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Indoor Localization Accuracy Estimation from Fingerprint Data

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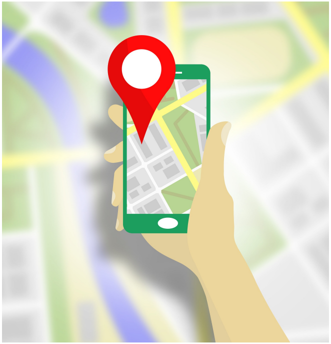
AALBORG UNIVERSITY

max planck institut informatik

Outline

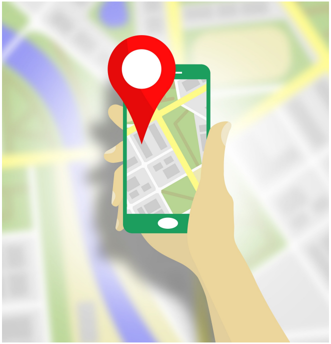
Motivation: Indoor Localization

- Indoor Navigation Services spread widely.
- Applications: localization, marketing, warehouse optimization, guides, games, etc.



Motivation: Indoor Localization

- Indoor Navigation Services spread widely.
- Applications: localization, marketing, warehouse optimization, guides, games, etc.
- Different sources of data: cellular, Wi-Fi, BT, magnetic field of the Earth, light, sound, etc.



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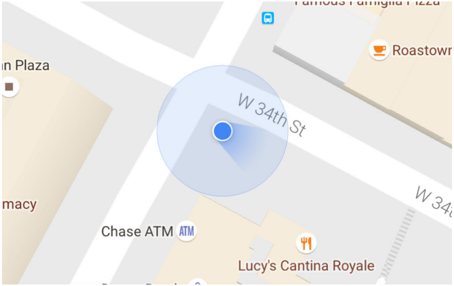
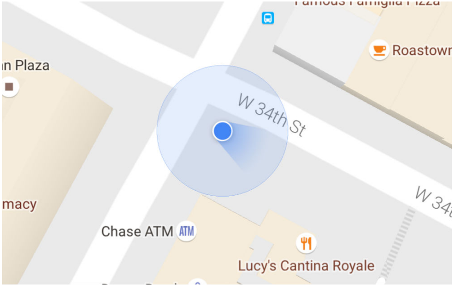
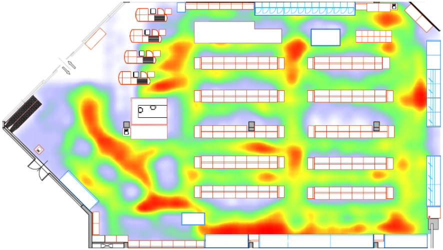


Motivation: Accuracy Estimation

- Important to estimate the accuracy of localization.
- Online: important for the end-user (Google Maps, CONE).
- Offline: important for the service provider.
  - Provide quality guarantees.
  - Perform decision making.





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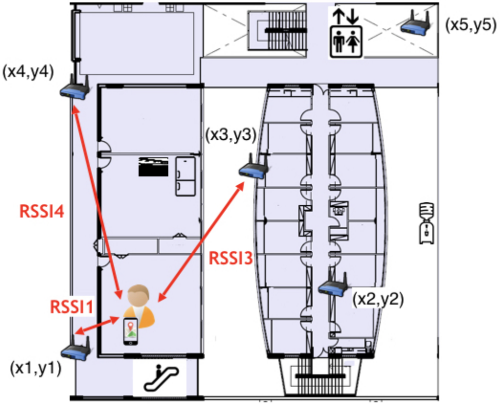
Modeling

- Known APs positions
- Known data model, e.g., Path Loss: $L = 10n\log_{10}(d) + C$



