No-Sweat Detective:
No Effort Anomaly Detection for Wi-Fi-Based Localization

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† Yahoo Japan Research
‡ Ritsumeikan University

Outline

- Motivation
- State of the Art
- Methodology
- Evaluation
  - Laboratory environment
  - Wild environment
- Summary

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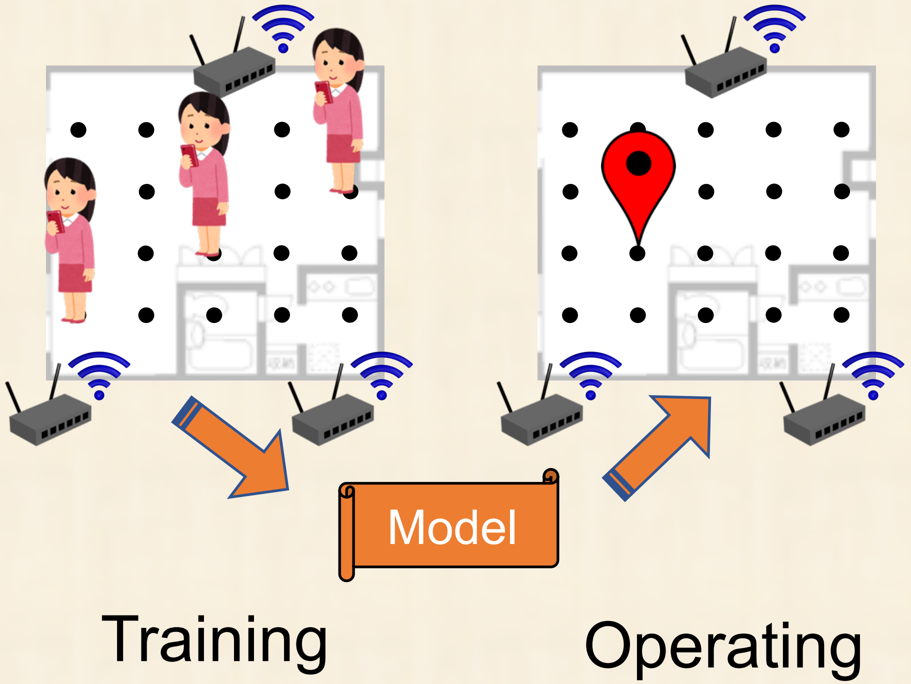
Motivation

- Wi-Fi fingerprinting is pervasive for indoor localization
- Wi-Fi localization consists of two phases:
  - Training phase
  - Operation phase



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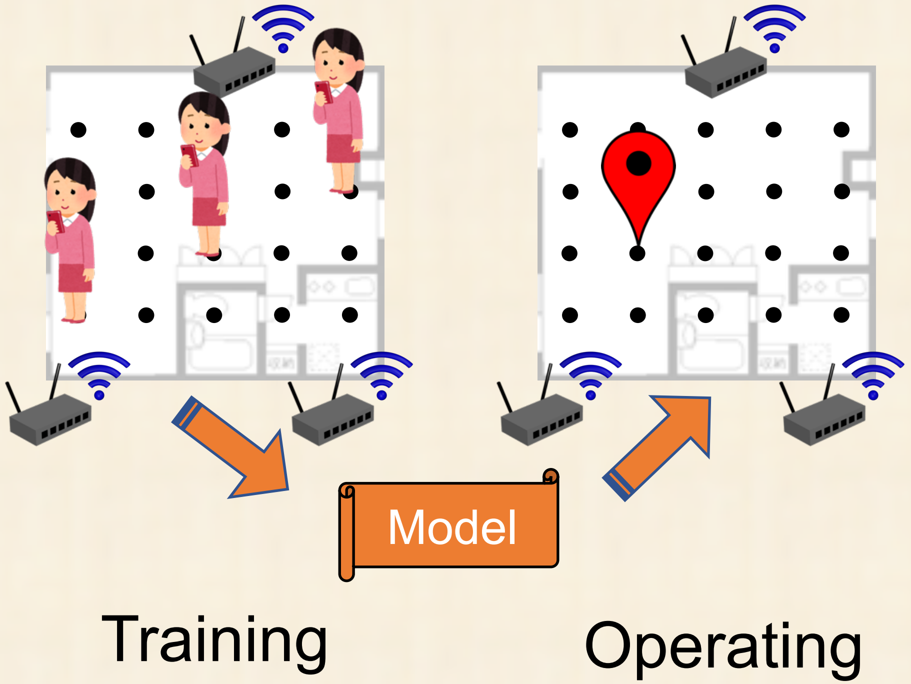

Environmental changes affect of the model (with aging)

Need to remake the entire model

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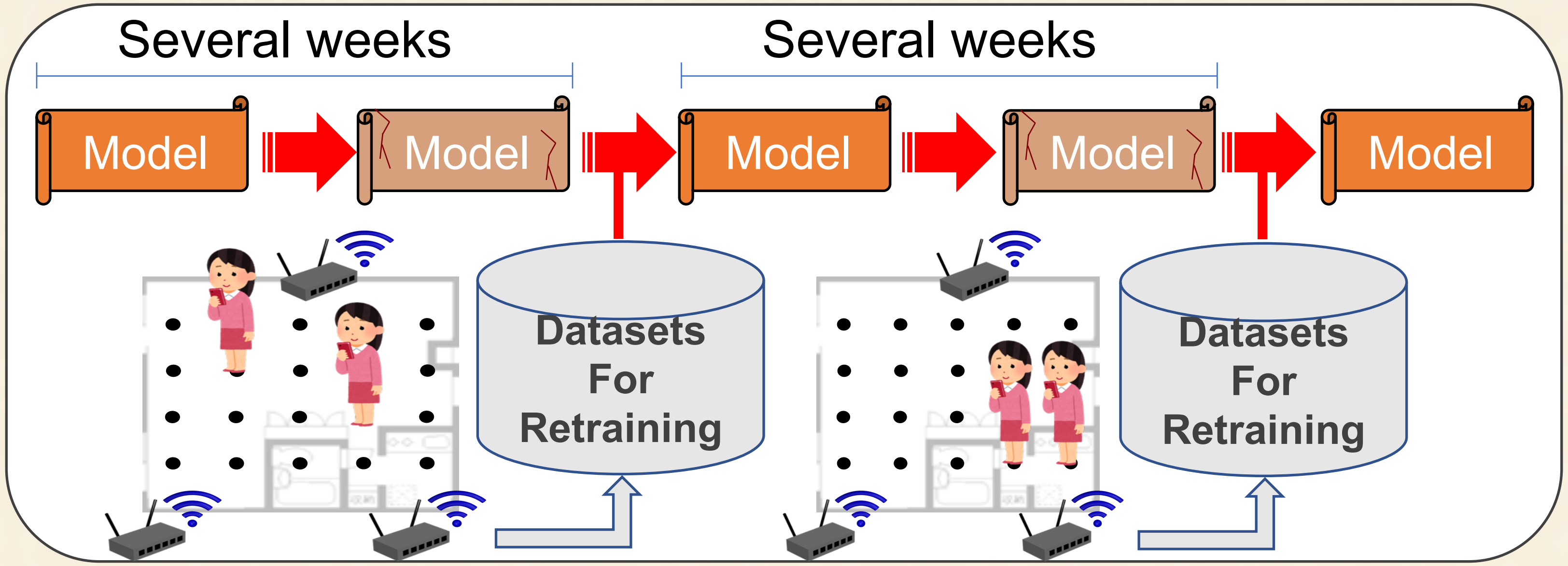
State of the Art

- Transfer learning is employed to retrain the model periodically
  - Require small additional datasets but remaking of the entire model
- Reference points for additional datasets are randomly selected
  - Result in overfitting and instable accuracy



Retraining

[23]: Pengcheng Wu and Thomas G. Dietterich. “Improving SVM Accuracy by Training on Auxiliary Data Sources.”

State of the Art

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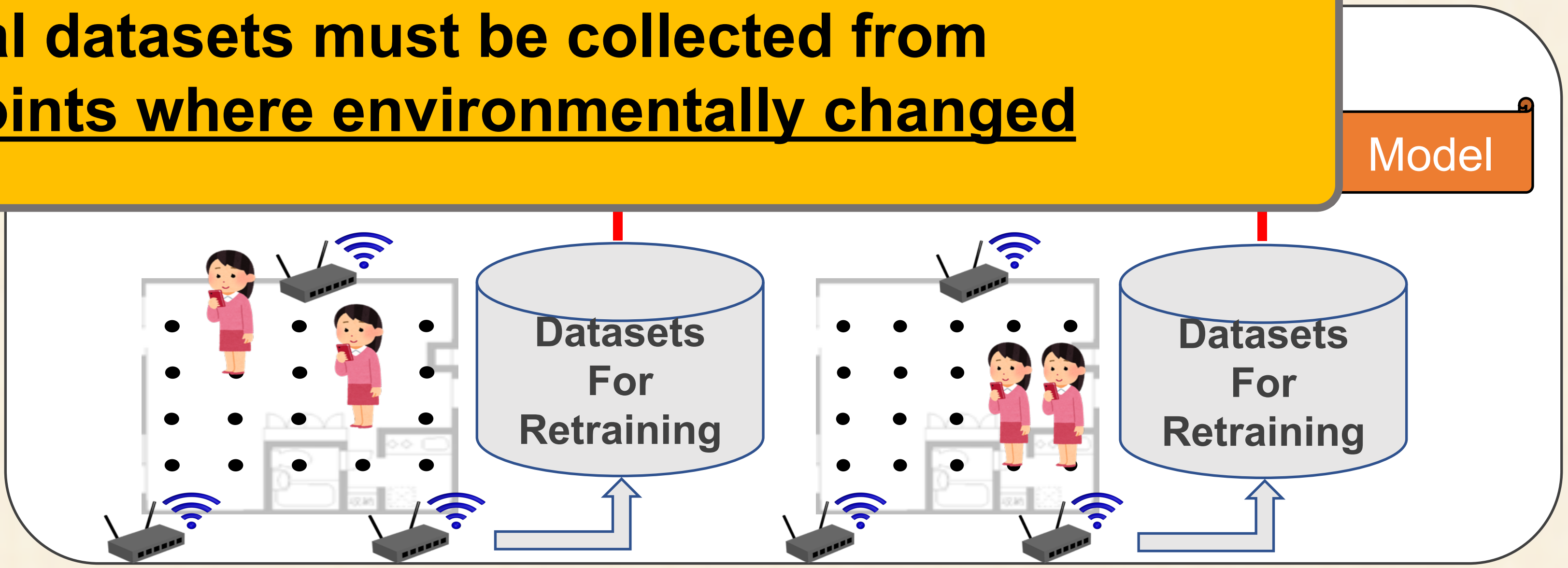
Additional datasets must be collected from
<u>reference points where environmentally changed</u>



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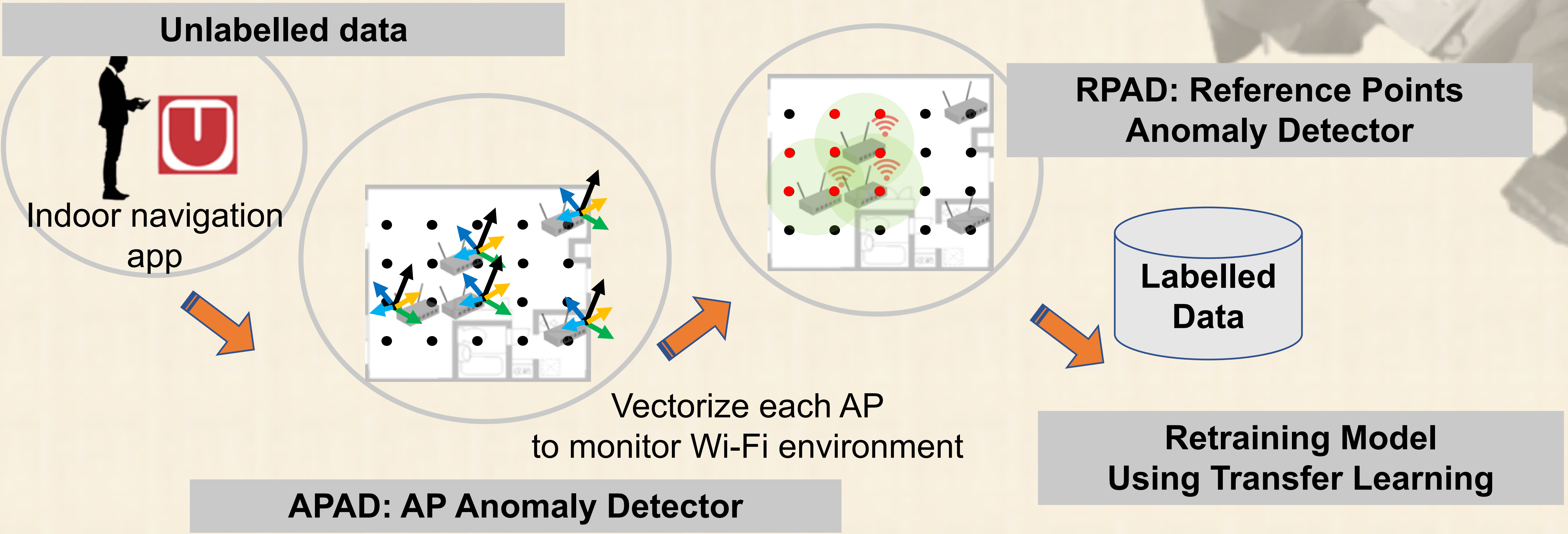
No-Sweat Detective

- Identify(detect) reference points where environmentally changed
  - Analyzing unlabelled data from off-the-shelf indoor navigation app



Umechika Navi: https://www.umechikanavi.jp/

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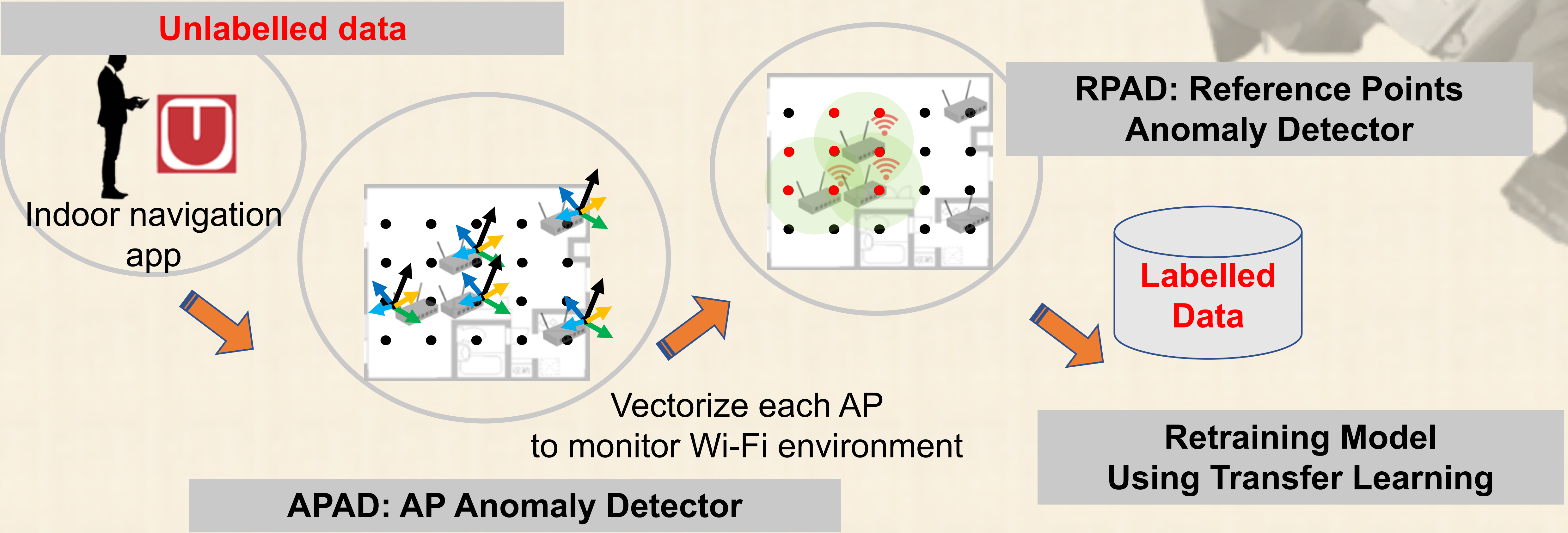

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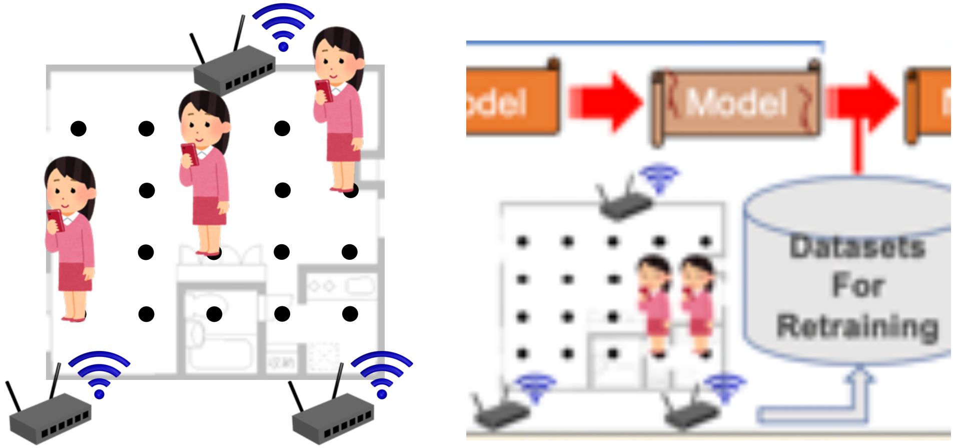
Labelled Data



Training/Retraining of the model

<u>Location is labelled on fingerprints</u>

Unlabelled Data

Indoor navigation/map app

<u>Not labelled</u>

Can be obtained with no effort (sweat)

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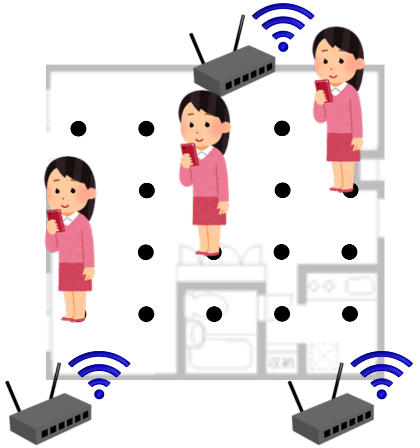
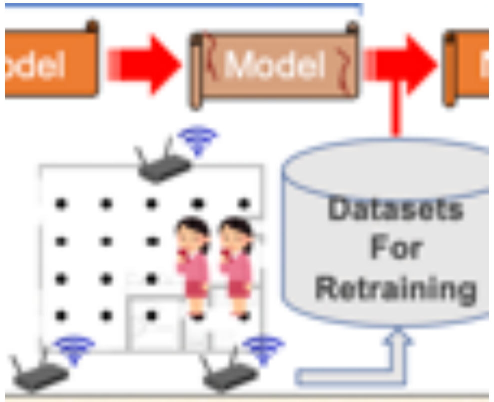
Labelled Data





Training/Retraining of the model

<u>Location is labelled on fingerprints</u>

Specify reference points to obtain labeled data for retraining

←

Unlabelled Data

Indoor navigation/map app

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Analysis

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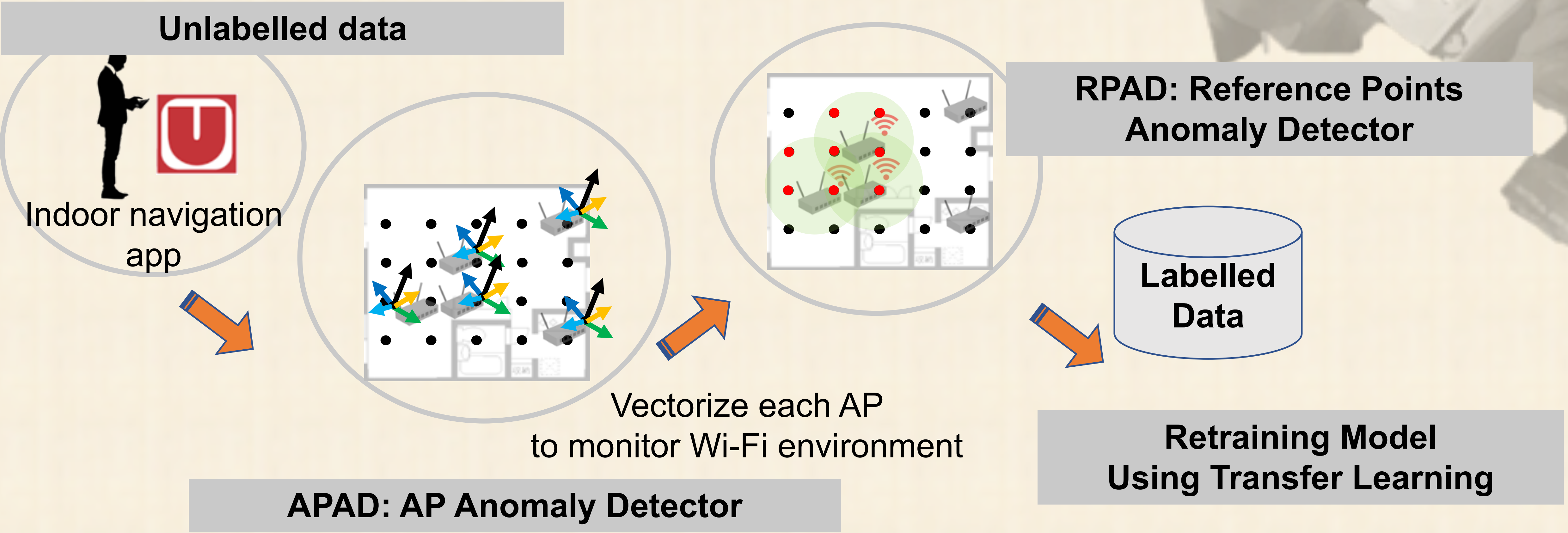

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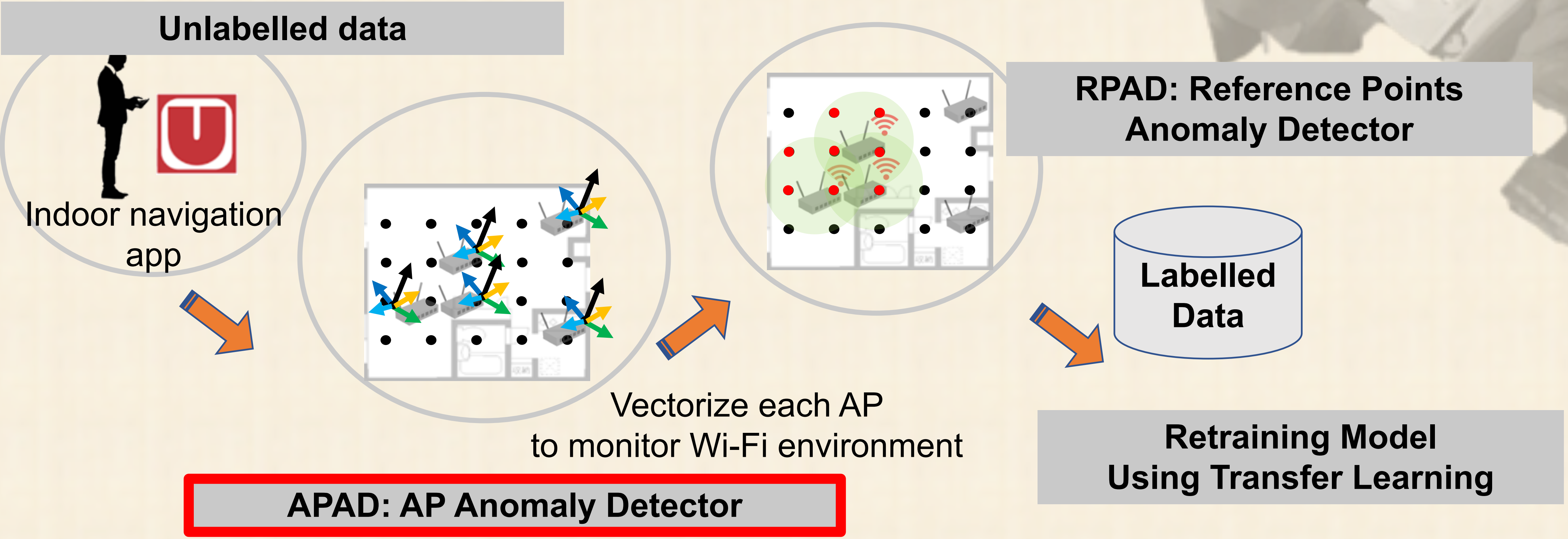

