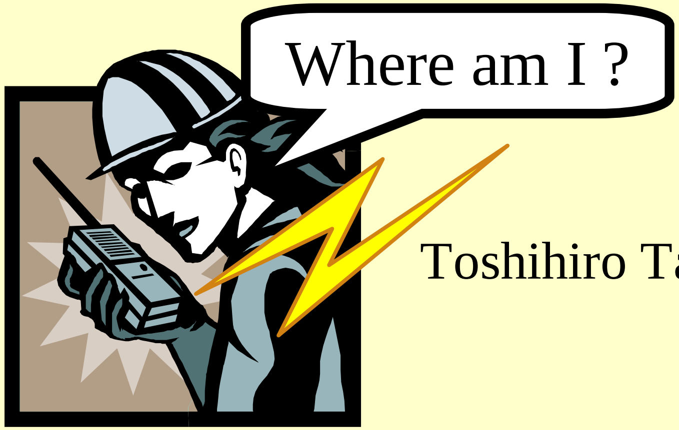
Tokyo Research Laboratory

Task 1:

A Semi-supervised Approach to Indoor Location Estimation



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Presentation for task 1:
A Semi-supervised Approach to Indoor Location Estimation

- We formulated task1 as a semi-supervised learning [1] problem
- We employed the *label propagation* [2] as the semi-supervised learning method
  - A multi-class version of the label propagation method
  - Design of similarity measure using spatial information(=RSS values) and temporal information (=time stamps)

[1] X. Zhu. *Semi-supervised learning literature survey*. Technical Report, TR 1530, University of Wisconsin Madison, 2006.
[2] X. Zhu, Z. Ghahramani, and J. Lafferty. *Semi-supervised learning using gaussian fields and harmonic functions*. In *ICML*, 2003.

Task Review: Indoor location estimation by using machine learning

- Problem setting:
  - You want to know where you are in some building
  - In the building, there are several access points emitting radio signals
  - You have a client device by which you can know signal strength from each access point
- Difficulty: Triangulation is unsatisfactory because of high uncertainty in signals
- Solution: Apply machine learning techniques to estimate locations from received signal strengths

The task is formulated as a semi-supervised learning problem

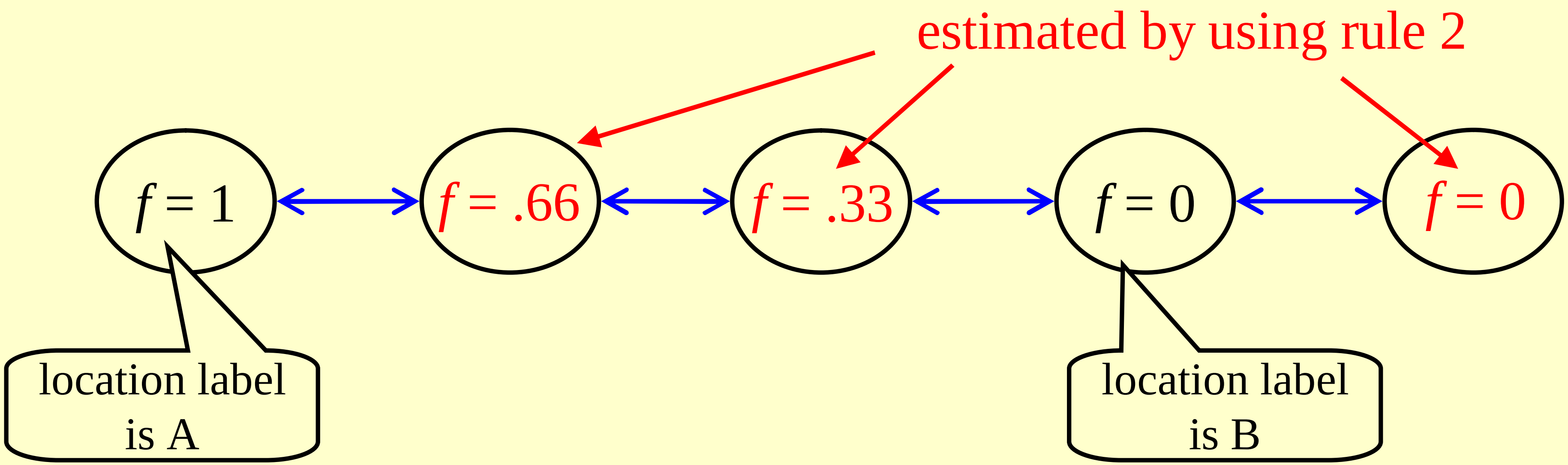
- Given: the i-th data is given as a tuple of $(\mathbf{x}^{(i)}, \mathrm{TID}^{(i)}, t^{(i)}, y^{(i)})$
  - spatial information: $\mathbf{x}^{(i)} \in \mathcal{X} = \mathbb{R}^{101}$ is the received signal strength (RSS) values
  - temporal information: $\mathrm{TID}^{(i)}$ (trace ID) and $t^{(i)}$ (time ID) indicate the time of the data observed
  - classs label: $y^{(i)} \in \mathcal{Y} = \{1, 2, ..., 247\}$ is a location label given only for a small fraction of the data
    - Semi-supervised learning problem
- Goal: predict $y^{(i)}$ for $\forall i \in$ UNLABELLED DATA whose location labels are " ? "(=not given)
  - Transduction problem

