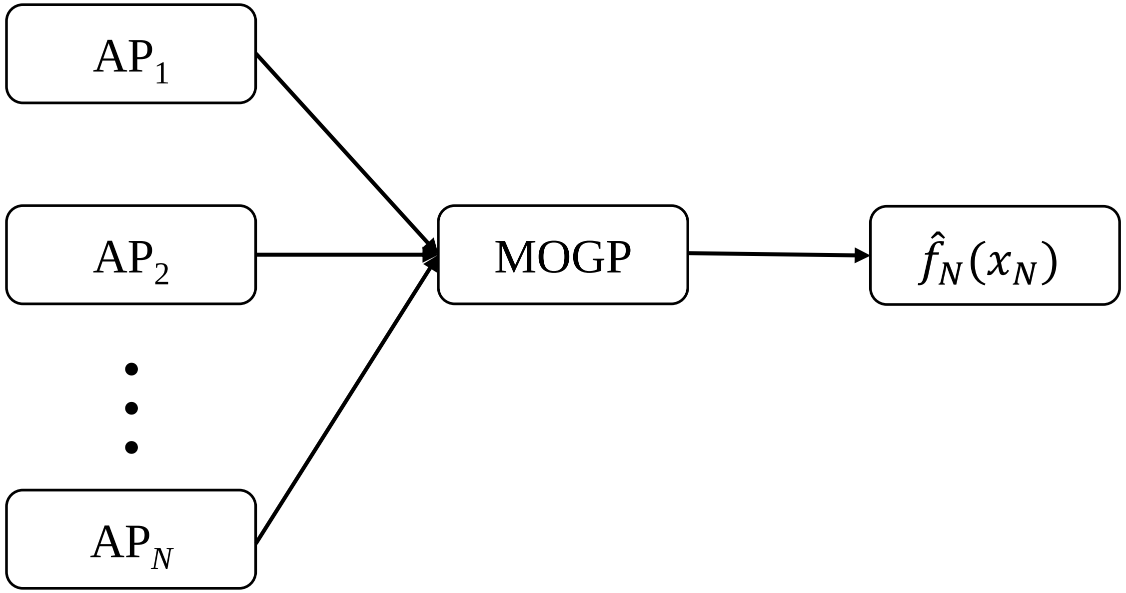
- GPs are mathematically equivalent to or closely related to well known models like
  - Bayesian linear models,
  - Spline models,
  - Large NNs (under suitable conditions),
  - Support vector machines (SVMs).
- GP models are easier to handle and interpret than NN models.
  - The hidden features of a problem could be captured by the covariance function (kernel) of GP.

Fingerprint Data Augmentation Based on GP



SOGP-Based.

vs.



MOGP-Based.

Multi-Output Gaussian Process (MOGP)

- For non sampled regions, GP regression can obtain linear unbiased prediction based on existing data, which is also called *Kriging* in geostatistics.
- MOGP can defined as follows:

$$\boldsymbol{f}(\boldsymbol{x}) \sim MOGP(\boldsymbol{m}(\boldsymbol{x}), \boldsymbol{K}(\boldsymbol{x}, \boldsymbol{x}')),$$

  - Function output: $\boldsymbol{f}(\boldsymbol{x}) = [f_1(\boldsymbol{x}), \cdots, f_N(\boldsymbol{x})]^T.$
  - Mean function: $\boldsymbol{m}(\boldsymbol{x}) = [m_1(\boldsymbol{x}), \cdots, m_N(\boldsymbol{x})]^T.$
    - Typically set to zero.
  - Covariance matrix (extended kernel): $\boldsymbol{K}(\boldsymbol{x}, \boldsymbol{x}') = \begin{bmatrix} K_{1,1}(\boldsymbol{x}, \boldsymbol{x}') & \cdots & K_{1,N}(\boldsymbol{x}, \boldsymbol{x}') \\ \vdots & \ddots & \vdots \\ K_{N,1}(\boldsymbol{x}, \boldsymbol{x}') & \cdots & K_{N,N}(\boldsymbol{x}, \boldsymbol{x}') \end{bmatrix}.$

MOGP-Based Fingerprint Augmentation - 1

- Dataset of *N*-dimensional RSSI observation at *M* reference points:

$$D = (\boldsymbol{X}, \boldsymbol{Y}),$$

  - Design matrix: $\boldsymbol{X} = [\boldsymbol{x}_1, \cdots, \boldsymbol{x}_M] \in R^{4 \times M}$ with $\boldsymbol{x}_i = [B_i, F_i, X_i, Y_i]^T$ where
    - B_i and F_i are building and floor IDs.
    - X_i and Y_i are the location coordinates of the *i*th reference point.
  - Collection of output vectors:$\boldsymbol{Y} = [\boldsymbol{y}_1, \cdots, \boldsymbol{y}_M] \in R^{N \times M}$ with $\boldsymbol{y}_i = \left[RSSI_{i,1}, \cdots RSSI_{i,N}\right]^T$ where
    - $RSSI_{i,j}$: RSSI of the *j*th AP measured at the *i*th reference point.

