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A Probabilistic Approach to WLAN User Location Estimation

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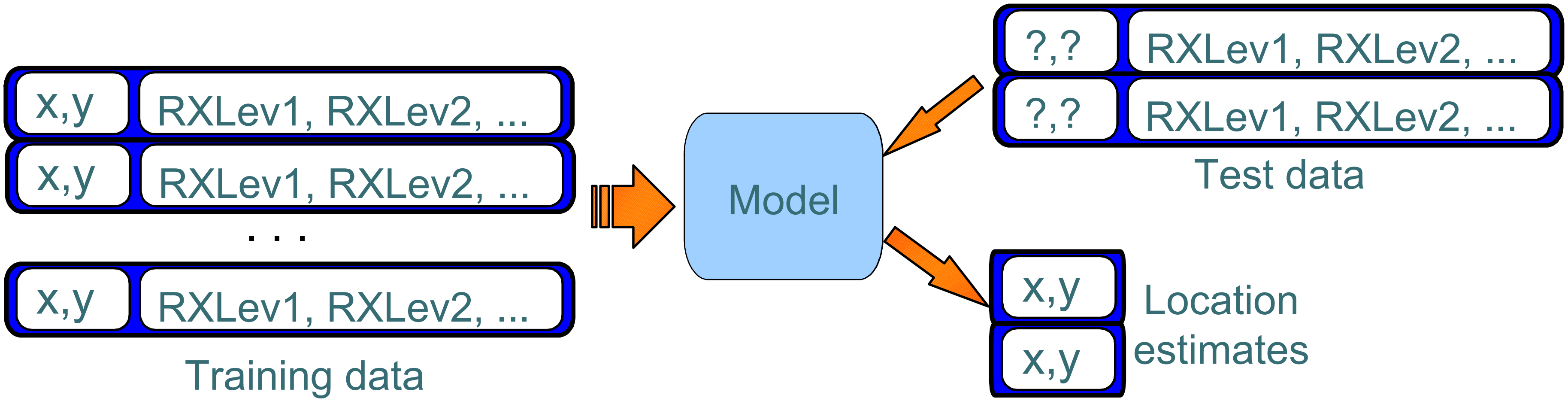
Location Estimation & Machine Learning

- **Machine Learning** (ML): Infer a *model* from a set of *training data* in order to obtain predictions concerning an unforeseen set of *test data*.
- Location Estimation as a ML Problem
  - training data: RXLev from various known locations
  - test data: RXLev from an unknown location
  - model: an estimator of the unknown location given RXLev



Location Estimation & Machine Learning (contd.)

- Let **L** denote the **location** variable, and let **O** denote the RXLev **observation** variable.
- Training data consists of N pairs denoted by (L_i, O_i) , for $i \in \{1, ..., N\}$.
- Location variable L can be either
  - discrete/nominal: “room B226”, “lobby”, ...
  - continuous: (x,y) or (x,y,z) in pixels, meters, ...
- A natural loss-function: distance from true location
- Accuracy is enhanced by *tracking*: The user is probably near the place where she was two seconds ago.

The Nearest Neighbor Method

- The Nearest Neighbor (NN) Method chooses the location for which the Euclidean distance between the current and stored RXLev observation vectors is minimized

$$\hat{L} = L_i, \text{ where } i = \text{argmin} \, || O - O_i ||$$

- An implementational problem: What is the distance between -50 dBmW and “not available”?
- k-Nearest Neighbor Method: Choose the k nearest observations and takes the average of the corresponding locations.
- Used for WLAN location estimation by Bahl et al. (2000): 90% of errors less than 6 meters.

A Probabilistic Approach

- A probabilistic model

$$P(L \mid O) = \frac{P(O \mid L)\, P(L)}{P(O)}$$

  assigns a probability for each possible location L given the RXLev observations O.

- P(O | L) is the conditional probability of obtaining observations O at location L.
- P(L) is the prior probability of location O. (Could be used to exploit user profiles etc.)
- P(O) is just a normalizing constant.
- <u>How to obtain</u> P(O | L) <u>from training data?</u>

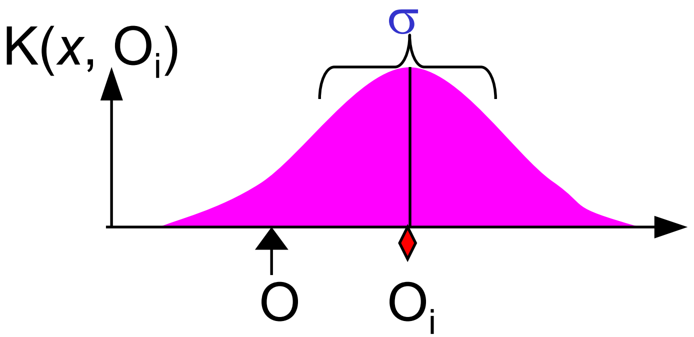
Probabilistic Approach I: The Kernel Method

- In the Kernel Method a probability mass is assigned to a "kernel" centered at the observation O_i:

$$P(O \mid L_i) = K(O, O_i),$$ where K is the *kernel function*.

