SURF-201830 Kick-Off Meeting: Review of Indoor Localisation Based on Wi-Fi Fingerprinting with Deep Neural Networks

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Outline

- XJTLU Camus Information and Visitor Service System
- Wi-Fi Fingerprinting
- SURF 2017: Demonstration of A DNN-Based Indoor Localization System
- Scalable DNN-Based Multi-Building and Multi-Floor Indoor Localisation
- Summary

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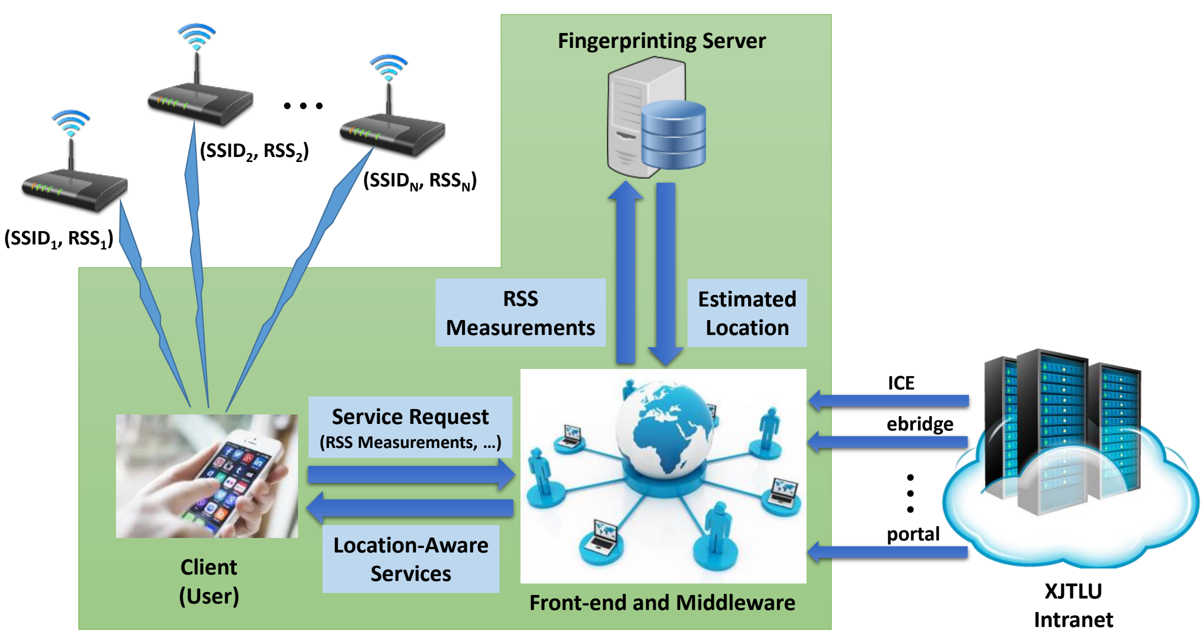
XJTLU Camus Information and Visitor Service System



XJTLU Camus Information and Visitor Service System

Examples: Indoor Navigation and Location-Aware Service

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Wi-Fi Fingerprinting

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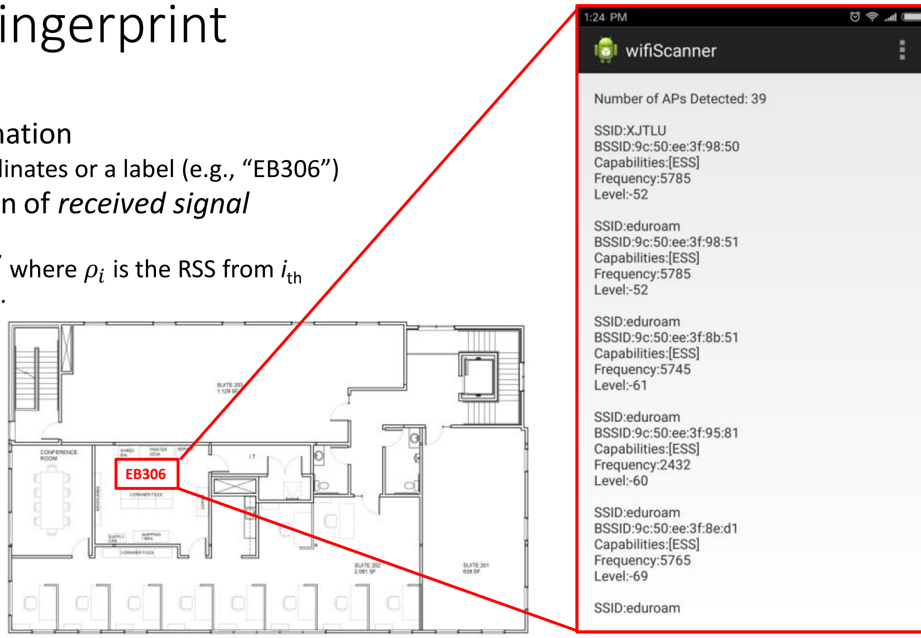
Location Fingerprint