MOGP-Based Fingerprint Augmentation - 2

- *N*-dimensional RSSI observation can be modelled as follows:

$$\boldsymbol{y} = \boldsymbol{f}(\boldsymbol{x}) + \boldsymbol{\epsilon}\ ,$$

  - i.i.d. Gaussian measurement noise: $\boldsymbol{\epsilon} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Sigma})$.
  - Covariance matrix: $\boldsymbol{\Sigma} = diag(\sigma_1^2, \cdots, \sigma_N^2)$.

- Likelihood function:

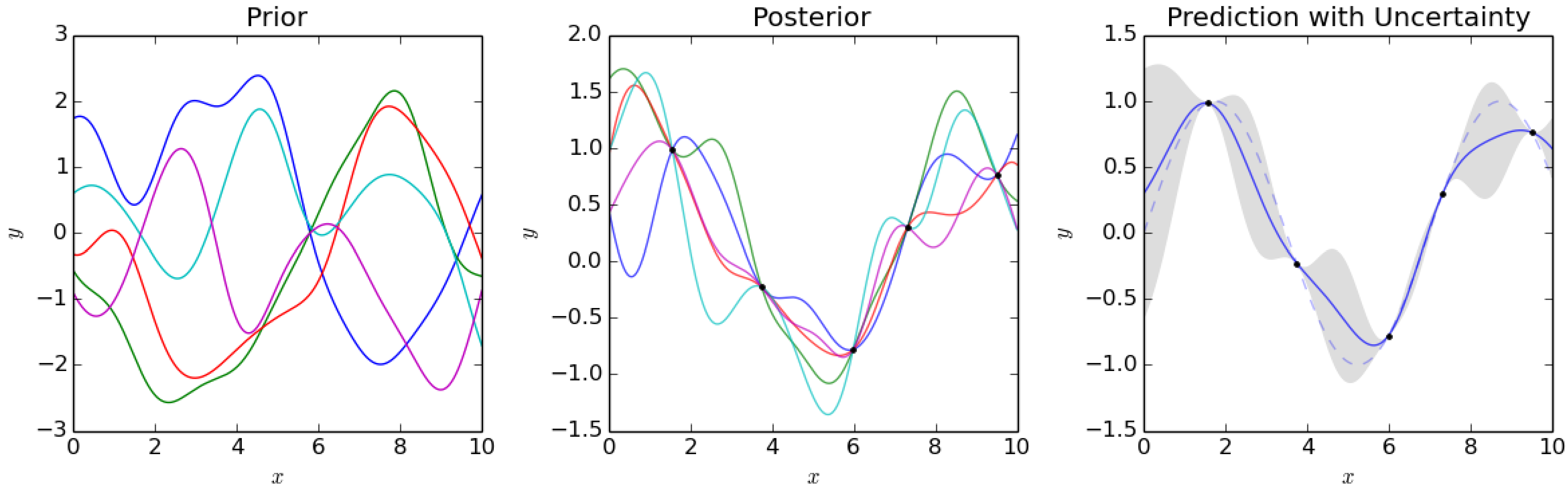
$$\mathcal{L}(\boldsymbol{x}|\boldsymbol{y}) = p(\boldsymbol{y}|\boldsymbol{f}, \boldsymbol{x}, \boldsymbol{\Sigma}) = \mathcal{N}(\boldsymbol{f}(\boldsymbol{x}), \boldsymbol{\Sigma}).$$

- Posterior distribution of the function value at a test point $\boldsymbol{x}_*$:

$$\boldsymbol{f}(\boldsymbol{x}_*)|\boldsymbol{X}, \boldsymbol{Y}, \boldsymbol{x}_* \sim \mathcal{N}\left(\hat{\boldsymbol{f}}(\boldsymbol{x}_*), \boldsymbol{\Sigma}_*\right)$$

  - Prediction mean: $\hat{\boldsymbol{f}}(\boldsymbol{x}_*)$.
  - Prediction covariance: $\boldsymbol{\Sigma}_*$.
  - $\left(\boldsymbol{x}_*, \hat{\boldsymbol{f}}(\boldsymbol{x}_*)\right)$ is added to the dataset as an augmented fingerprint.