Modeling + Fingerprinting

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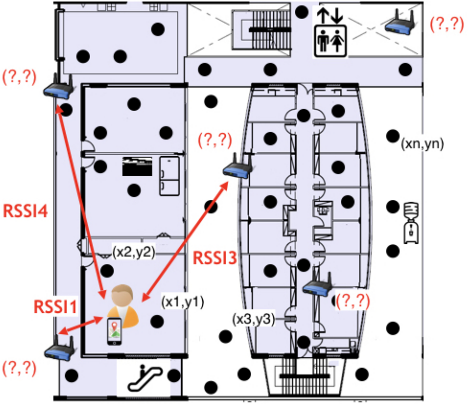

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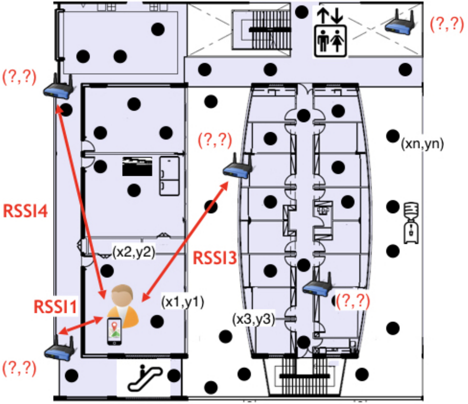

Background: Accuracy Estimation

Existing solutions

- Heuristics: e.g., fingerprint density, cluster & merge, etc.
  - $+$ Do not require models
  - $-$ No theoretical guarantees
- Theoretical: e.g., use *Cramer-Rao Lower Bound* (CRLB)
  - $+$ Provide theoretical guarantees
  - $-$ Model is required

Our goal:

- $+$ No model required
- $+$ Provide guarantees via CRLB

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Common theoretical approach for offline accuracy estimation:

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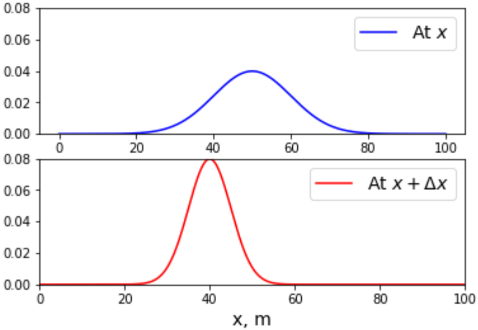

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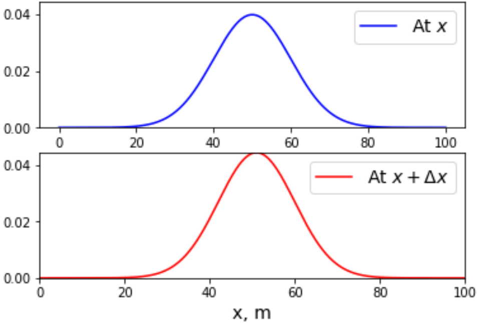

How to find the *likelihood*?

Modeling. We know:

- Model, e.g., Path Loss: $L = 10n\log_{10}(|x - x_{AP}|) + C$
- Model parameters, e.g., $n = 2, C = 20\log_{10}\frac{4\pi}{\lambda}$ (FSPL)
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- Noise

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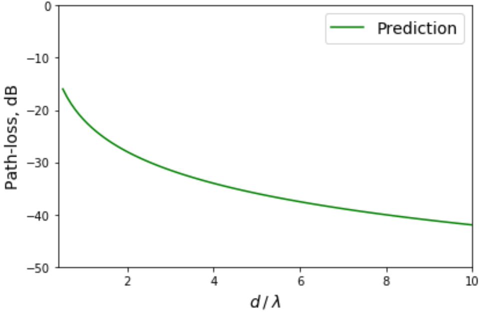

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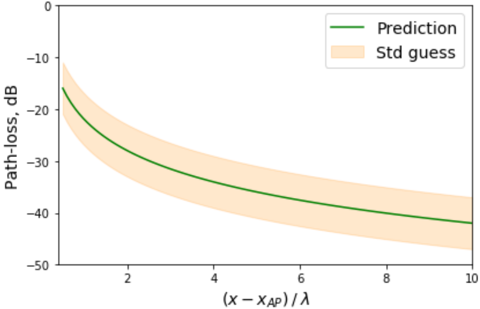