- 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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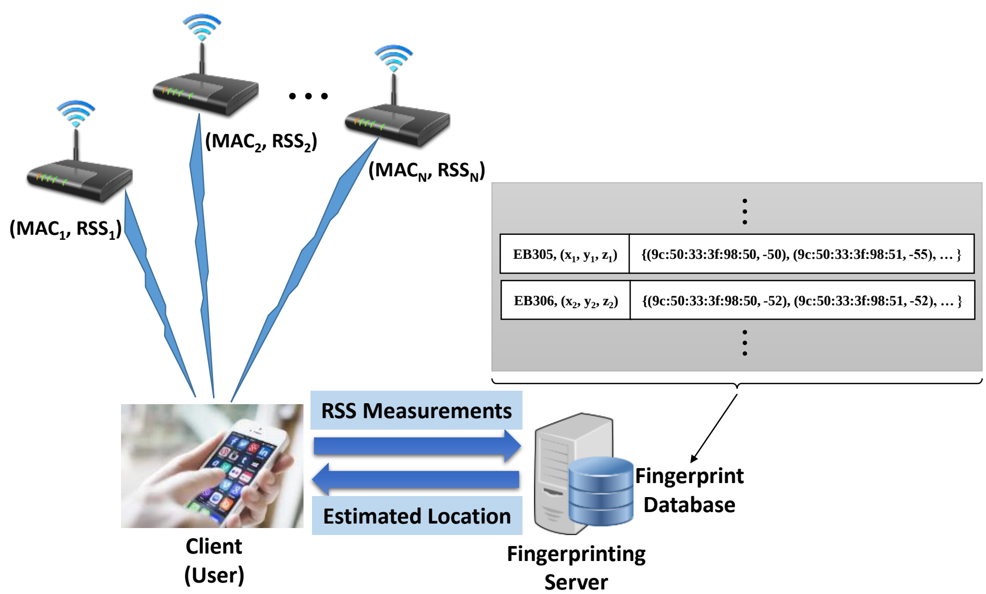

Location Estimation

- 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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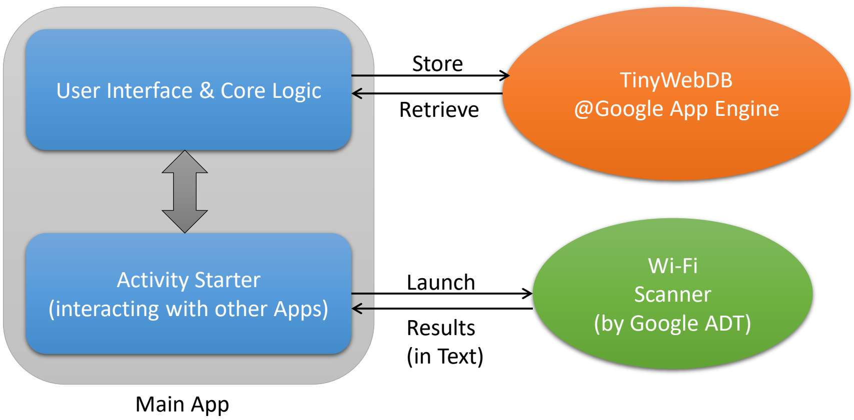
Implementation Example - 1



Implementation Example - 2

Start the app and
press the 'Find' button.

Results of Wi-Fi scanning.

Find the location and
display the picture.