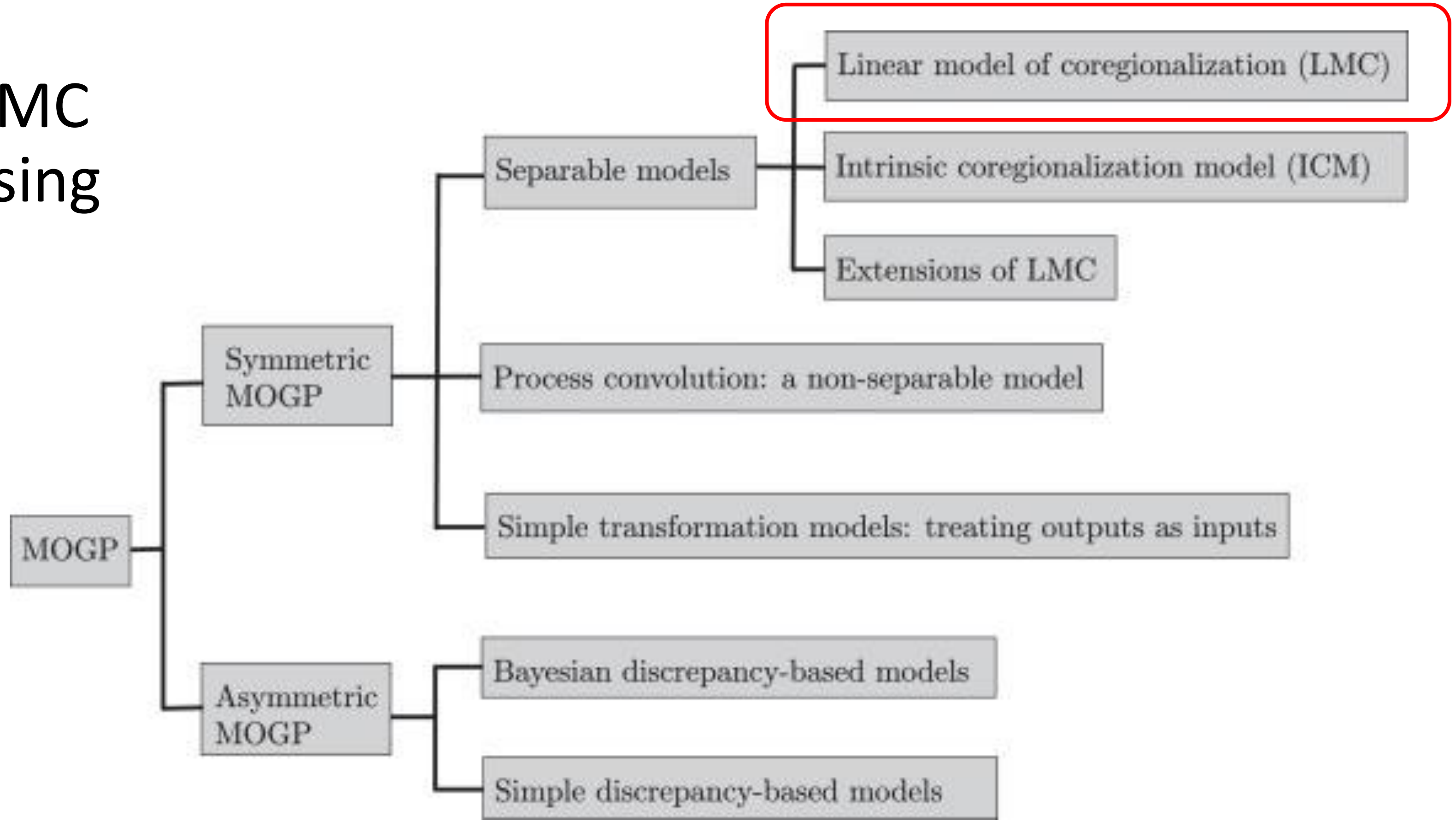
GP Prediction Example*



* Wikipedia, "Gaussian process prediction, or Kriging, Wikipedia," https://en.wikipedia.org/wiki/Gaussian_process#Gaussian_process_prediction,_or_Kriging.

MOGP Models*

- Our work is based on the LMC model and implemented using GPy** Python package.