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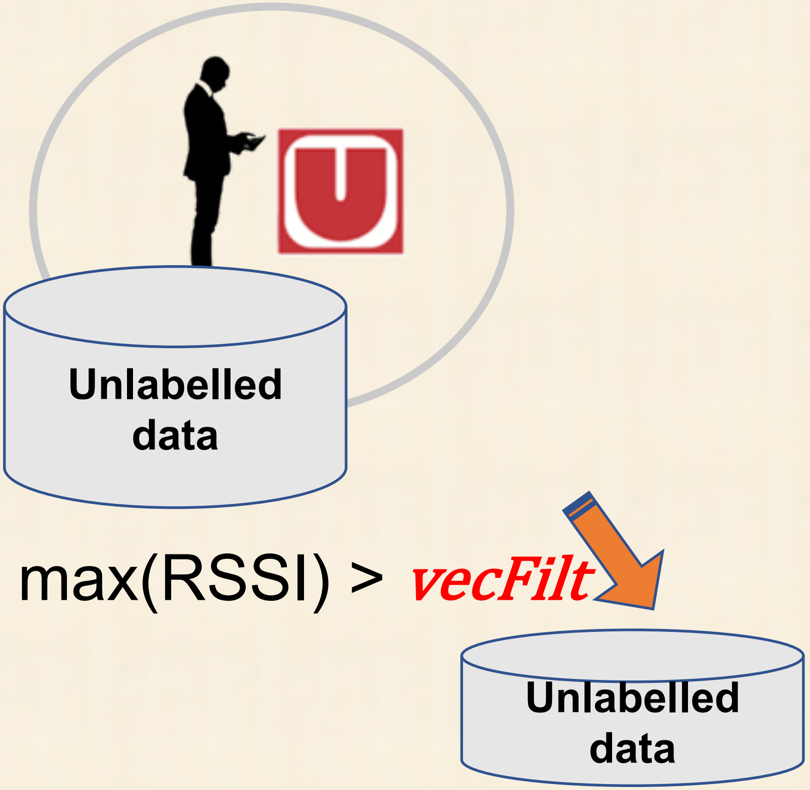
APAD: AP anomaly detector

- Detect APs close to where Wi-Fi-environmentally changed
- Vectorize each AP to reflect each Wi-Fi environment



Filtered unlabelled data are observed close to a certain AP

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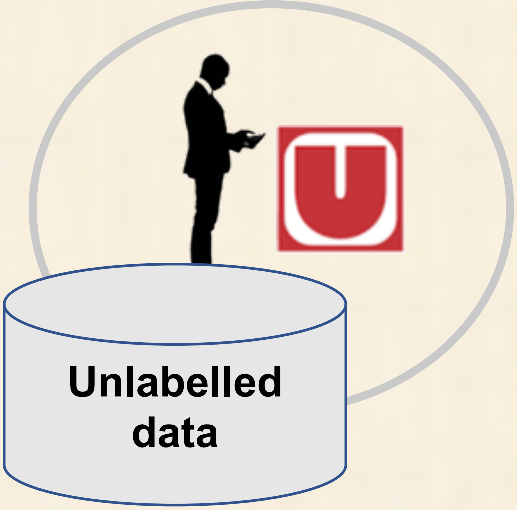
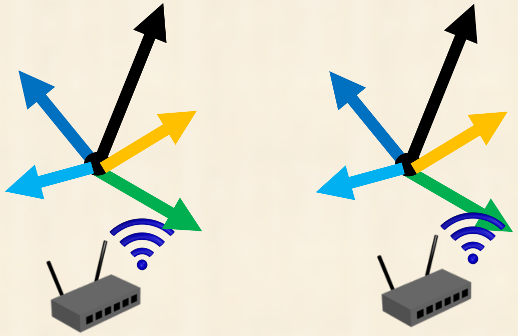
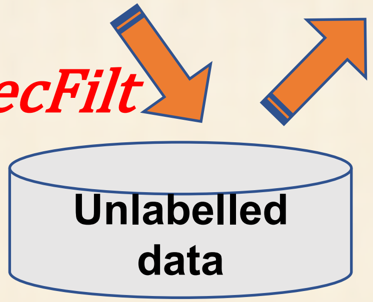




vecWidth to define size of vector

max(RSSI) > *vecFilt*



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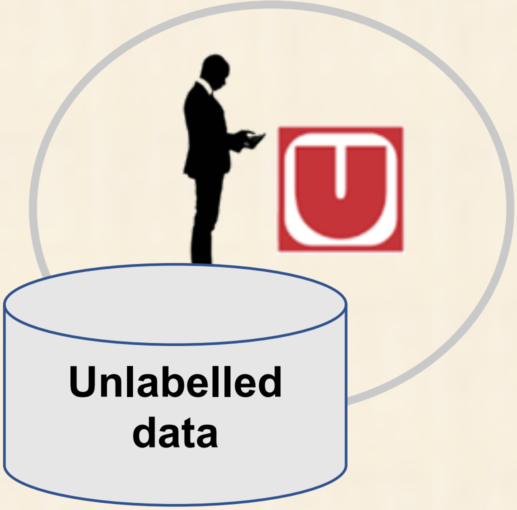

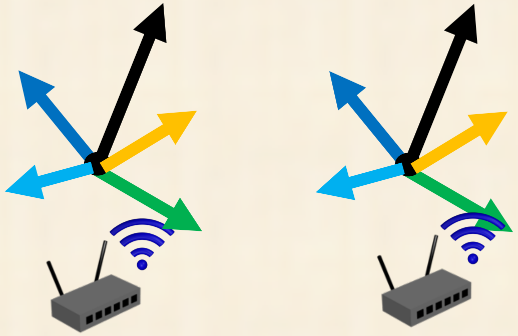

Calculate similarity over time for each AP vector

$$\cos(\vec{A},\vec{A}') = \frac{\vec{A}\cdot\vec{A}'}{|\vec{A}||\vec{A}'|} = \frac{\vec{A}}{|\vec{A}|}\cdot\frac{\vec{A}'}{|\vec{A}'|} = \frac{\sum_{i=1}^{|V|} A_i {A'}_i}{\sqrt{\sum_{i=1}^{|V|} A_i^2}\cdot\sqrt{\sum_{i=1}^{|V|} {A'}_i^2}} \quad \cdots (3)$$

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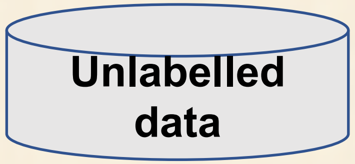

If similarity < *CosSim*:
detect the AP
as its surroundings changed

Filtered unlabelled data are observed close to a certain AP

No-Sweat Detective

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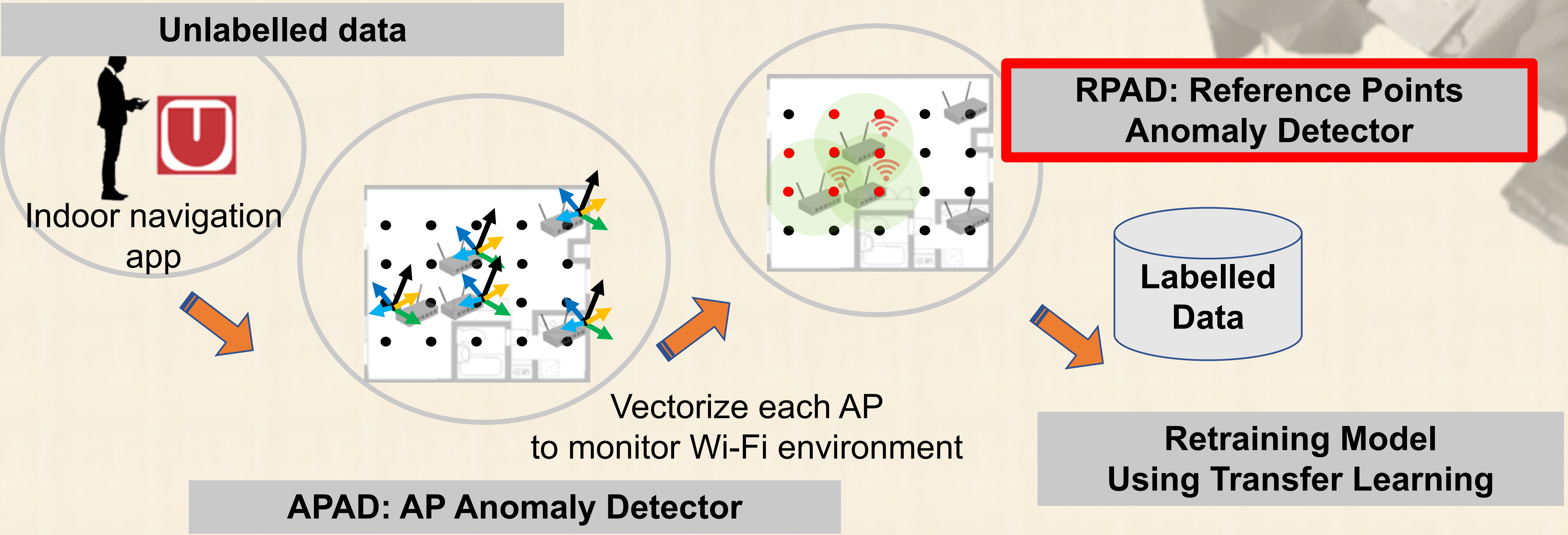

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RPAD: Reference Points Anomaly Detector

- Identify reference points where Wi-Fi environmentally changed
- 2 cases to handle:

Singular AP detected

Plural APs detected

RPAD: Reference Points Anomaly Detector

- Identify reference points where Wi-Fi environmentally changed
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- Likely that small change affect the AP
- Nullify the AP + estimate its locus and collect labelled data

Plural APs detected

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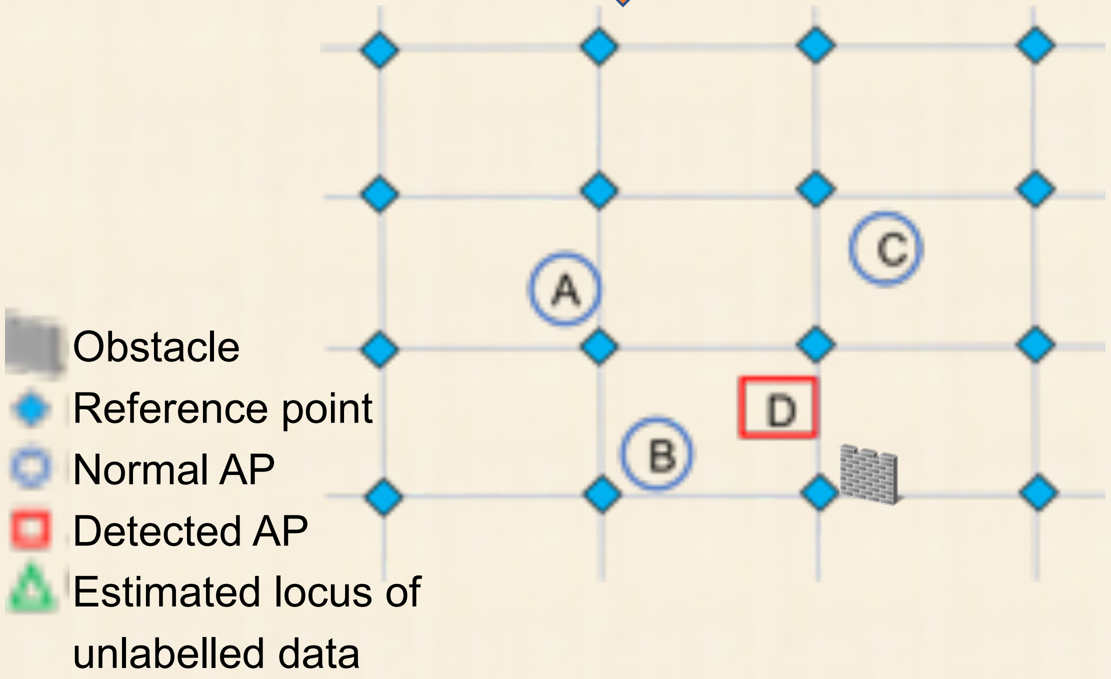

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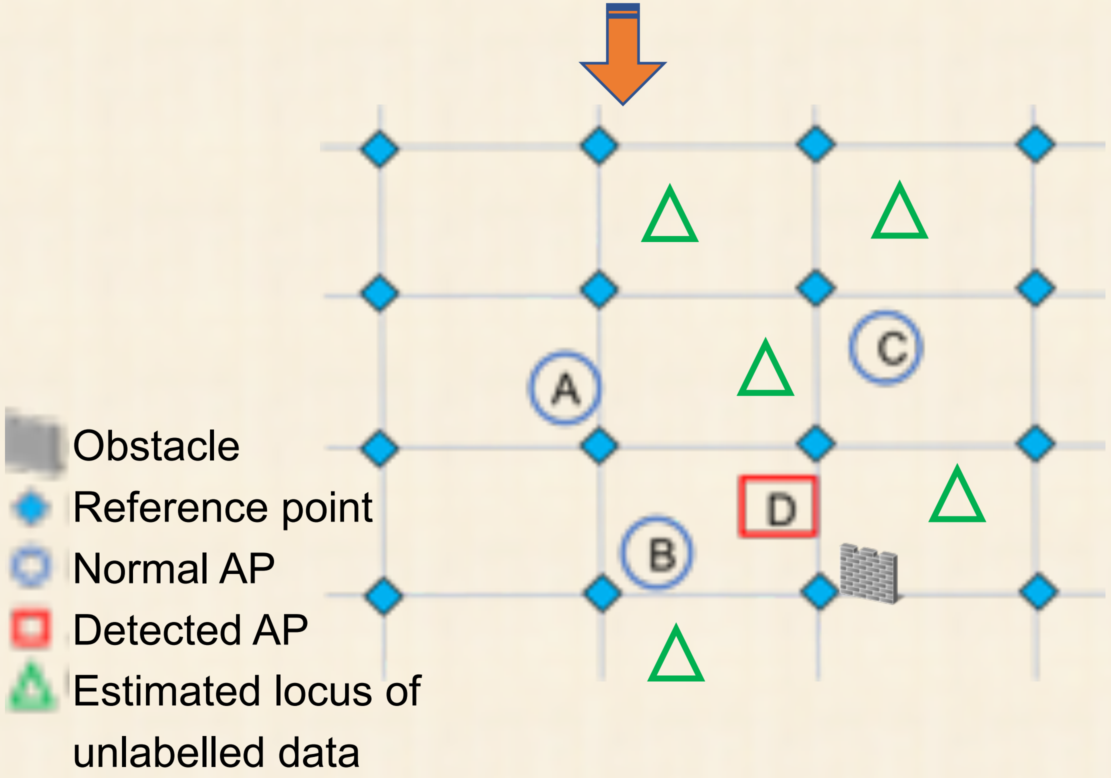

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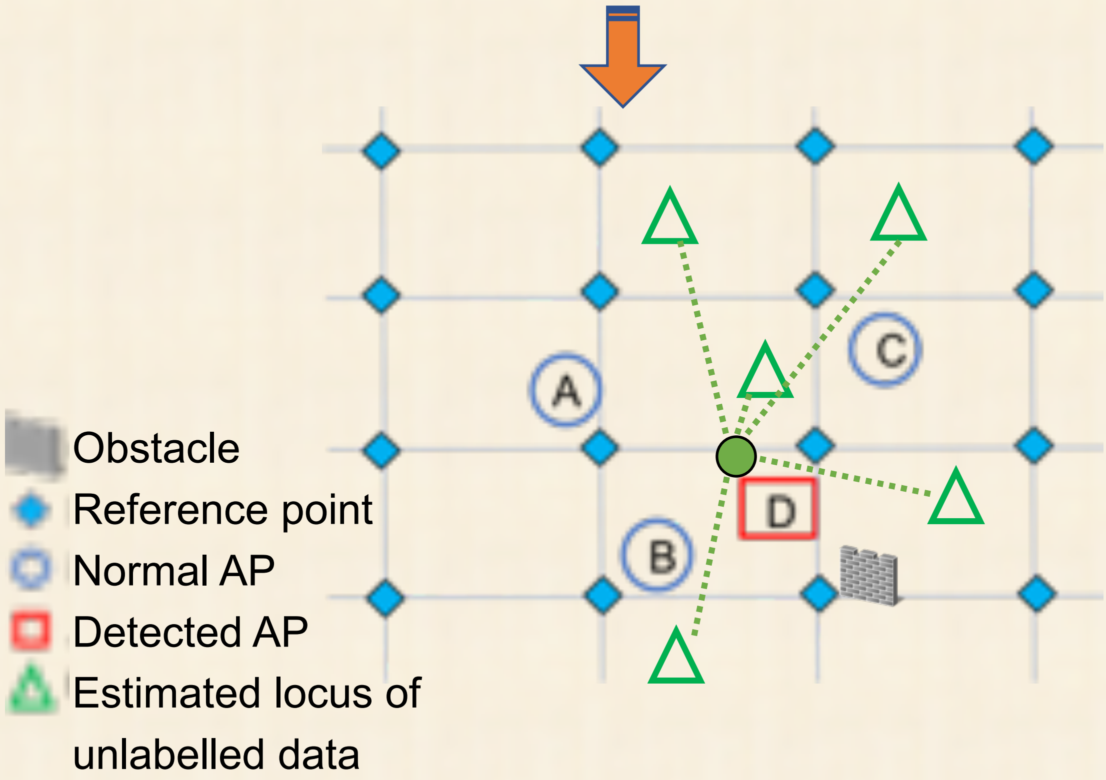

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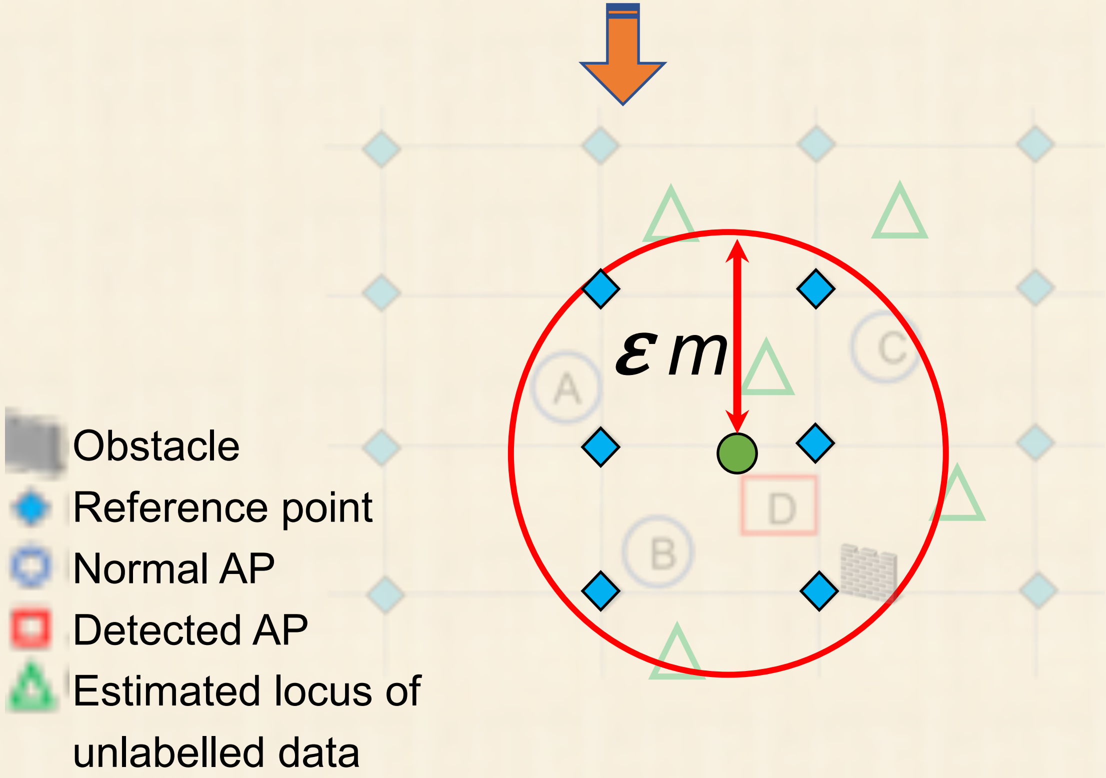

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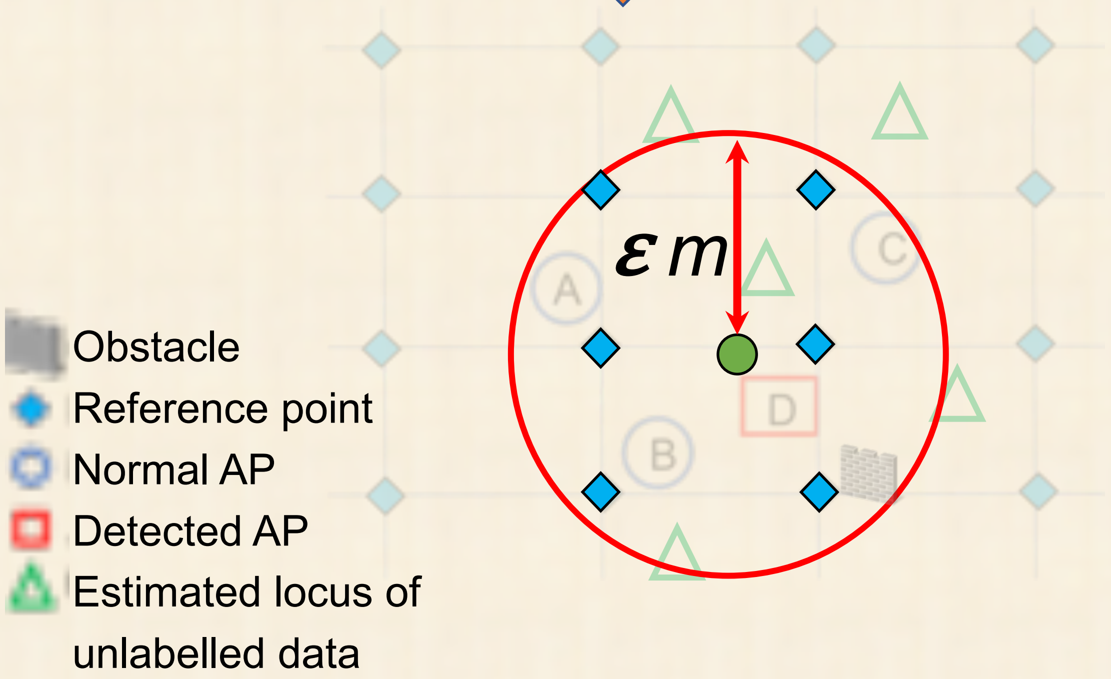

Plural APs detected

- Likely that huge change occurred
  - Spatial relationship of APs is clueless
- DBSCAN and collect labelled data

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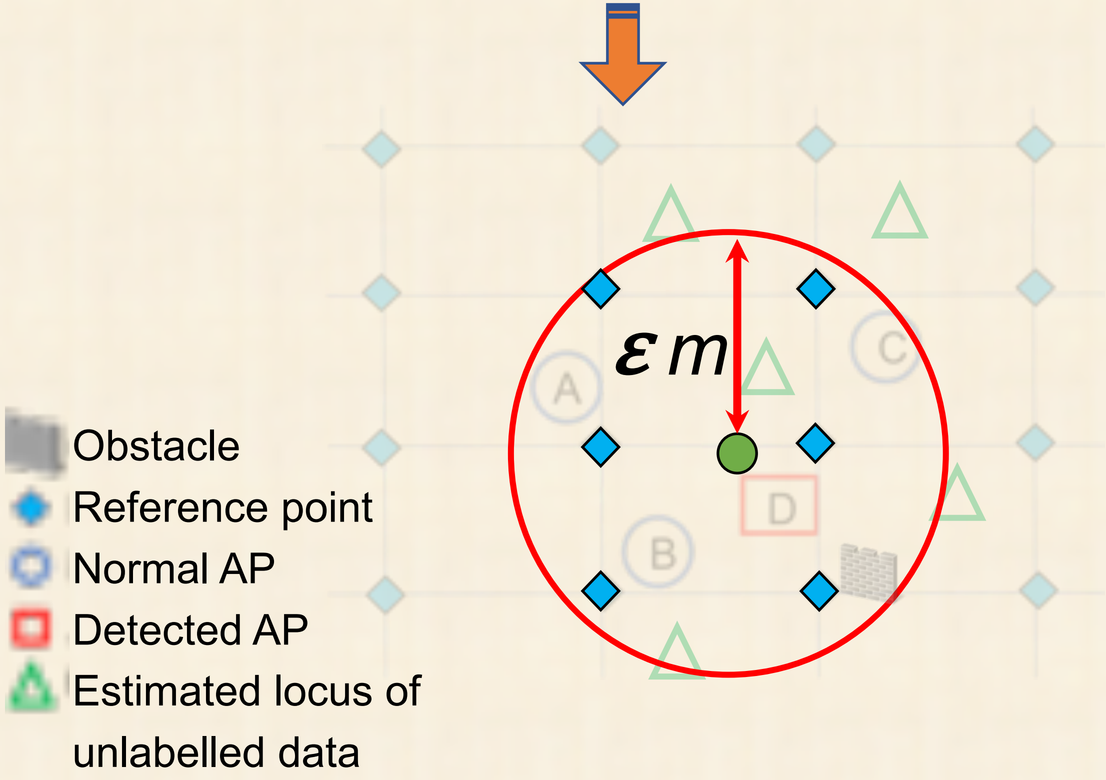