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: Demonstration of A DNN-Based Indoor Localization System

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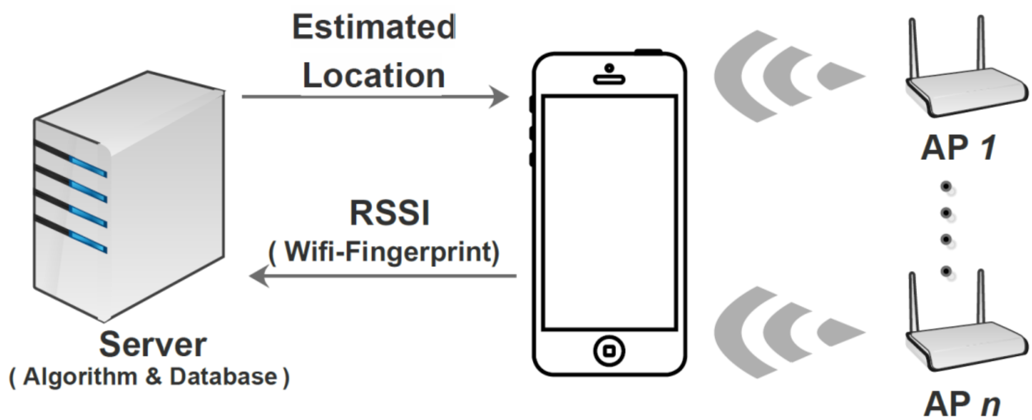
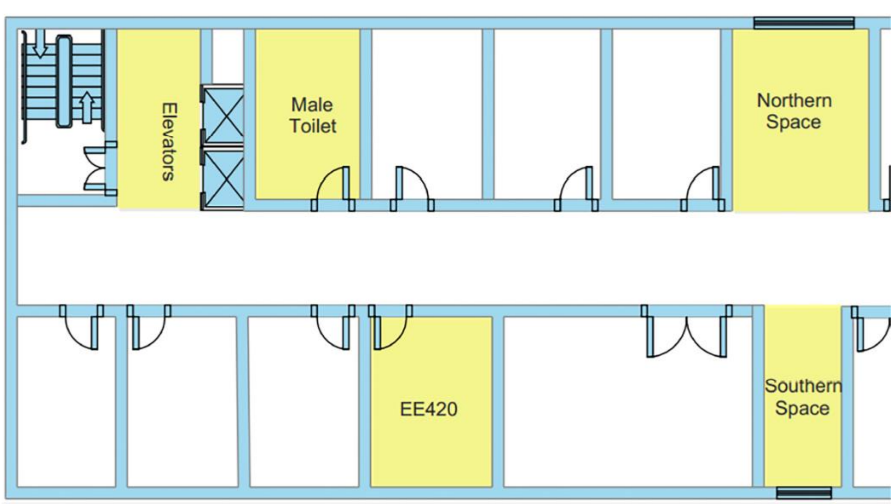
A Prototype of DNN-Based Indoor Localization System for Floor-Level Location Estimation



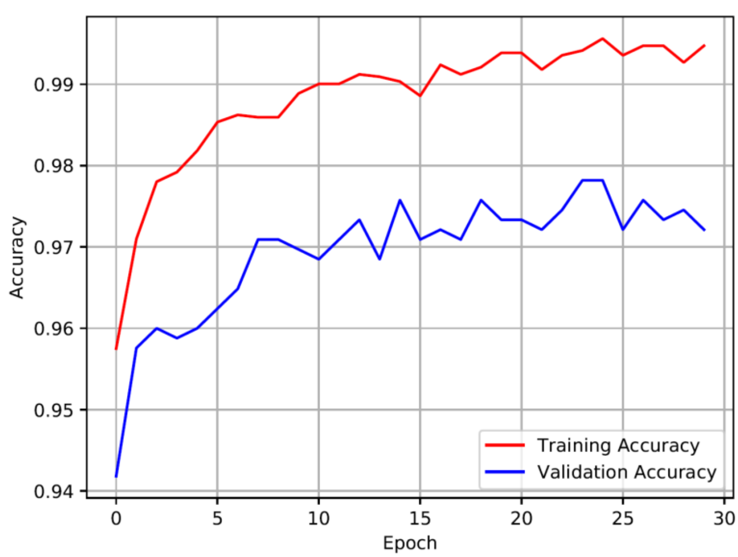
A Partial Layout of the Fourth Floor of EE Building