** H. Liu, J. Cai, and Y.-S. Ong, "[Remarks on multi-output gaussian process regression]()," Knowledge-Based Systems, vol. 144, pp. 102–121, 2018.*

** GPy - A Gaussian Process (GP) framework in Python: https://gpy.readthedocs.io/en/deploy/.

Kernels - 1

- Radial basis function(RBF; also known as Gaussian kernel):

$$k_{RBF}(x, x') = \sigma^2 e^{\left(-\frac{\|x-x'\|^2}{2l^2}\right)}.$$

- Rational quadratic (RQ) kernel:

$$k_{RQ}(x, x') = \sigma^2 e^{\left(1+\frac{\|x-x'\|^2}{2\alpha l^2}\right)^{-\alpha}} \quad \text{for } \alpha > 0.$$

Kernels - 2

- Matérn family of kernels:

$$k^{\nu}_{Matérn}(x,x') = \sigma^2 \frac{2^{1-\nu}}{\Gamma(\nu)}\left(\frac{\sqrt{2\nu}\|x-x'\|}{l}\right)^{\nu} K_\nu\left(\sqrt{2\nu}\|x-x'\|\right),$$

  - K_ν: Modified Bessel function.
  - $\nu = d + \frac{1}{2}$, where d is the order of a polynomial function.
  - Examples:

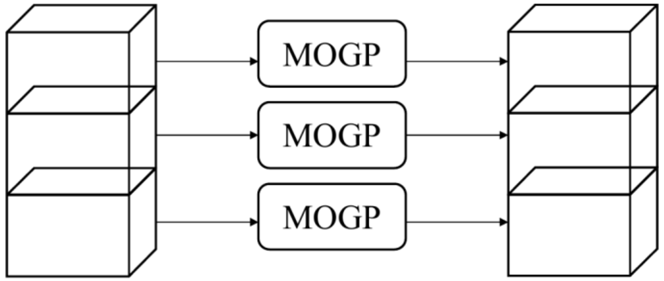
$$k_{Matérn3/2}(x,x') = \sigma^2\left(1+\sqrt{3}\frac{\|x-x'\|}{l}\right)e^{\left(-\sqrt{3}\frac{\|x-x'\|}{l}\right)}.$$

$$k_{Matérn5/2}(x,x') = \sigma^2\left(1+\sqrt{5}\frac{\|x-x'\|}{l}+\frac{5\|x-x'\|^2}{3l^2}\right)e^{\left(-\sqrt{5}\frac{\|x-x'\|}{l}\right)}.$$

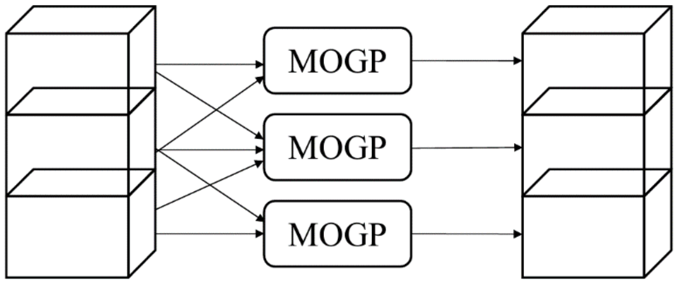
$$k_{Matérn1/2}(x,x') = k_{OU}\ (x,x') = \sigma^2 e^{\left(-\frac{\|x-x'\|}{l}\right)}.$$

  - Matern1/2 kernel is also known as Ornstein-Uhlenbeck (OH) kernel.

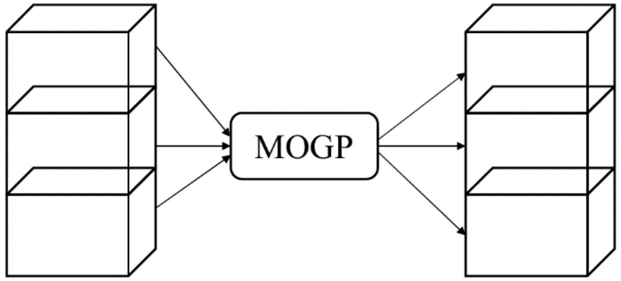
Data Augmentation Modes



By A Single Floor.



By Neighboring Floors.