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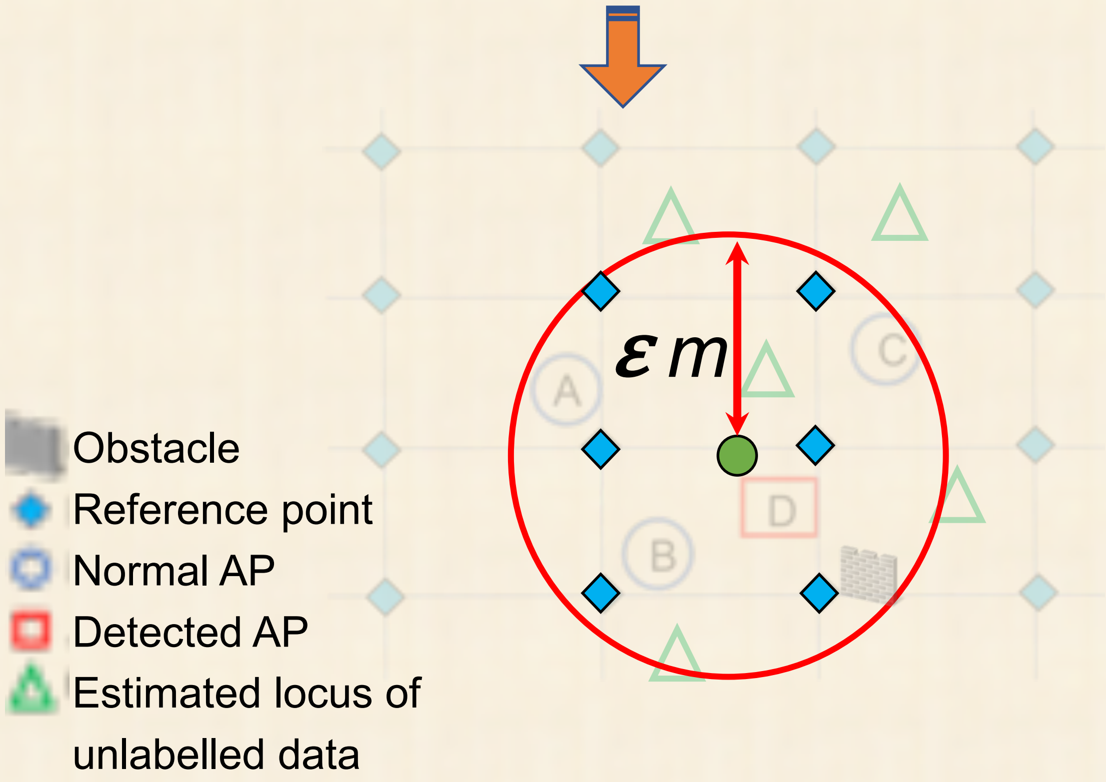

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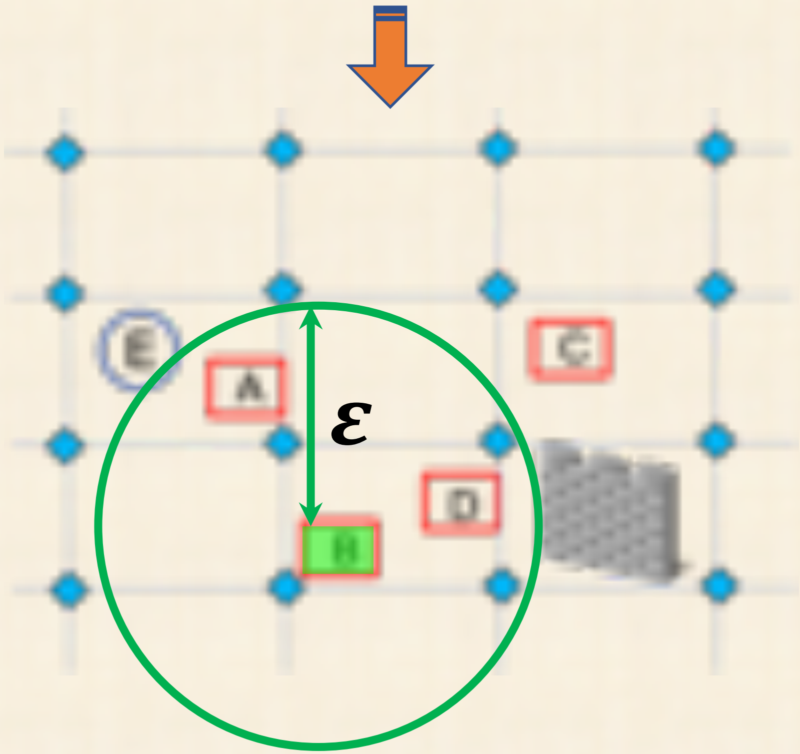

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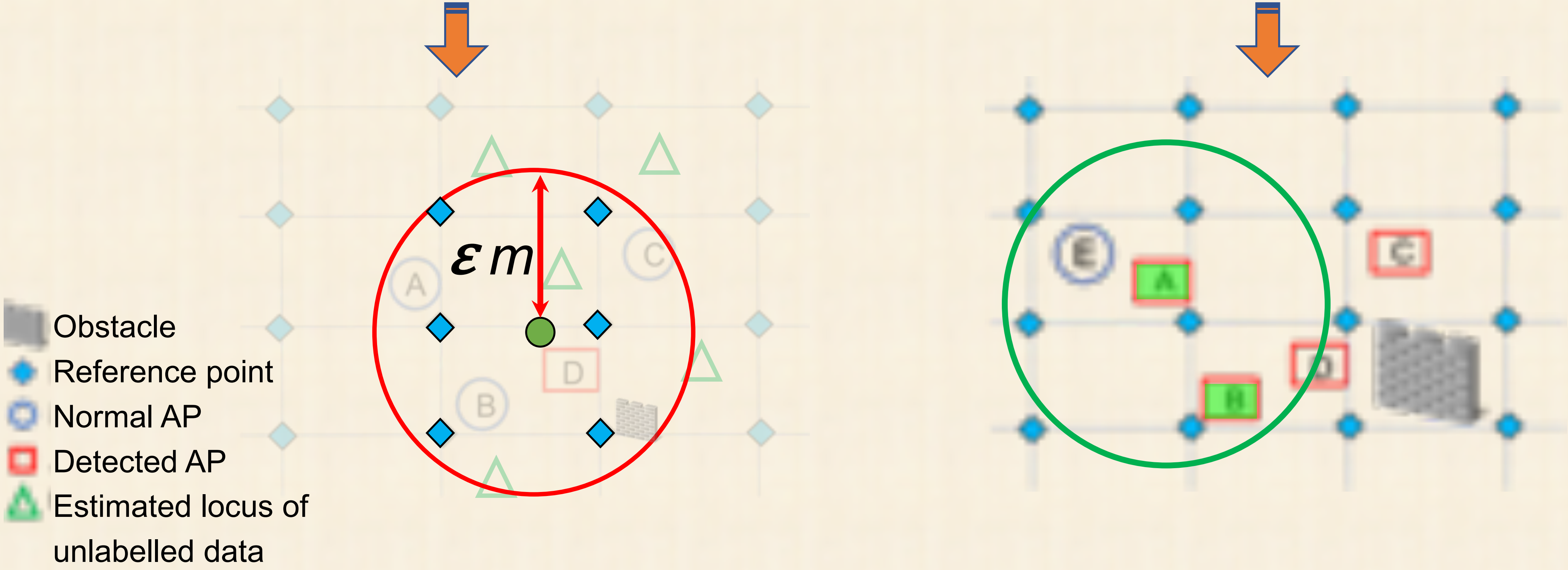

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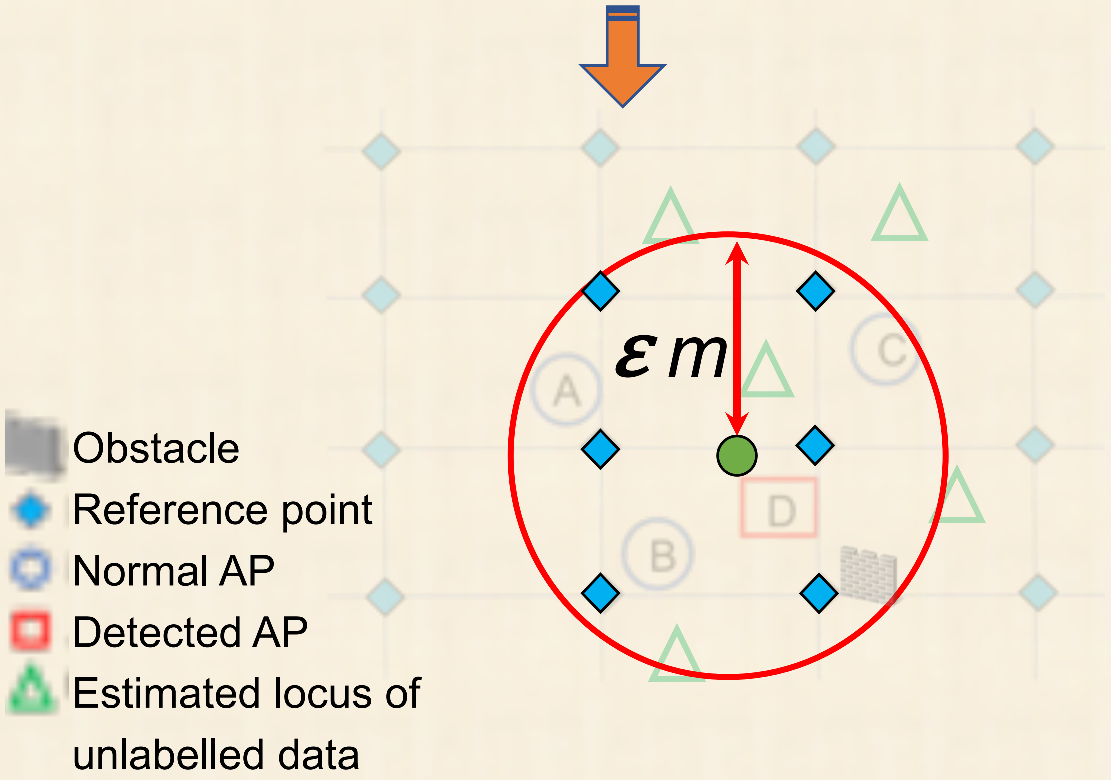

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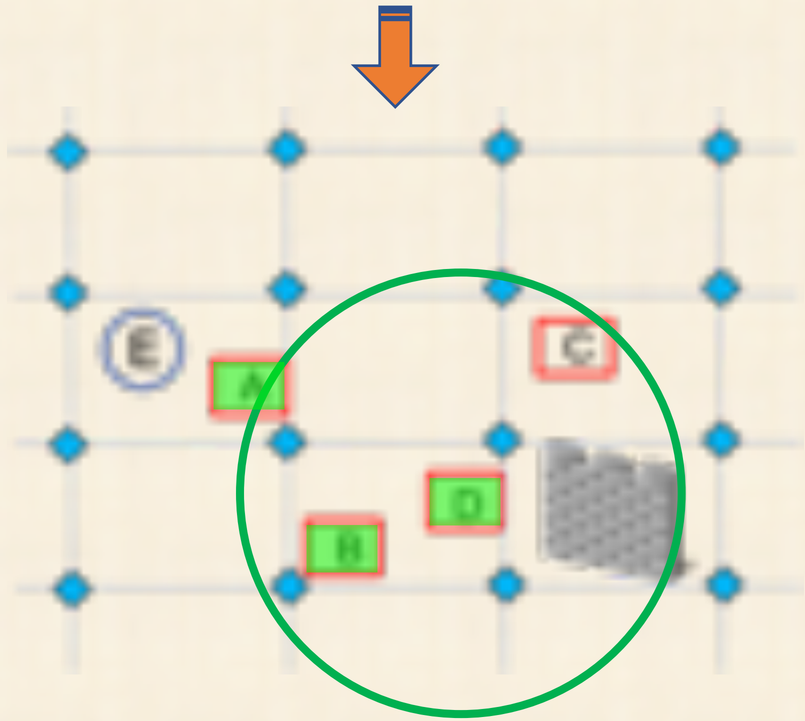

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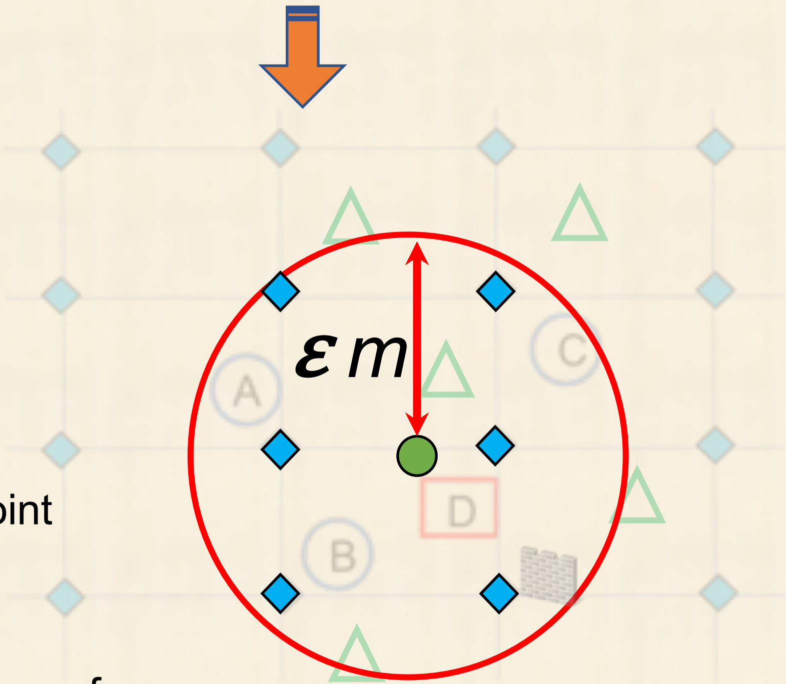

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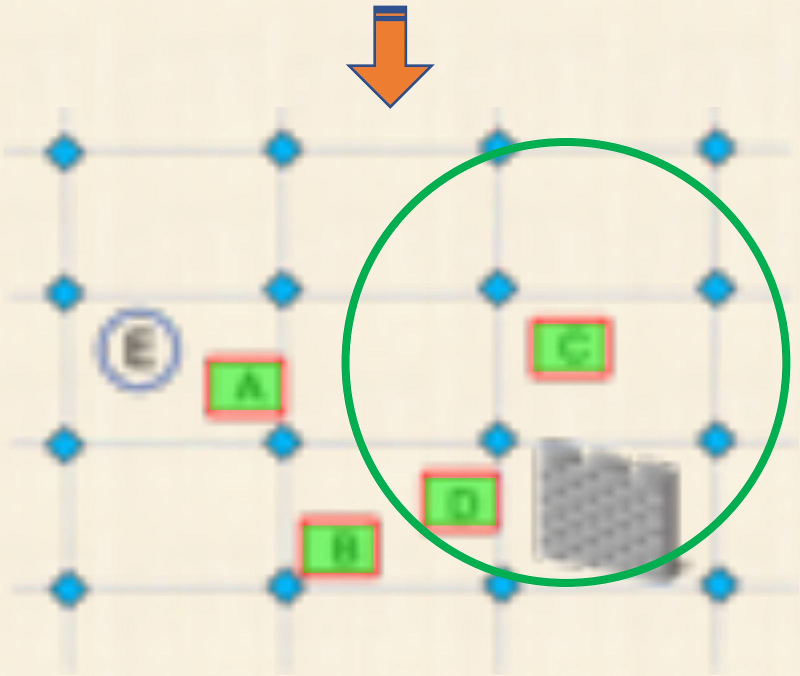

Obstacle
Reference point
Normal AP
Detected AP
Estimated locus of unlabelled data

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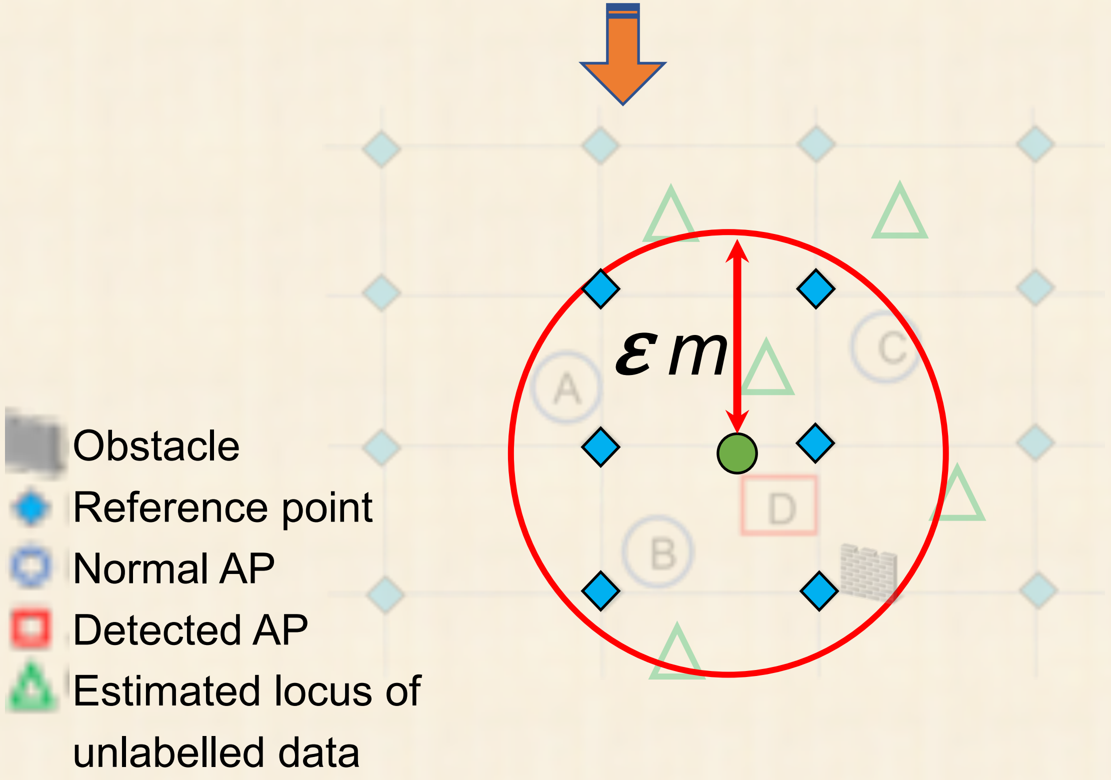

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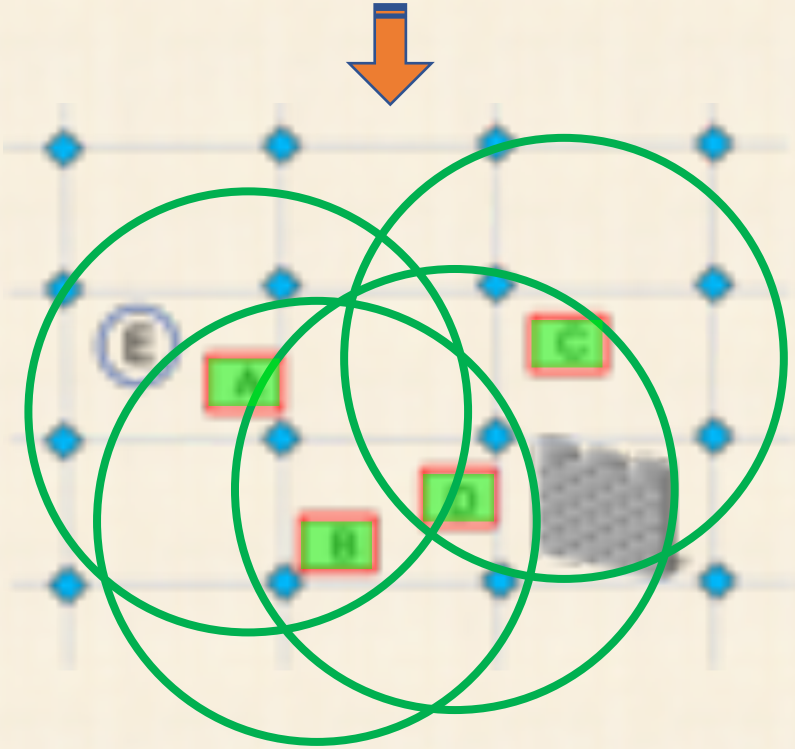

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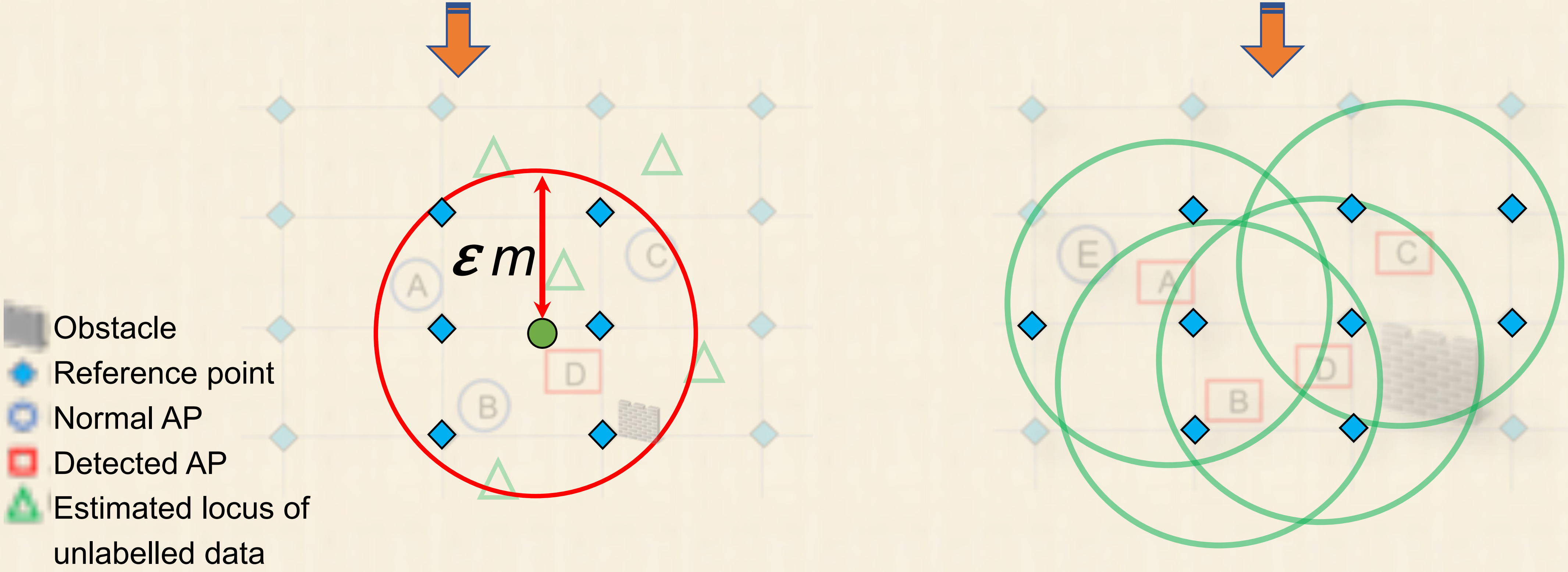

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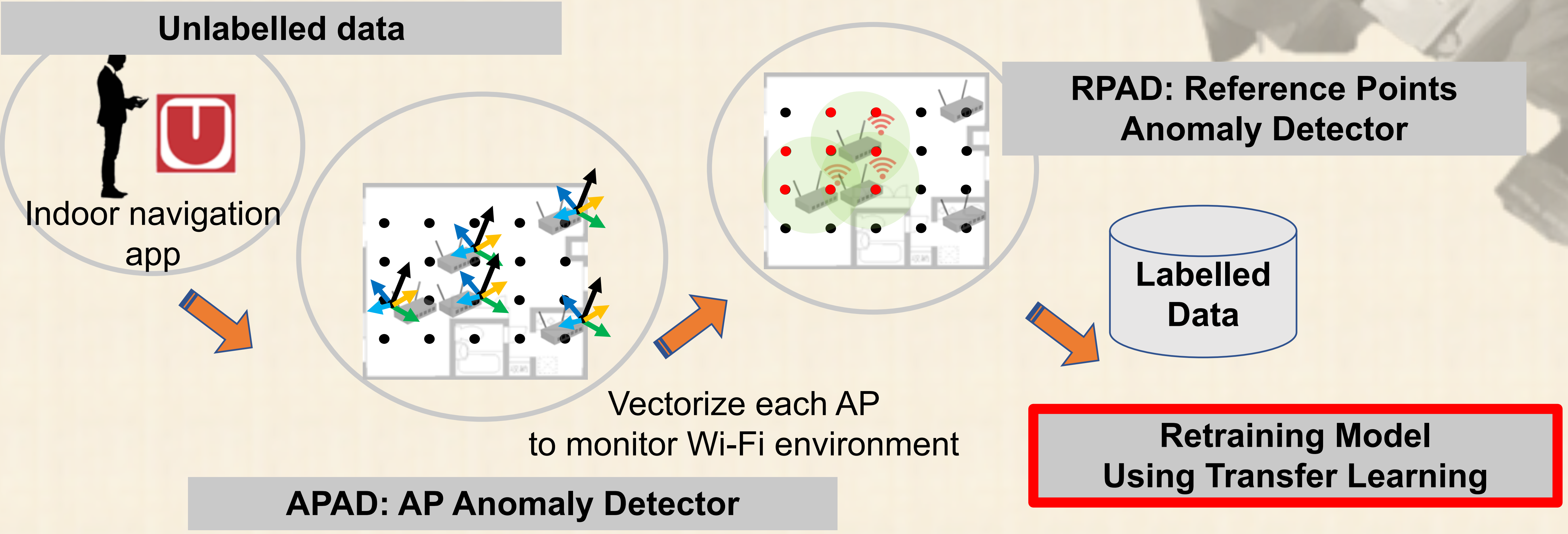

