The Hong Kong Polytechnic University
Department of Electronic and Information Engineering

Honor Project: RSSI-based SigFox Localization by using Machine Learning

2019-2020 EIE4433 Honor Project

HST 150xxxxxD

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01 Introduction

Introduction

- Localization is very important.
- Many applications need your location.
  - Current method: GPS module embedded
  - Limitation 1: high power consumption
  - Limitation 2: Not support indoor environment

Introduction

- Objective: Use Sigfox technology in localization with machine learning.

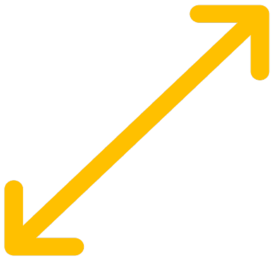
Introduction

- Sigfox is operated by Thinxtra Network Ltd. in Hong Kong.

Wireless communication technology

Low-power

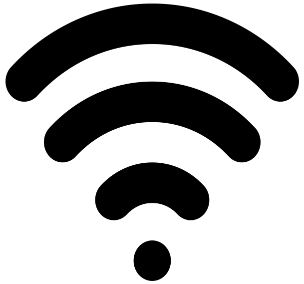
(several years battery life)



Long-range

163.3 dBm link budget

(urban: 10km)



Frequency

920 - 925 MHz in HK

Introduction

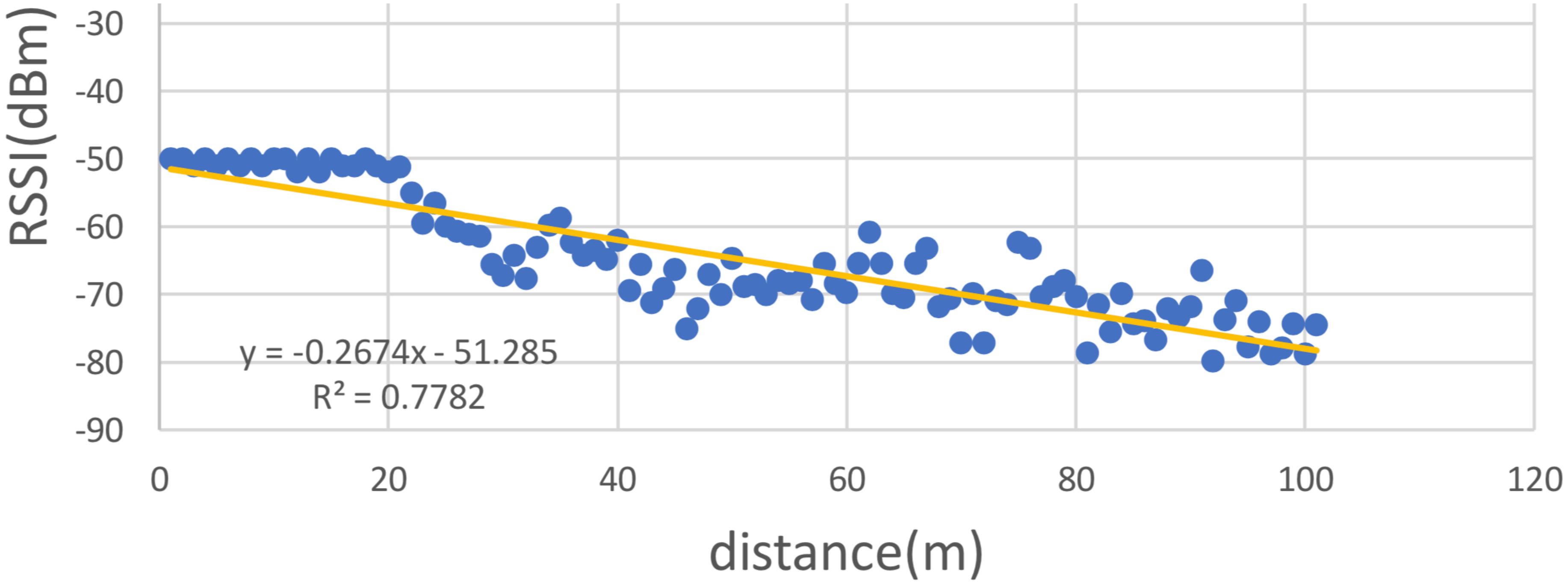
- Advantages to use Sigfox in localization:
    - Can also be used in communication.
    - Can be used in both indoor and outdoor localization.
    - Low power consumption.

Introduction

$$RSSI = Z_0 - 10\alpha \log_{10} distance + noise$$

where Z_0 and α are constant.

- Use Received Signal Strength Indicator (RSSI) in localization



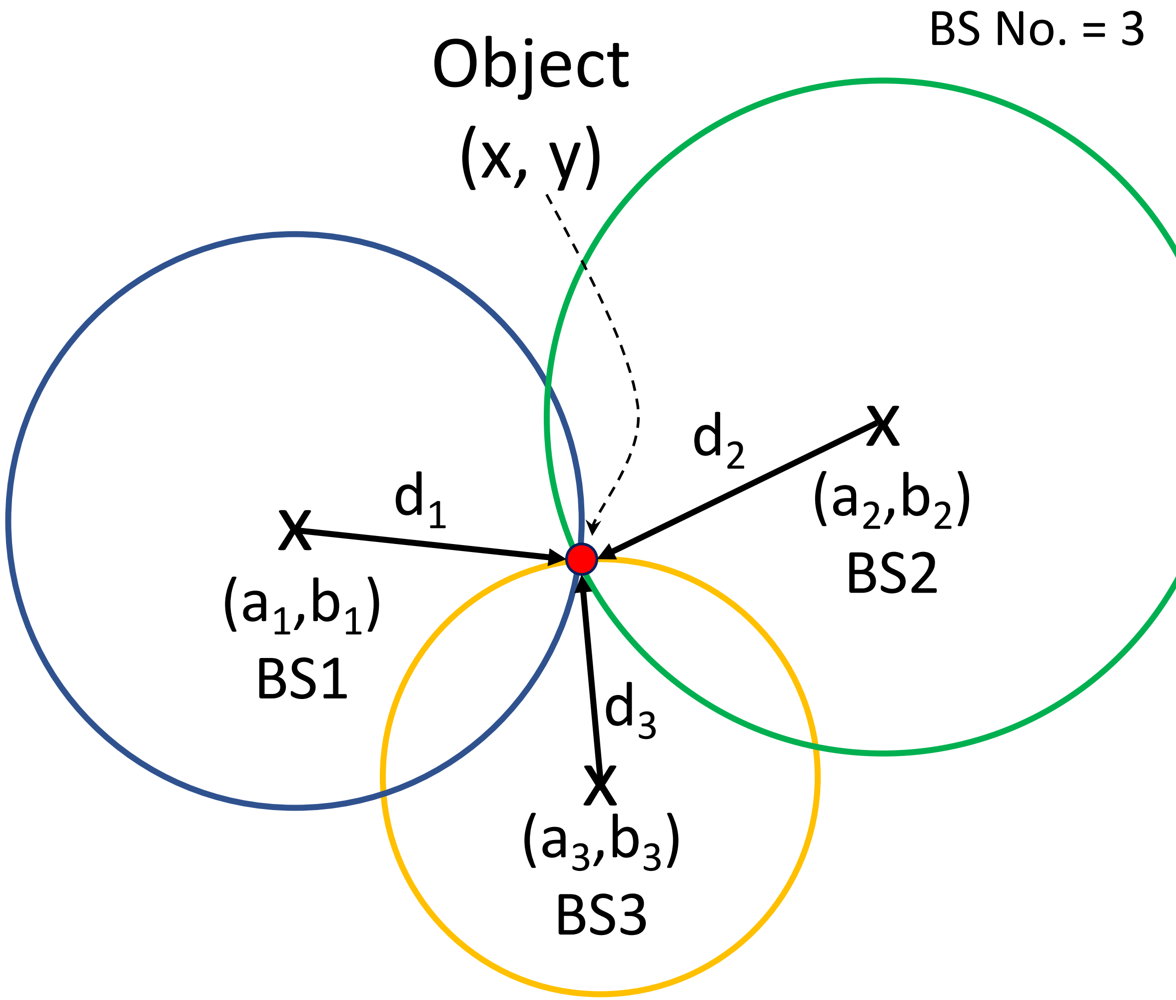
02 Methodology

Trilateration – Locate an Object

- Object's location
- $(x, y) = f\big((a_i, b_i), d_i\big)\ \forall\ i = 1,2,3$

- where
- $(a_i, b_i) = location\ of\ a\ BS$
- $d_i = distance\ btw\ object\ and\ the\ ith\ BS$
- $distance \propto RSSI$

