SURF-201913 Preparation Meeting: Analysis of XJTLUIndoorLoc Multivariate Dataset for DNN-Based Indoor Localisation

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Outline

- XJTLU Camus Information and Visitor Service System
- Wi-Fi Fingerprinting
- SURF 2017
- SURF 2018
- Scalable DNN-Based Multi-Building and Multi-Floor Indoor Localisation
- Plans

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XJTLU Camus Information and Visitor Service System

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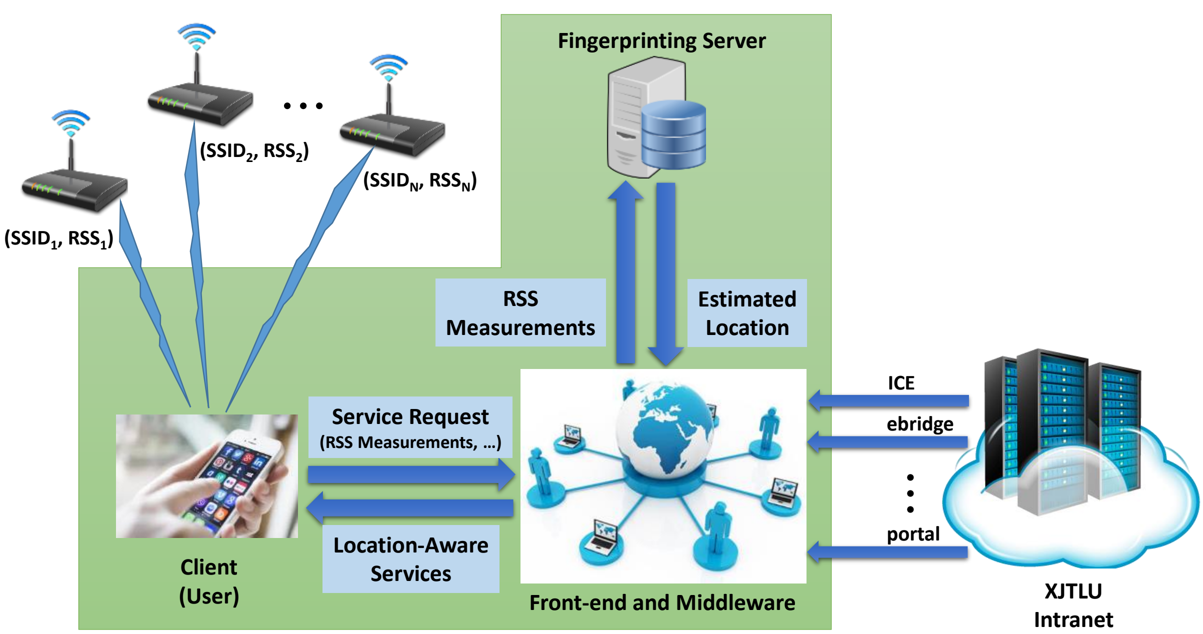

XJTLU Camus Information and Visitor Service System

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Examples: Indoor Navigation and Location-Aware Service