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Transfer Learning (TLM)

- Machine learning used for chronological datasets
- MixTrain method
  - Learn parameters θ from all the dataset
  - Update model by adding regularization term of L1 norm ($\sum_{i=1}^{|\theta|} |\theta i|$)
- Lasso method
  - Learn θ from variation of θ
  - Learn from L1 norm and regularization term $\left(\sum_{i=1}^{|\theta|} \left| \theta_i^{(k-1)} - \theta_i^{(k)} \right| \right)$
  - Regularization minimizing variation between θ at period $k-1$ and θ at period k

TLM can be replaceable

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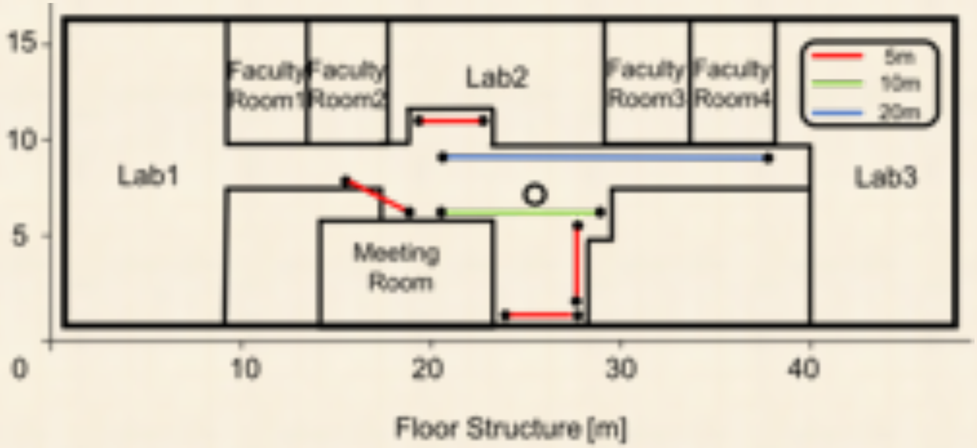
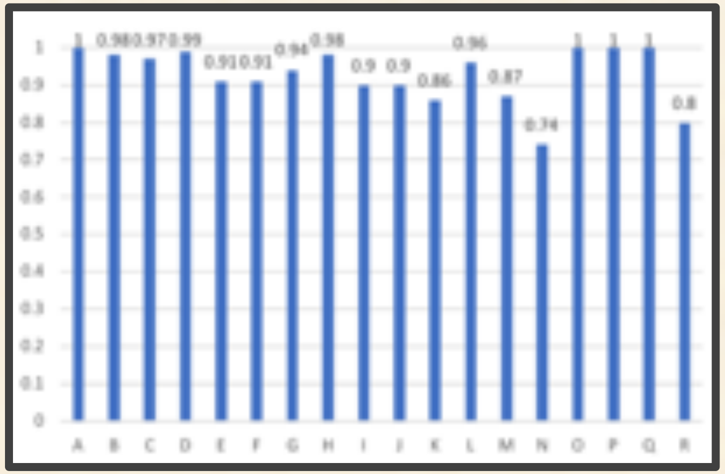
Laboratory environment

- Simulate environmental changes by displacement of APs
  - Validate if anomalies are detected
- Settings
  - 5m*4, 10m*1, and 20m*1 displacements
  - 105 reference points with 1m interval
  - 2000 labelled data

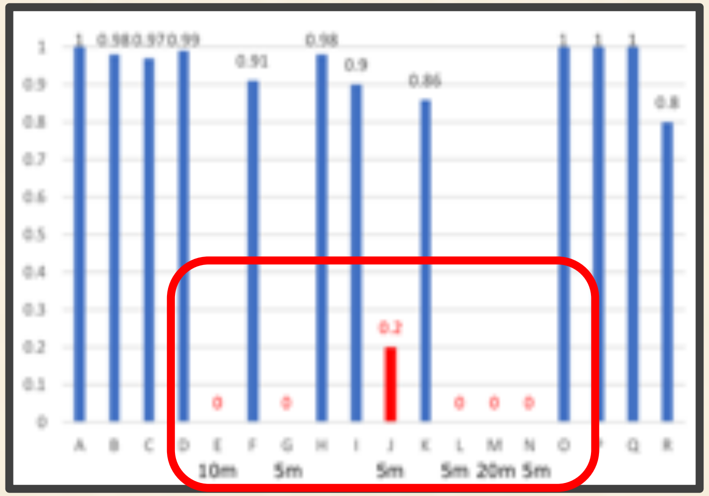




Un-simulated

Normal

Anomalous



Simulated

Laboratory environment

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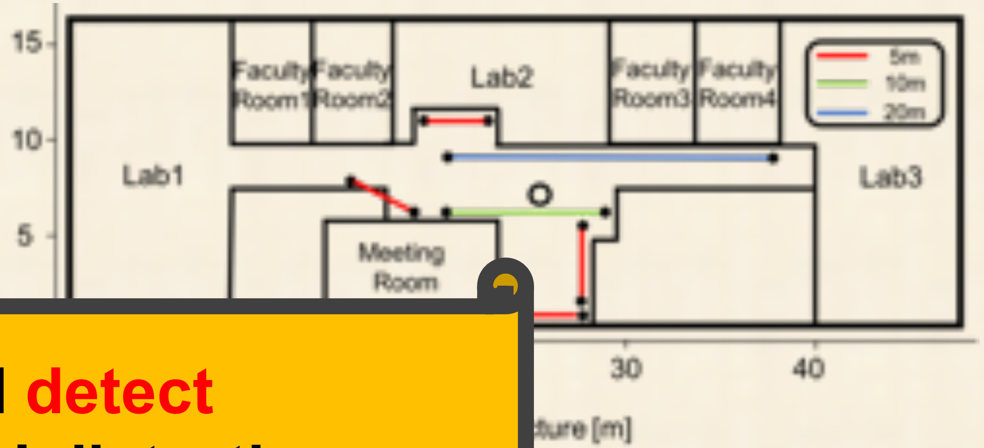
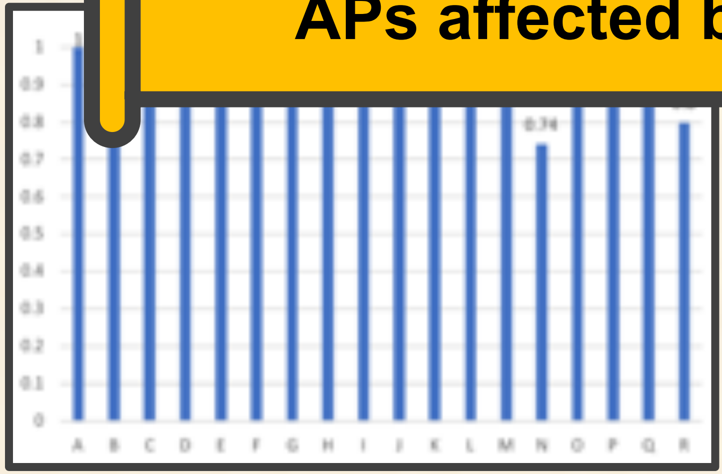


No-Sweat Detective could detect
APs affected by environmental distortion



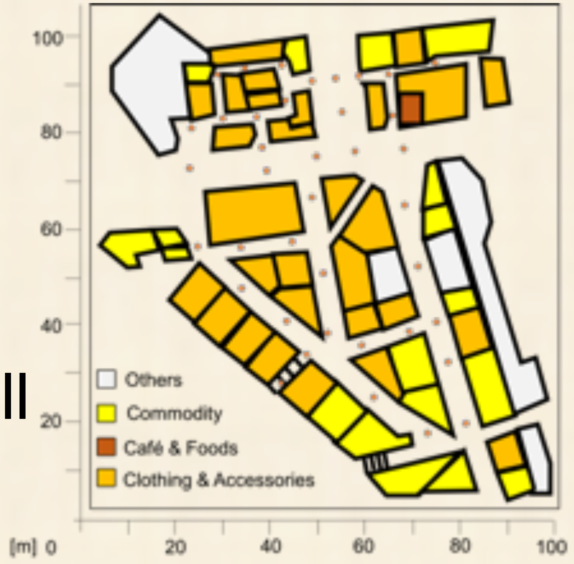
Un-simulated

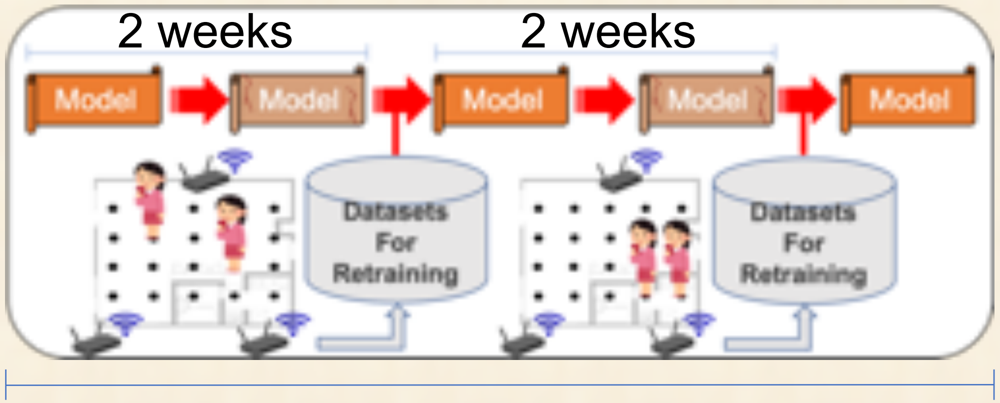
Anomalous

Simulated

Wild environment

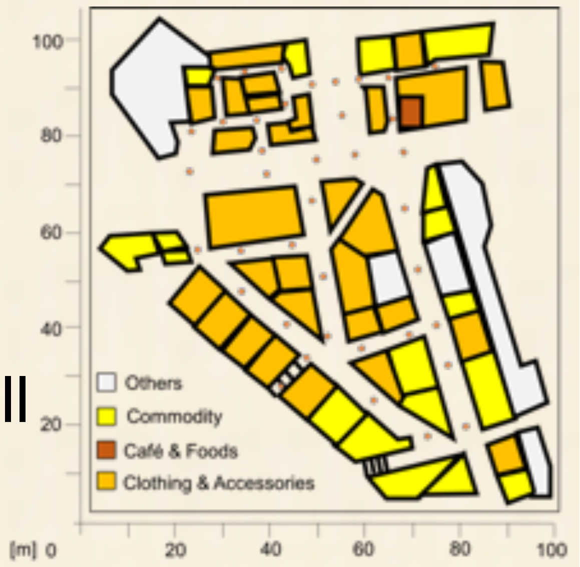
- Settings
  - Slide amount of reference points: 10, 20, 30, 60, 100% of all
  - 39 reference points with 8m interval
  - 764 unlabeled data, 2693 labelled data
    - Unlabelled data from indoor navigation app





5 month-long observation

Wild environment



- Settings
  - Slide amount of reference points: 10, 20, 30, 60, 100% of all
  - 39 reference points with 8m interval
  - 764 unlabeled data, 2693 labelled data
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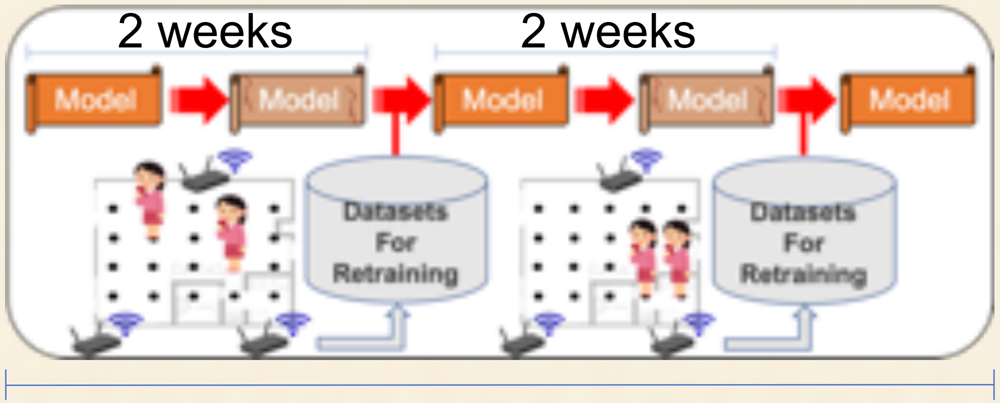
- Evaluate the accuracy of the model at the end
  - Compare with Baseline and transfer-learning-but-random-sampling ways

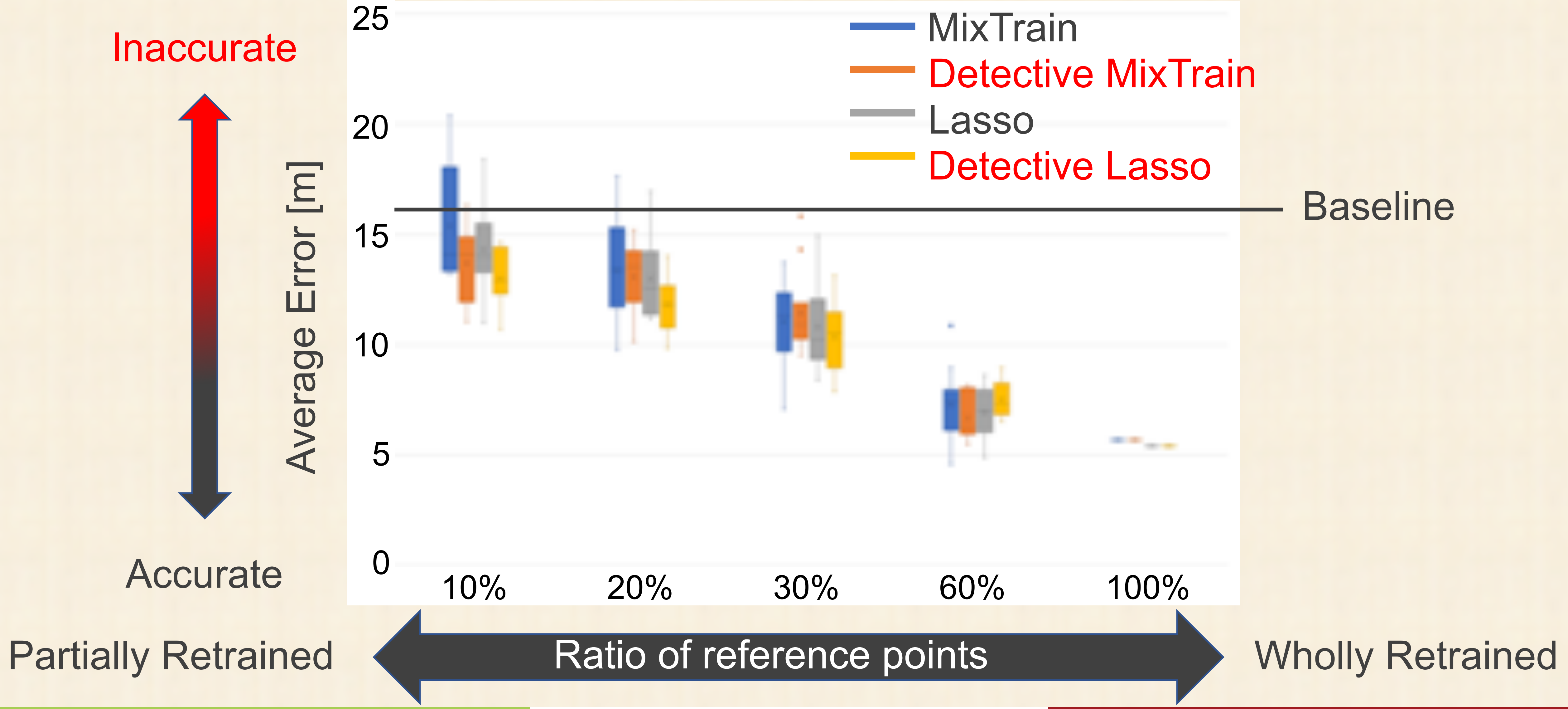


5 month-long observation

- Baseline: never retrained
- MixTrain: TLM
- Lasso: TLM

- **Detective MixTrain**: MixTrain + No-Sweat Detective
- **Detective Lasso**: Lasso + No-Sweat Detective

Results after 10 trials



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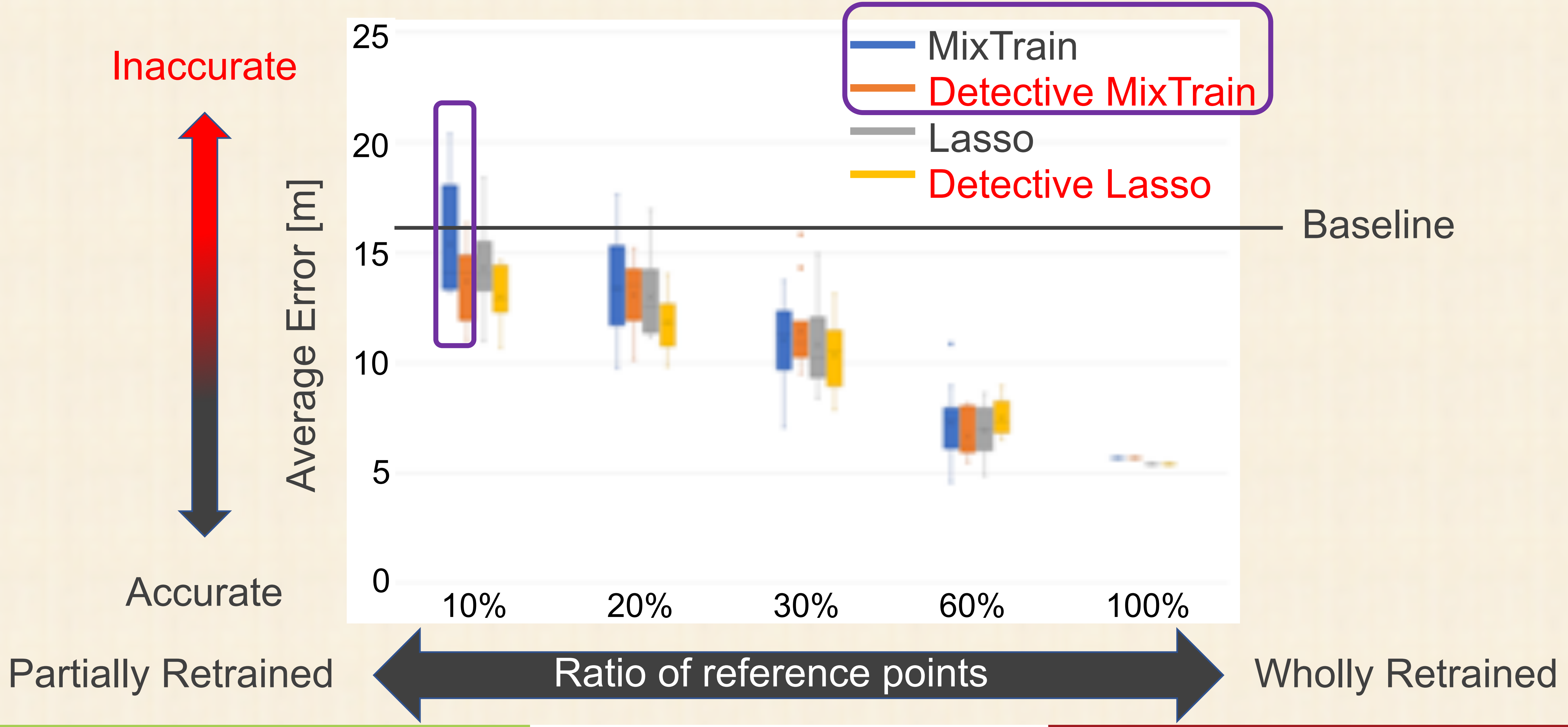

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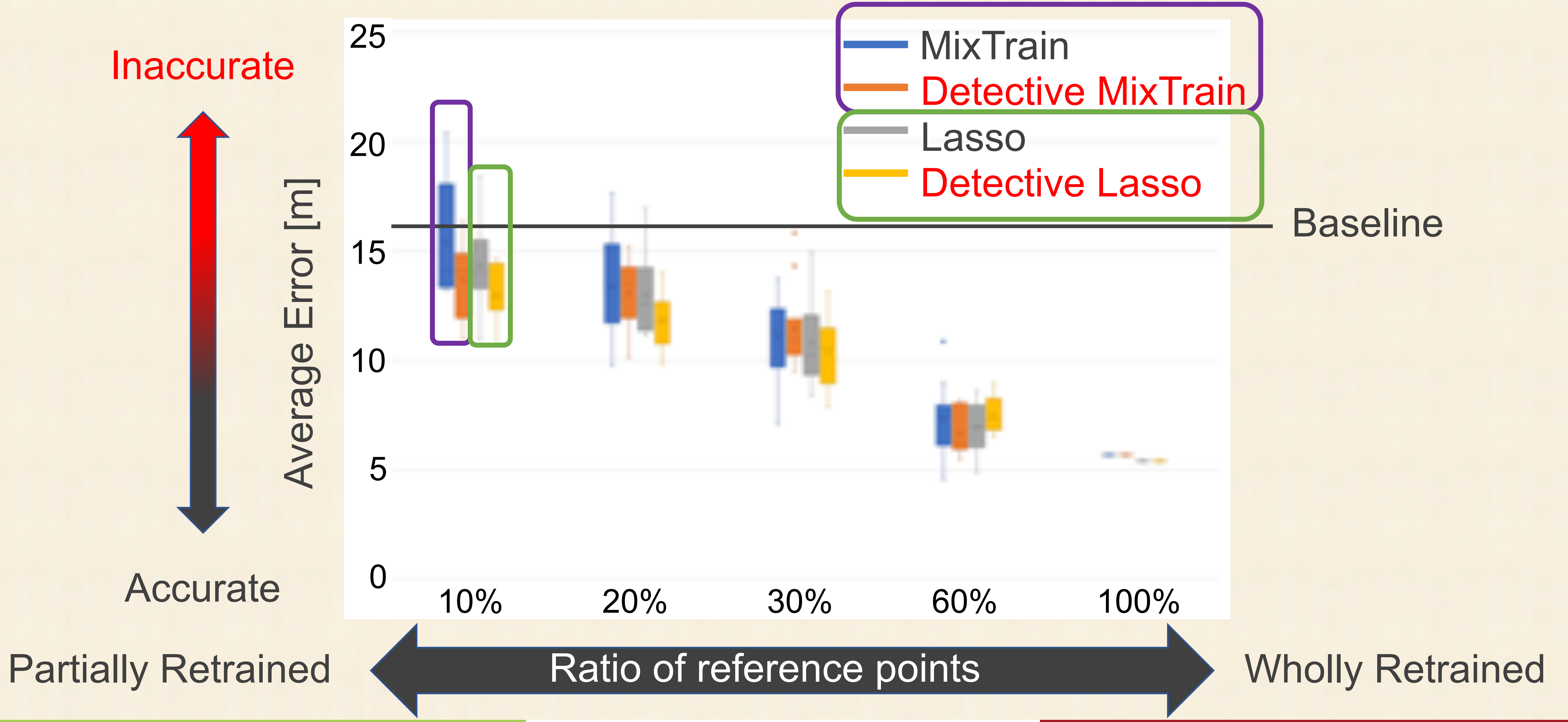