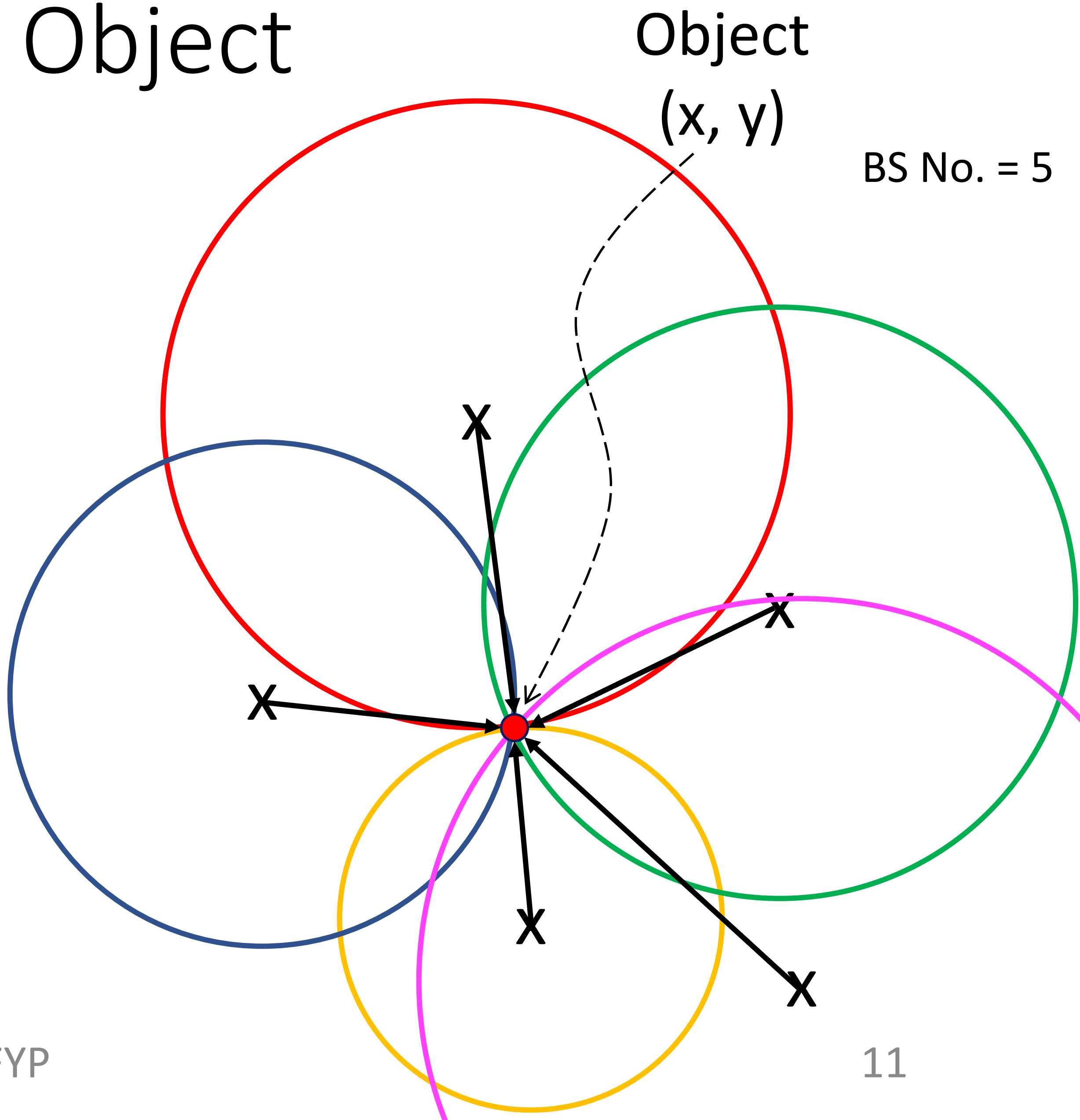
- At Least 3 BS are needed.



Trilateration – Locate an Object

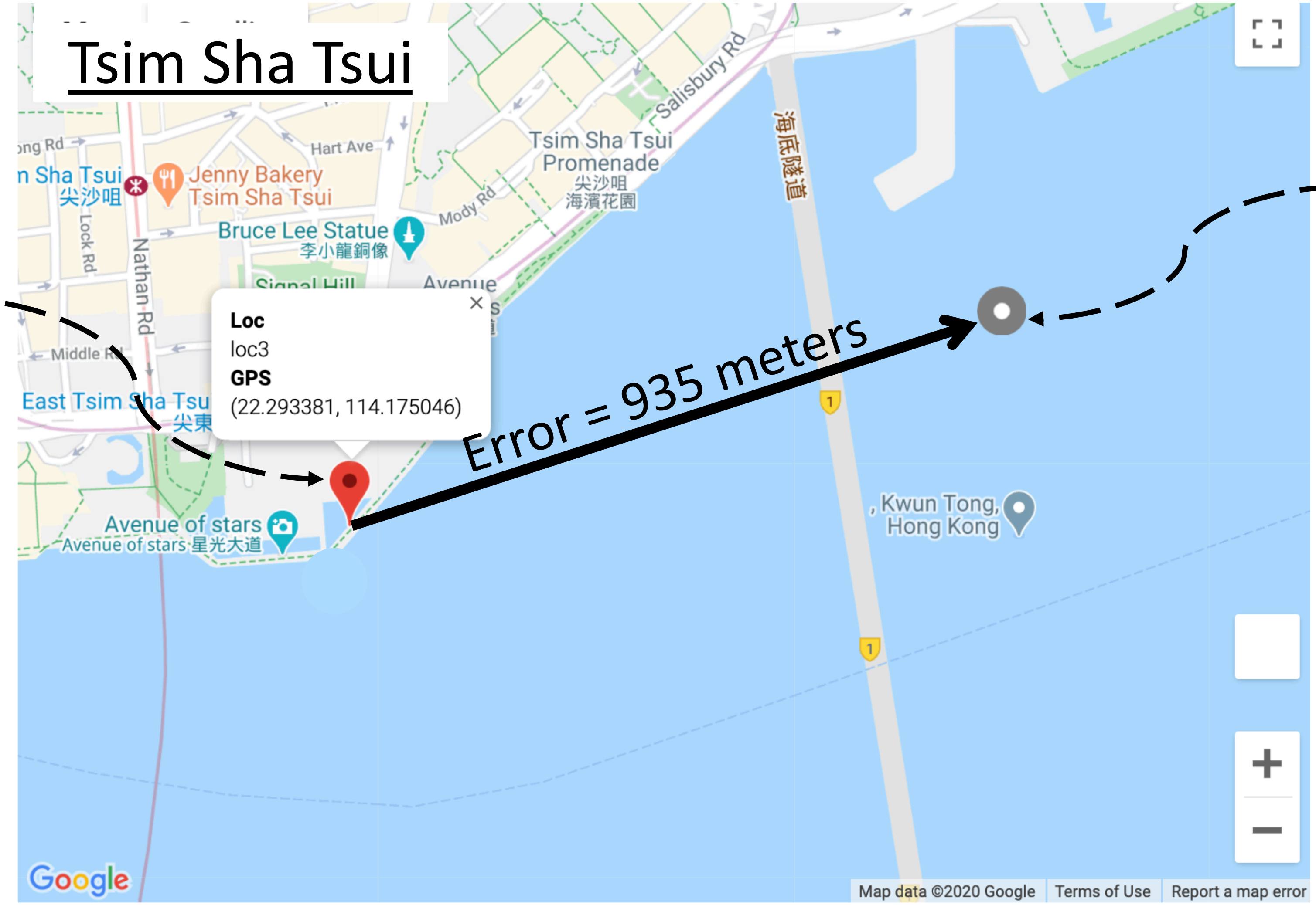
- If more base stations present, apply the same mathematical model.

- i.e., Object's location
- $(x, y) = f\big((a_i, b_i), d_i\big)\ \forall\ i = 1,2,3, \dots, N$