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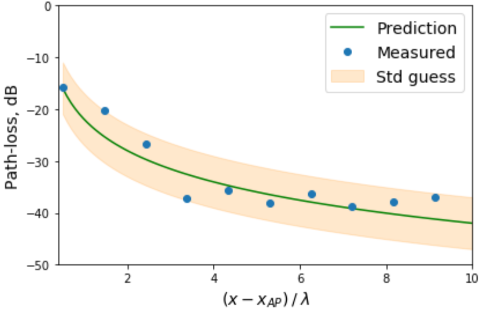
1. Predict using model
2. Estimate noise
3. Compare to measurements



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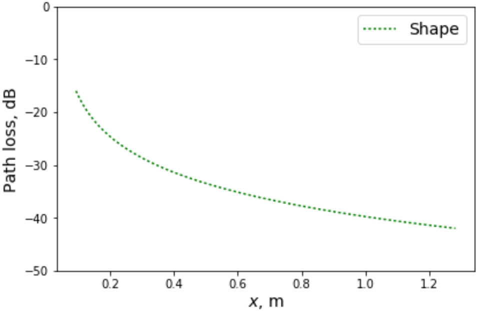

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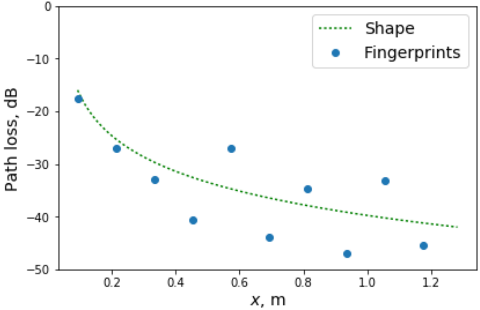
2. Get fingerprints



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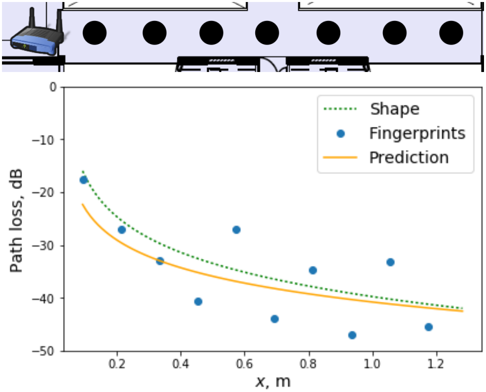

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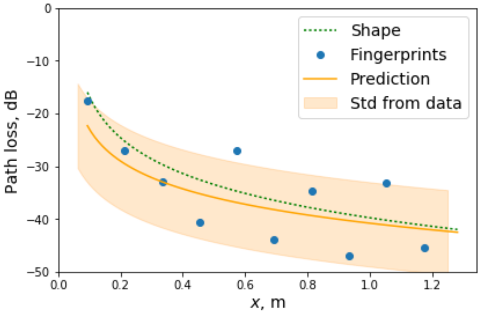

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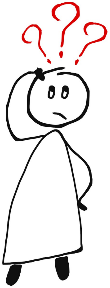

Outline

Our solution: Goal

- Pure fingerprinting approach
- Arbitrary data sources
- $FM = \{(\mathbf{r}_i, \mathbf{m}_i) : i = \overline{1, N}, \mathbf{r}_i \in \mathbb{R}^{d_r}, \mathbf{m}_i \in \mathbb{R}^{d_m}\}$
  $\mathbf{m}_i$ - d_m-dimensional vector of measurements at location $\mathbf{r}_i$.
- Given the FM, assign to any location a *navigability score*.
- Visualize navigability scores to assist INS deployer.