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Wi-Fi Fingerprinting

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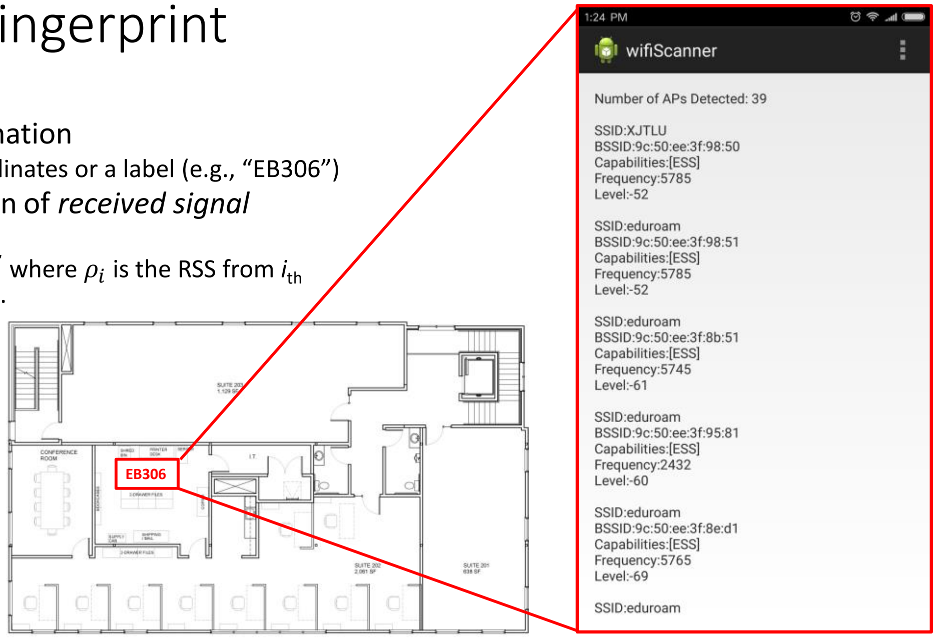
Location Fingerprint

- 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 strengths (RSSs)*
    - e.g., $(\rho_1, \cdots, \rho_N)^T$ where ρ_i is the RSS from i_{th} access point (AP_i).



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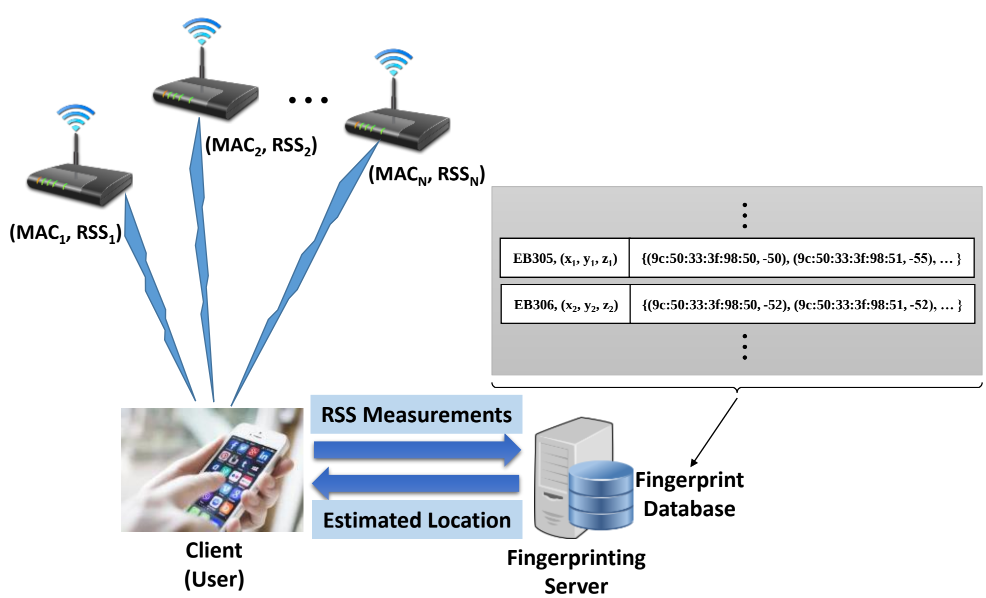

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Location Estimation

- Deterministic
  - **Nearest Neighbour Methods**
  - Neural Network Methods
    - Deep neural networks (DNNs) enabled by deep learning
- Probabilistic
  - Bayesian Inference
  - Support Vector Machine (SVM)
  - Gaussian Process Latent Variable Model (GP-LVM)

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Nearest Neighbour Methods*

- A simple approach based on the notion of distance in the signal space:
  - Given a fingerprint of $(\mathcal{L}, (\rho_1, \cdots, \rho_N)^T)$ and an RSS measurement of $(s_1, \cdots, s_N)^T$, the *Euclidean distance measure* between them is defined as

$$\sqrt{\sum_{i=1}^{N} (s_i - \rho_i)^2}$$

  - Then, we find a fingerprint providing a minimum distance, $\mathcal{L}$ of which is the estimated location.