Trilateration – Performance

Object's real location

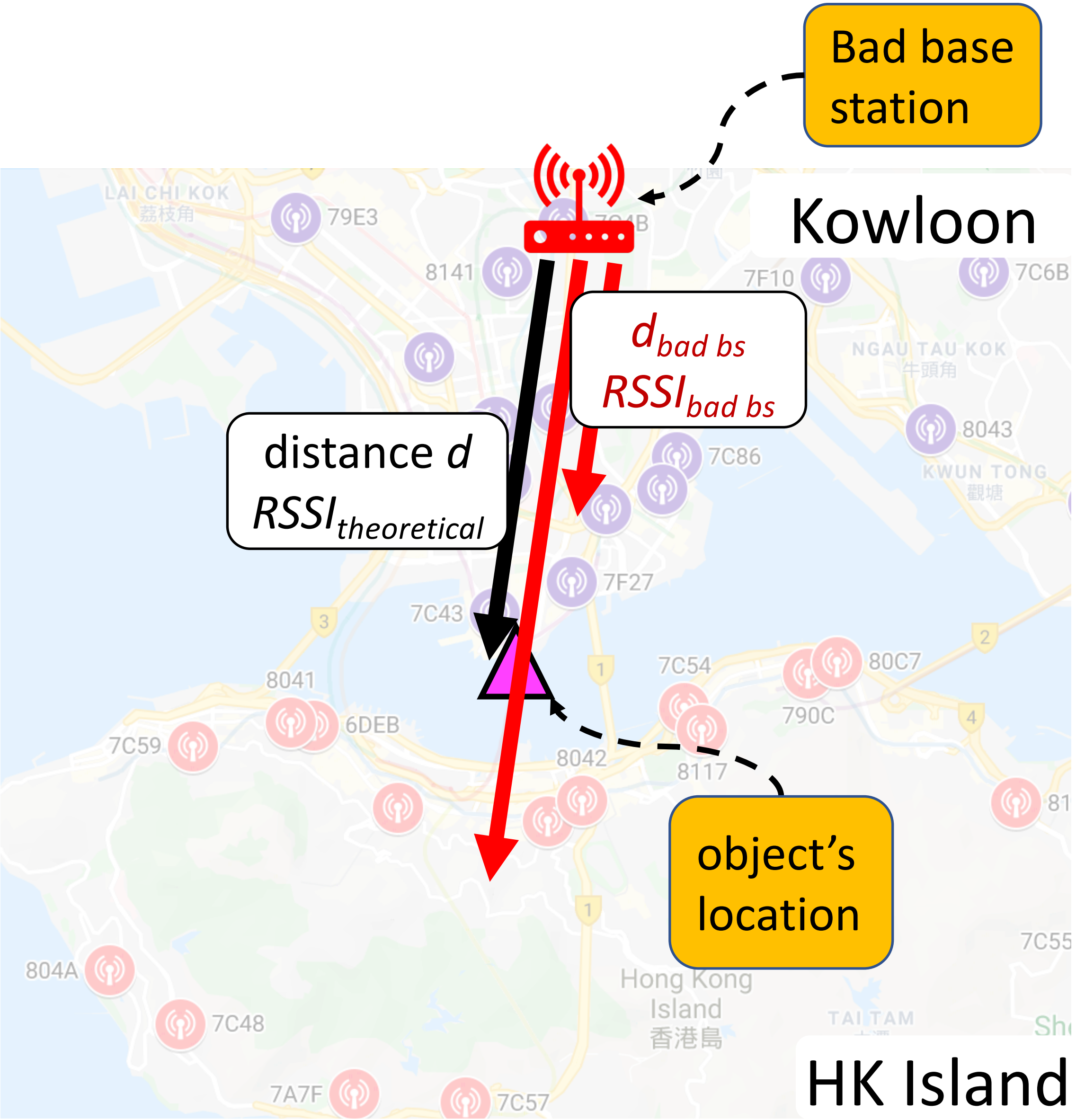


Localization result with all BS

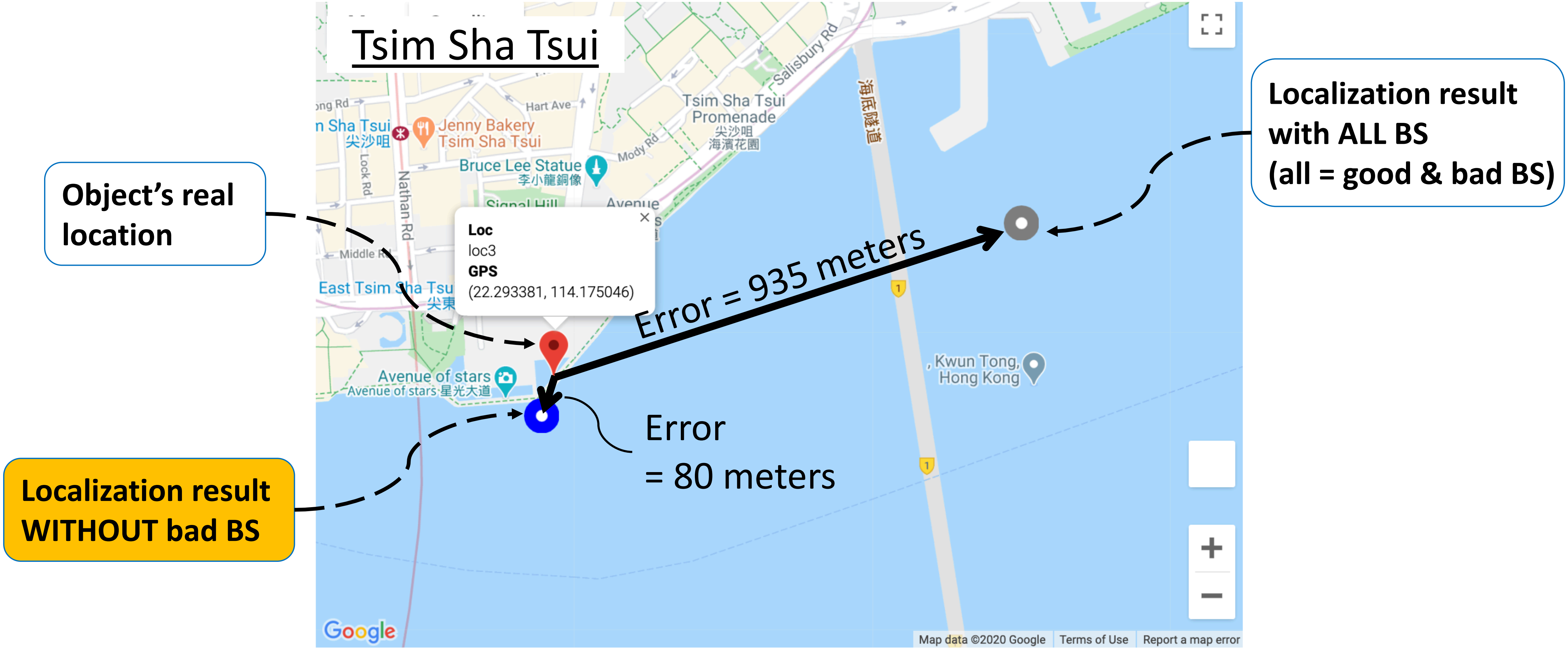
What is Bad Base Station

- $|d_{bad\ bs} - d| \gg 1$, or
- $|RSSI_{bad\ bs} - RSSI_{theoretical}| > threshold$

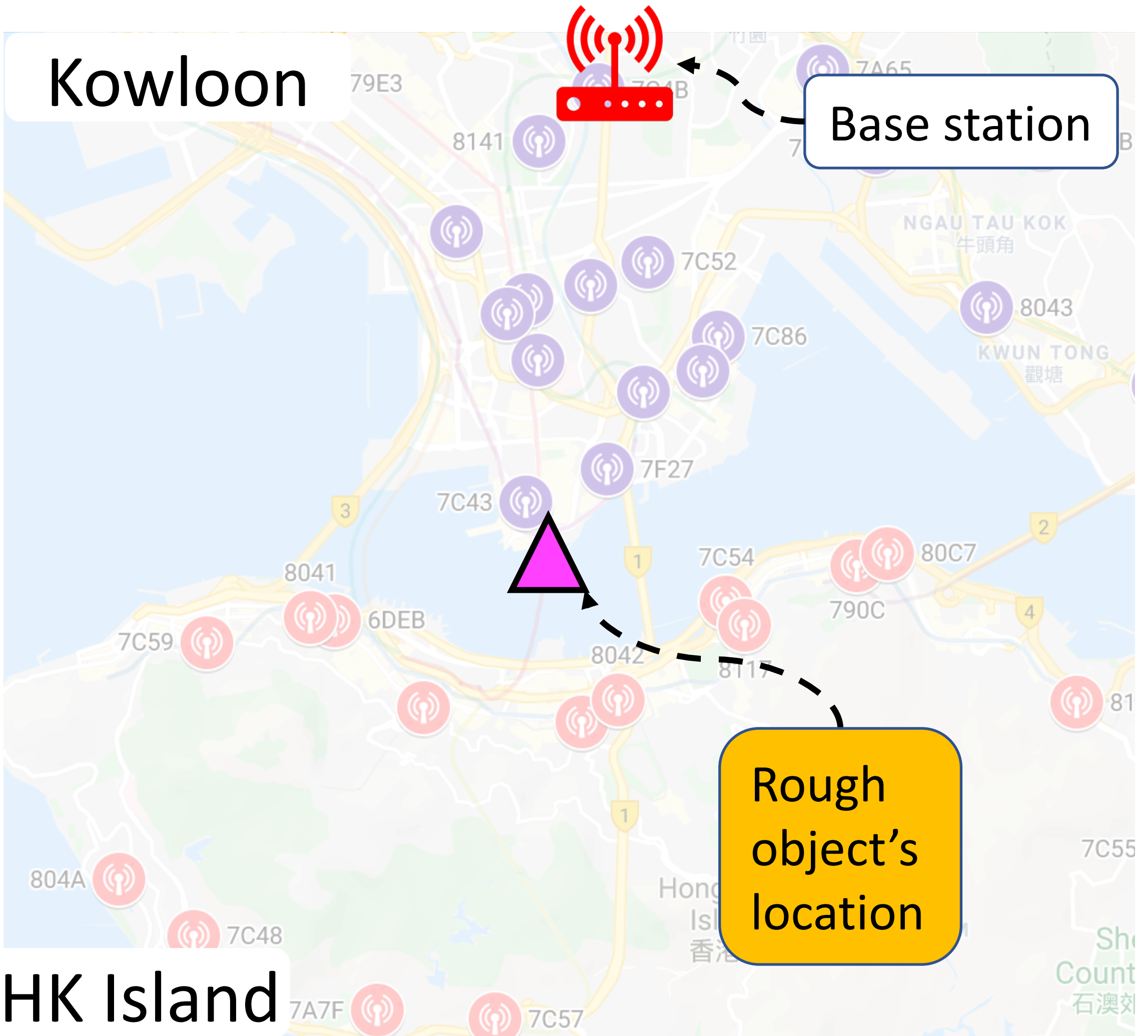
- $where\ distance \propto RSSI$



More Accurate Localization without Bad BS



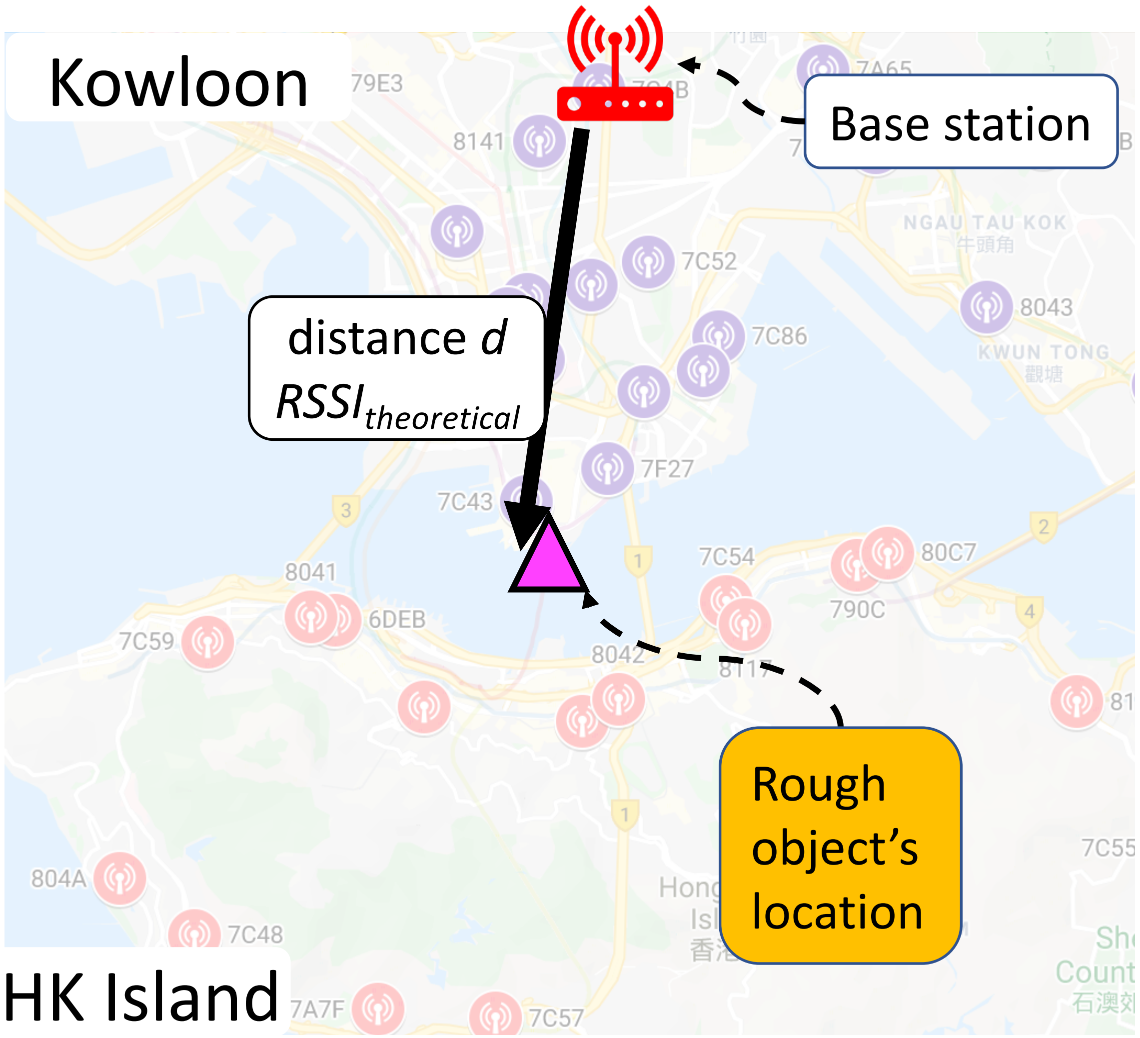
Steps to Identify Bad Base Stations



- Steps:

1. Know about the rough location of the object.
2.
3.

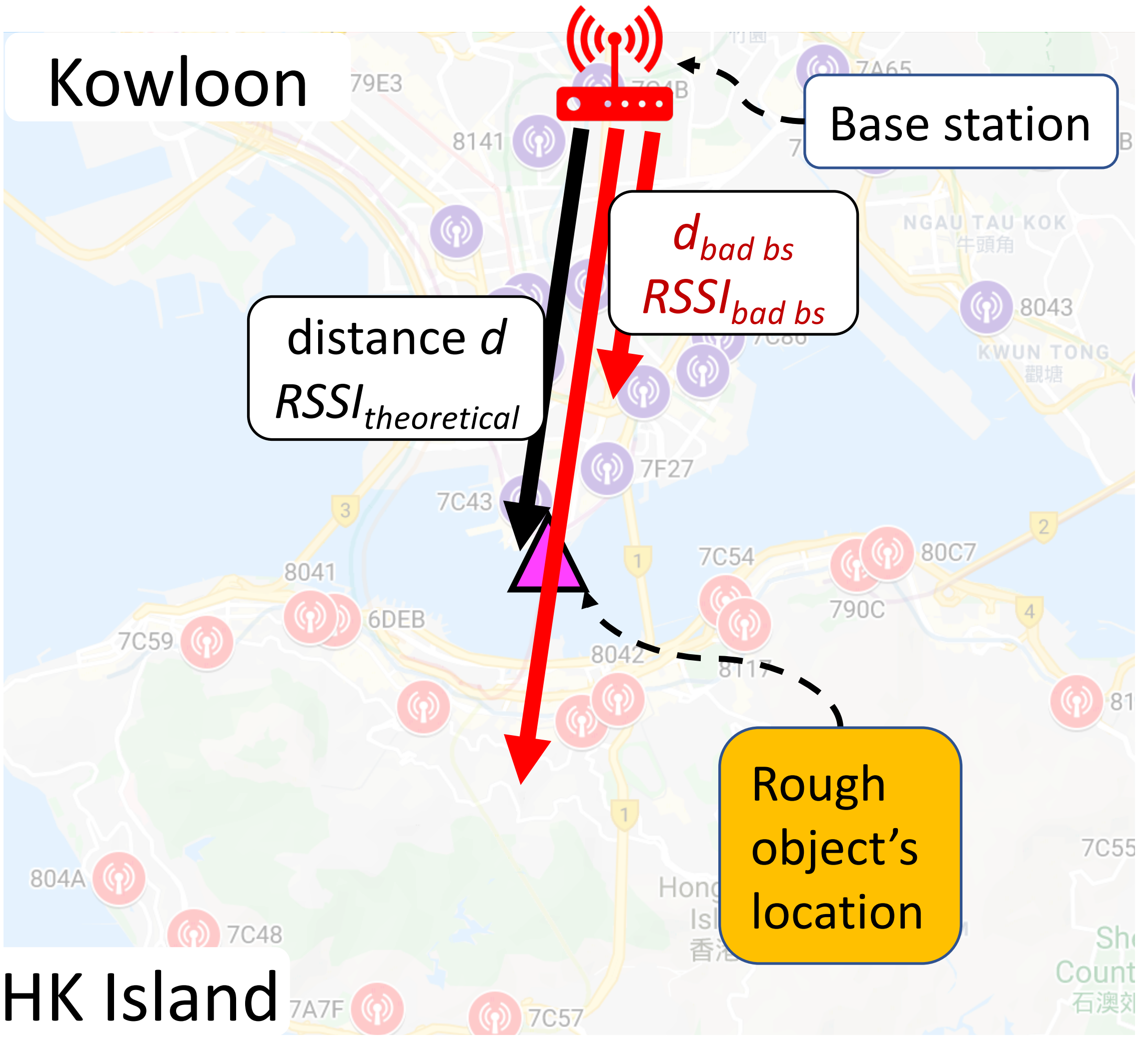
Steps to Identify Bad Base Stations



- Steps:

1. Know about the rough location of the object.
2. Calculate the distance and the theoretical RSSI between the rough location and the base station.
3.

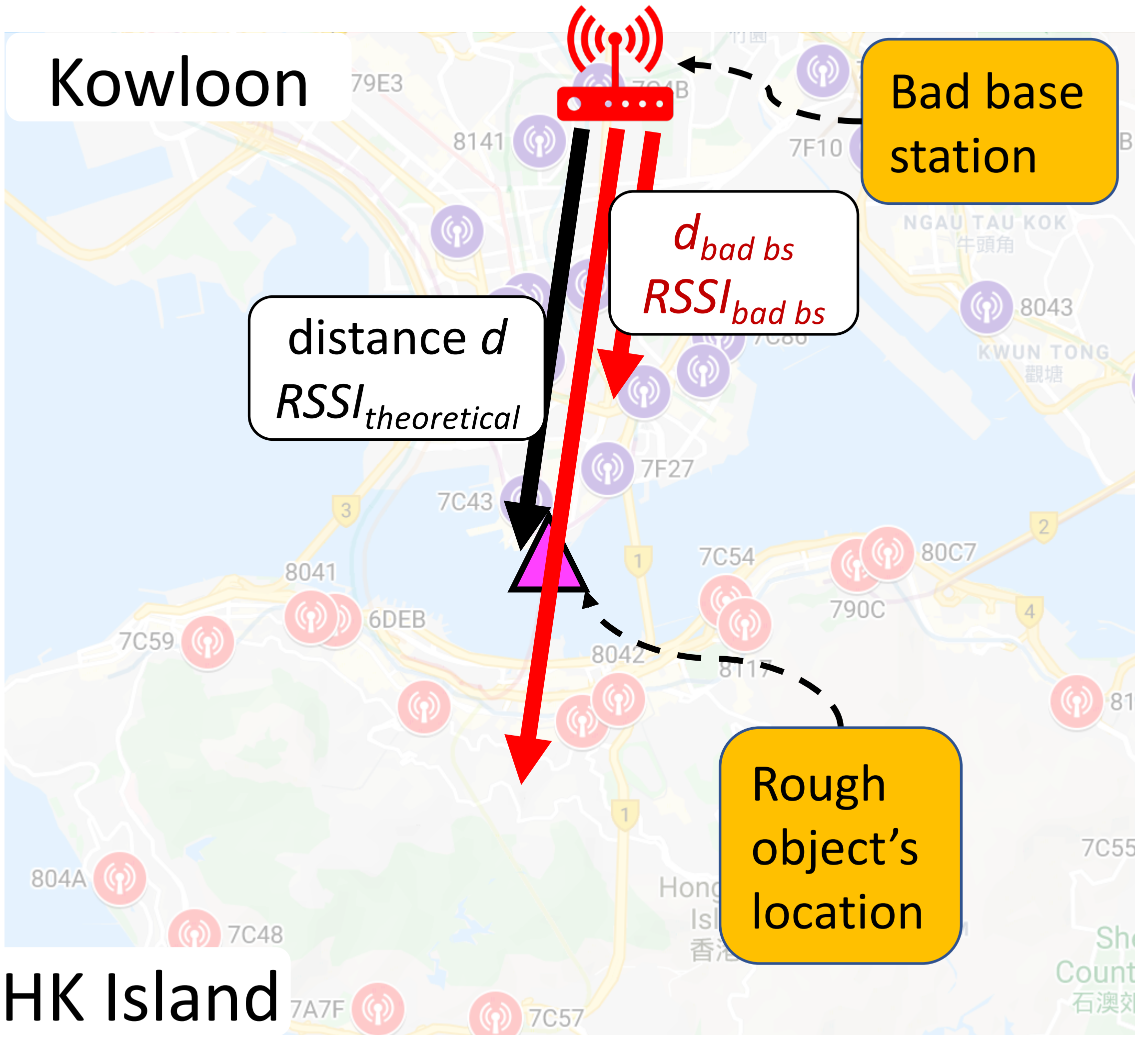
Steps to Identify Bad Base Stations



- Steps:

1. Know about the rough location of the object.
2. Calculate the distance and the theoretical RSSI between the rough location and the base station.
3. Identify the bad base stations,
   - $|d_{bad\ bs} - d| \gg 1$, or
   - $|RSSI_{bad\ bs} - RSSI_{theoretical}| > threshold$

Steps to Identify Bad Base Stations



- Steps:

1. Know about the rough location of the object.
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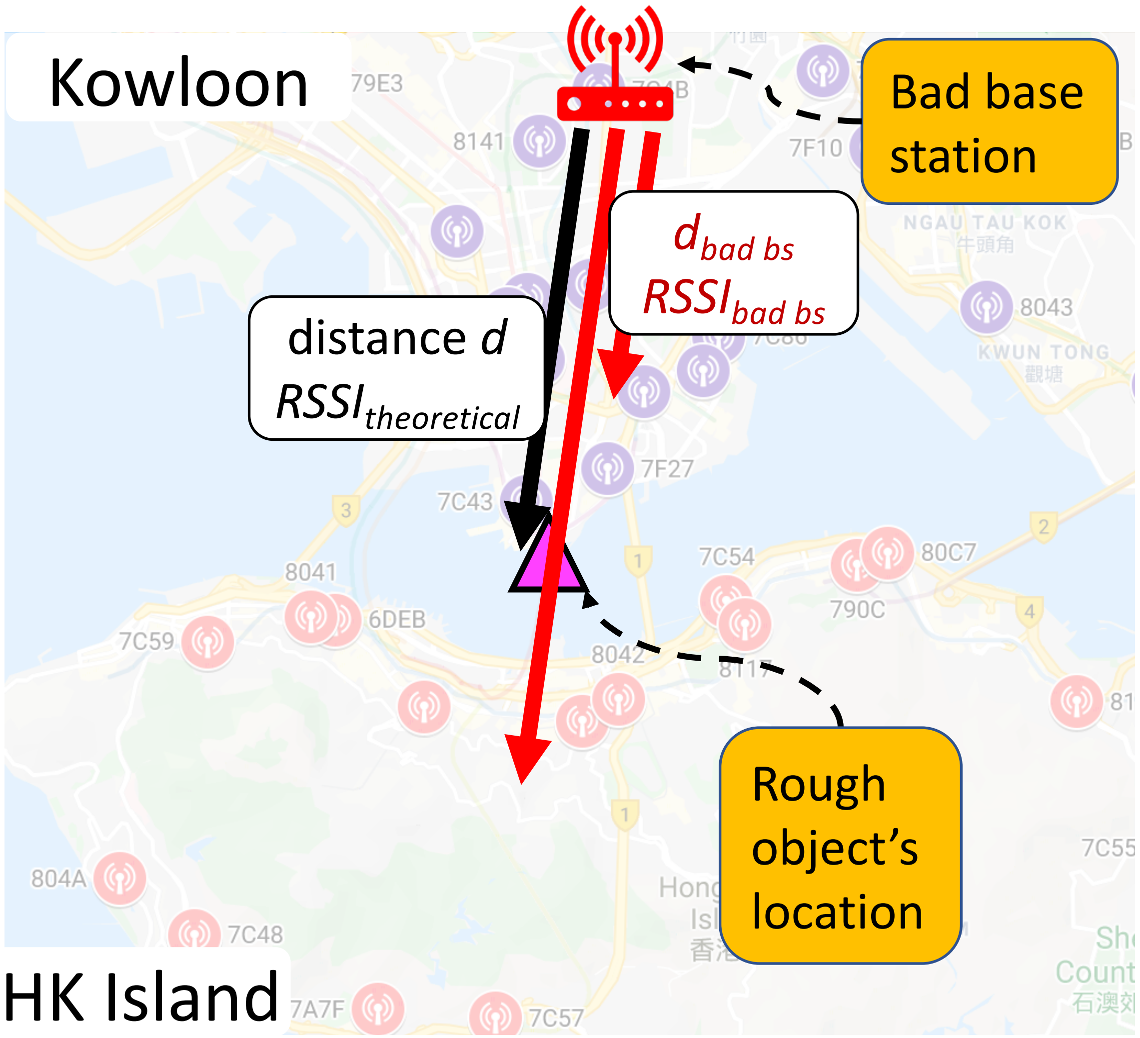
Steps to Identify Bad Base Stations