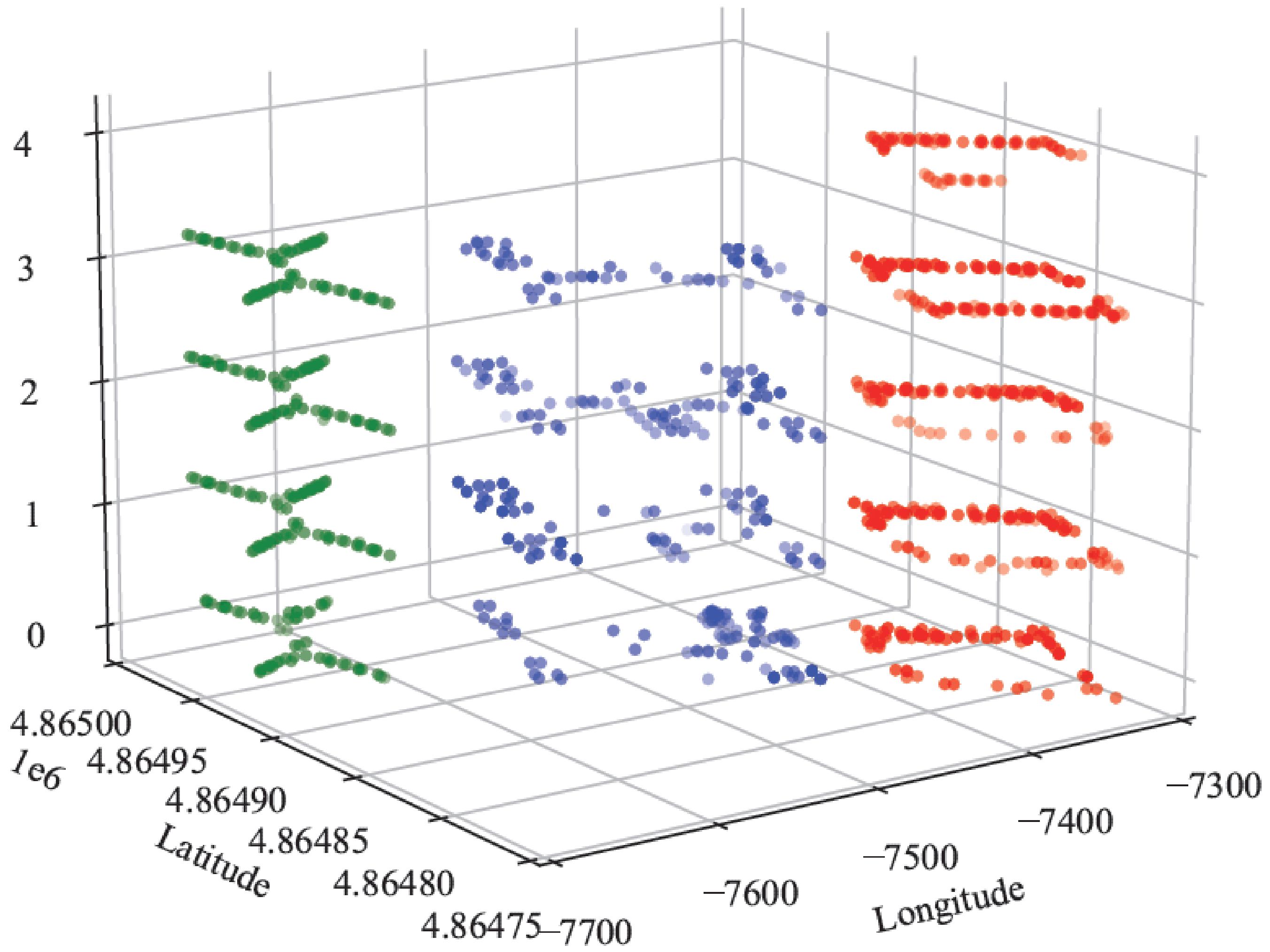


By A Single Building.