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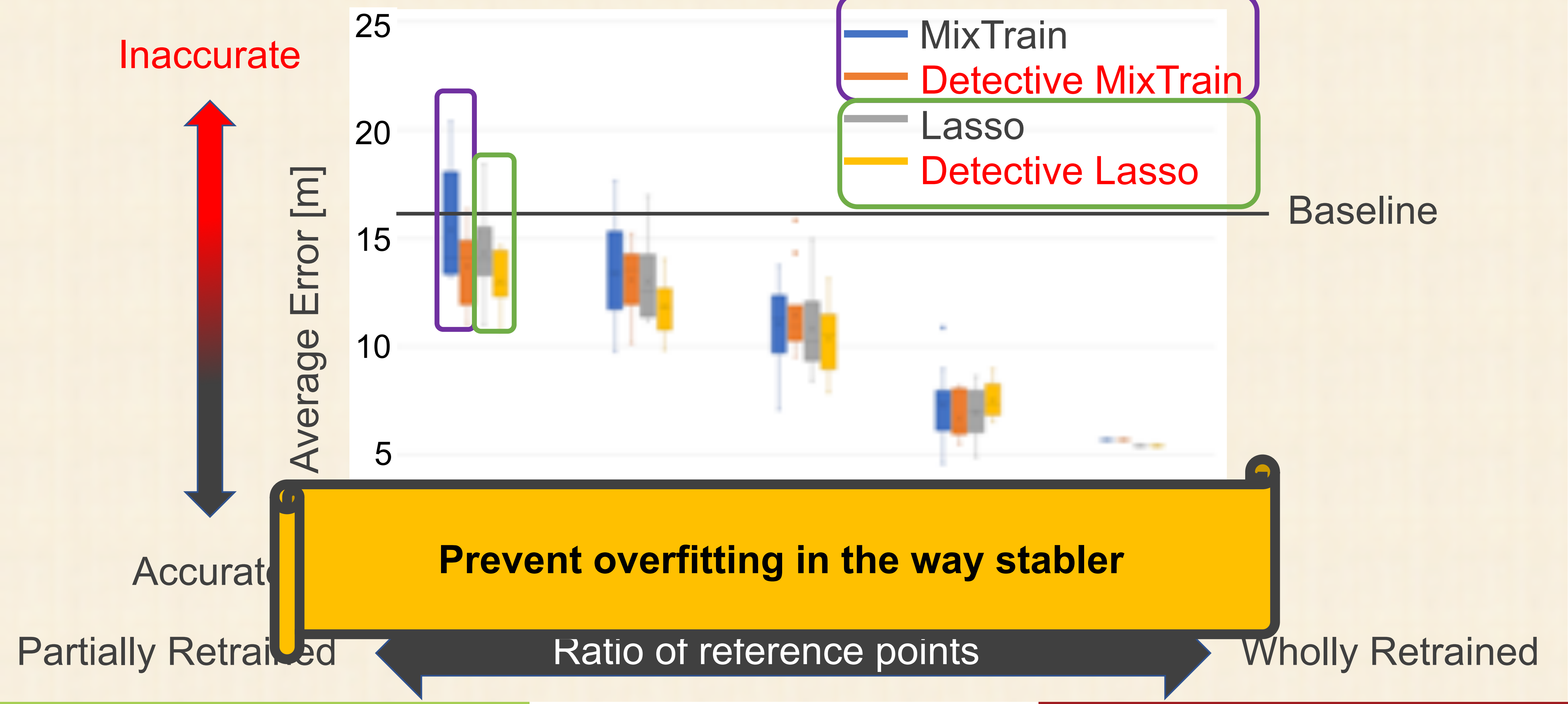
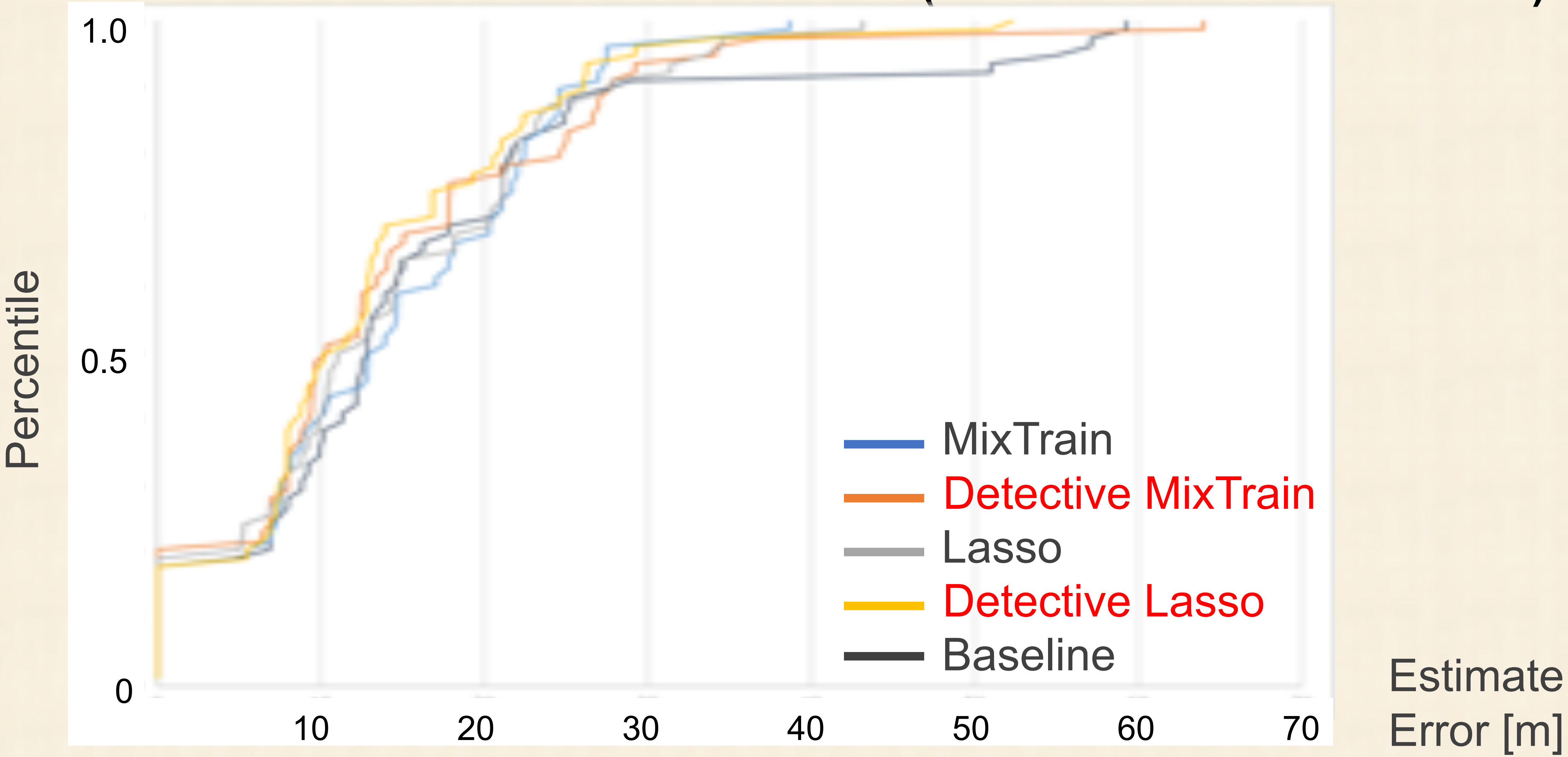


Prevent overfitting in the way stabler

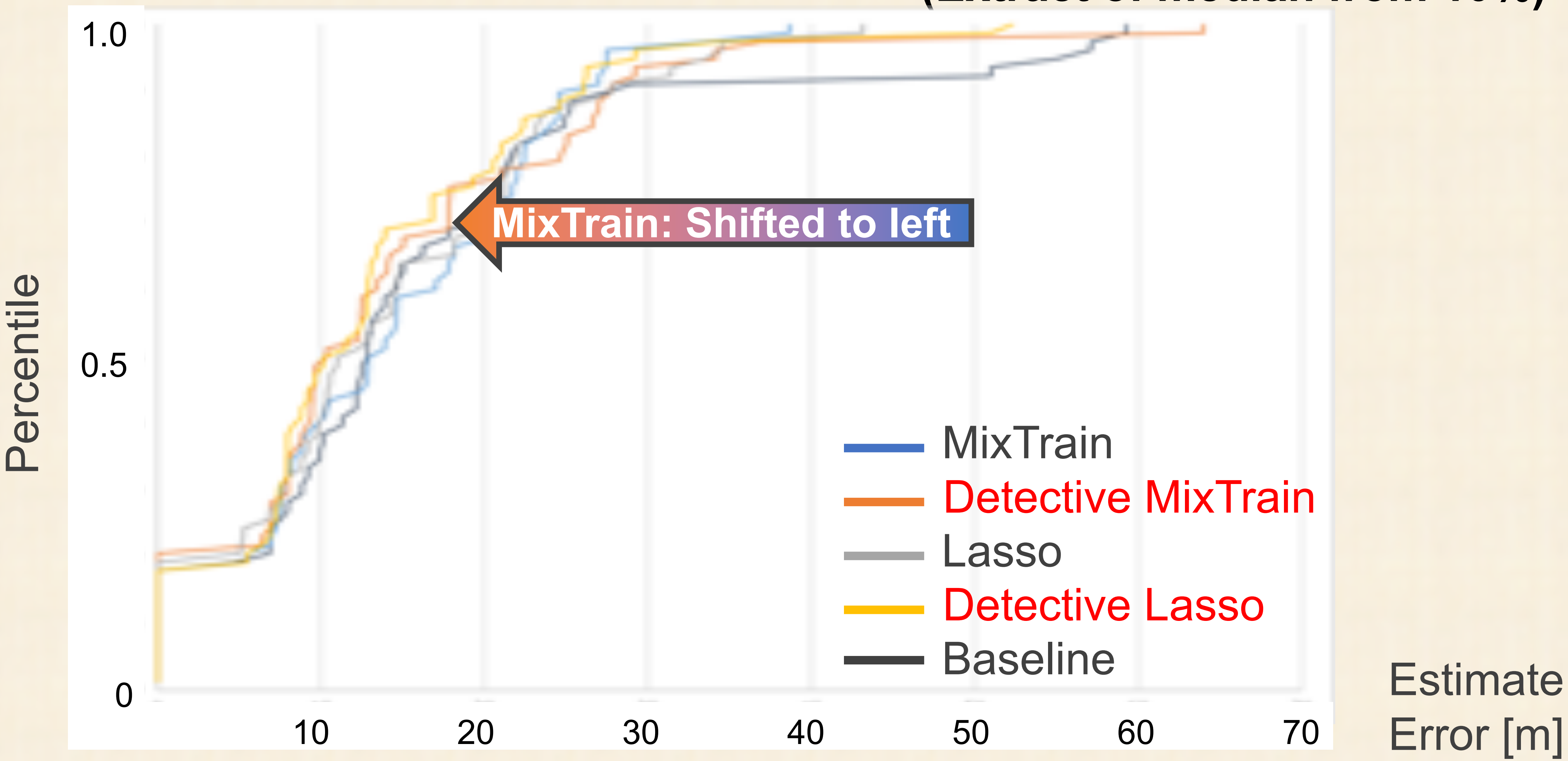
Cumulative Distribution of Estimate Error

(Extract of median from 10%)



Cumulative Distribution of Estimate Error

(Extract of median from 10%)



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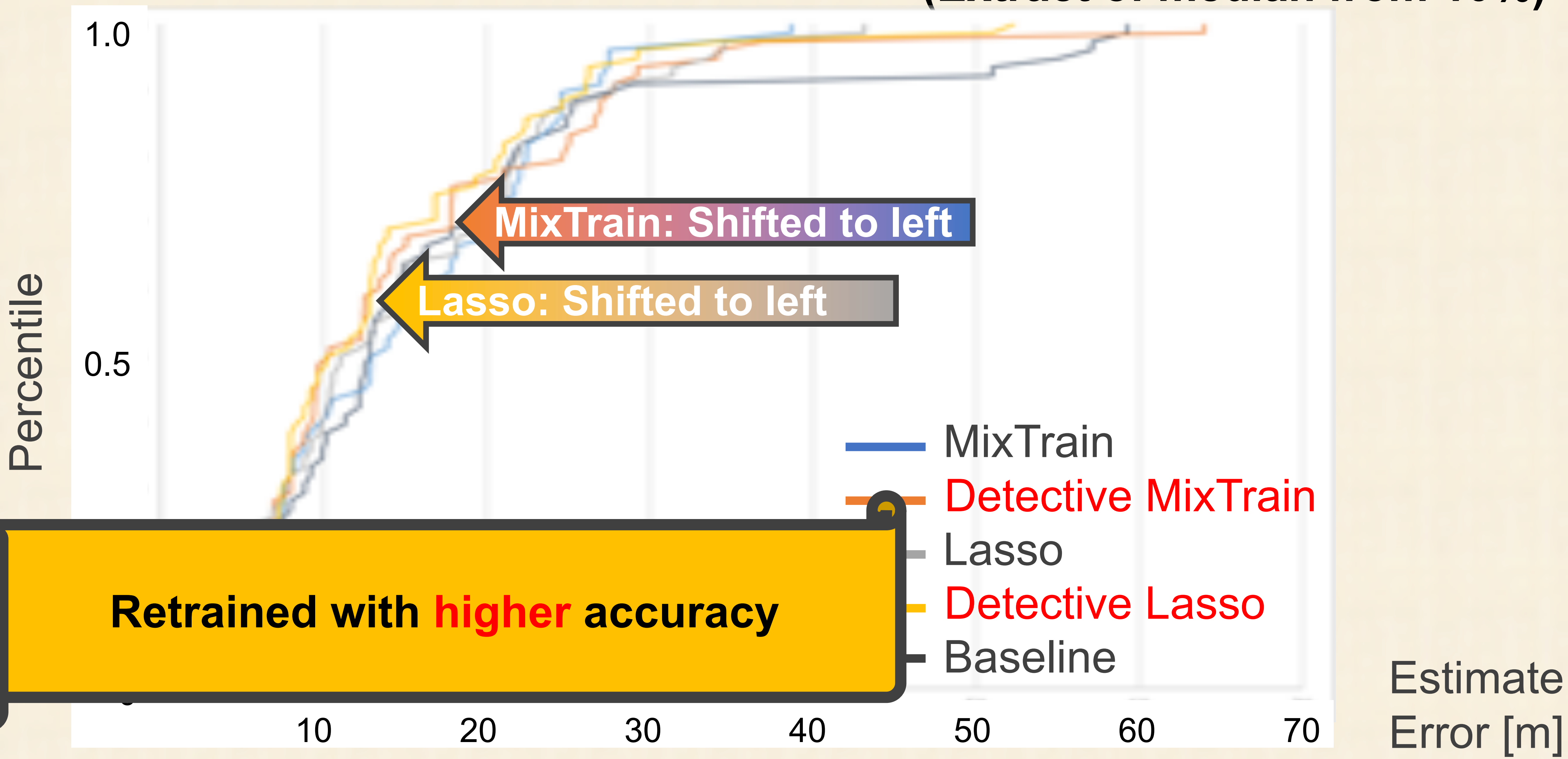
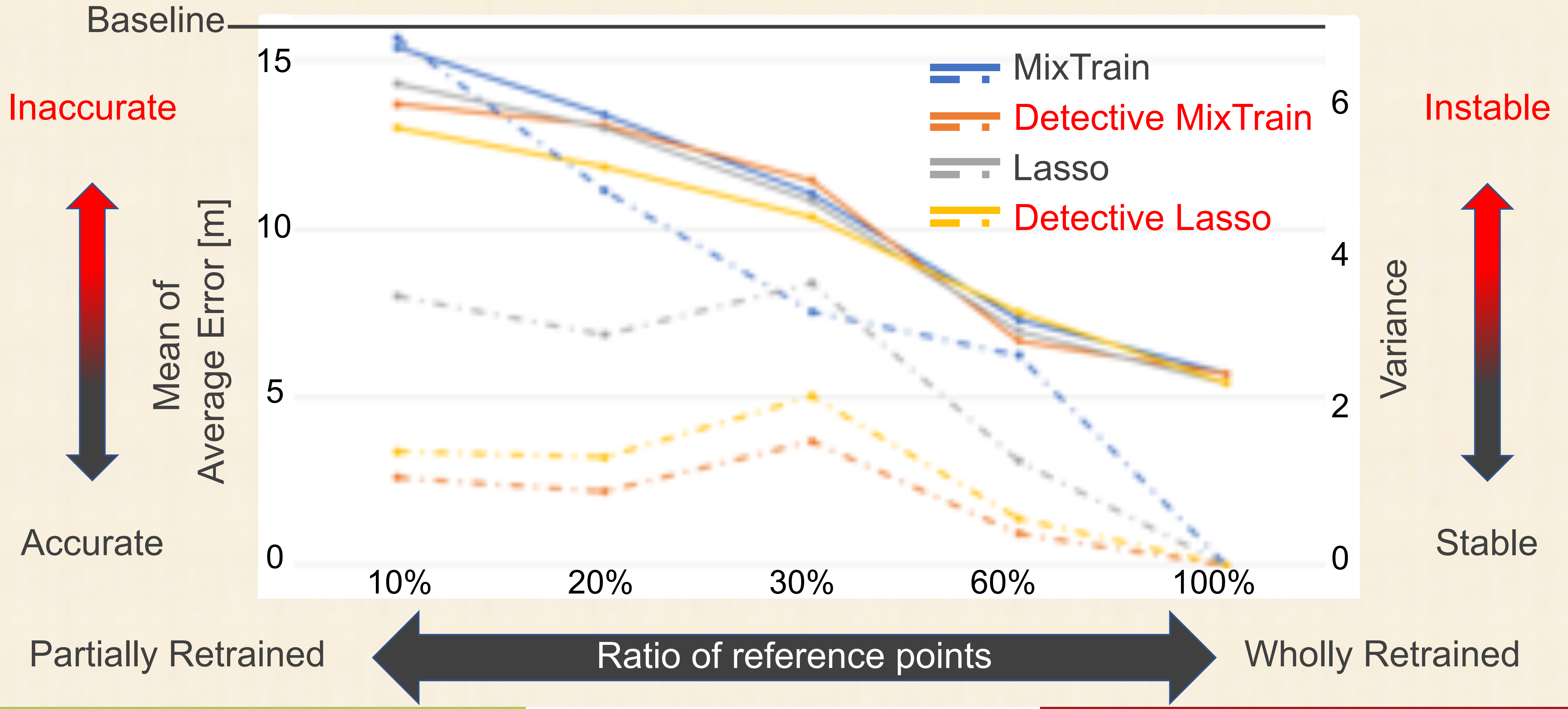
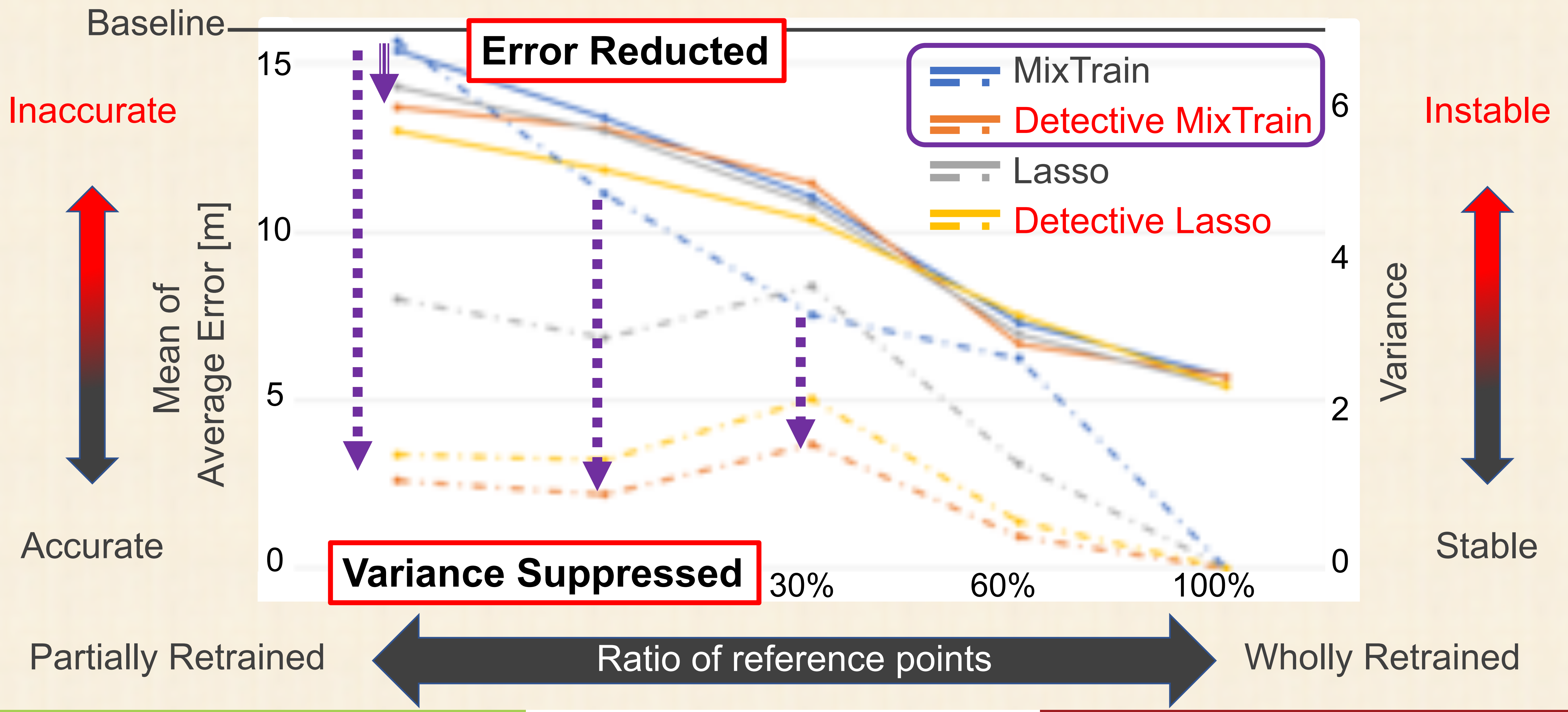


Retrained with higher accuracy

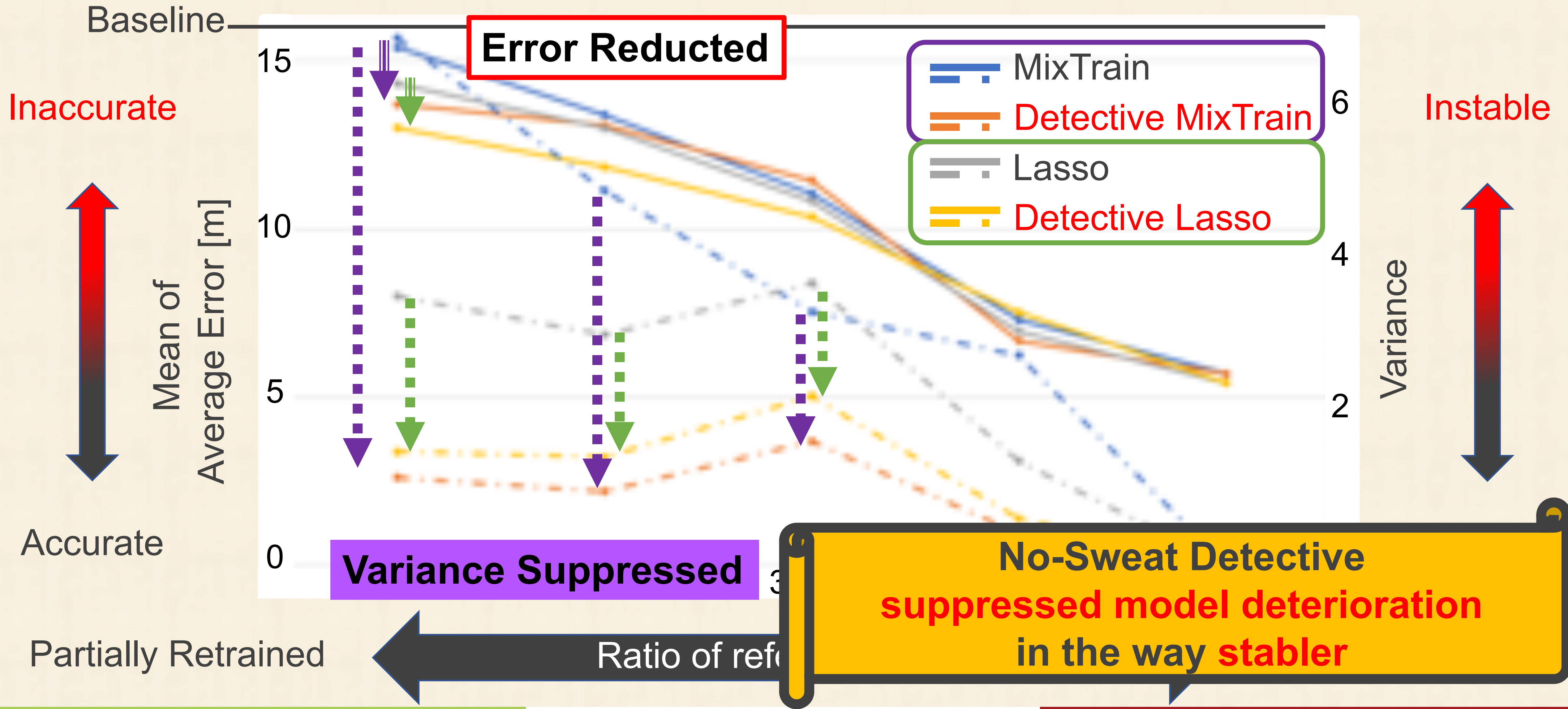
Means and Variance



Means and Variance



Means and Variance



No-Sweat Detective
suppressed model deterioration
in the way stabler

Outline

- Motivation
- State of the Art
- Methodology
- Evaluation
  - Laboratory environment
  - Wild environment
- Summary

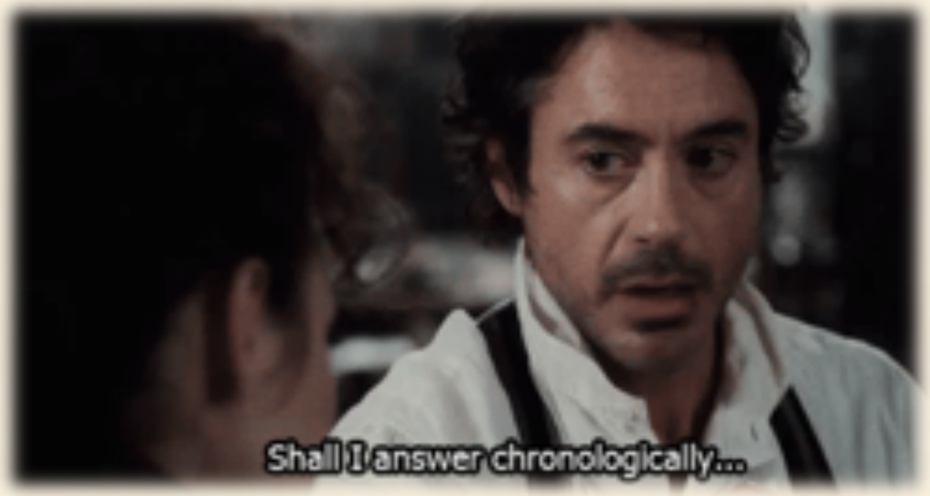
Summary

- Transfer learning is employed to retrain Wi-Fi localization model
- Additional Datasets are randomly selected for retraining
  - Result in overfitting and instable accuracy
- No-Sweat Detective
  - Identify reference points where environmentally changed
    - Analyzing unlabelled data obtained with no effort (sweat)
  - Prevent overfitting in the way stabler
- Outlook
  - Substitute unlabelled data as labelled data to retrain the model

Thank You!