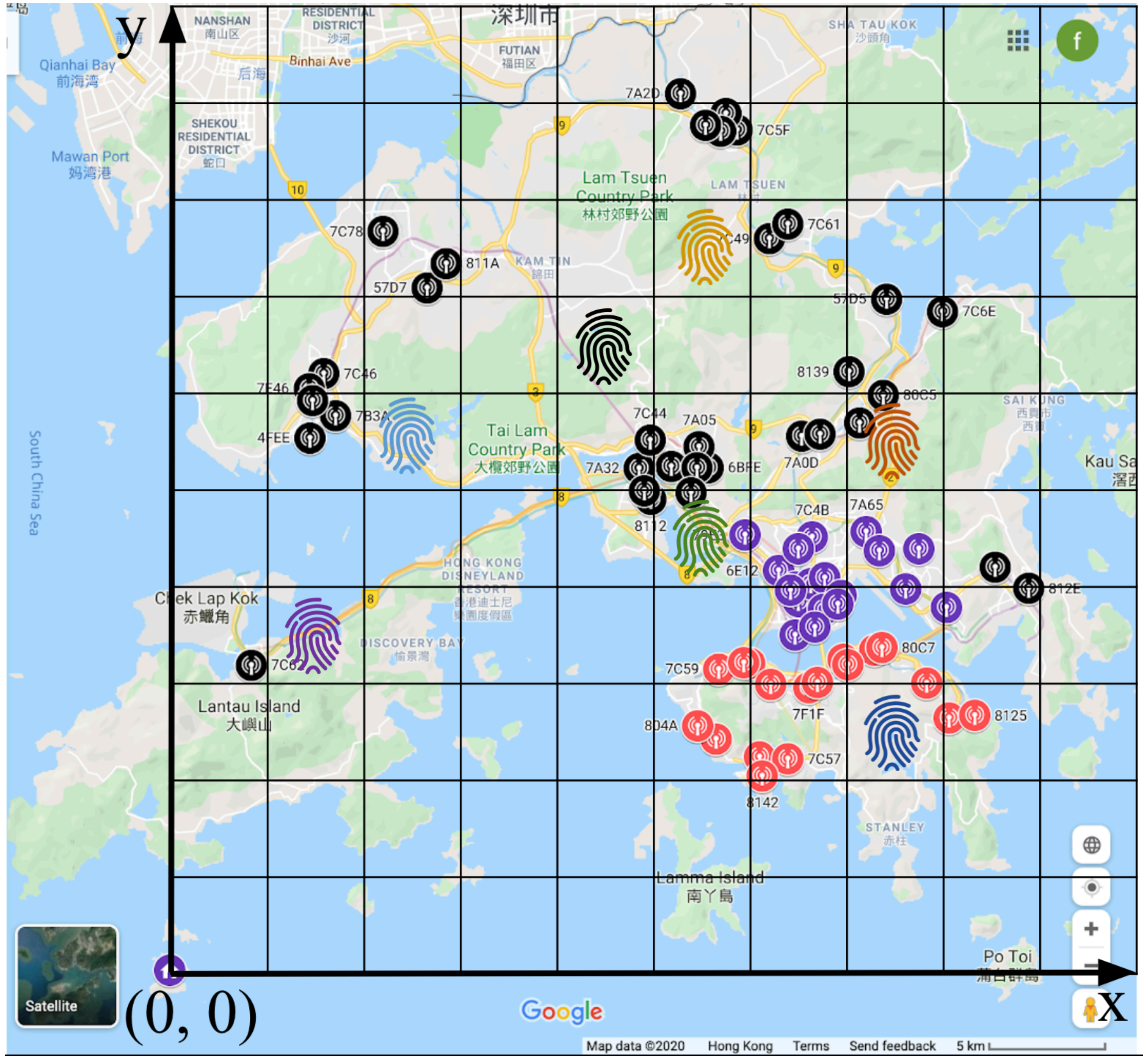
Employ Machine Learning to help

- Steps:

1. Know about the rough location of the object.
2. Calculate the distance and the theoretical RSSI between the rough location and the base station.
3. Identify the bad base stations,
   - $|d_{bad\ bs} - d| \gg 1$, or
   - $|RSSI_{bad\ bs} - RSSI_{theoretical}| > threshold$

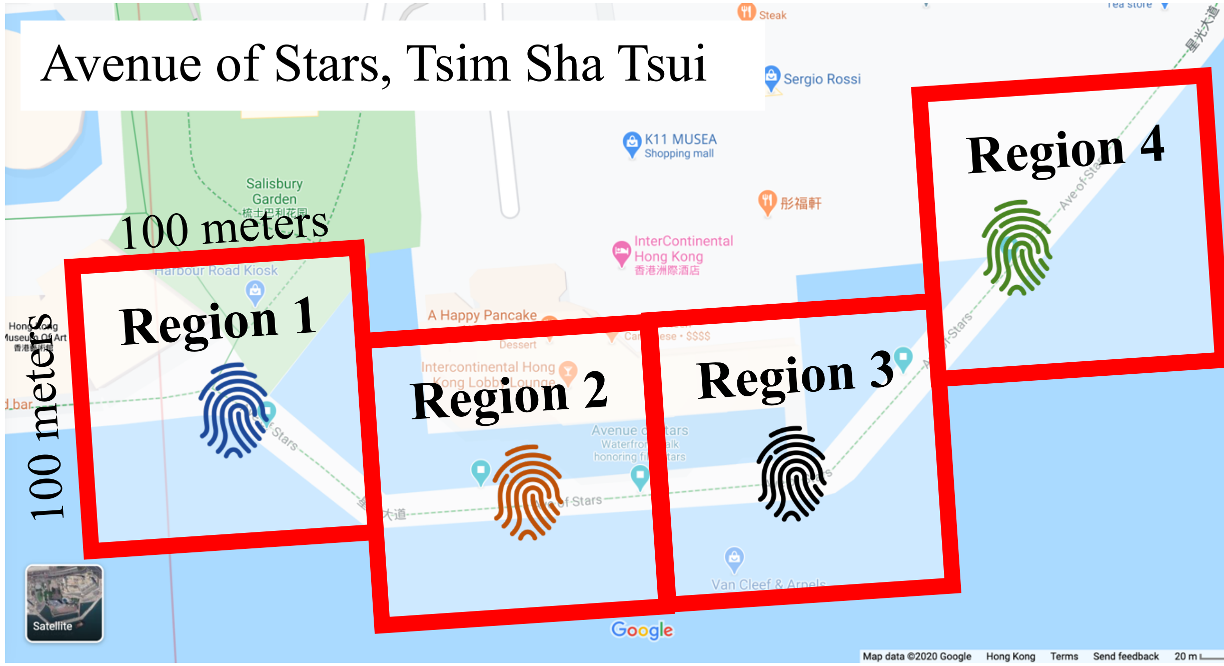
Region Recognition by Machine Learning (1)

- Believed that unique Radio Frequency (RF) features exist in the measured RSSI at different locations.
- Unique RF feature = fingerprint
- Divide the Hong Kong map into regions and collect RSSI within regions, then we can obtain a map full of RF features.