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

Training and Validation Accuracy of Floor-Level Location Estimation



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

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Changes in XJTLU Campuses

2006

2017~

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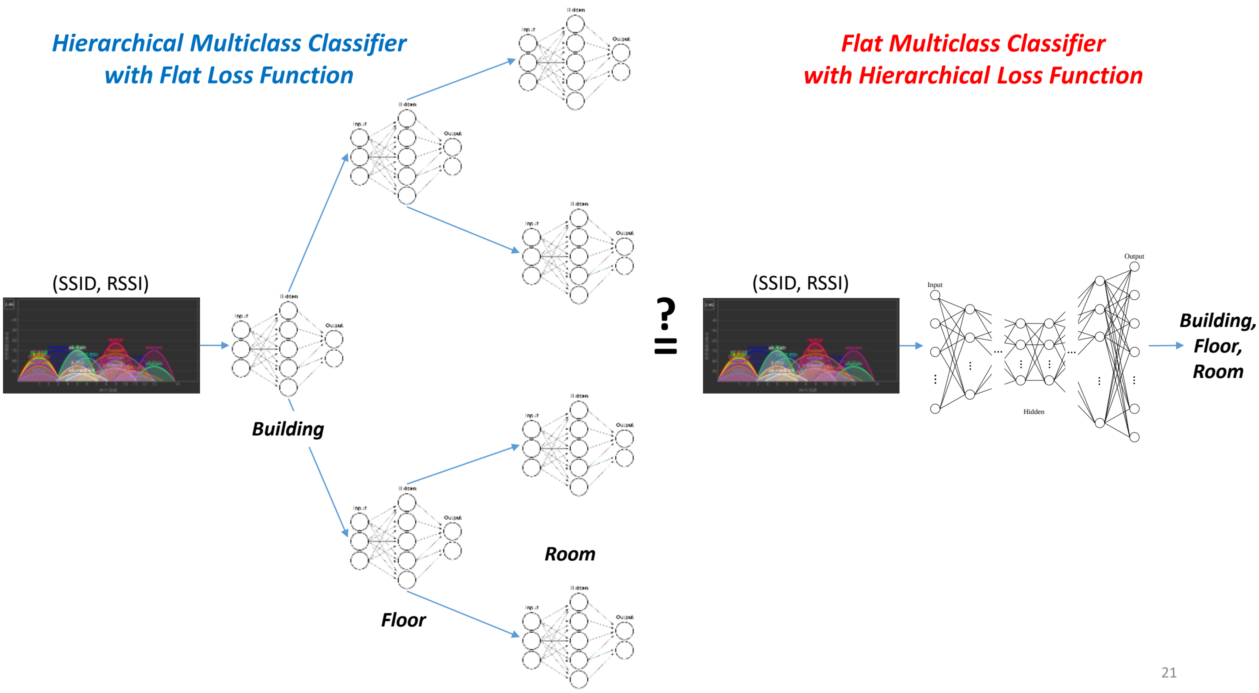

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Two Ways of Representing Locations - 1

- Flattened labels
  - As one-dimensional vectors
    - e.g., “EB-3-06” (→ “Building_ID-Floor_ID-Location_ID”)
  - For ***multi-class classification***.
- Multi-labels
  - As multi-dimensional vectors
    - e.g., (“EB”, “3”, “06”)
  - For ***multi-label classification***.

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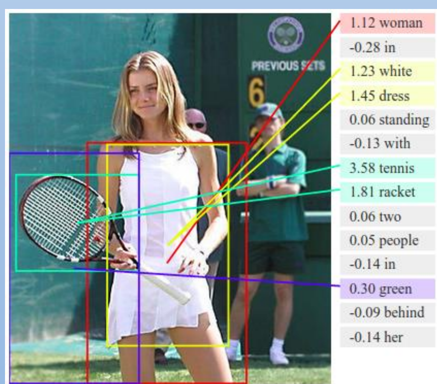
Multi-Label vs. Multi-Class Classification



Multi-Label Classification

- Multiple labels can be assigned to each instance.

Multi-Class Classification

- Classifying an instance into (*only*) one of multiple classes.
- A special case of multi-label classification.
  - Also called *single-label classification*.