ACCES framework

1. **Interpolation:**
   FM + *Gaussian Process Regression* (GPR) ⇒ *likelihood*

2. **CRLB:**
   Likelihood + CRLB ⇒ lower bound on localization error

3. Lower bound on localization error ⇒ navigability score
   - Theoretical bound on localization error
   - Assume that behaves similar to real error

Gaussian Process Regression:

- **Input:** fingerprint map of measurements
- **Output:** Gaussian likelihood $p(\mathbf{m}|\mathbf{r})$ of measuring $\mathbf{m}$ at $\mathbf{r}$ (prediction + uncertainty)
- **Intuition:**
  - measurements are Gaussian random variables
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- **Properties:**
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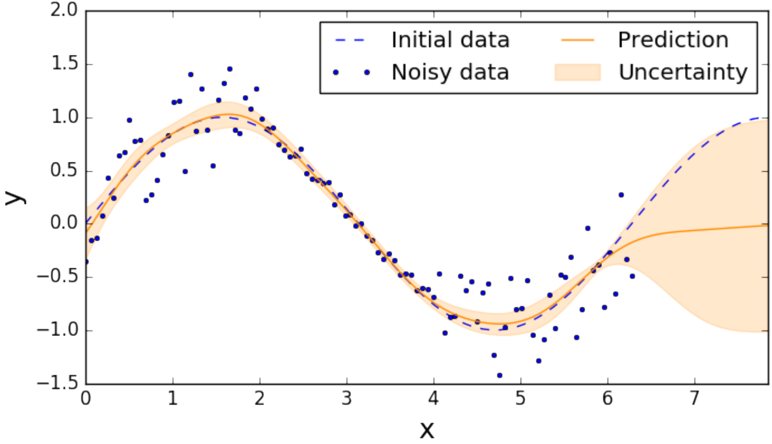
  - captures FM's spatial sparsity
- **Nuances:**
  - parameters tuning is required (kernel, length scale, etc.)
  - assume normality condition (does not directly work for NLOS)
  - directly applicable only to scalar data $\Rightarrow$ assume independence
  - computationally expensive $\Rightarrow$ clustering

Our Solution: Interpolation

Gaussian Process Regression (1-D example)



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Cramer-Rao Lower Bound:

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- **Properties:**
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- **Nuances:**
  - an underestimation of the real error $\Rightarrow$ we care about qualitative behavior
  - analytical representation depends on GPR parameters $\Rightarrow$ we involve numerical methods

Our Solution: CRLB

CRLB: error of any unbiased location estimator is bounded as

$$RMSE \geq \sqrt{tr(\mathcal{I}^{-1}(\mathbf{r}))},$$

where $\mathcal{I}(\mathbf{r})$ is a *Fisher Information Matrix*:

$$\mathcal{I}(\mathbf{r}) = -\mathbb{E}\left(\frac{\partial^2 \log p(\mathbf{m}|\mathbf{r})}{\partial \mathbf{r}_i \partial \mathbf{r}_j}\right)$$

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From GPR:

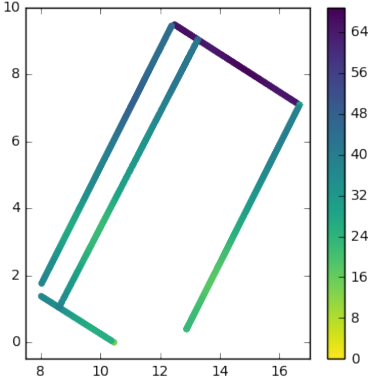
$$\mathbf{m}|\mathbf{r} \sim \mathcal{N}(\boldsymbol{\mu}(\mathbf{r}), \Sigma(\mathbf{r}))$$

Thus,

$$\mathcal{I}(\mathbf{r}) = \frac{1}{2}\sum_{k=1}^{d_m}\left[(\sigma_k^2+\mu_k^2)H(\sigma_k^{-2})+H(\mu_k^2\sigma_k^{-2})-2\mu_k H(\mu_k\sigma_k^{-2})+2H(\log\sigma_k)\right]$$