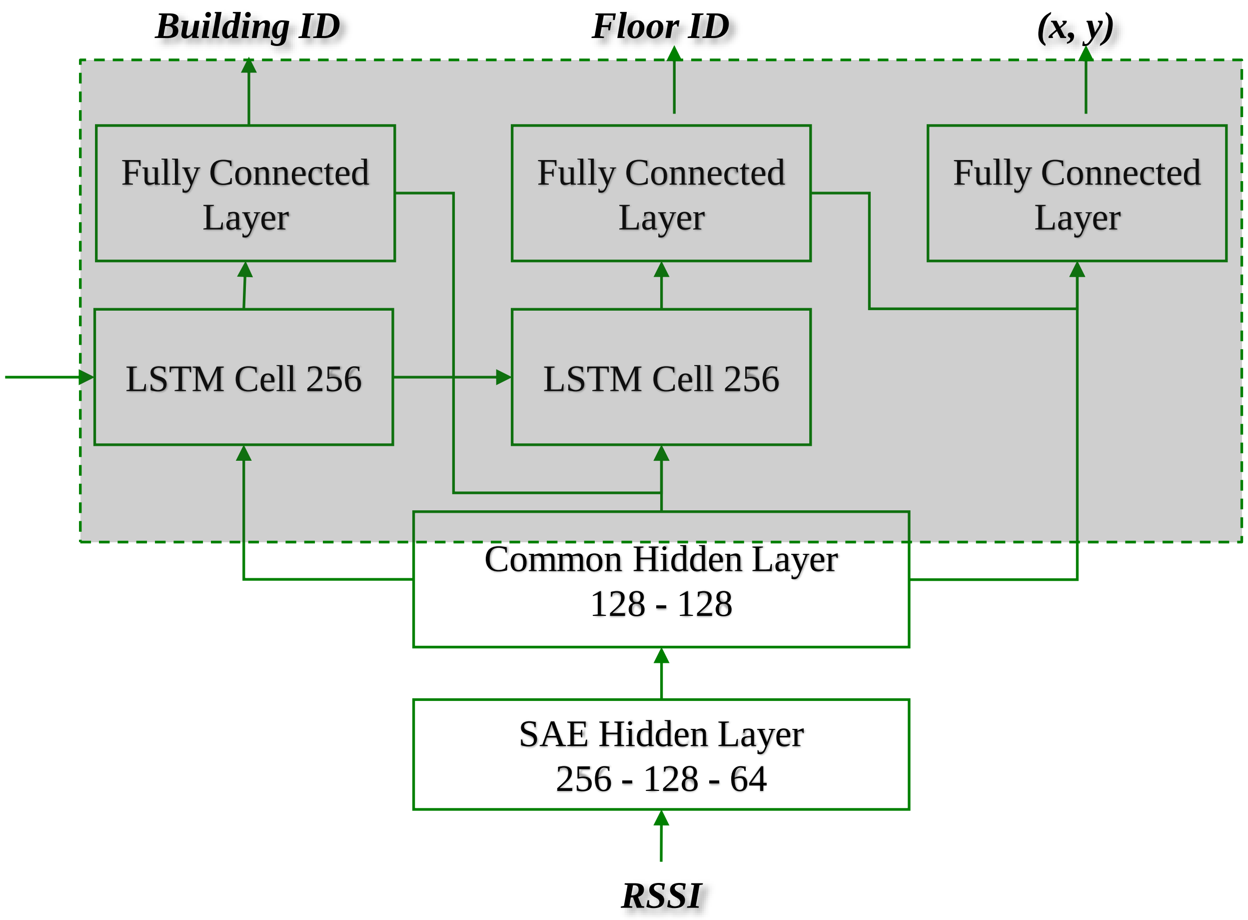
Experimental Results

Spatial Distribution of UJIIndoorLoc RPs

- Building 0: Green
- Building 1: Blue
- Building 2: Red



RNN Structure and Parameters*

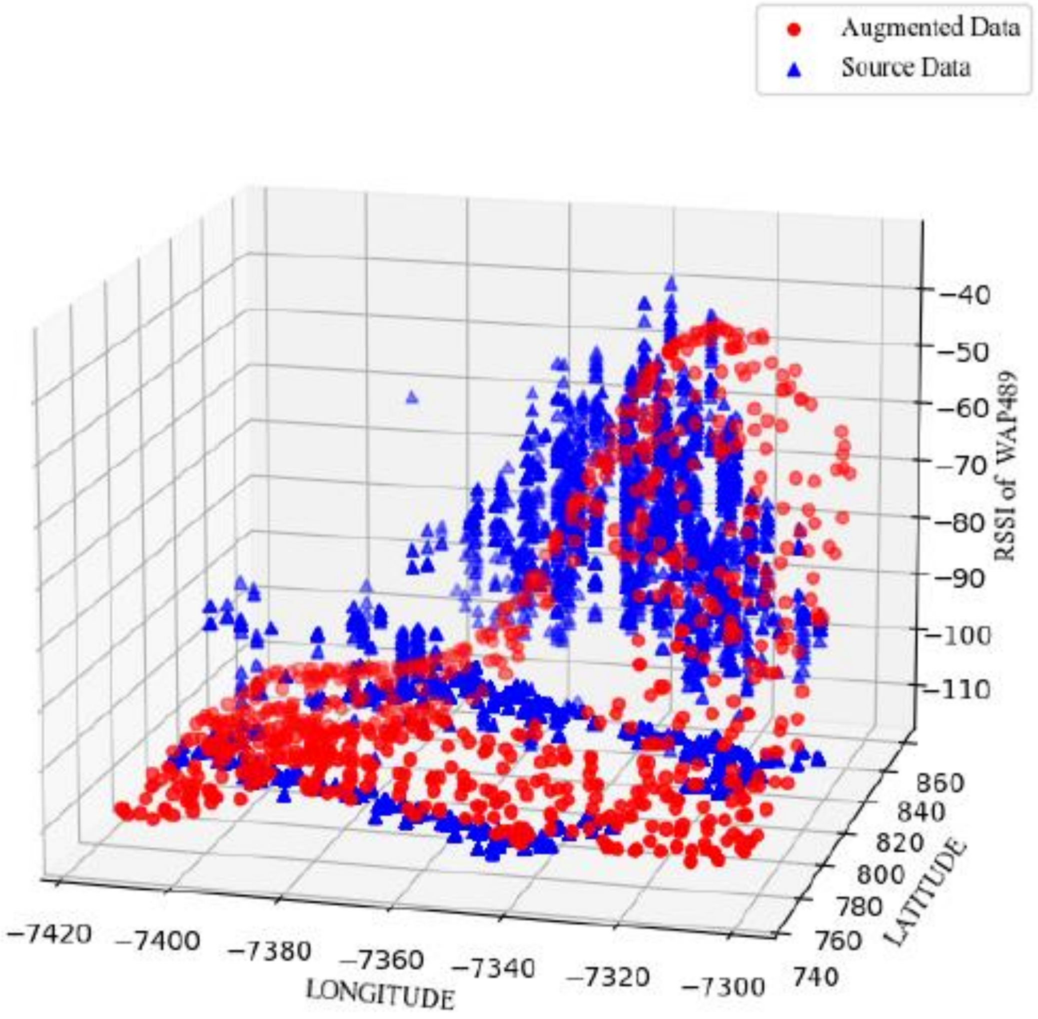


Parameter	Value
SAE Hidden Layers	256-128-64
SAE Activation	ReLu
SAE Optimizer	Adam
SAE Loss	MSE
Common Hidden Layers	128-128
Common Activation	ReLu
Common Dropout	0.2
Common Loss	MSE
LSTM Cells	256-256
LSTM Activation	ReLu
LSTM Optimizer	Adam
LSTM Loss	MSE
BF Classifier Hidden Layers	32-1
BF Classifier Activation	MSE
BF Classifier Optimizer	Adam
BF Classifier Dropout	0.2
BF Classifier Loss	ReLu
Position Hidden Layers	512-512-2
Position Activation	MSE