Questions?

https://koheiyamamoto.net/



©Sherlock Holmes

Supplements

TABLE I

CONFUSION MATRIX OF DETECTED APS OUT OF DISPLACED APS IN SLIDING SCALE {VECFILT AND VECWIDTH}

VecFilt\VecWidth	-25	-30	-35	-40	-45	-50	-55	-60
-25	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0
-30	-	4/4	4/4	4/4	3/4	2/4	1/4	0/4
-35	-	-	**6/6**	**6/6**	4/6	2/6	1/6	0/6
-40	-	-	-	**6/6**	4/6	2/6	1/6	1/6
-45	-	-	-	-	4/6	2/6	1/6	1/6
-50	-	-	-	-	-	2/6	1/6	1/6
-55	-	-	-	-	-	-	1/6	1/6
-60	-	-	-	-	-	-	-	1/6

Motivation

- Indoor position is now of considerable importance for IoT
  - To capture user contexts and her interests
- Fingerprinting localization based on Wi-Fi RSSI is major
  - Workflow consists of training and operational phases

I. Primary signal model created from primary datasets of labeled fingerprint
II. Estimate her location by comparing her current fingerprint with model

- **But** accuracy of model deteriorates with age
  - Caused by environmental changes
    - Movement of objects, construction of obstacles, automatic power adjustment, etc.

Requires **calibration** of model at certain periodic cycle

- Laborious effort and time-consuming overhead

State of the Art 1/2

- Reconstruction of model with less or no effort
  - TuRF, QRFC, and UnLoc can obtain labeled fingerprint installing sensors

- Detection of signal changes in wireless networks
  - Song et al. showed detecting node redeployment focusing neighborship
  - Ohara et al. showed detecting environmental changes observing CSI (Wi-Fi channel state information)
  - Meng et al. proposed probabilistic algorithm to detect distortion

State of the Art 1/2

- Reconstruction of model with less or no effort
  - TuRF, QRFC, and UnLoc can obtain labeled fingerprint installing sensors

Forcing user to put on sensors is far from practical use

- Detection of signal changes in wireless networks
  - Song et al. showed detecting node redeployment focusing neighborship

Forcing environment to have installment is not pragmatic

  - Ohara et al. showed detecting environmental changes observing CSI (Wi-Fi channel state information)

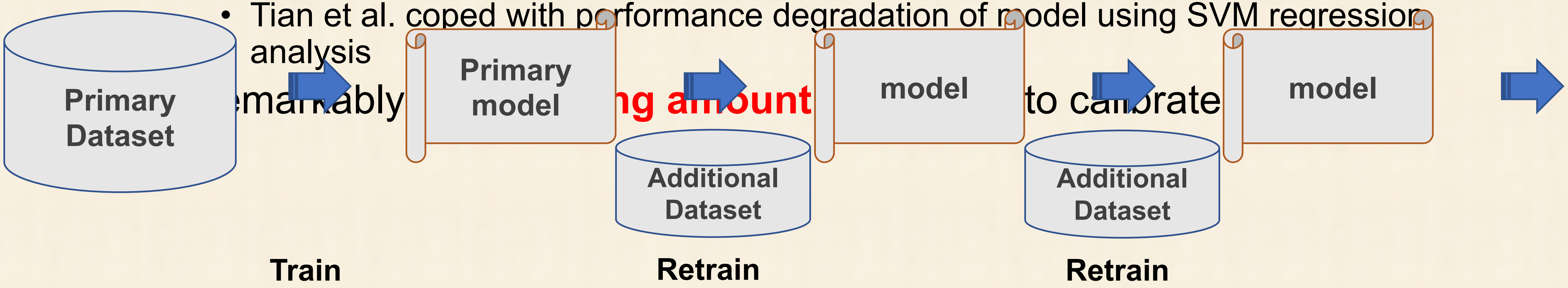
Requires pairs of connection and CSI is scarcely used

  - Meng et al. proposed probabilistic algorithm to detect distortion

Only proven in test-bed and does not target calibration

State of the Art

- Major current is to employ **transfer learning**[1)]
  - Reflects current Wi-Fi environment in model
  - Retrains model with adding a small amount of labeled fingerprint
    - Yang et al. proved higher accuracy with much less calibration effort
    - Yin et al. materialized regression and model-tree based algorithm
    - Tian et al. coped with performance degradation of model using SVM regression analysis
  - emarkably ... **ng amount** ... to calibrate



[1]: Pengcheng Wu and Thomas G. Dietterich. “Improving SVM Accuracy by Training on Auxiliary Data Sources.”

State of the Art

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- Remarkably suppressing amount of dataset to calibrate model

- These methods pick up additional dataset (labeled fingerprint) randomly or comprehensively
  - Spilled into destabilization of accuracy recovery at every calibration
  - Recovery rate heavily relies on selection of labeled fingerprint

Prim
Data

Train Retrain Retrain

[1]: Pengcheng Wu and Thomas G. Dietterich. "Improving SVM Accuracy by Training on Auxiliary Data Sources."

State of the Art

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  - Remarkab...

Prim...

Labeled fingerprint should be convergently collected from specific (anomalous) reference points

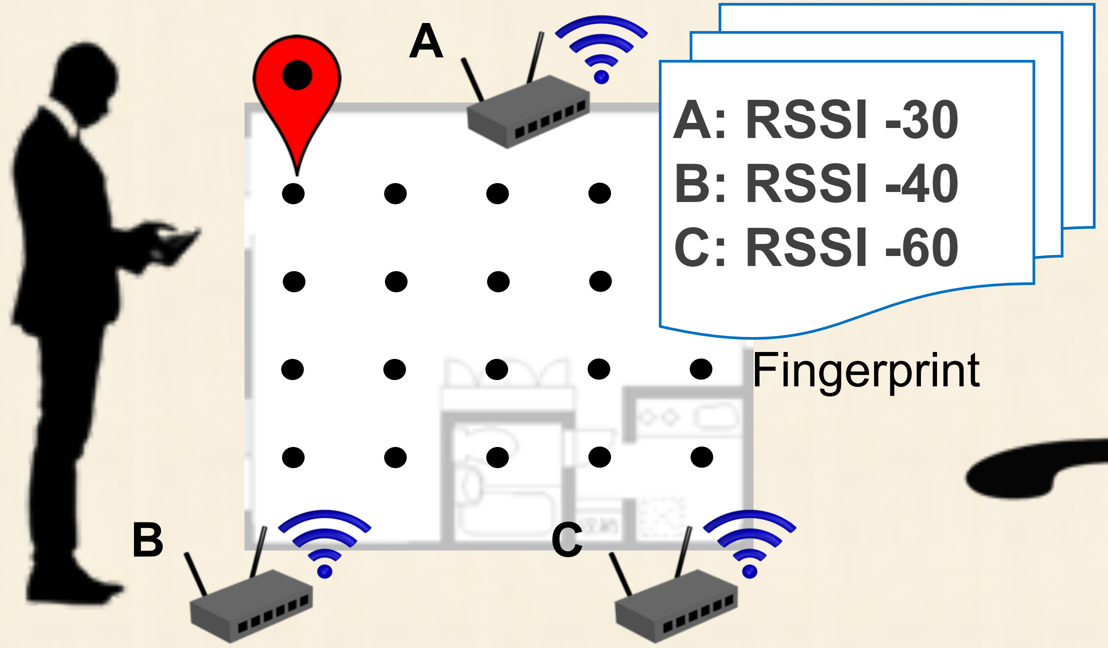
Tra... ...rain **Retrain**

[1]: Pe... Wu and Thomas G. Dietterich. "Improving SVM Accuracy by Training on Auxiliary Data Sources."

Two Types of Fingerprint

Labeled

- Used for training primary model
- Small amount used for retraining model
- Manual collection by administrator



Unlabeled

- Collected from user of location services
- Automatically but not labeled

Plenty

Two Types of Fingerprint

Identify reference points where environmentally changed

Unlabeled

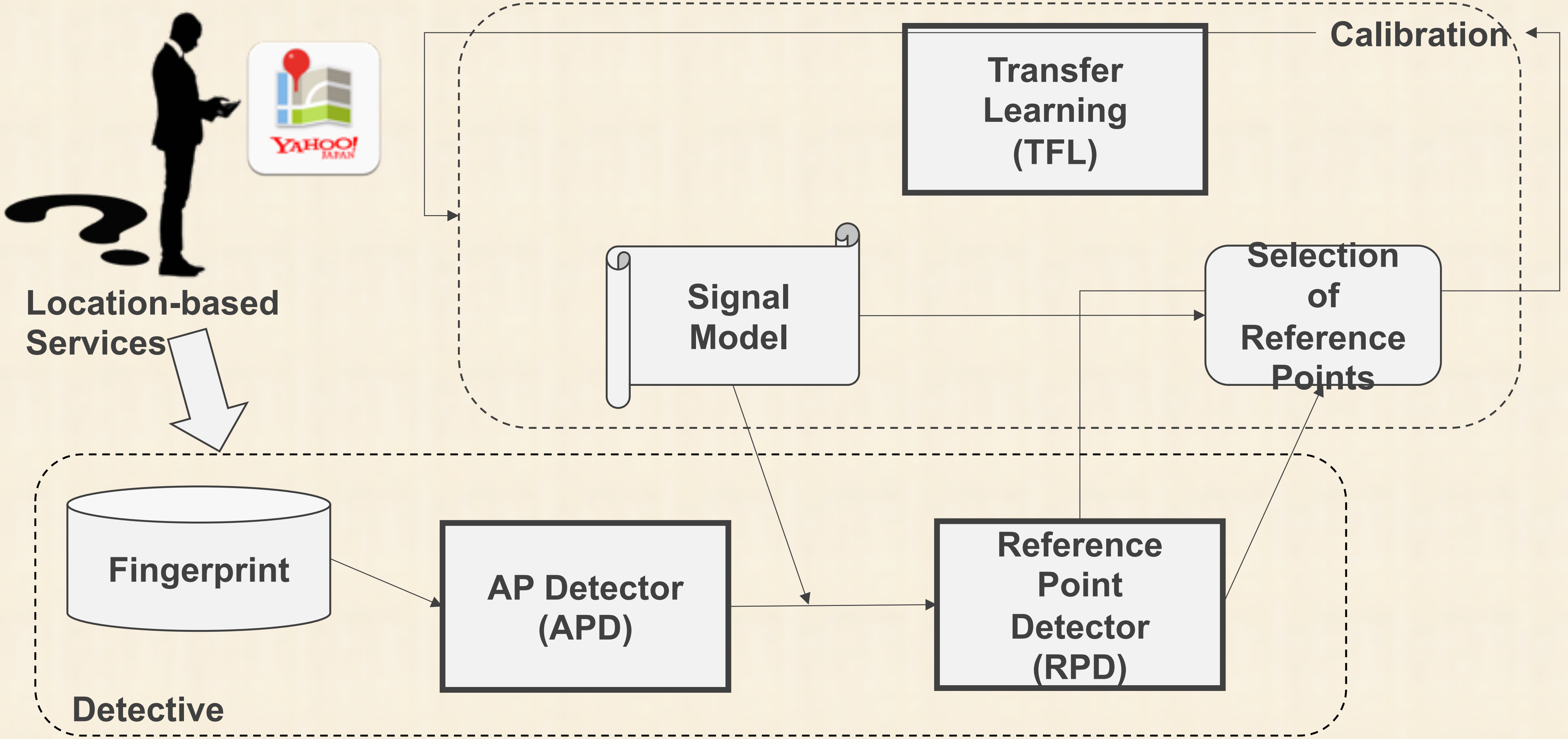
- Collected from user of location services
- Automatically but not labeled

Plenty

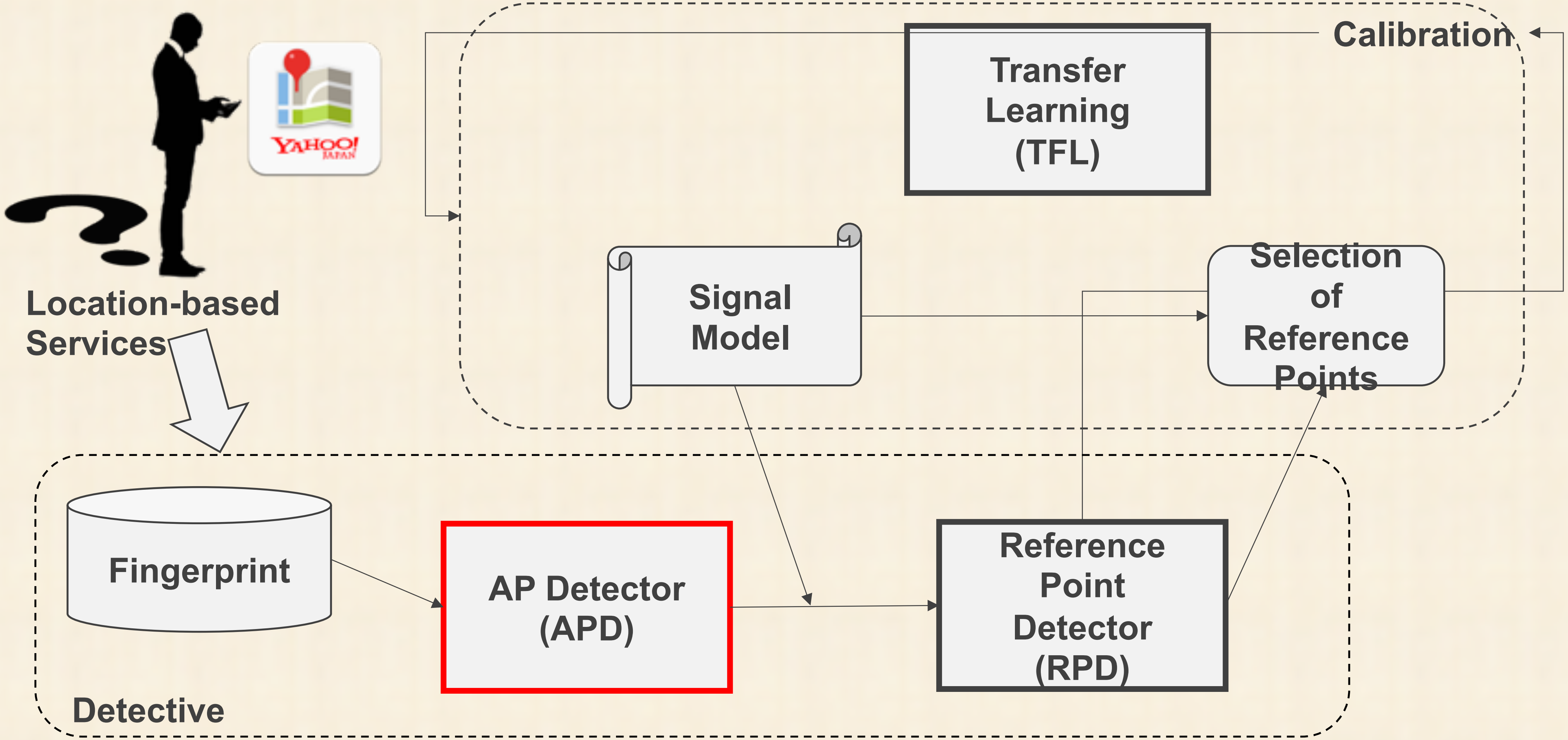
Methods

- Identify reference points where environmentally changed as anomaly
  - Build a system named **No-sweat Detective**
  - Perform with **no effort** using unlabeled fingerprint
  - Work strongly even in a **real world** with **long**-period observation
  - Achieve **higher accuracy recovery** in comparison with existing transfer learning methods using the **same amount** of labeled fingerprint

No-sweat Detective



No-sweat Detective



AP Detector (APD)

- Detects anomalous AP
  - Utilizes co-occurrence and analyzes relative position with other AP
- Workflow

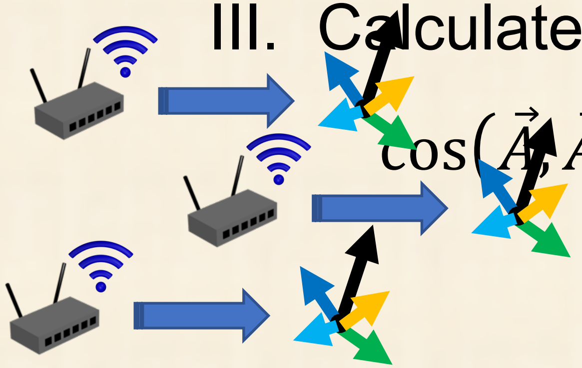
I. Picks up unlabeled fingerprint having maximum RSSI over ***vecFilt***

$(R1_{r1}, R2_{r2}, R3_{r3}, \cdots, Rx_{rx})$ {***vecFilt*** < max(r1,rx)} [R: AP, r: RSSI] ⋯ (1)

II. Vectorizes unlabeled fingerprint in sparse space with ***vecWidth***

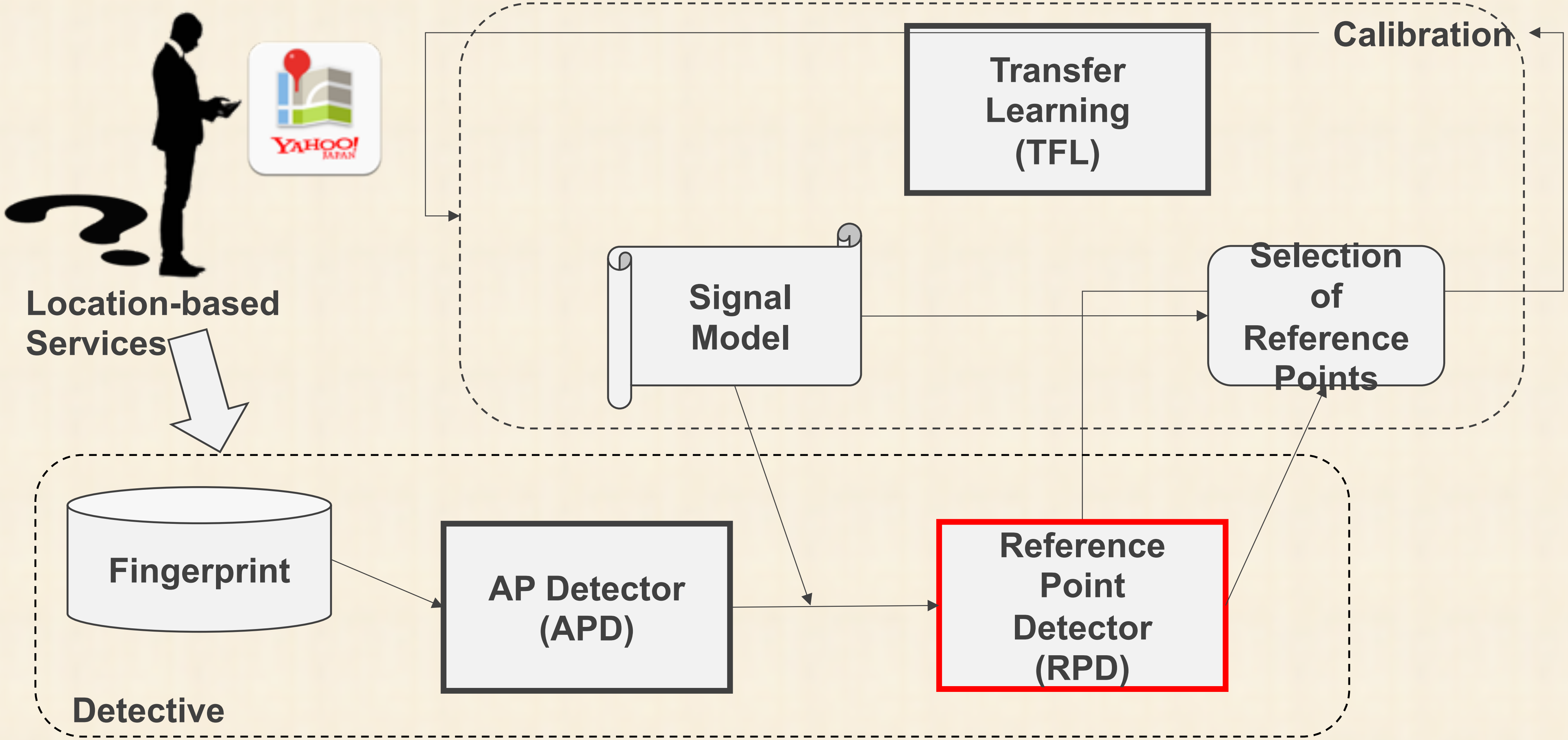
$\vec{A} = (R1_{r1}, R2_{r2}, R3_{r3}, \cdots, Rx_{rx})$ {***vecFilt*** < max(r1,rx), **vecWidth** < rx} ⋯ (2)

III. Calculates similarity of vector model



$$\cos(\vec{A}, \vec{A}') = \frac{\vec{A} \cdot \vec{A}'}{|\vec{A}||\vec{A}'|} = \frac{\vec{A}}{|\vec{A}|} \cdot \frac{\overrightarrow{A'}}{|\vec{A}'|} = \frac{\sum_{i=1}^{|V|} A_i A'_i}{\sqrt{\sum_{i=1}^{|V|} A_i^2} \cdot \sqrt{\sum_{i=1}^{|V|} A'^2_i}} \quad \cdots (3)$$

No-sweat Detective



Reference Point Detector (RPD)

- Detects anomalous Reference Point
  - Environmentally changed around detected Wi-Fi source
- Workflow

I. Singularly detected:

   i. Roughly estimates location where each unlabeled fingerprint were observed by ignoring distorted radio wave
   ii. Gets weighted average center
   iii. Recollect labeled fingerprint at reference points where within radius $\boldsymbol{\varepsilon}$ m from center

II. Plurally detected:

   - Employ DBSCAN to Wi-Fi source location retrieved from past model with radius $\boldsymbol{\varepsilon}$ m
     - Regarding collective changes hardly caused by displacement of Wi-Fi source

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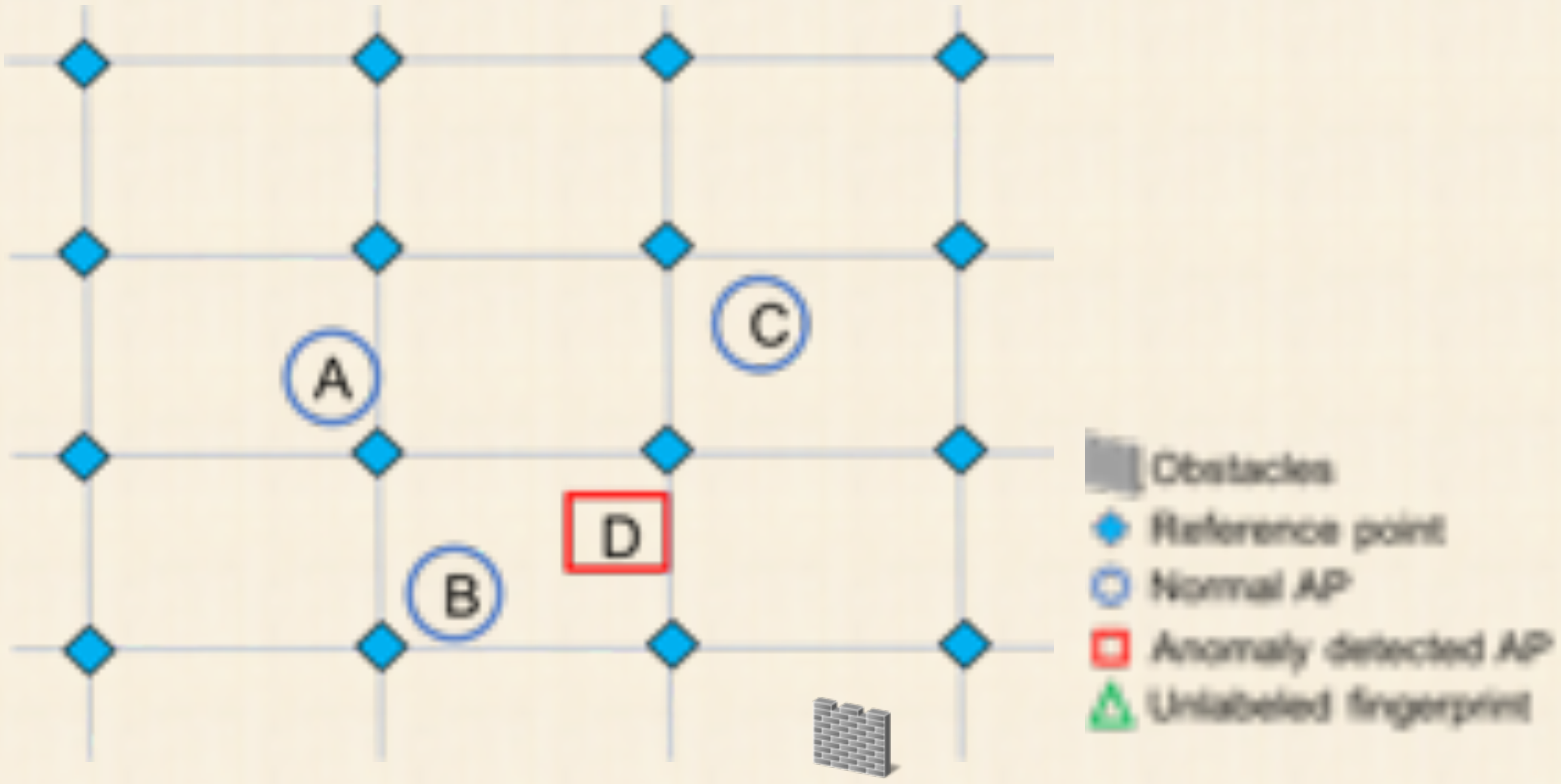