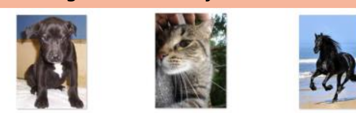


	Image #1	Image #2	Image #3
Dog	-0.39	-4.61	1.03
Cat	1.49	3.28	-2.37
Horse	4.21	1.46	-2.27

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Two Ways of Representing Locations - 2

- Scalability of the two representations
  - In machine learning, categorical data containing labels are ***one-hot encoded*** (see the table on the right).

Dog	Cat	Horse
1	0	0
0	1	0
0	0	1

  - A flattened label is one-hot encoded as a whole, while each component of a multi-label can be one-hot encoded independently, e.g.,
    - "EB-3-06" → "0…010….0" vs ("EB", "3", "06") → (0…01, 010…0, 10…0)
  - For a campus with 10 buildings, 10 floors/building, and 10 locations/floor, ***the number of bits*** required for each representation with one-hot encoding is as follows:
    - Flattened labels: 10×10×10 = 1,000
    - Multi-labels: 10+10+10 = 30

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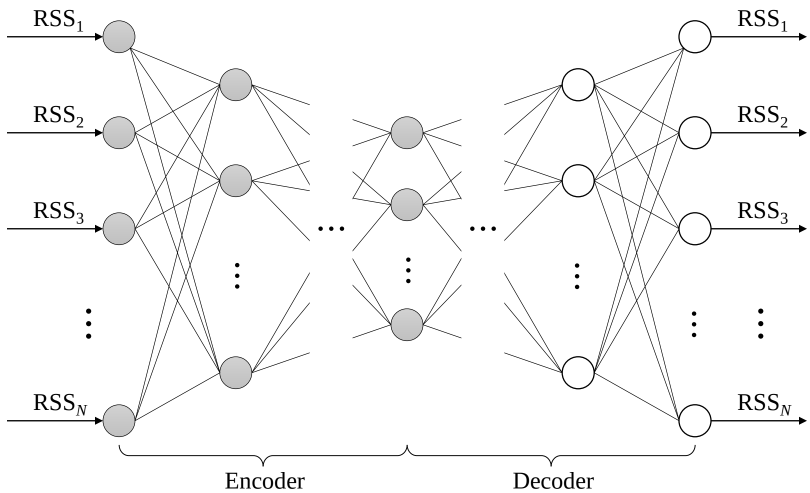
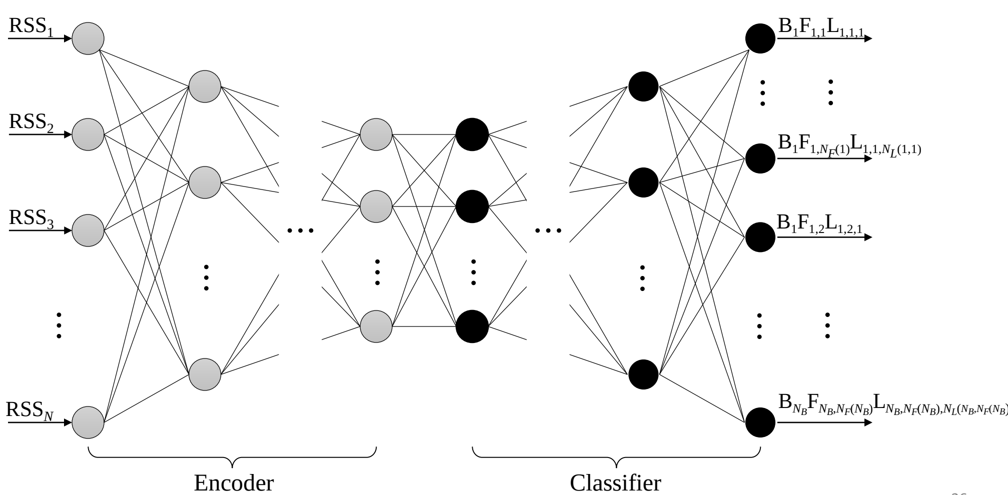
Stacked Autoencoder (SAE) for the reduction of feature space dimension



DNN Architecture for Combined Estimation of Building, Floor, and Location based on *Multi-Class Classifier* and Flattened Labels