* *P. Bahl and V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," Proc. of INFOCOM 2000, vol. 2, pp. 775-784, Mar. 2000.*

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Major Challenges in Large-Scale Implementation

- ***Scalability***
- ***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.*

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SURF 2017: Indoor Localisation Based on Wi-Fi Fingerprinting with Fuzzy Sets

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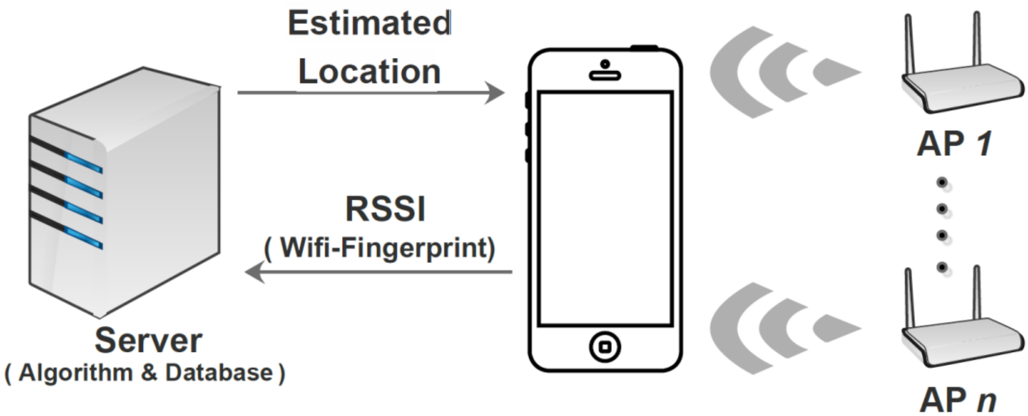
A Prototype of DNN-Based Indoor Localization System for Floor-Level Location Estimation



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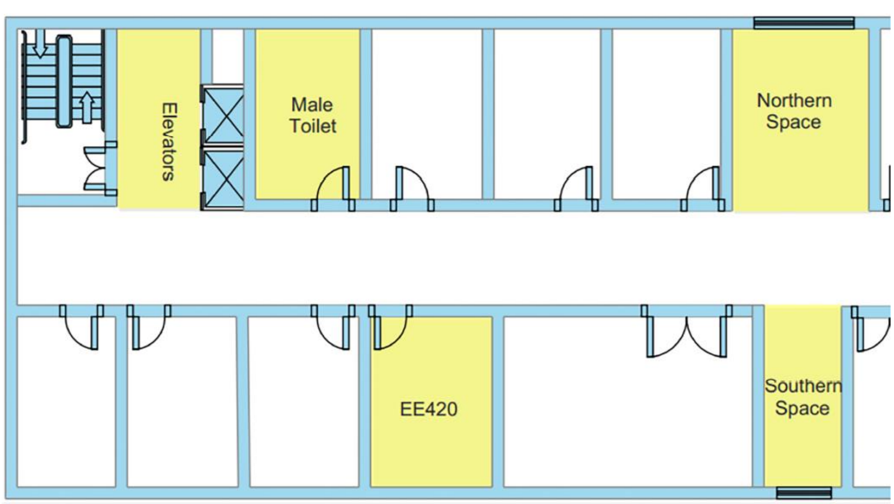
A Partial Layout of the Fourth Floor of EE Building



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DNN Parameter Values for Floor-Level Location Estimation

DNN Parameter	Value
Ratio of Training Data to Overall Data	0.75
Batch Size	10
SAE Hidden Layers	128-64-8-64-128
SAE Activation	Hyperbolic Tangent (TanH)
SAE Optimizer	ADAM
SAE Loss	Mean Squared Error (MSE)
Classifier Hidden Layers	64-32-7
Classifier Activation	ReLU
Classifier Optimizer	AdaGrad
Classifier Loss	Cross Entropy
Classifier Dropout Rate	0.50
Classifier Epochs	30