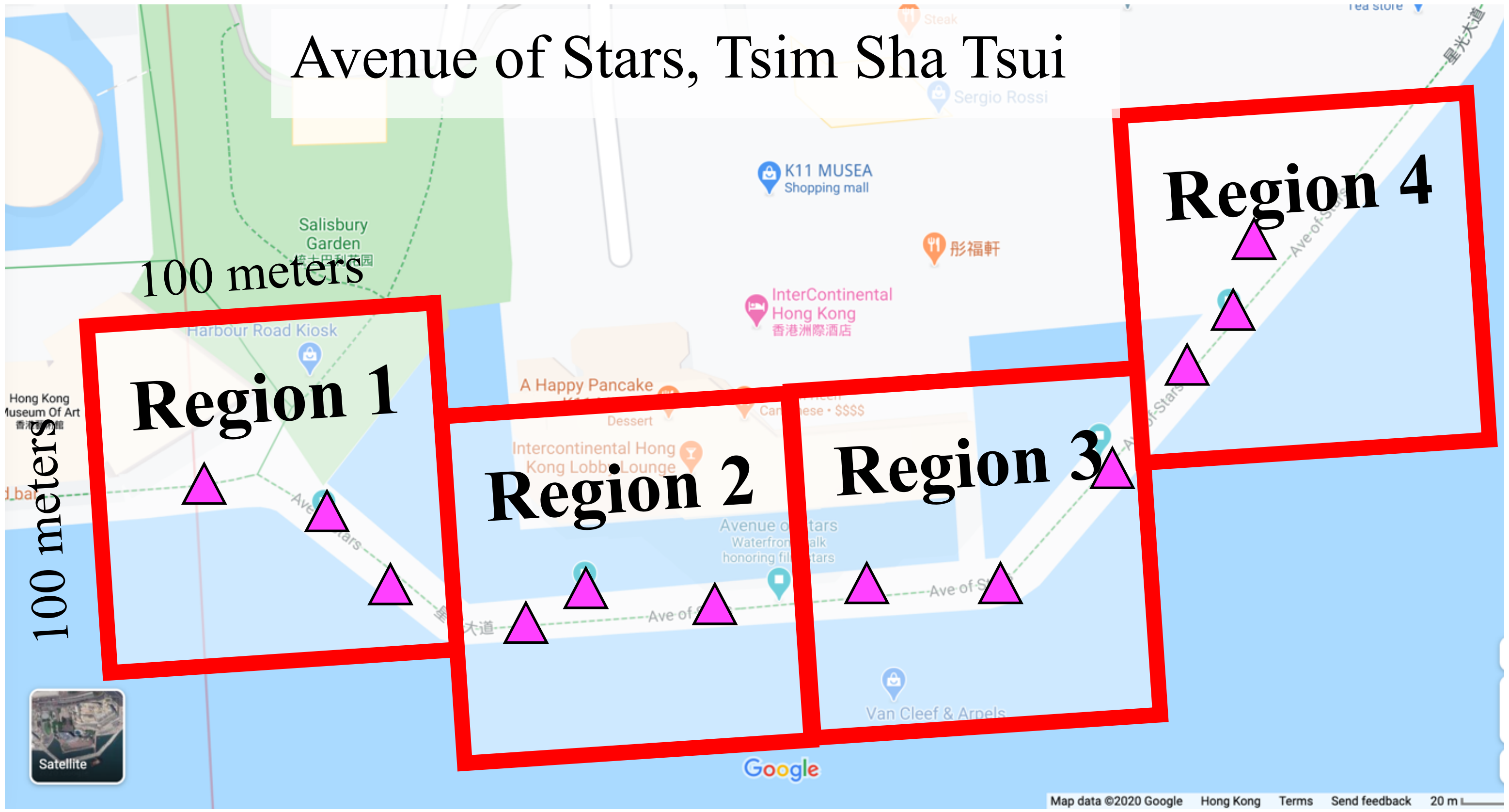
Region Recognition by Machine Learning (2)

- Machine learning can be trained to learn the RF features from the known regions (training data with labels) and recognize the region from the new RSSI data (test data).
- It is a classification problem.
- After recognizing the region, bad base stations can be identified and can be removed, and localization can be performed.

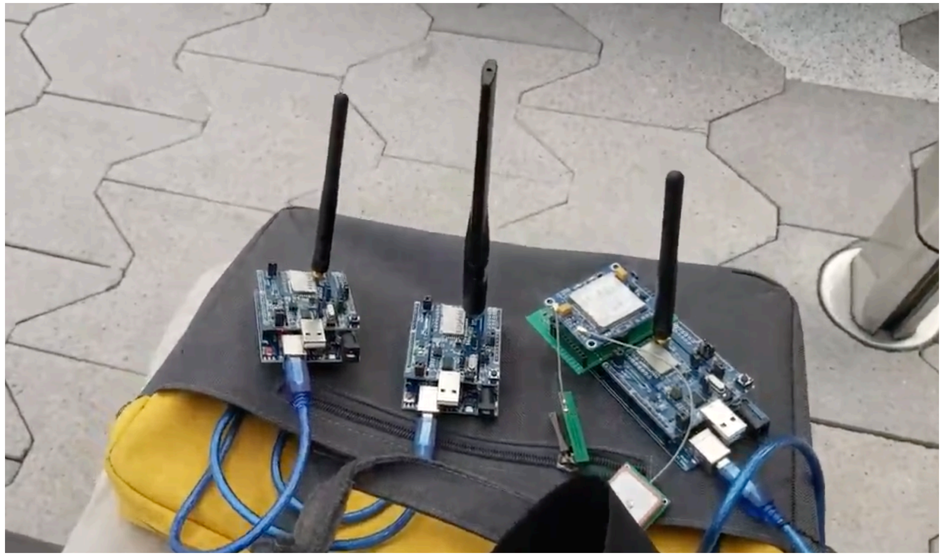


03 Implementations

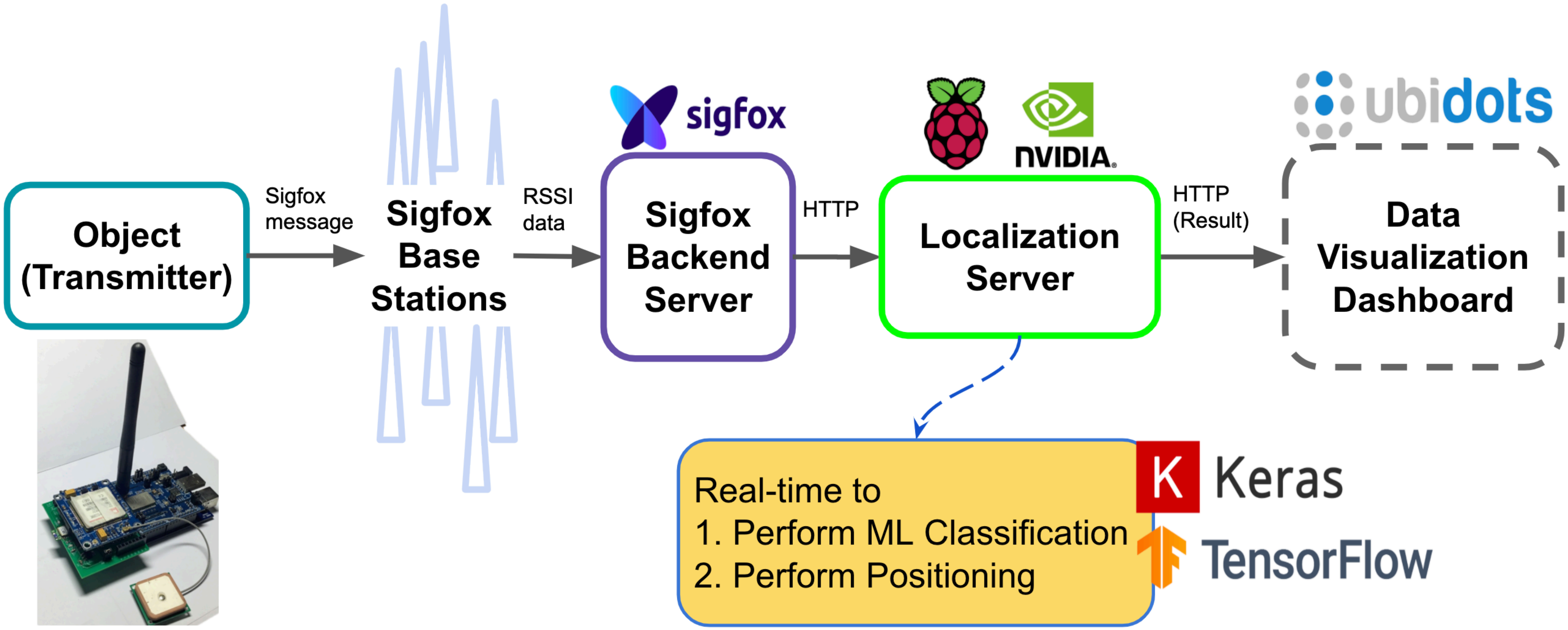
Implementations – Data Collection



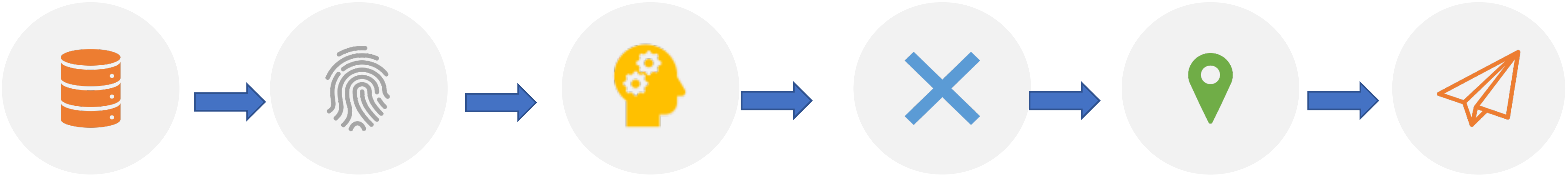
- Collected 1,336 RSSI measurements



Implementations – Real-time Localization



Process in Localization Server



(1)
RSSI Data comes

(2)
Data Pre-processing (Normalization)