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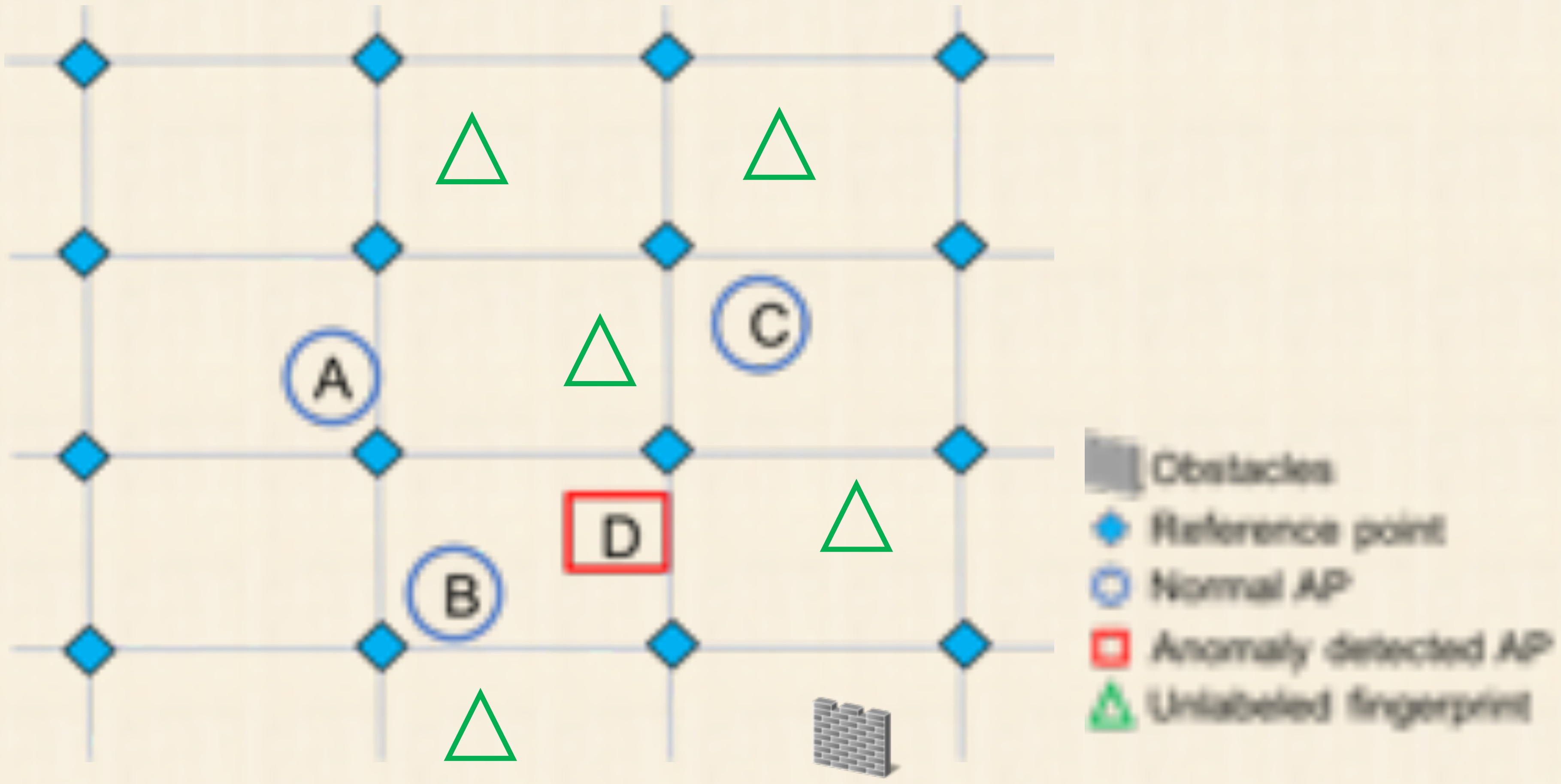

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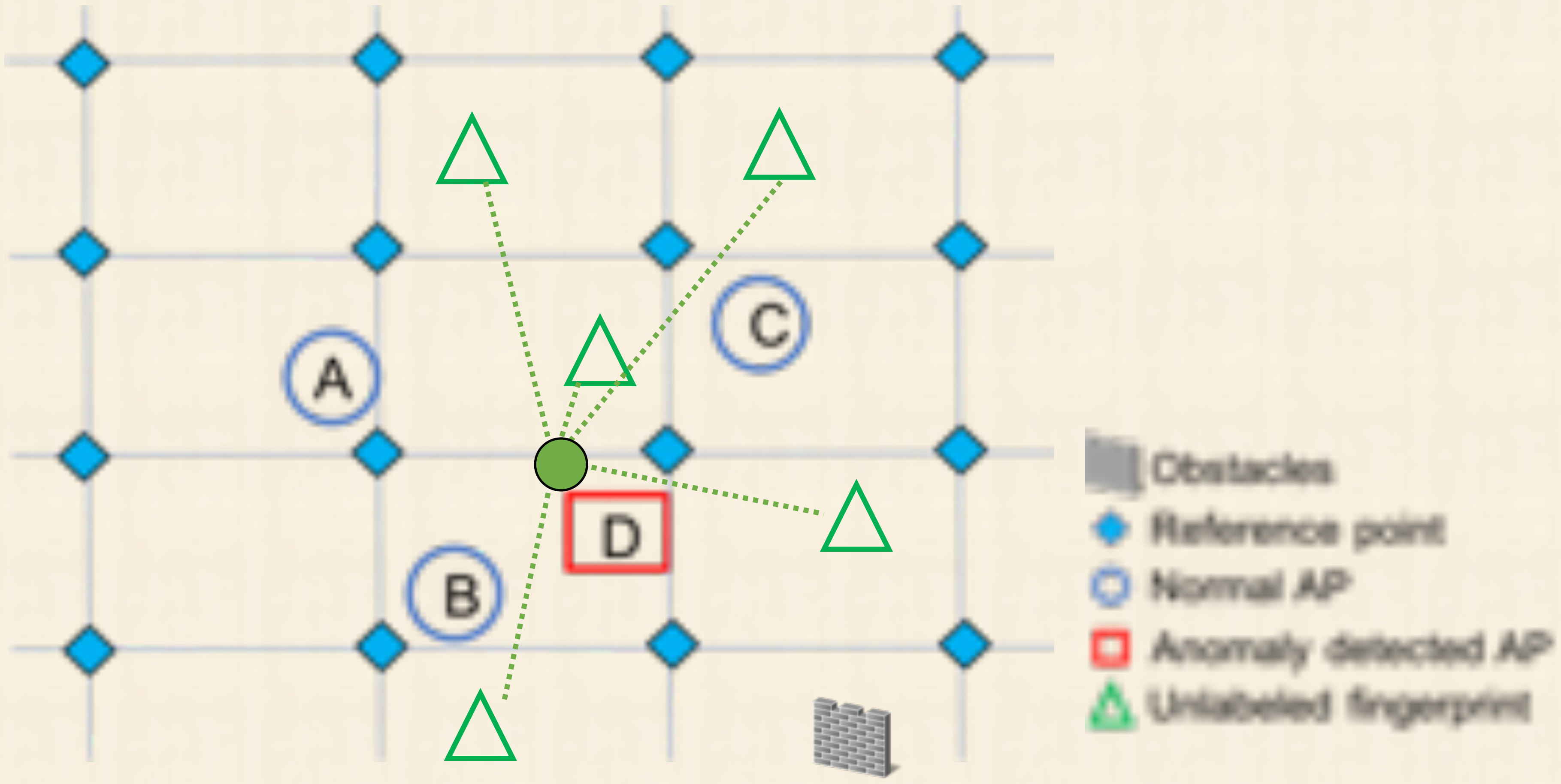

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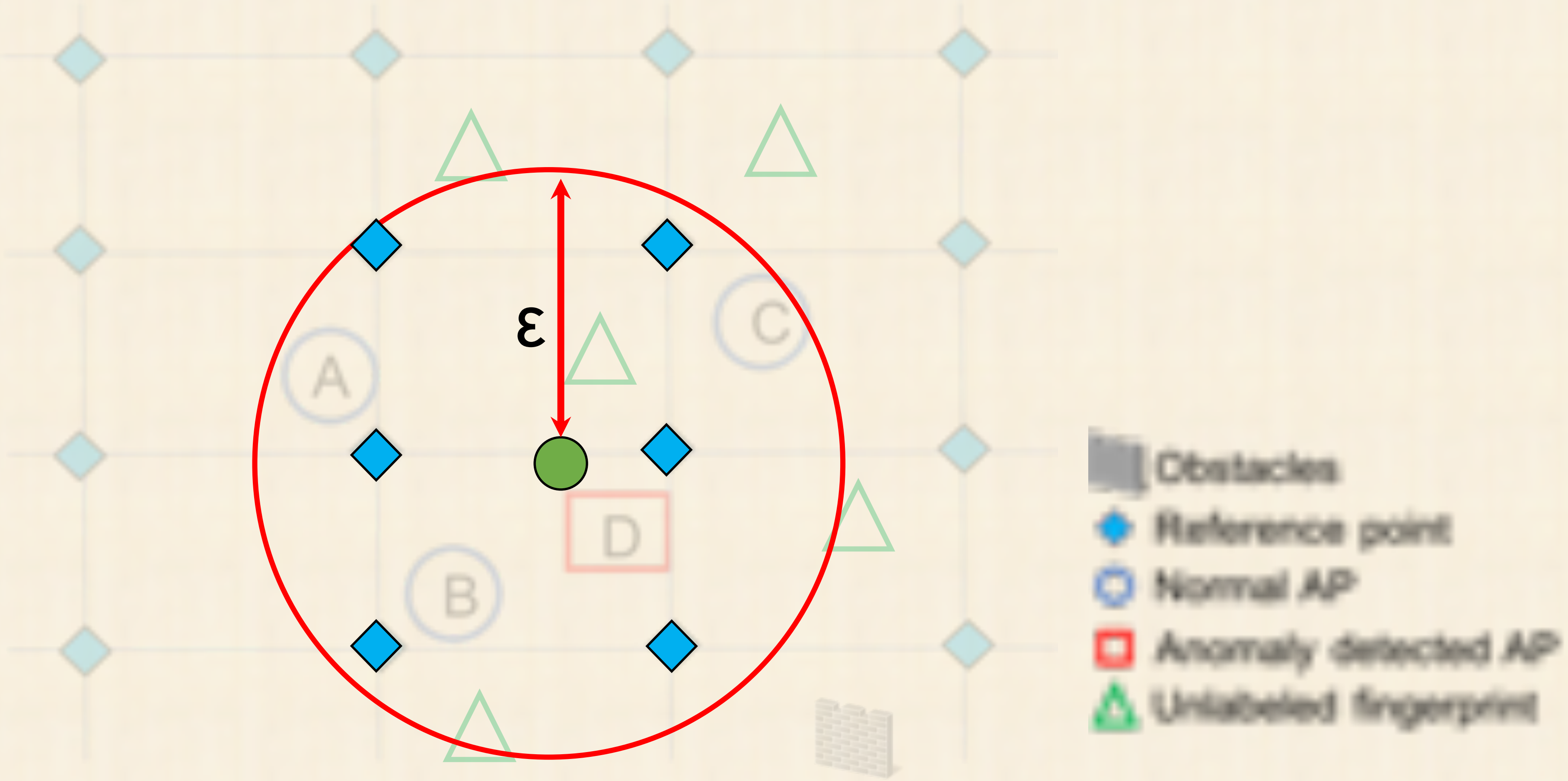

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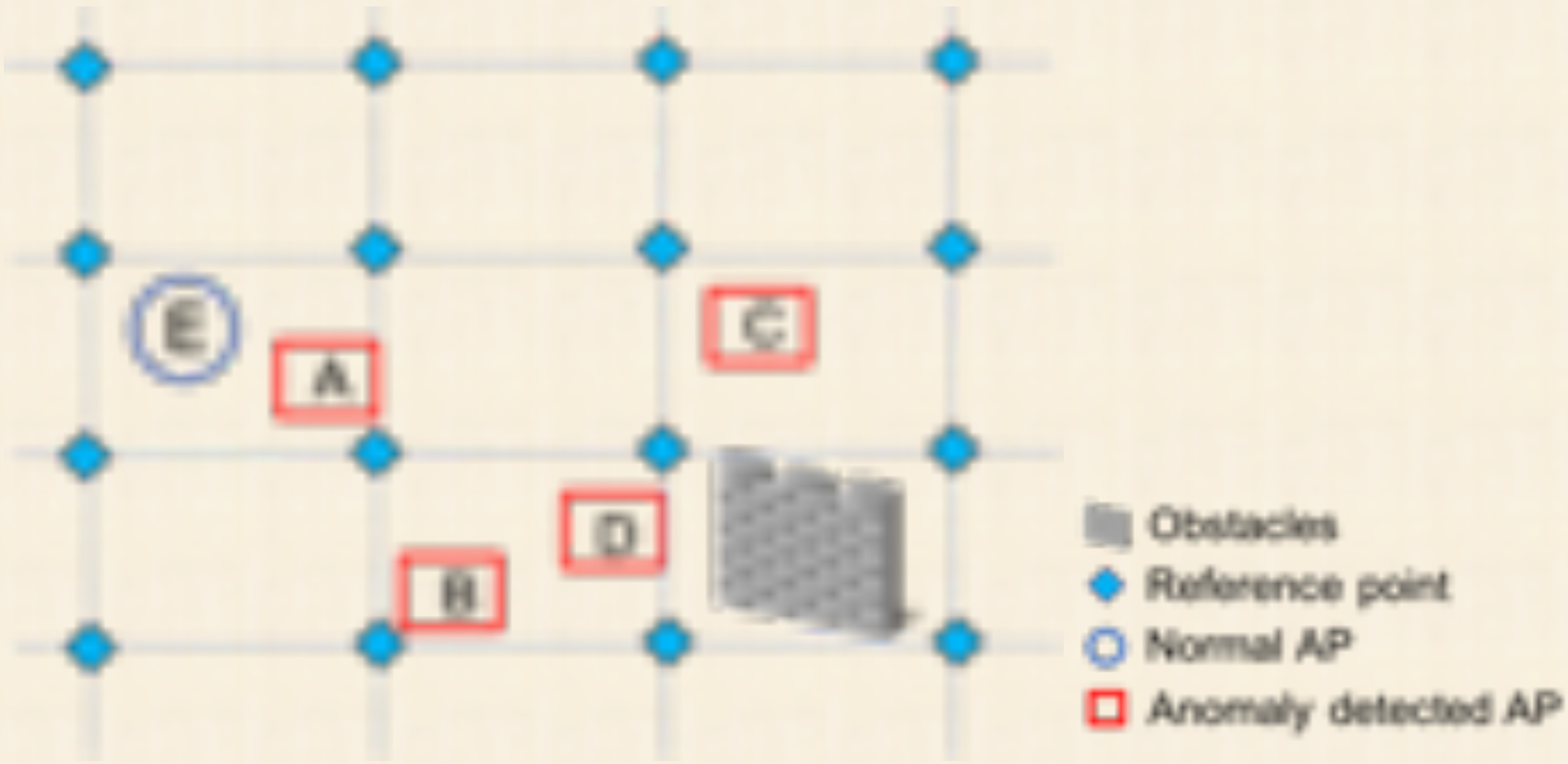

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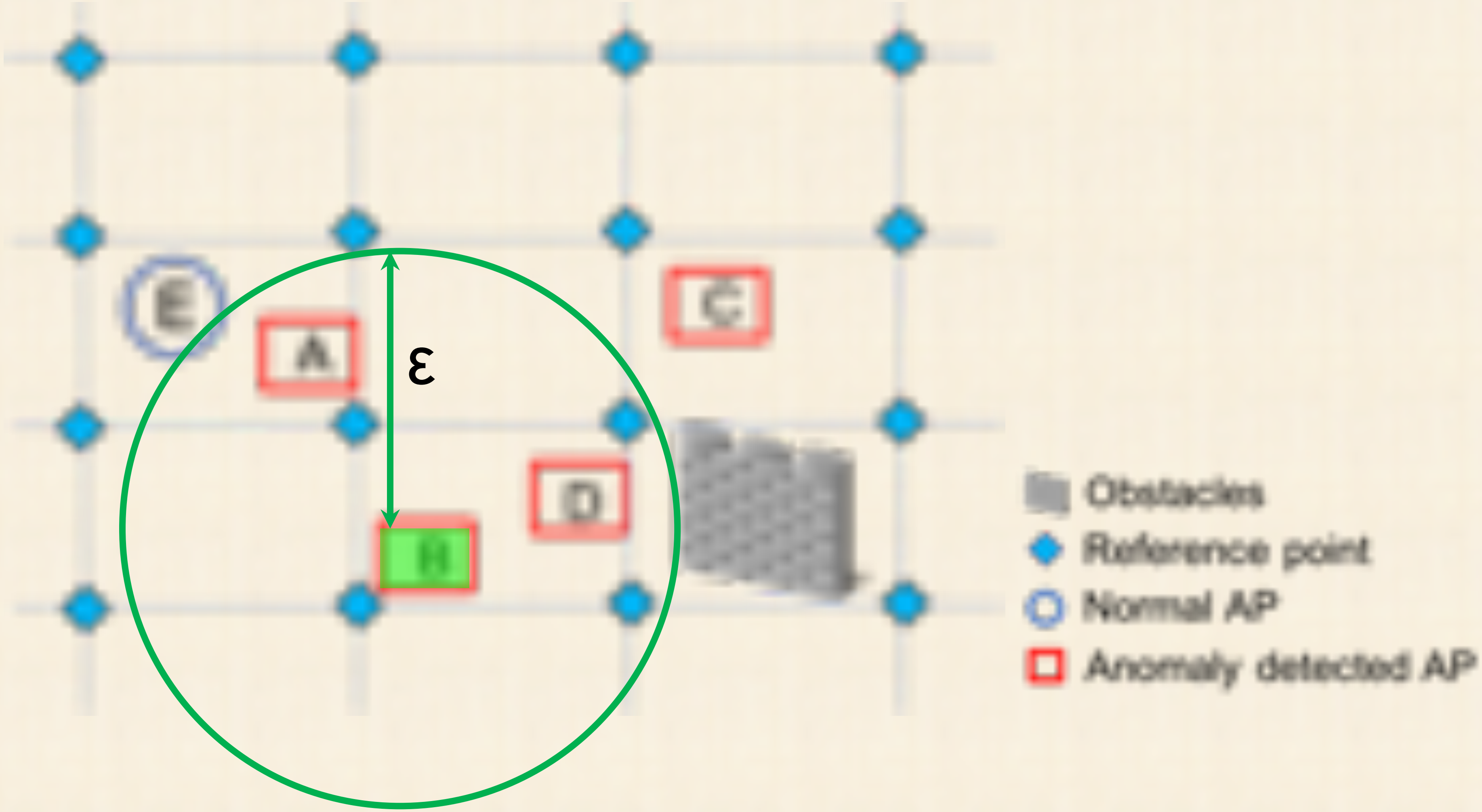

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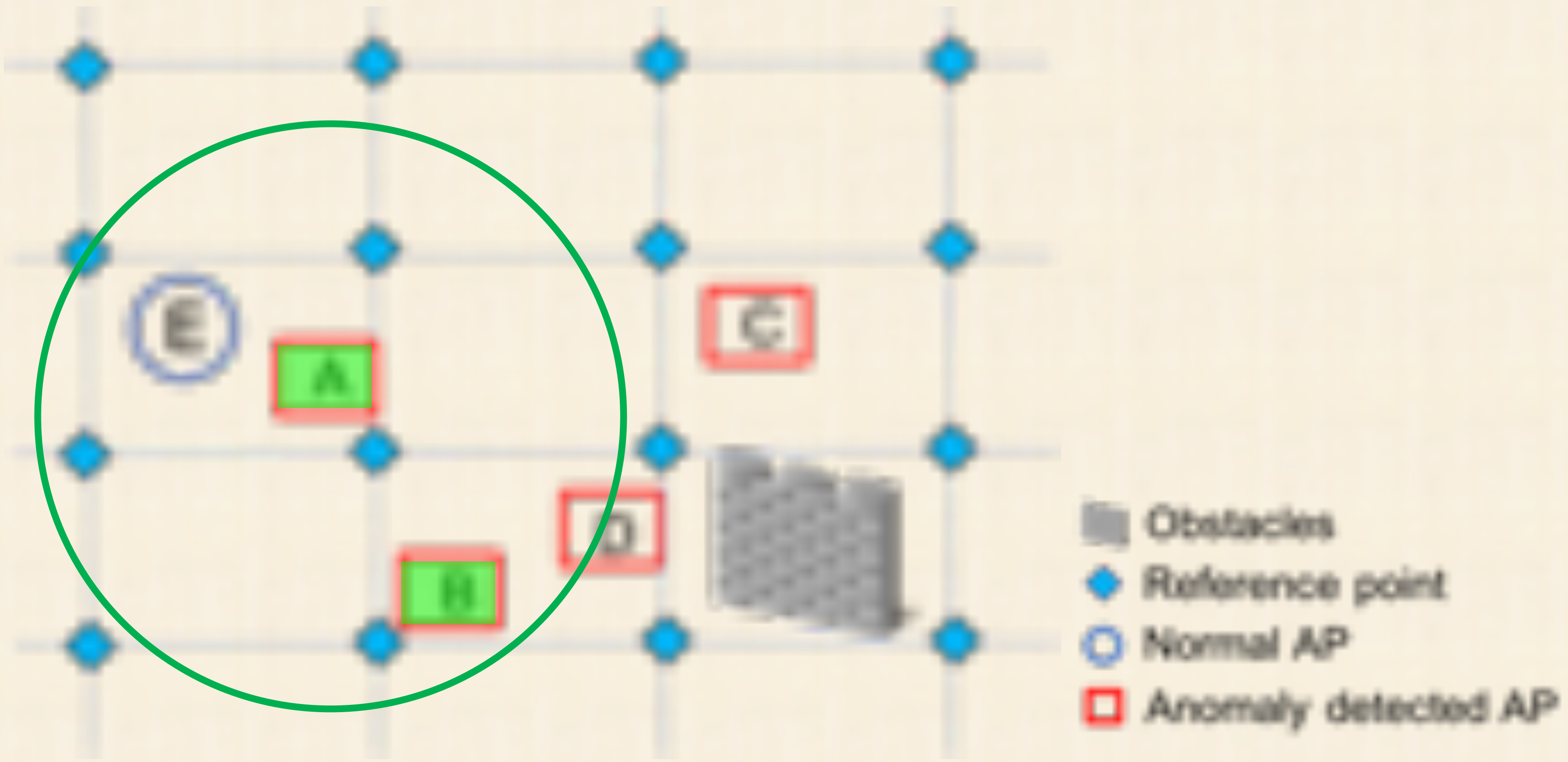