- Gaussian kernel:

$$K(O, O_i) = C\, e^{\left(\frac{-\| O - O_i \|^2}{\sigma^2}\right)}$$

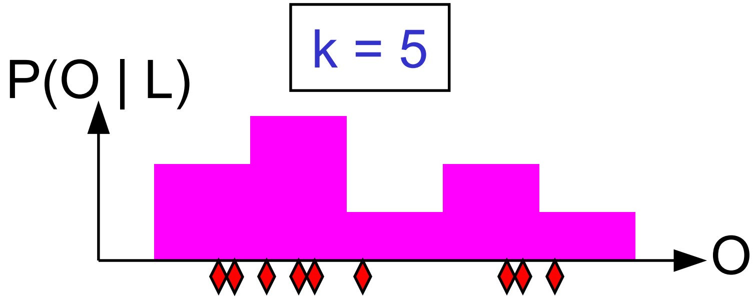


where C is a normalizing constant, and σ is an adjustable variance (*bandwidth*) parameter.

- The Nearest Neighbor Method is obtained as a limiting case when σ goes to zero.

Probabilistic Approach II: The Histogram Method

- In the Histogram Method the RXLev values are discretized into *k* bins:



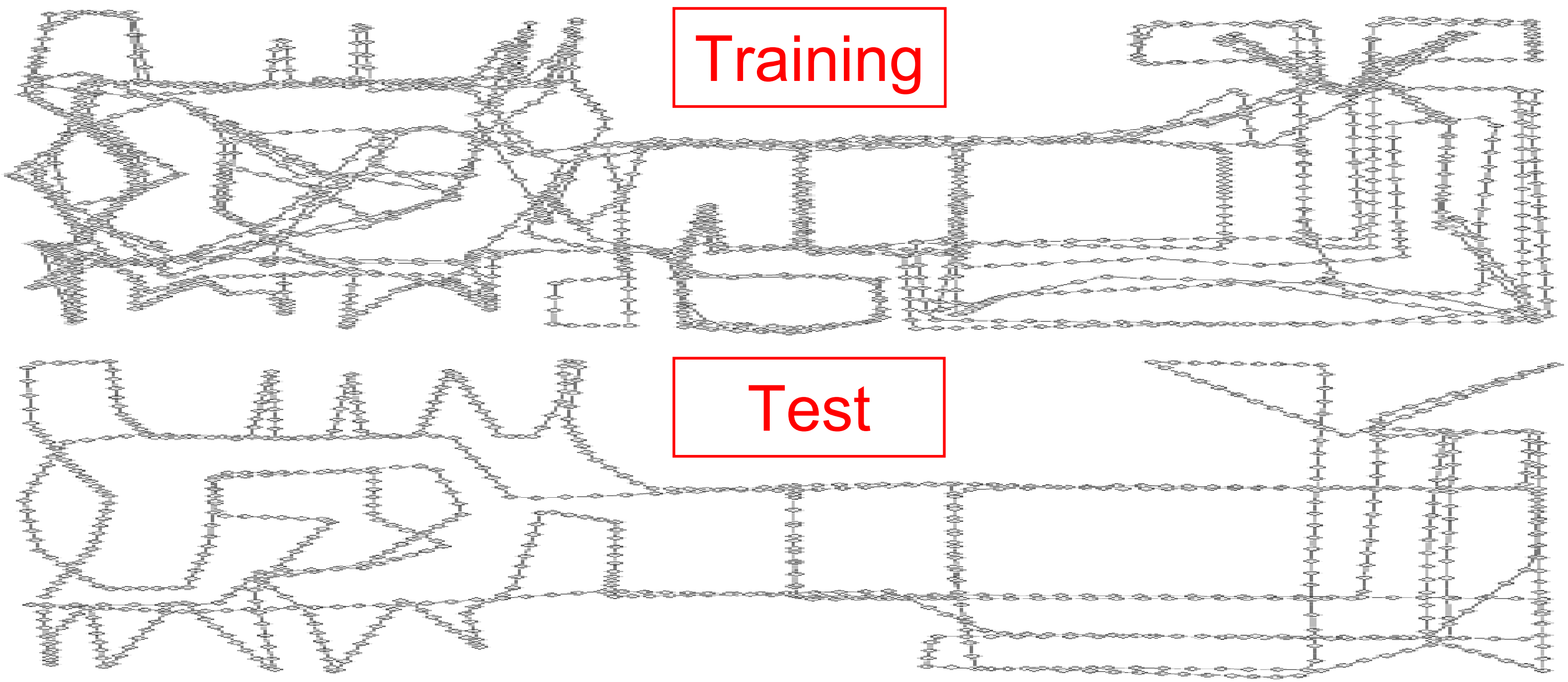
- The location variable should also be discretized. (Otherwise there is only one observation per location.)
- How to choose *k* ? How to choose the bin intervals? (Equal width is not always good.)