(3)
Region Recognition (Classification) By trained ML model

(4)
Bad Base Station Elimination

(5)
Localization

(6) Send the localization result to the dashboard

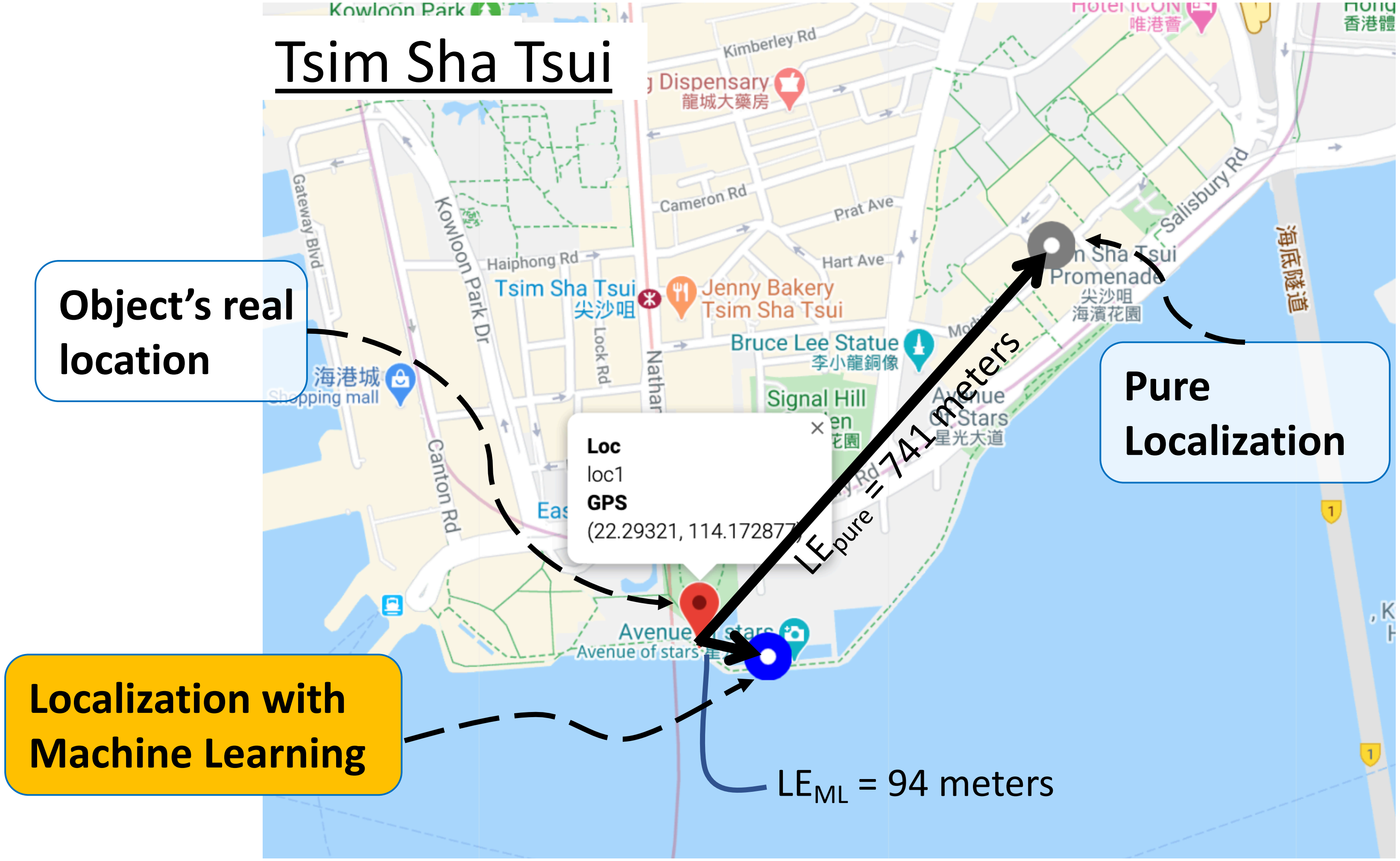
04 Performance Measure

Performance Measure – Localization Error

- Localization Error (LE):
- The distance between the object’s actual location and the localization result.

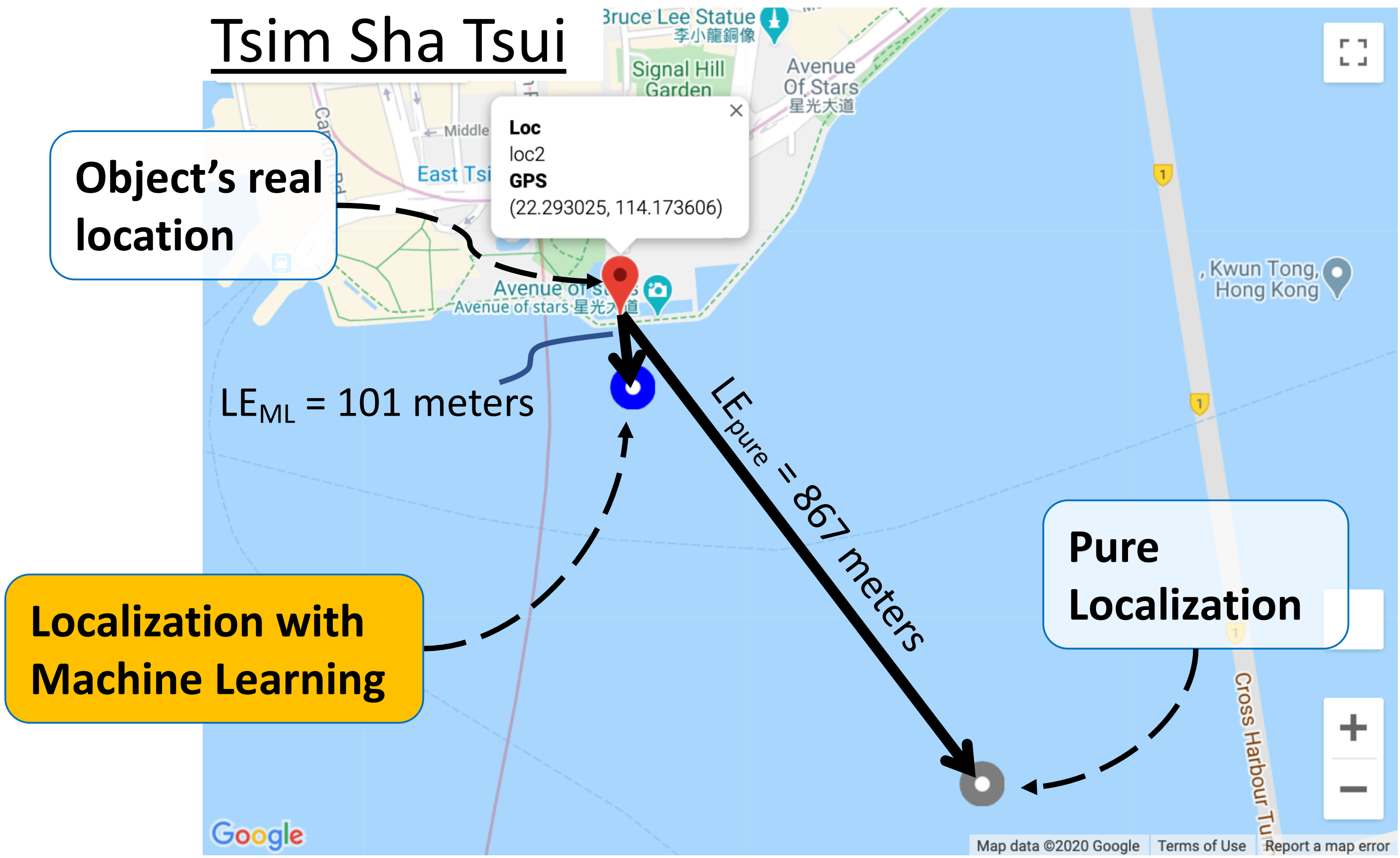
- Smaller LE, better performance of the localization algorithm

Performance Measure – Localization Error (1)



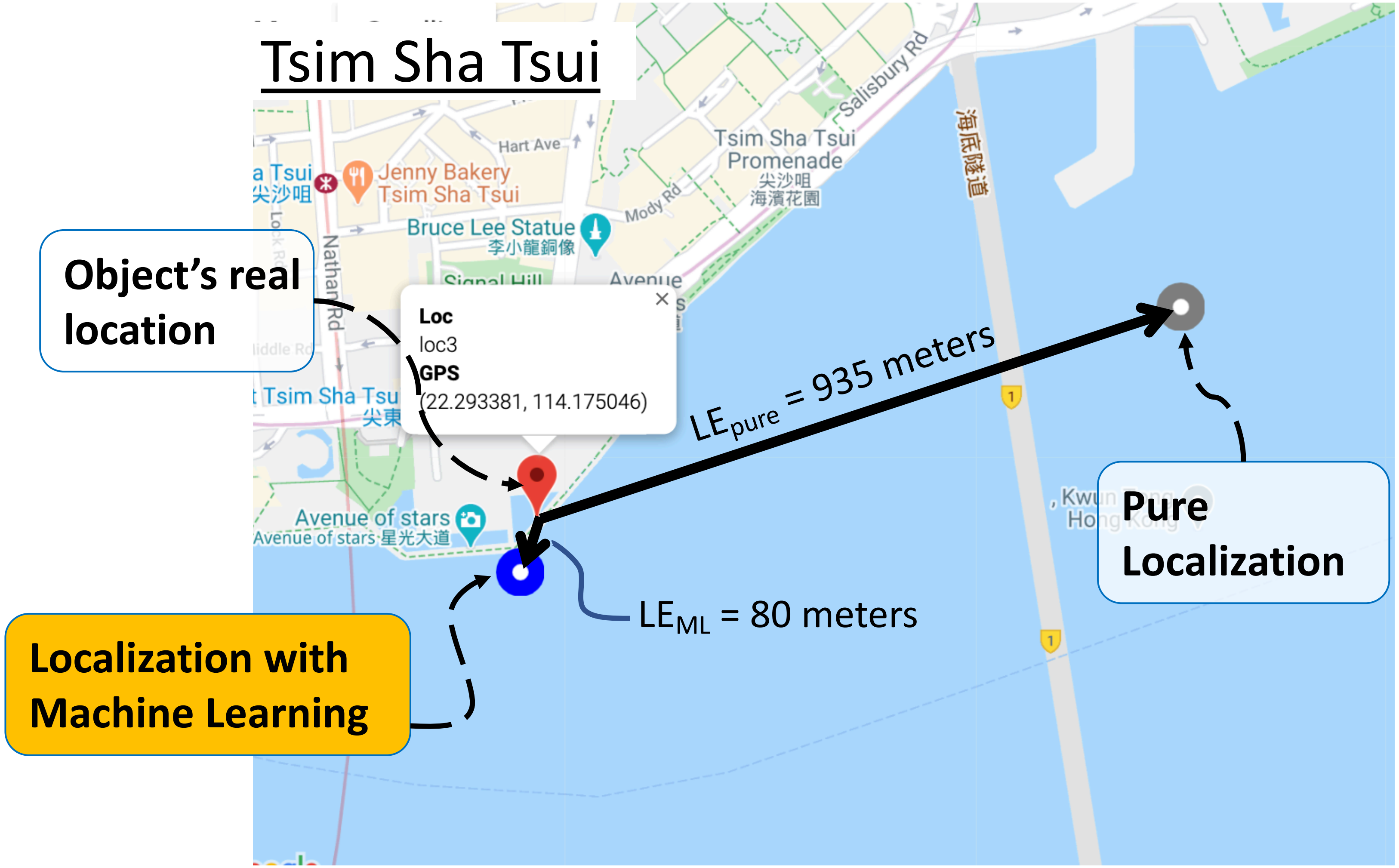
Testing point	Min. LE (with Bad BS)	Min. LE (without Bad BS)
1	741 m	94 m
2		
3		
4		

Performance Measure – Localization Error (2)