Position Optimizer	Adam
Position Dropout	0.1
Position Loss	tanh

** A.E.A. Elesawi and K. S. Kim, "Hierarchical multi-building and multi-floor indoor localization based on recurrent neural networks, Proc. CANDARW 2021, Matsue, Japan, pp. 193–196, Nov. 23–26, 2021.*

Original and Augmented RSSIs

- For RSSIs from WAP489 based on the Matérn5/2 kernel.



Localization Performance Comparison

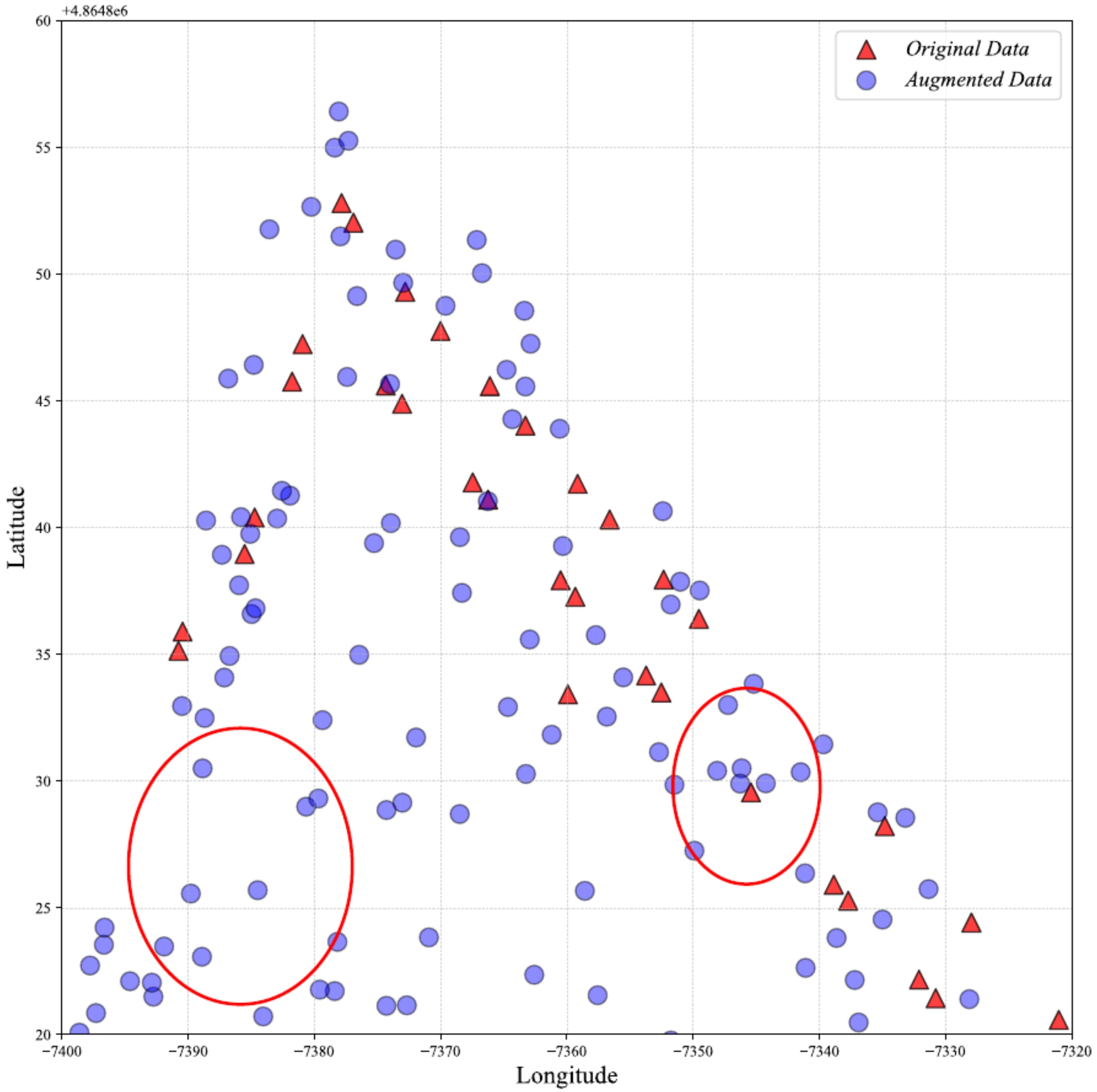
Localization Scheme	Building Hit Rate [%]	Floor Hit Rate [%]	3D Error [m]
Proposed*	**100**	94.20	8.42
Hierarchical RNN[1]	**100**	95.23	8.62
MOSAIC[2]	98.65	93.86	11.64
HFTS[2]	**100**	**96.25**	8.49
RTLS@UM[2]	**100**	93.74	**6.20**
ICSL[2]	**100**	86.93	7.67