data ID (i)	trace ID (TID)	time ID (t)	location label ($y \in \{1, 2, ..., 247\}$)	RSS values ($\mathbf{x} \in [-100, 0]^{101}$) x_1	x_2	x_3	x_4	…	x_{101}
1		1	6	-58	-88	-100	-100	…	-80
2	1	2	?	-58	-95	-100	-100	…	-100
3		3	1	-65	-95	-100	-100	…	-75
4	2	1	23	-62	-83	-59		…	-93
5	3	1	?						-100
6		2	9						-100
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Missing values are filled with -100 (the lowest RSS value)

We employed the *label propagation* as a semi-supervised learning method

- *Label propagation* tries to assign a location label to each observation with satisfying that
  1. labeled instances have the given labels, and
  2. similar instances have the similar class labels
- Example of two-class {A, B} case
  - f : the probability of the location label of the i-th instance being A
  - $(1 - f)$: the probability of the location label of the i-th instance being B
  - $ means "two observations are similar to each other"



We employed the *label propagation* as a semi-supervised learning method

- *Label propagation* tries to realize label assignments satisfying that
  1. labeled instances have the given labels, and
  2. similar instances have the similar class labels
- (Multi-class) label propagation is cast as an optimization problem

$$\textit{minimize}_{\mathbf{f}} \ \sum_{(i,j)} \mathrm{w}^{(i,j)} \sum_{y} \left(f^{(i)}(c) - f^{(j)}(c) \right)^2$$

where

- $f^{(i)}(c)$: the probability of the location label of the *i*-th instance being c
- $\mathrm{w}^{(i,j)}$: the similarity measure between the *i*-th and *j*-th examples

s.t. for each labeled instance i,

- $f^{(i)}(c) = 1$, if c is the true class label
- $f^{(i)}(c) = 0$, otherwise

- Prediction is made by $\mathrm{argmax}_c \ f^{(i)}(c)$ for each i
- Instead of a closed form solution requiring the inverse of a large matrix, we can use the following simple iterative update

$$f^{(i)}(c) \quad (\quad \left(\sum_j \mathrm{w}^{(i,j)} \sum_c f^{(j)}(c) \right) \Big/ \left(\sum_j \mathrm{w}^{(i,j)} \right)$$

Similarity measure $w^{(i,j)}$ is defined by RSS values and time stamps

- We have to define the *similarity measure* $w^{(i,j)}$ used in the label propagation
- Each instance is accompanied by two types of information
  1. spatial information: RSS values
  2. temporal information: a time stamp
- Two instances are similar if
  – their RSS values are similar, or
  – their time stamps are similar
- The similarity measure is defined by the maximum of two similarity measures

$$w^{(i,j)} = \max \{ w_X^{(i,j)},\ w_T^{(i,j)} \}$$

where

- $w_X^{(i,j)}$: similarity based on spatial information (=RSS values)
- $w_T^{(i,j)}$: similarity based on temporal information (=time stamps)