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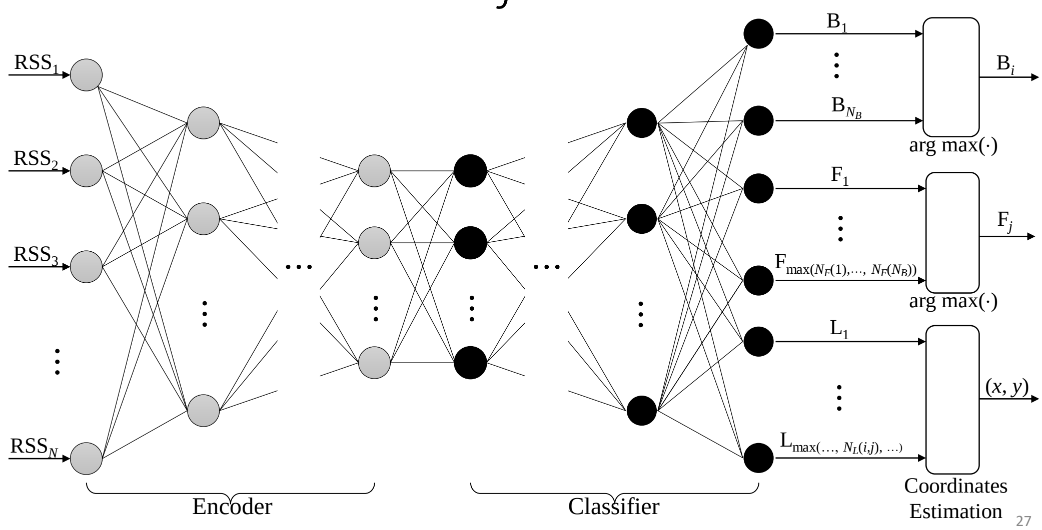
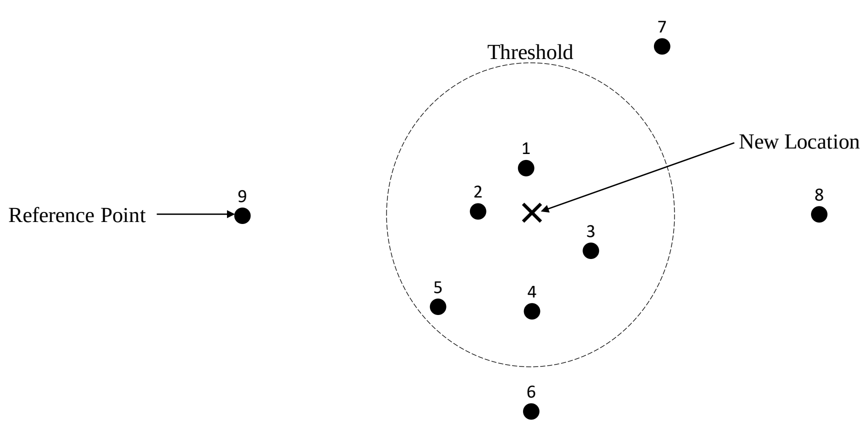
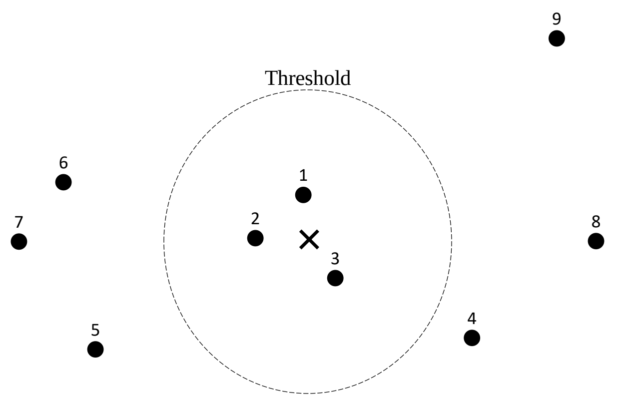
DNN Architecture for *Scalable* Building/Floor Classification and Floor-Level Coordinates Estimation based on *Multi-Label Classifier*



Location Coordinates Estimation: Many Reference Points Centred around A New Location



Location Coordinates Estimation: Only Few Reference Points Centred around A New Location