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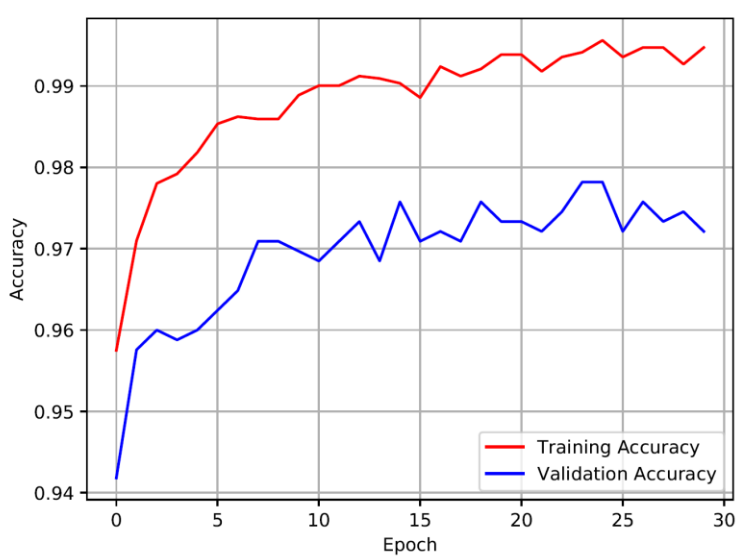
Training and Validation Accuracy of Floor-Level Location Estimation



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SURF 2018: Trajectory Estimation of Mobile Users/Devices Based on Wi-Fi Fingerprinting and Deep Neural Networks

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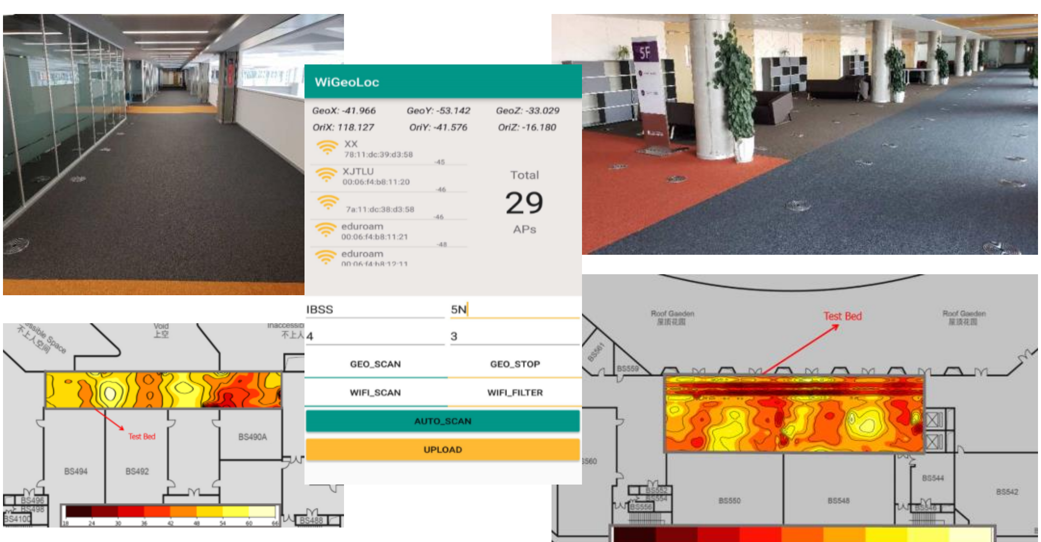
Toward A Campus-Wide Indoor Localization System:
Multi-Floor Indoor Localization with RSS/Geomagnetic Field in 2018