* Hierarchical RNN[1] and the proposed MOGP-based data augmentation with the following options:

- Data augmentation mode: By a single building
- Augmentation ratio: 1
- Number of latent functions (Q): N
- Kernel: Matérn5/2
- Variance (σ^2): 1
- Length scale (l): 10

1. *A.E.A. Elesawi and K. S. Kim, Proc. CANDARW 2021, Matsue, Japan, Nov. 2021, pp. 193–196, doi: 10.1109/CANDARW53999.2021.00038.*
2. *A. Moreira et al. Proc. IPIN 2015, Banff, AB, Canada, Oct. 2015, pp. 1-10, doi: 10.1109/IPIN.2015.7346967.*

Spatial Distributions of Original and Augmented RSSIs



- For the corner of the 4th floor of Building 2 of the UJIIndoorLoc DB.
  - The red circles indicate two potential problems of the lack of original RSSI data and insufficient RP coverage.

Comparison of Data Augmentation Schemes for Indoor Localization

Augmentation Scheme	Model Interpretability	Localization Type	Notes
Proposed	High	Multi-Building	MOGP
s-GAN[1]	Low	Multi-Floor	GAN
DataLoc+[2]	Low	Single-Floor	Dropout
DL Augmentation[3]	Low	Single-Floor	Deep Learning
CAN[4]	Low	Single-Floor	Conditional Adversarial Networks
DL Approach[5]	Low	Single-Floor	AlexNet
Between-Location[6]	Low	Single-Floor	Between-Class Learning

1. *W. Njima et al., IEEE Access 2021, 9, 98337–98347, doi: 10.1109/ACCESS.2021.3095546.*
2. *A. Hilal et al., Proc. WCNC 2021, doi: 10.1109/WCNC49053.2021.9417246.*
3. *R. S. Sinha et al., Electronics 2019 8(5), 554, doi: 10.3390/electronics8050554.*
4. *L. Chen et al., IEEE Access 2020, 8, 26975–26983. doi: 10.1109/ACCESS.2020.2971269.*
5. *L. Xiao et al., Proc. INTAC 2017, doi: 10.1109/ATNAC.2017.8215428.*
6. *M. Sugasaki et al., IEEE Sensors Journal 2022, 22, 5407–5416, doi: 10.1109/JSEN.2021.3106765.*

Conclusions and Future Work

Conclusions

- Proposed MOGP-based multi-dimensional fingerprint data augmentation for indoor localization in a large-scale building complex.

- Investigated the effects of MOGP models, augmentation modes and ratios, and kernels and their hyperparameters on the localization performance through extensive experiments and found the best options as follows:
  - By a single building.
  - $\frac{\text{Number of Augmented Data}}{\text{Number of Origianl Data}} = 1.$
  - LMC with $Q = N$.
  - Matérn5/2 kernel with $\sigma^2 = 1$ and $l = 10$.

Future Work

- Extension to other MOGP models.
- Extension to other fingerprint databases.
- Extension from spatial to time domain data augmentation.
  - This will be based on time-varying fingerprint datasets, which we are constructing now on XJTLU campus.