Parameter Values for Scalable DNN-Based Indoor Localization

DNN Parameter	Value
Ratio of Training Data to Overall Data	**0.90**
Number of Epochs	**20**
Batch Size	**10**
SAE Hidden Layers	**256-128-256**
SAE Activation	**Rectified Linear (ReLU)**
SAE Optimizer	**ADAM**
SAE Loss	**Mean Squared Error (MSE)**
Classifier Hidden Layers	**64-128**
Classifier Activation	**ReLU**
Classifier Optimizer	**ADAM**
Classifier Loss	**Binary Crossentropy**
Classifier Dropout Rate	**0.20**

κ	σ	Building Hit Rate [%]	Floor Hit Rate [%]	Success Rate [%]	Positioning Error [m]	
					Centroid	Weighted Centroid
1	N/A*	99.82	91.90	91.81	11.40	11.40
2	0.0	99.37	92.44	91.81	10.62	10.54
	0.1	100.00	91.81	91.81	10.40	10.33
	0.2	99.82	92.62	92.44	9.74	9.66
	0.3	99.64	91.99	91.81	9.78	9.71
	0.4	99.73	91.54	91.45	10.29	10.21
	0.5	100.00	90.01	90.01	10.16	10.09
3	0.0	99.73	91.54	91.36	10.14	9.79
	0.1	99.91	90.91	90.82	9.92	9.76
	0.2	98.83	90.91	90.28	9.98	9.80
	0.3	99.55	92.08	91.90	10.13	10.01
	0.4	99.91	91.99	91.99	10.63	10.47
	0.5	99.82	90.37	90.37	9.94	9.89
4	0.0	99.82	90.91	90.91	10.27	9.66
	0.1	99.37	91.99	91.63	10.37	9.92
	0.2	99.64	92.08	91.90	10.26	10.09
	0.3	99.82	91.45	91.36	10.24	10.16
	0.4	99.91	92.26	92.17	10.35	10.23
	0.5	99.82	91.27	91.18	10.10	10.07
5	0.0	99.91	91.36	91.27	11.29	10.36
	0.1	99.91	91.63	91.63	9.90	9.62
	0.2	99.91	90.73	90.73	9.89	9.57
	0.3	99.82	90.91	90.82	10.27	9.99
	0.4	99.73	92.17	92.08	10.17	10.01
	0.5	99.82	92.98	92.89	10.59	10.54
6	0.0	99.82	91.90	91.72	10.84	9.71
	0.1	99.64	92.08	91.81	10.35	9.86
	0.2	100.00	91.99	91.99	9.85	9.56
	0.3	99.82	92.80	92.80	10.49	10.22
	0.4	99.37	91.09	91.00	10.32	10.17
	0.5	99.64	90.91	90.64	9.55	9.52
7	0.0	99.82	89.29	89.29	11.74	10.22
	0.1	99.82	90.19	90.01	10.43	9.82
	0.2	99.91	91.45	91.45	10.00	9.55
	0.3	99.91	91.63	91.54	9.75	9.53
	0.4	99.64	90.46	90.19	10.42	10.28
	0.5	99.55	91.45	91.36	9.83	9.73
8	0.0	99.91	90.19	90.10	11.32	9.27
	0.1	100.00	91.27	91.27	10.62	10.14
	0.2	99.82	91.27	91.18	9.76	9.29
	0.3	99.82	90.55	90.37	9.95	9.82
	0.4	99.91	90.37	90.28	10.21	10.14
	0.5	99.91	90.55	90.55	9.86	9.79

Effects of the number of largest elements from the output location vector (κ) and the scaling factor for a threshold (σ)

Best Results from EvAAL/IPIN 2015 Competition*

	MOSAIC	HFTS	RTLSUM	ICSL
Building Hit Rate [%]	98.65	100	100	100
Floor Hit Rate [%]	93.86	96.25	93.74	86.93
Positioning Error (Mean) [m]	11.64	8.49	6.20	7.67
Positioning Error (Median) [m]	6.7	7.0	4.6	5.9

***** *Moreira A et al., “Wi-Fi fingerprinting in the real world – RTLSUM at the EvAAL competition.,” Proc. IPIN, 2015. pp. 1–10.*