Case-study

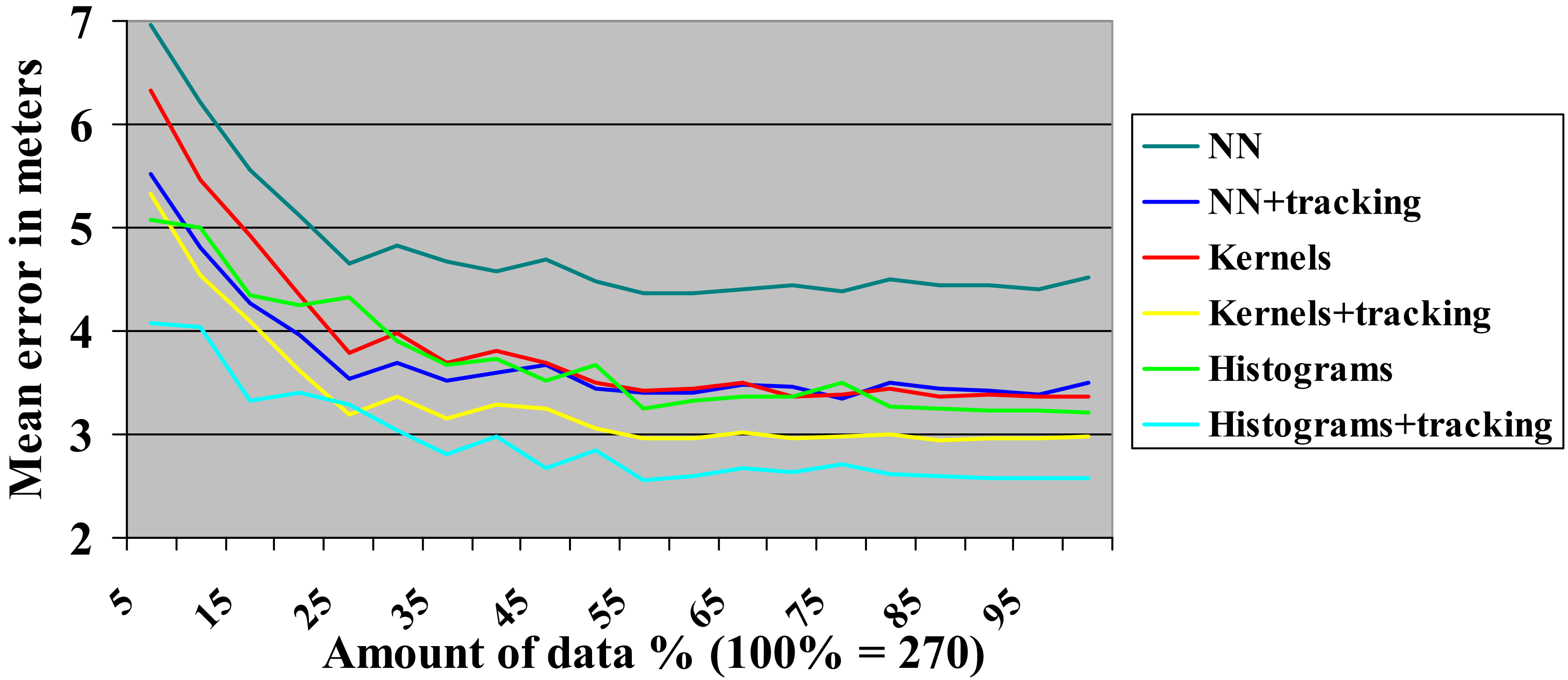
- Eight base-stations in five physically separate sites.
- Office building, 16 x 40 meters, concrete/wood/glass structures.