4th Floor of IBSS Building

5th Floor of IBSS Building

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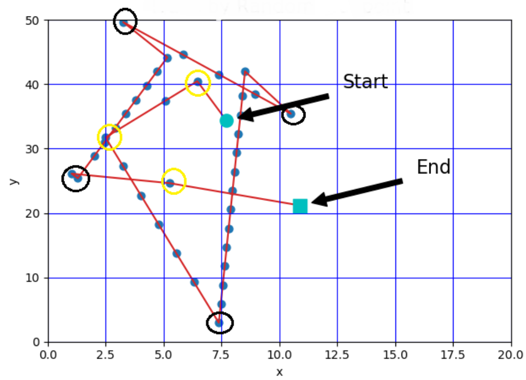
Trajectory Estimation Based on Human Walking Model and LSTM

Data Processing – Random Waypoint Model (RWM)



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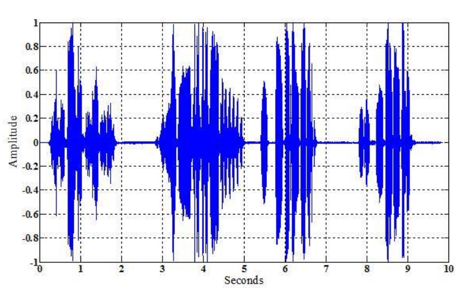
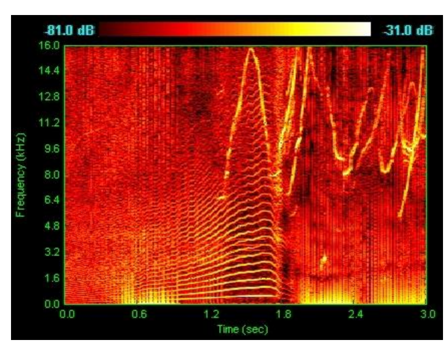
Use of CNN for Time Series Data (e.g., Audio)

Time Domain



Spectral Domain



Treat the above as 2-dimensional image!

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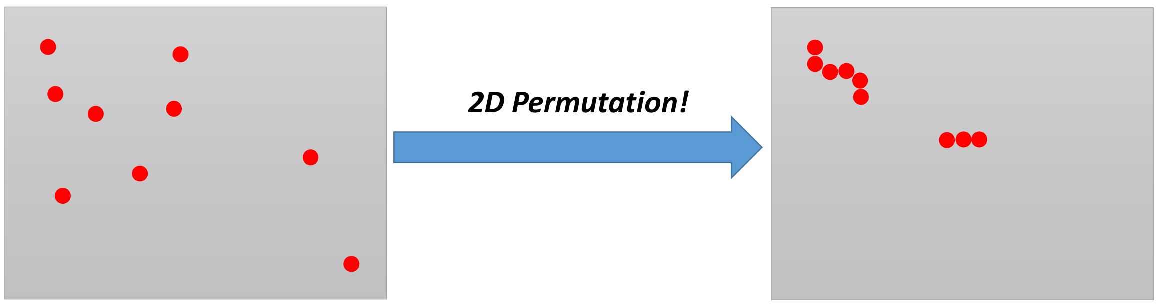
Mapping of Unstructured Data into Images



Unstructured Data (e.g., RSSs in2D arrangement)

Image-Like 2D Data

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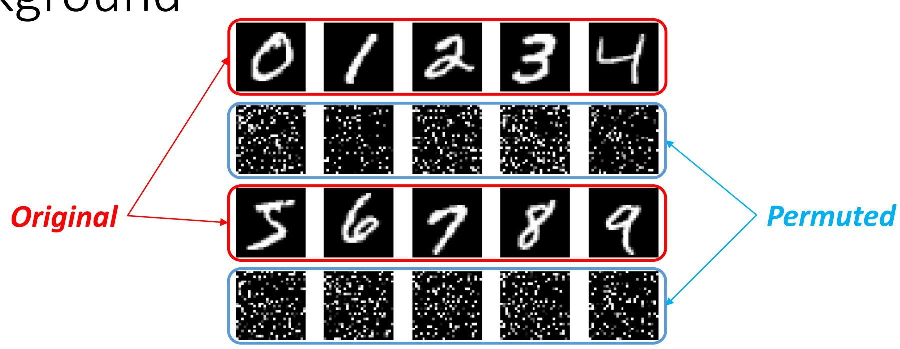
Mapping of Unstructured Data into Images: Background