Summary

- Introduced the feasibility study project on the *XJTLU Campus Information and Visitor Service system*.
- Reported results of our investigation on *the use of DNNs for large-scale multi-building and multi-floor indoor localization*.
  - Results shows that scalable DNN-based approaches could provide localization performance favorably comparable to the best results from EvAAL/IPIN 2015.
- Further study is needed for hierarchical building/floor classification and location estimation, including
  - Single-input, multi-output (SIMO) DNN architecture
  - Stage-wise training
  - Use of CNNs and/or RNNs based on different representation of RSSs

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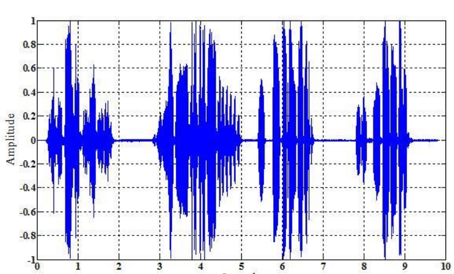
Work Packages

Work Packages

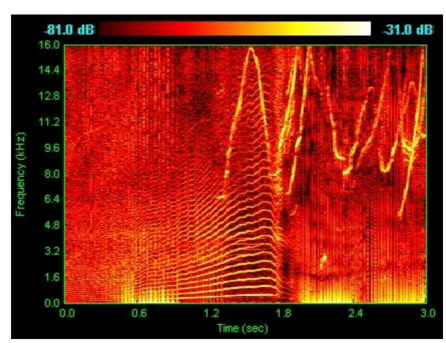
- **Theoretical and simulation study**
  - Advanced DNN-based indoor localization.
    - Including CNN-based approaches.
  - RNN-based trajectory estimation.
    - With geomagnetic field measurements and time stamps.
- **Prototyping and demonstration**
  - Build a sample RSS and geomagnetic field measurement database at XJTLU.
    - e.g., for the 5th floor of IRS building.
  - Implement the proposed algorithm and demonstrate indoor localization with the sample database.
    - Offline demonstration with a PC
    - (*Optional*) Online demonstration with a smartphone

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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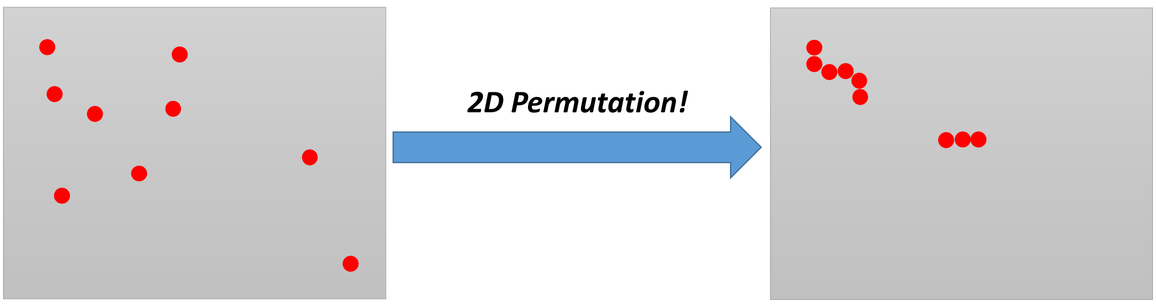
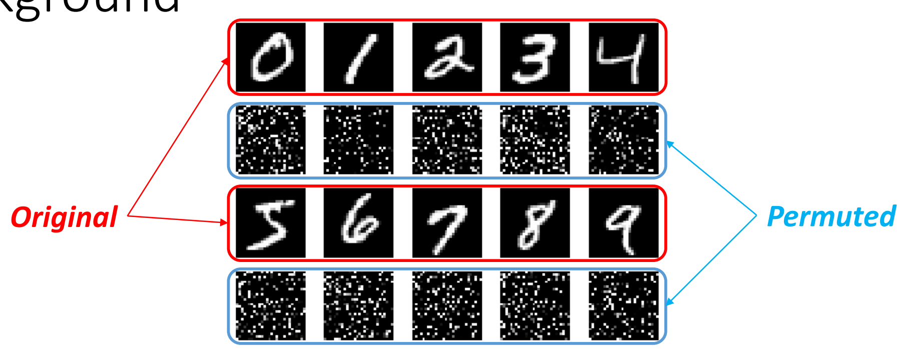
Mapping of Unstructured Data into Images



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

Image-Like 2D Data

Mapping of Unstructured Data into Images: Background



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

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 = $28^2! \approx 10^{1930.50\dots}$