Testing

- Test data must be independent of the training data.
- If both training and test data are collected at the same time, accuracy estimates can be too optimistic, even if one uses sophisticated empirical methods like cross-validation.

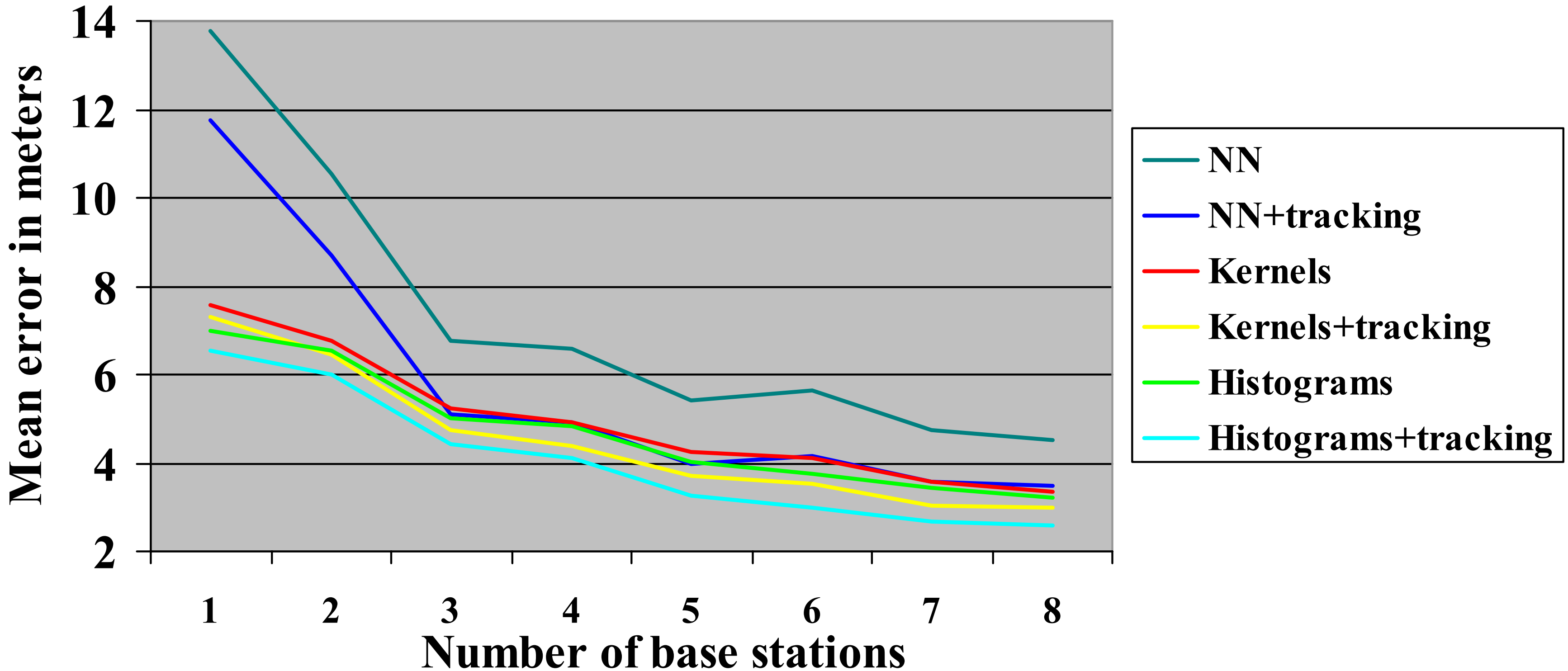


Accuracy vs. Amount of Data



- Best result: mean error 2.57 meters (90% below 4.52 meters) obtained with the probabilistic histogram method with tracking.
- Surprisingly robust with respect to the amount of training data.

Accuracy vs. Number of Base Stations



- Number of base stations is a significant factor.
- Does not affect the ranking of the methods.

Conclusions

- To build an accurate location system, one needs either to collect training data or to have access to detailed information on the topology of the building.
- Collecting the training data is surprisingly easy, a reasonable level of accuracy can be obtained quickly.
- No standardized setup for measuring the accuracy — "cheating" is easy.
- No dramatic differences in accuracy between different location estimation methods.
- Probabilistic methods seem to perform slightly better due to the "noisyness" of the domain.
- Ongoing work: fully automated parameter tuning for increased robustness.