Outline

- UJIIndoorLoc-Mag database
- 8 corridors over 260 m^2 lab
- 40,159 discrete captures
- Magnetometer readings
- Measurements along the corridors ⇒ 1-D data



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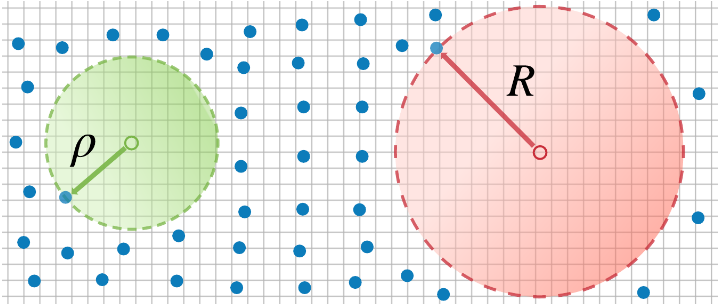
considers only distance between measurements



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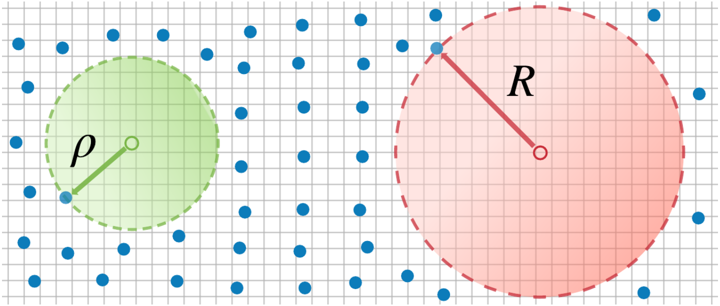
- **ACCES:** our solution



$DQRelSim(X, Y)$ - behavior similarity of sequences $X = X_i$, $Y = Y_i$ for 1-D case.

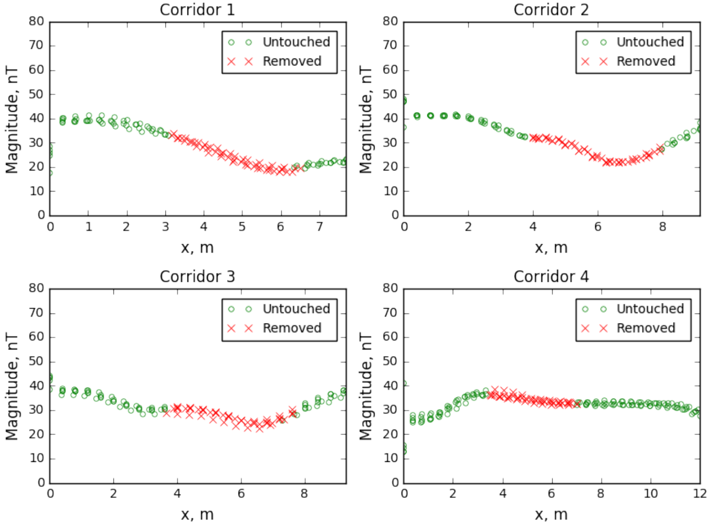
- **Construction:**
  - Difference Quotient $\Rightarrow DQ(X)$ and $DQ(Y)$
  - DTW $\Rightarrow$ optimally warped $DQ(X)'$ and $DQ(Y)'$ from
  - Normalization
- **Values:**
  - Similar: 1, if $X = Y + const$
  - Dissimilar: 0, if either X or Y is constant
  - Opposite: -1, if $X = -Y + const$