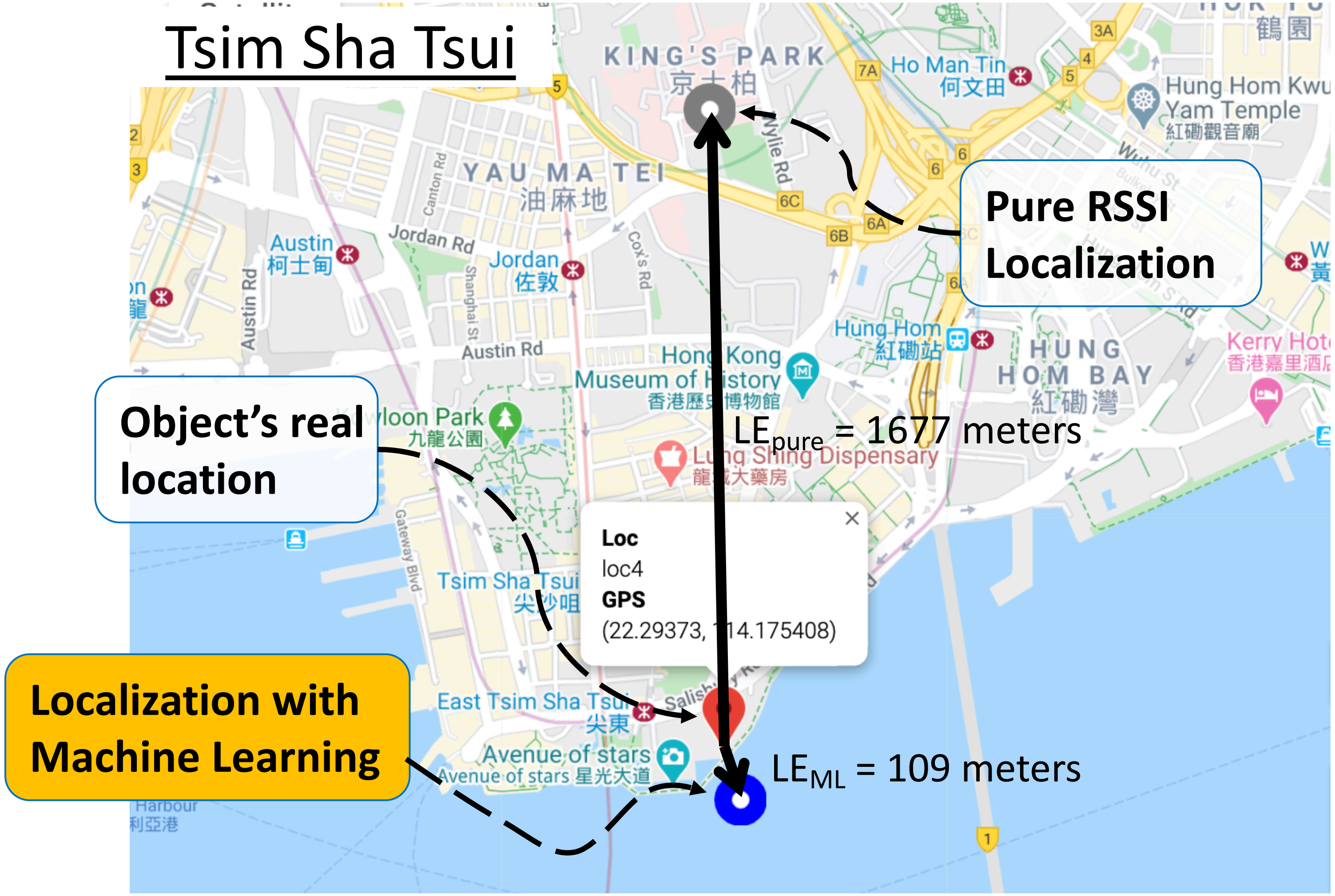
Testing point	Min. LE (with Bad BS)	Min. LE (without Bad BS)
1	741 m	94 m
2	867 m	101 m
3		
4		

Performance Measure – Localization Error (3)



Testing point	Min. LE (with Bad BS)	Min. LE (without Bad BS)
1	741 m	94 m
2	867 m	101 m
3	935 m	80 m
4		

Performance Measure – Localization Error (4)



Testing point	Min. LE (with Bad BS)	Min. LE (without Bad BS)
1	741 m	94 m
2	867 m	101 m
3	935 m	80 m
4	1677 m	109 m

Performance Measure – Localization Error (5)

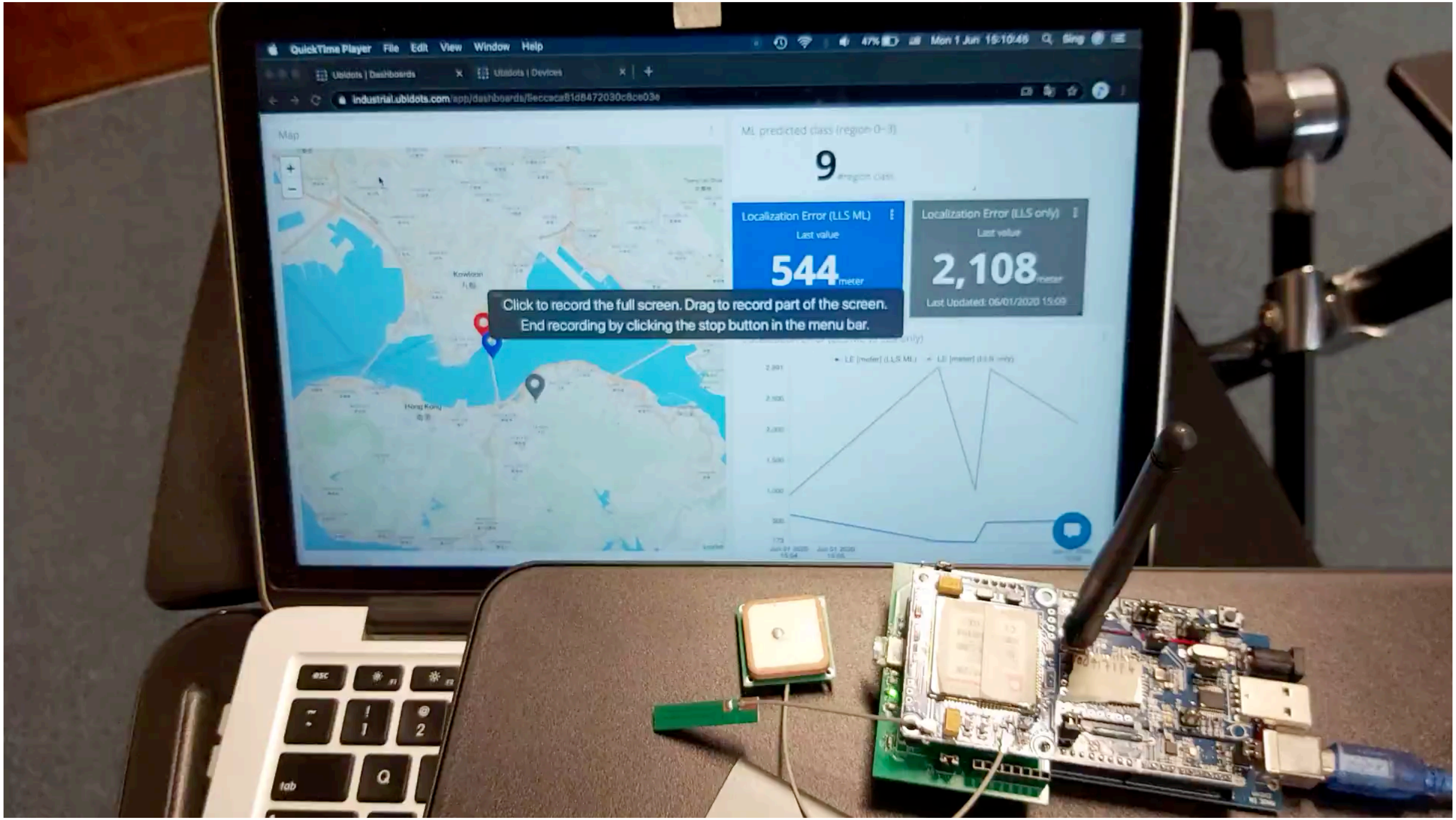
Testing point	Min. Localization Error	
	WITH Bad BS	WITHOUT Bad BS
1	741 m	94 m
2	867 m	101 m
3	935 m	80 m
4	1677 m	109 m

Performance Measure – Classification Accuracy

	Linear SVM	Deep Neural Network	1D-Convolutional Neural Network
Accuracy	75.5556 %	77.722 %	88.148 %

05 Demonstration

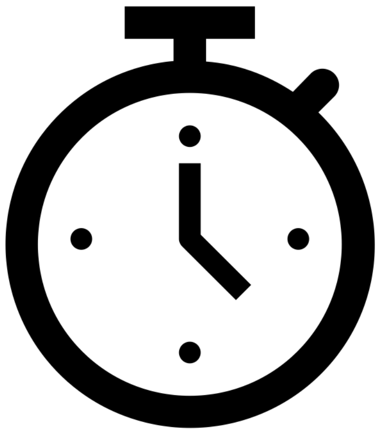
Demo

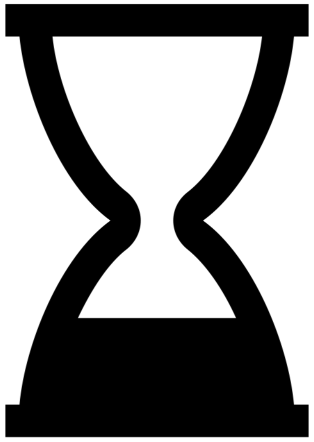

QuickTime Player File Edit View Window Help
ML predicted class (region 0~3)
9
Localization Error (LLS ML)
Last value
544 meter
Localization Error (LLS only)
Last value
2,108 meter
Click to record the full screen. Drag to record part of the screen.
End recording by clicking the stop button in the menu bar.

06 Difficulties

ML Model Training – Prepare Training Data

- Spent lots of time to collect data
- Total number of RSSI measurements
  - = 1,336
- Total time taken
  - = 5 to 6 hours in total





ML Model Design – Hyperparameter Search

- Cost lots of time to find the optimal value of hyperparameters when designing neural network.
- E.g., the optimal structure of 1D-CNN:
  - Filter size = 10
  - No. of filters in a conv. layer = 128
  - No. conv. blocks = 1

Hyperparameters	Values	Average Accuracy
Filter Size, S	4	83.333 %
	7	82.222 %
	10	86.222 %
	12	84.000 %
	15	84.222 %
	20	80.667 %
Number of Filters, N	32	86.222 %
	64	86.222 %
	128	88.148 %
	256	85.556 %
Number of convolution blocks, L	1	80.000 %
	2	79.111 %
	3	68.889 %
	4	70.222 %

07 Conclusion and Future Work

Conclusion and Future Work

- The localization with machine learning is an effective method to reduce the localization error.

- In the future:
  - Increase the number of regions = collect more RSSI data from different locations.
  - So that the ML model can recognize more locations and expand the localization service.

Q&A