- CNN
  - With original data: 0.99
  - With permuted data: 0.98
    - 1% drop in accuracy
- Multi-layer perceptron (MLP)
  - With original data: 0.98
  - With permuted data: 0.98
    - Virtually no difference

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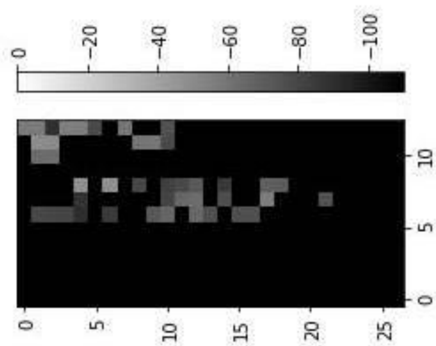
Mapping of Unstructured Data into Images: Challenges

- How to quantify the ***image-likeness***?
  - Number of connected regions (e.g., *skimage.measure.label*)
  - …
- How to overcome the extremely huge ***size of the search space***?
  - e.g., # of possible permutation for MNIST image = $28^2! \approx 10^{1930.50\ldots}$



Results from SURF-201830

Scalable DNN-Based Multi-Building and Multi-Floor Indoor Localization

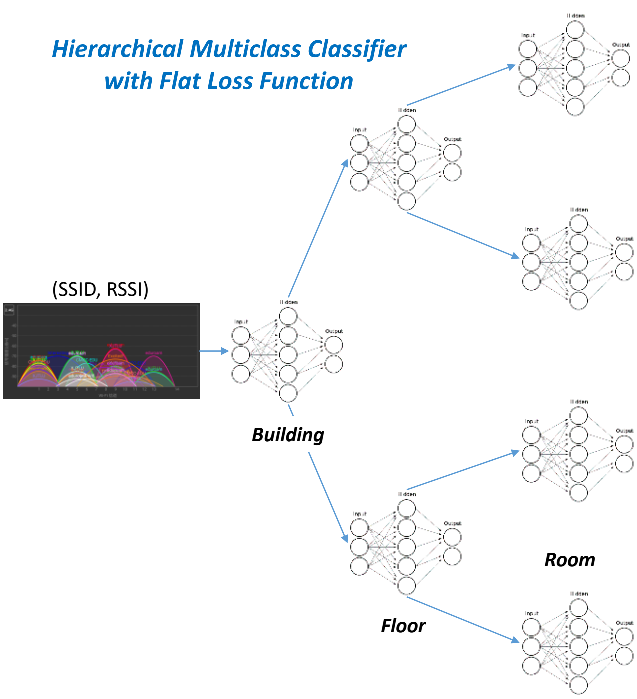
Changes in XJTLU Campuses

2006

2017~

Hierarchical Multiclass Classifier with Flat Loss Function

Flat Multiclass Classifier with Hierarchical Loss Function



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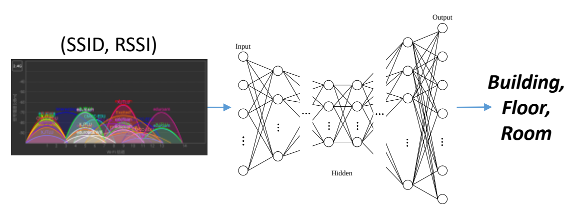

Plans

- WP1: Statistical analysis of XJTLUIndoorLoc dataset.
    - To quantify the dependency of measurement data on mobile devices.
    - To investigate the impact of mobile devices on indoor localization/trajectory estimation performance
    - To do additional measurements with new mobile devices.
- WP2: Handling device orientation information for geomagnetic field intensity.
    - To study the device coordinate frame and rotation data of smartphones based on their built-in accelerometer, gyroscope, and compass.
    - To investigate how to handle mismatch between the device orientation of geomagnetic filed data in the dataset and that of a new measurement during the online indoor localization/trajectory estimation phase.