Experiments: Settings

$DQRelSim(ACCES, RMSE)$ vs $DQRelSim(FSSI, RMSE)$

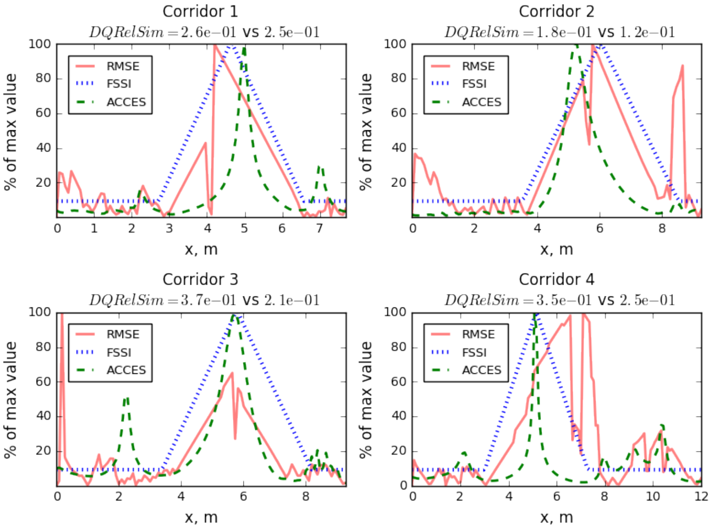
1. **“Cut” scenario:**
   - Contiguous sequence of measurements is removed
   - $\Leftrightarrow$ fingerprints were not collected
2. **“Flat” scenario:**
   - Contiguous sequence of measurements is made constant
   - $\Leftrightarrow$ low signal variability
3. **“Sparse” scenario:**
   - Measurements are removed uniformly
   - $\Leftrightarrow$ different frequency of fingerprint collection

"Cut" scenario: magnetic field magnitude



Experiments: Evaluation

"Cut" scenario: similarity of RMSE, ACCES, FSSI



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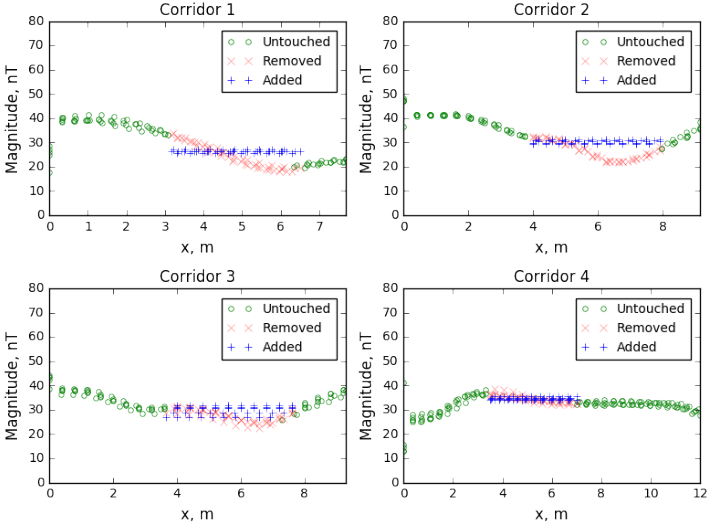