Robust similarity measure based on spatial information: $w_X^{(i,j)}$

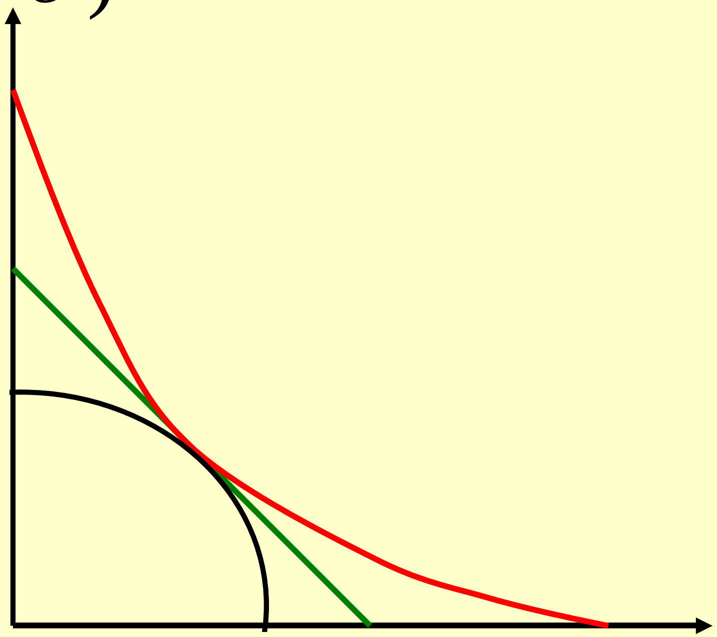
- Since RSS values are noisy,
  we need a similarity robust to noise caused by reflection, interference, and shielding
- RSS-based similarity $w_X^{(i,j)}$ is defined as

$$w_X^{(i,j)} = \exp\left(- \| \mathbf{x}^{(i)} - \mathbf{x}^{(j)} \|_p \; / \; \sigma \right)$$

where

- $\|\cdot\|_p$ is the p-norm (in submission, p = 0.5 (0.5-norm))
- σ is a constant scale parameter (in submission, σ = 0.5)

- We used p-norm with $p < 1$, which puts more importance on presence/absence of signals than the amount of change
  - Robust to drastic change of each RSS value
  - Sensitive to change of multiple RSS values



level curve of p-norm

Similarity measure based on temporal information: $w_T^{(i,j)}$

- Time-stamp-based similarity $w_T^{(i,j)}$ is defined as

$$w_T^{(i,j)} = \rho, \text{ if } i \text{ and } j \text{ are consecutive observations in a trace}$$
$$= 0, \text{ otherwise}$$

  – In submission, we used $\rho = 1$

- Probably, we could improve the similarity further ...
  – $\rho = 0.01$ performs better
  – Similarity function like that for RSS values

So, what was most important for performance improvement ? Design of similarity function is crucial

- Design of similarity function contributed most to improvement of prediction accuracy
  - Use of 0.5-norm in RSS similarity
  - Use of time-stamp-based similarity

- Nearest neighbour with 2-norm RSS similarity (baseline)

⇓ **+7% accuracy**

- Nearest neighbour with **0.5-**norm RSS similarity

⇓ + 1% accuracy

- **Label propagation** with 0.5-norm RSS similarity

⇓ **+ 5% accuracy**

- Label propagation with 0.5-norm RSS similarity and **time stamp similarity**

Conclusion and future work

- We applied a multi-class version of the label propagation to this task
- We designed a similarity measure using spatial information(=RSS values) and temporal information (=time stamps)
  - Metric design >> semi-supervised learning
- It is very difficult to beat the simple methods such as kNN

- Possible future work includes
  - Refinement of the time-based similarity
  - Out-of-sample prediction
    - In real situation, test data are not given in advance of test phase
    - Approximation or explicit learning of the mapping function

Thank you

WE ARE...
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