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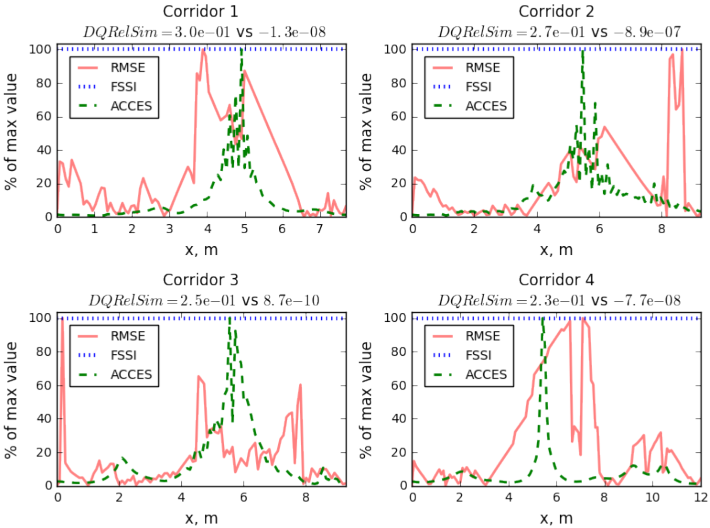
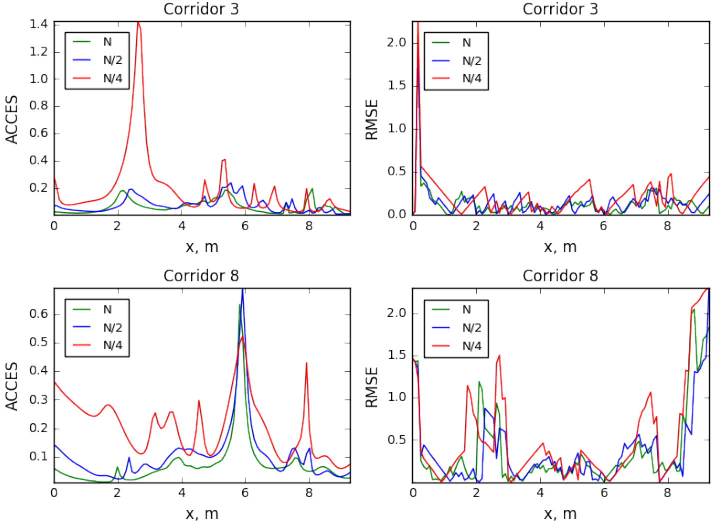


"Sparse" scenario: behaviour of RMSE, ACCES



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- Does not consider the origin of the data.
- Applicable to pure fingerprinting.
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Future work:

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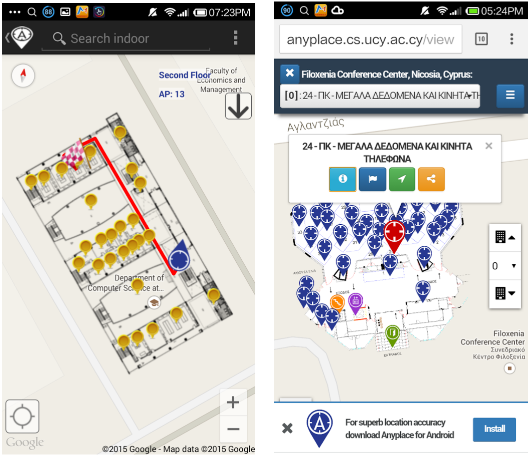
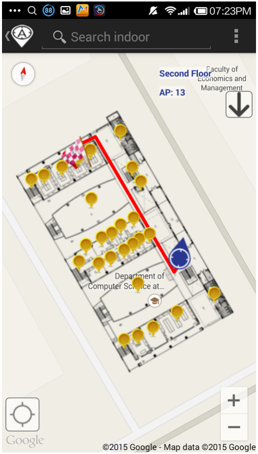
- Comparison to online accuracy estimation algorithms.
- Adding support for arbitrary models.

Anyplace Indoor Information Service



Anyplace Indoor Information Service

- Wi-Fi + IMU
- Optimize data usage
- 3 awards



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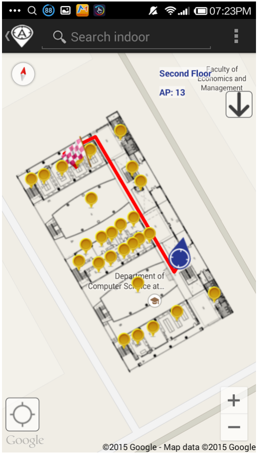

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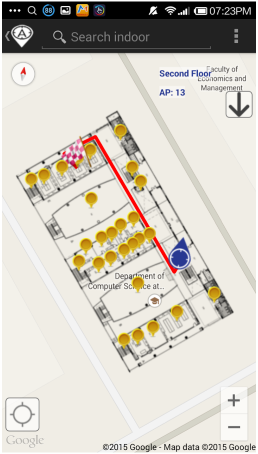
- anyplace.cs.ucy.ac.cy
- github.com/dmsl/anyplace



Thank You!

Come to see our demo yesterday!

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