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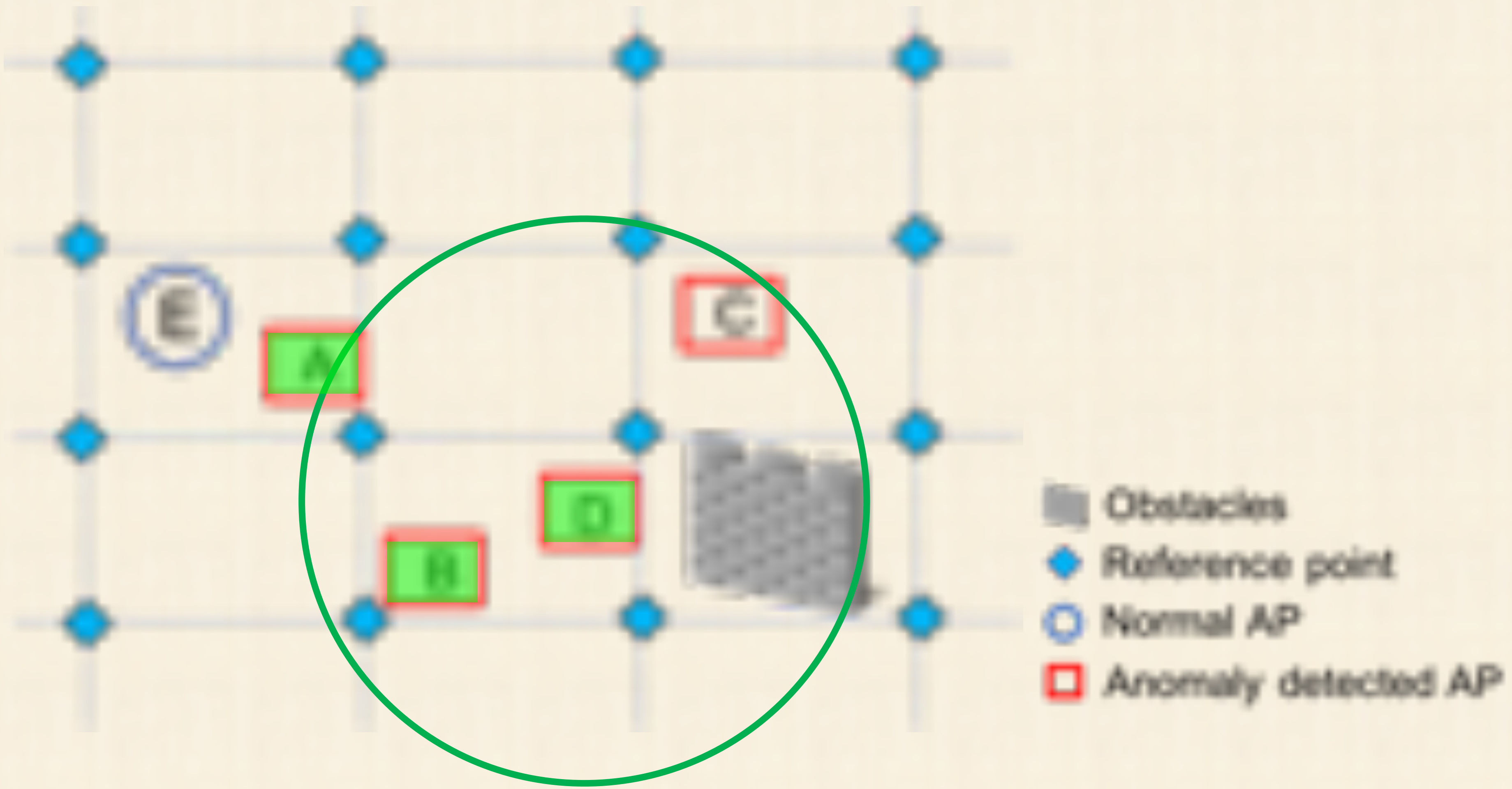

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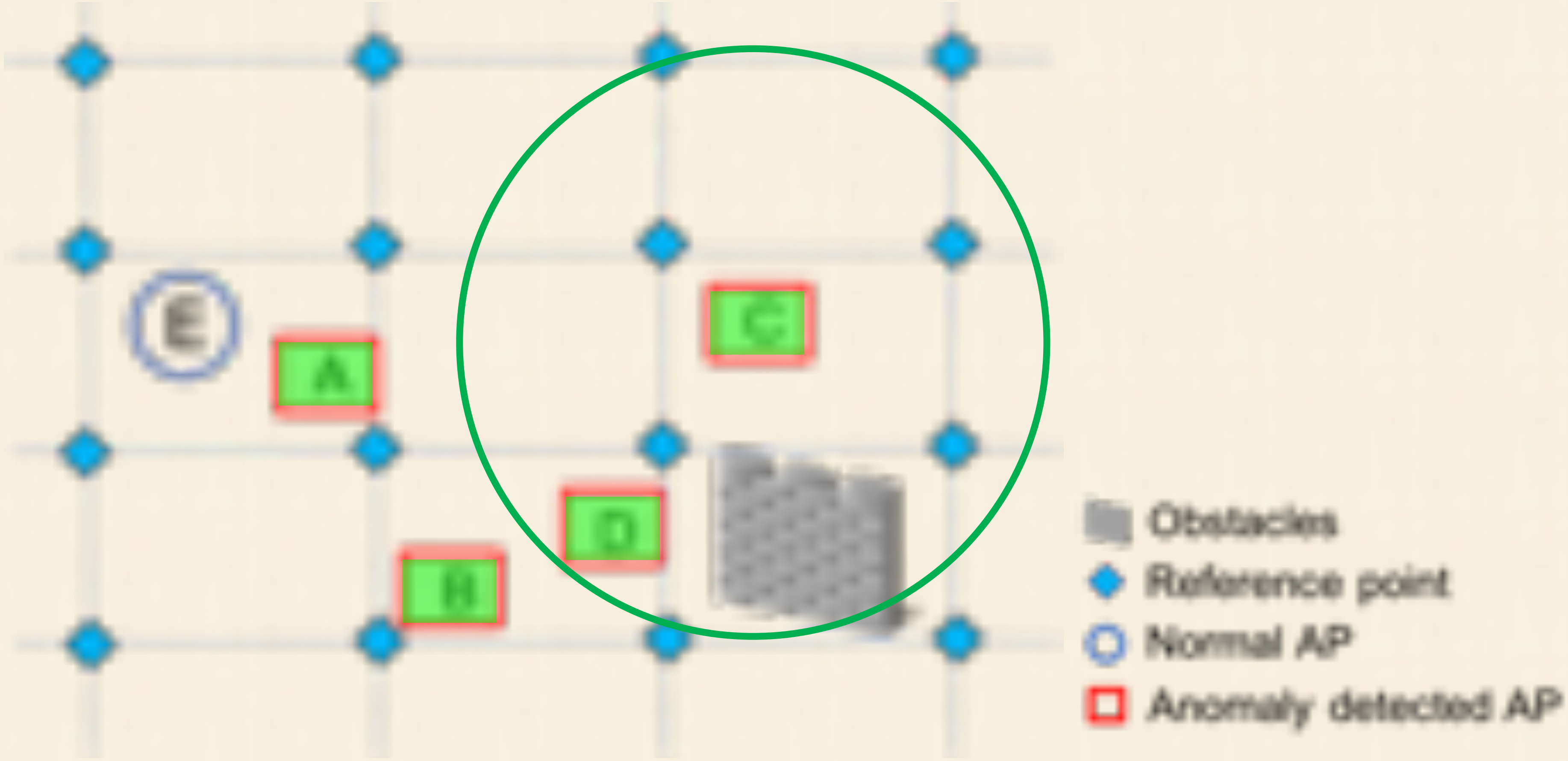

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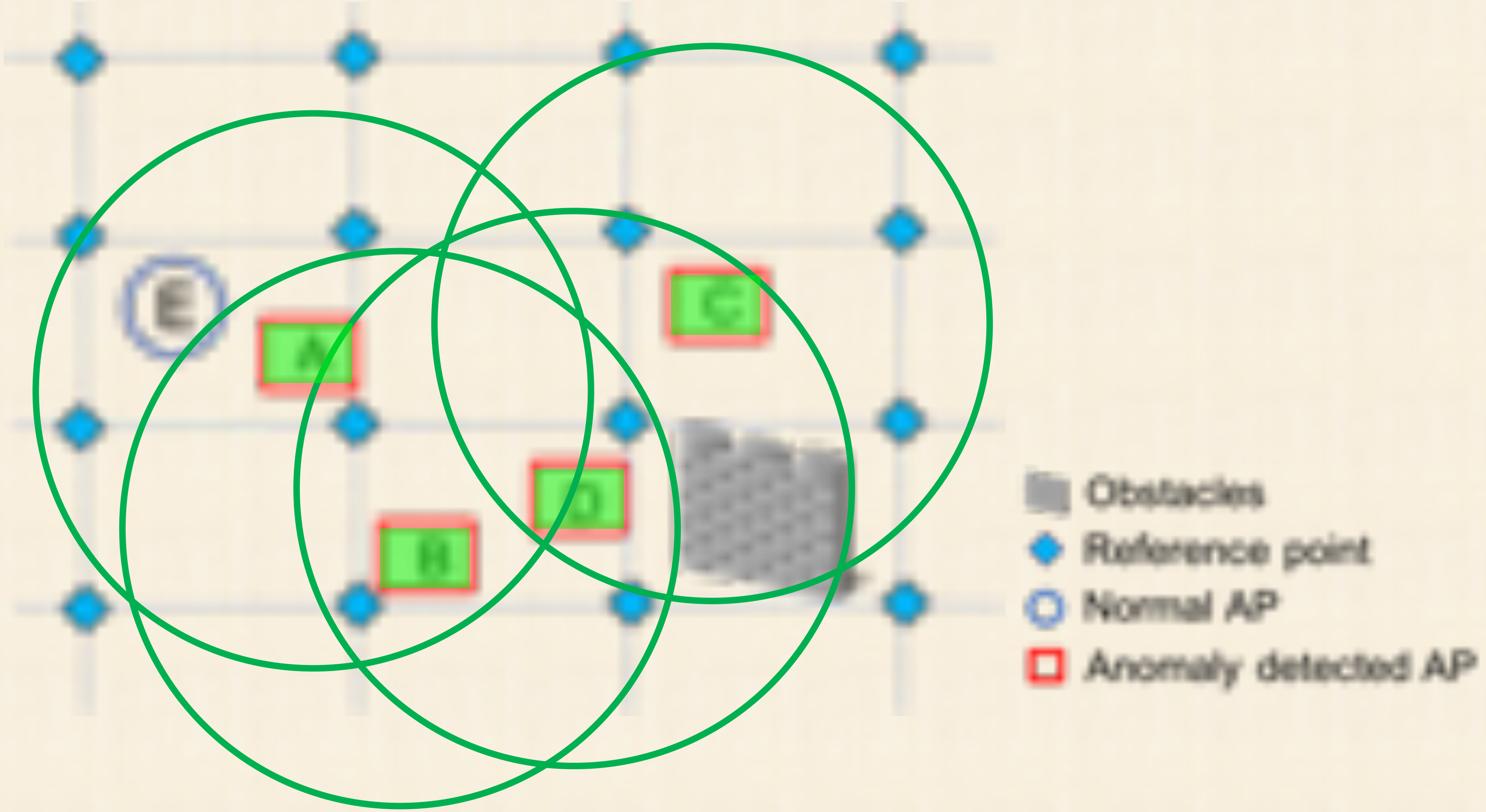

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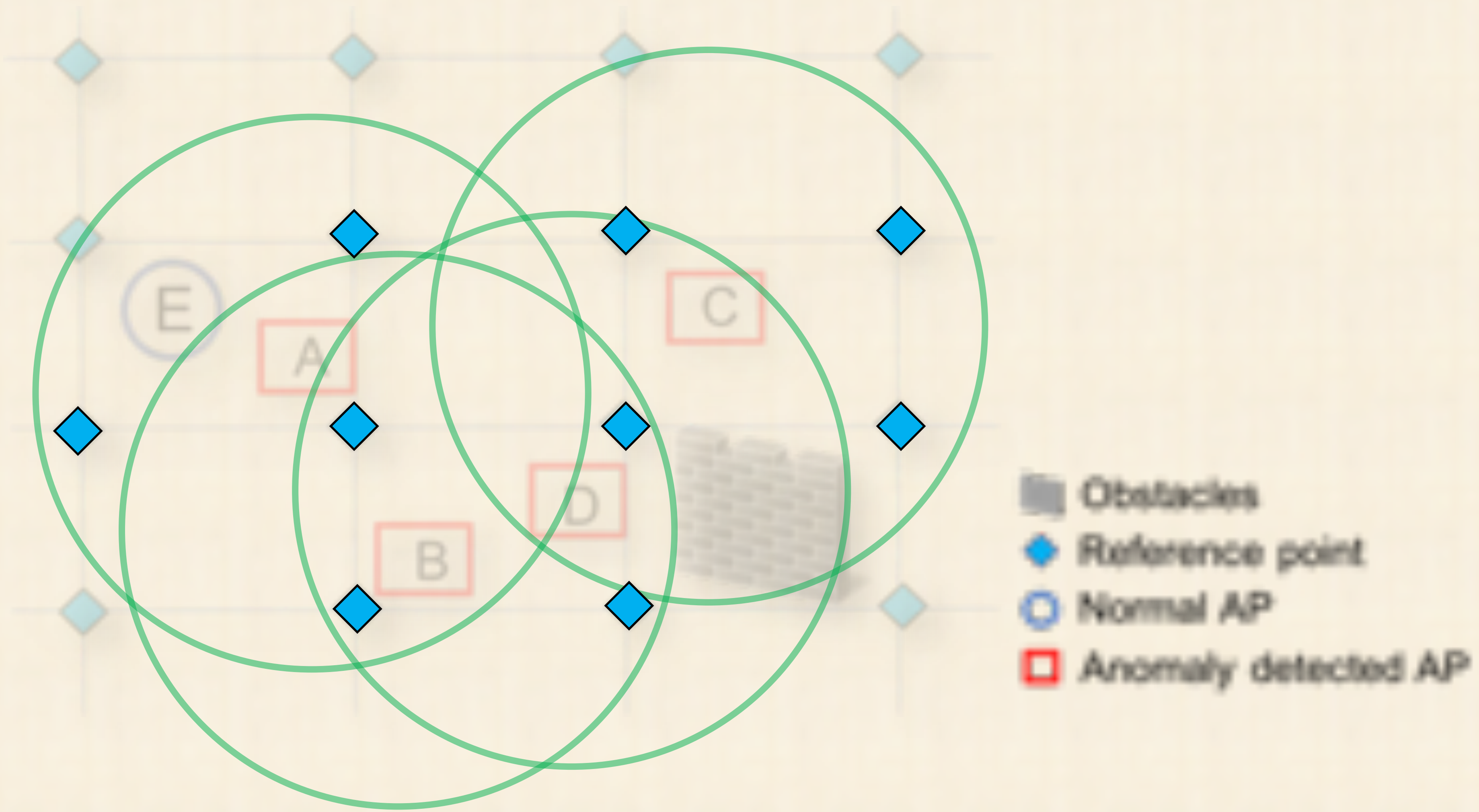

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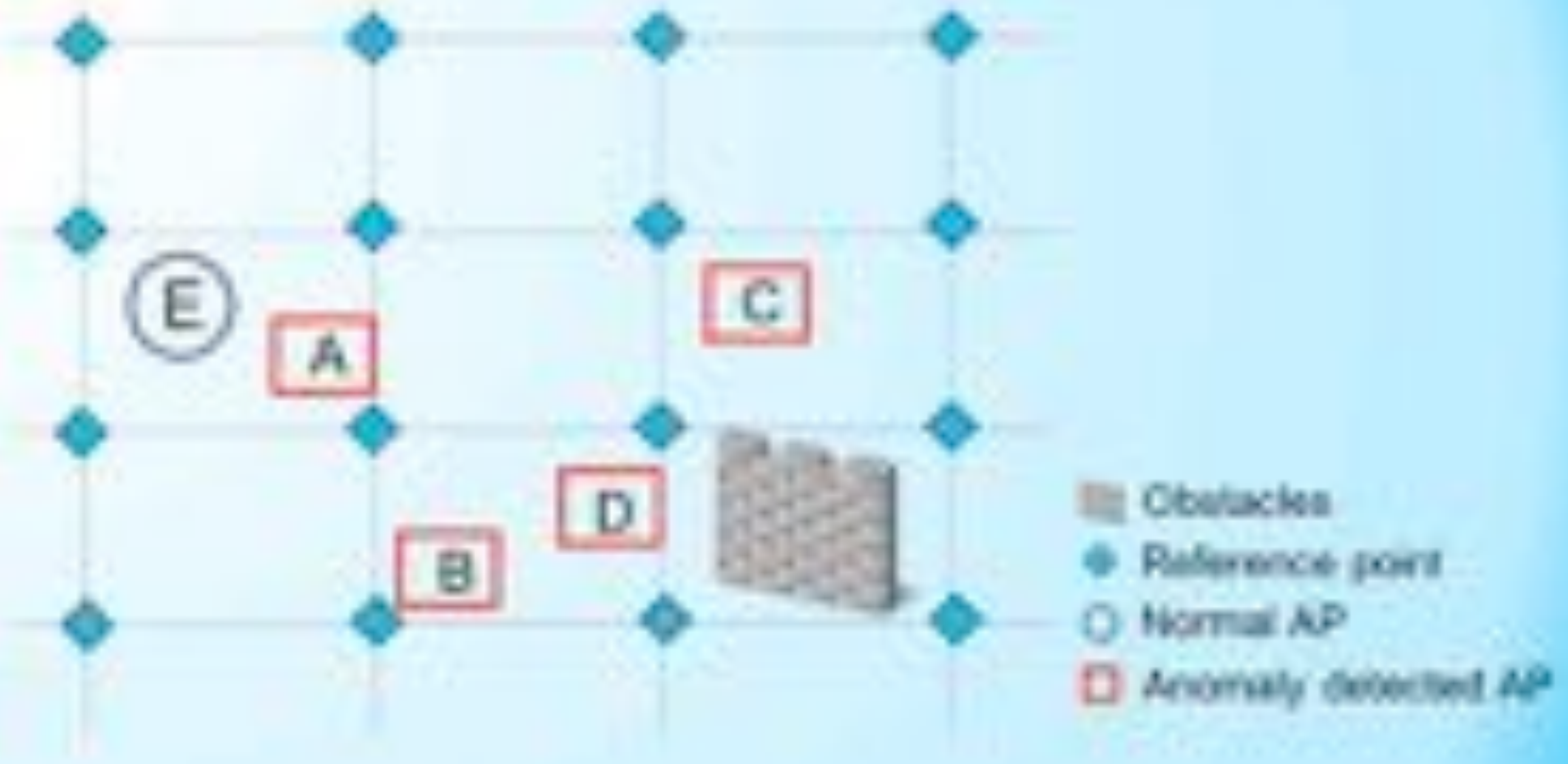
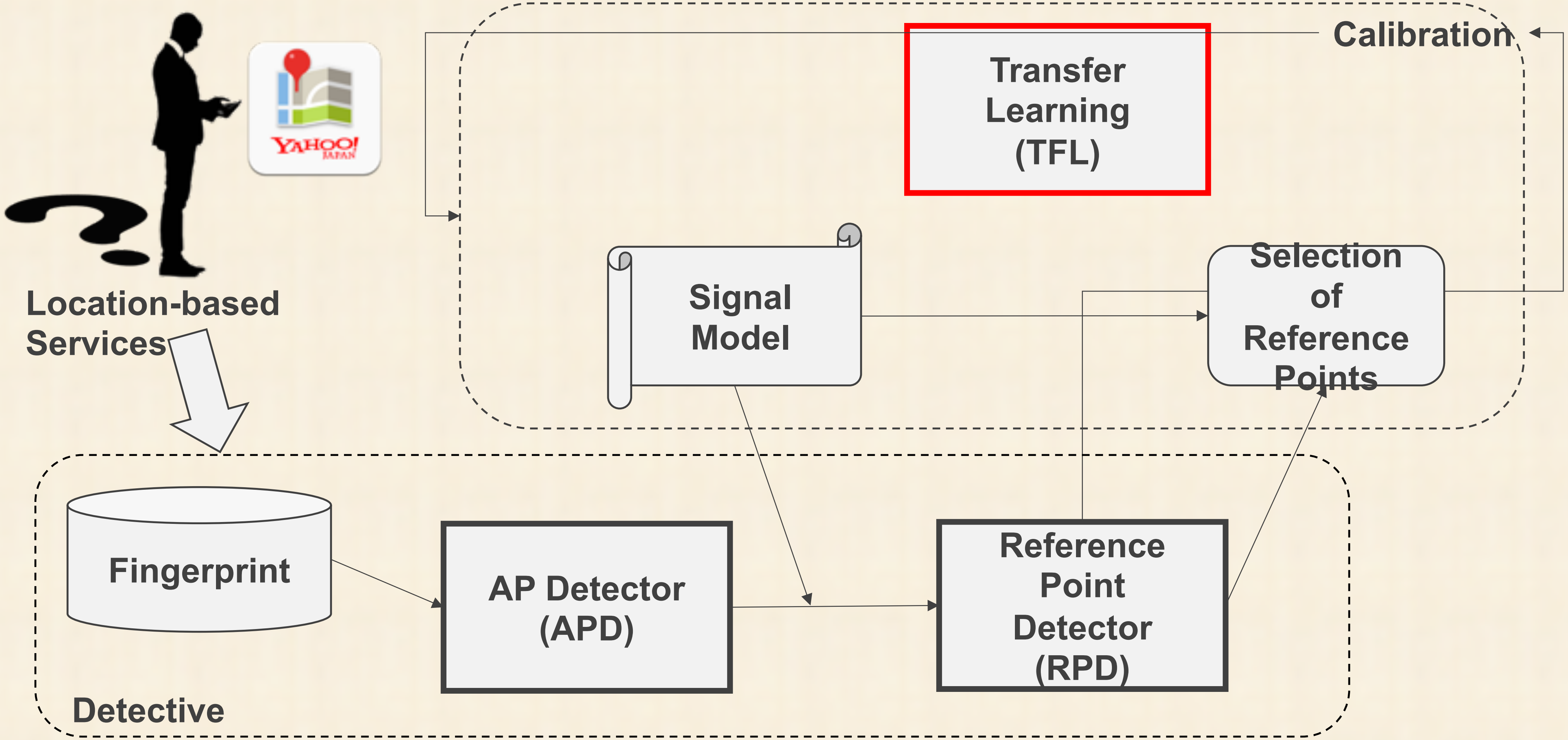


No-sweat Detective



Transfer Learning (TFL)

- TFL can be any colors and replaceable
  - Testify No-sweat Detective's performance by being applied to MixTrain and Lasso transfer methods[1)]
- MixTrain method
  - Closer to basis of transfer learning
  - Learns parameters $\boldsymbol{\theta}$ itself utilizing all the dataset from primary to additional dataset at each calibration
  - Updates model adding regularization term of L1 norm ($\sum_{i=1}^{|\theta|} |\theta i|$)
  - Simply for keeping weights given to features from being hyper-activated by usual L1 norm
- Lasso method
  - Learns parameters from variation of parameters
  - Does not store anything other than previous parameters and additional dataset
  - Learns from L1 norm and regularization term $\left(\sum_{i=1}^{|\theta|} \left| \theta_i^{(k-1)} - \theta_i^{(k)} \right| \right)$
  - Regularization minimizing variation between $\boldsymbol{\theta}$ at period $\boldsymbol{k-1}$ and $\boldsymbol{\theta}$ at period $\boldsymbol{k}$

[1]: Pengcheng Wu and Thomas G. Dietterich. "Improving SVM Accuracy by Training on Auxiliary Data Sources."

Evaluation

- Tested in two different situations
  - Laboratory dataset
    - Testify anomaly detection modules
    - Simulate environmental changes
  - Underground dataset
    - Testify performance in real world scenario
    - With five-month-long labeled fingerprint and unlabeled fingerprint from Umechika-navi[1)]

[1]: http://www.umechikanavi.jp/

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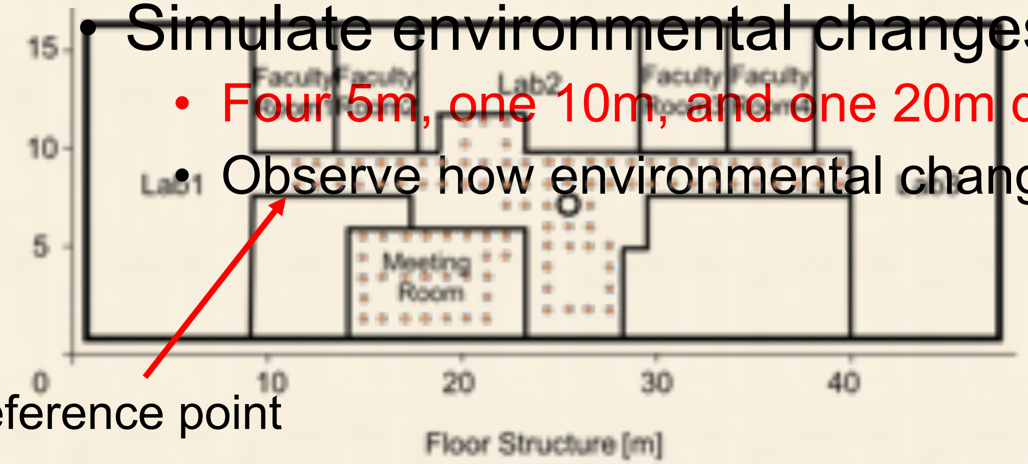
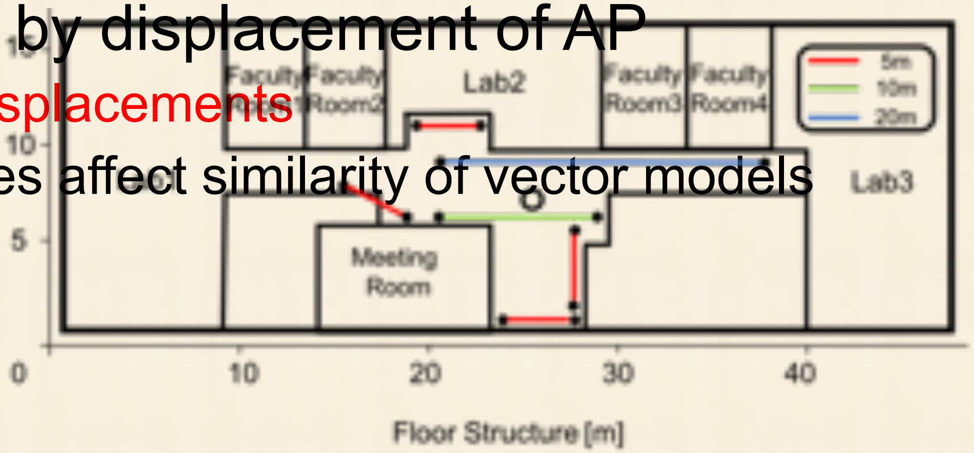
Laboratory Dataset

- Details:
  - Set 105 reference points within $1m^2$ of floor covering $348m^2$ ($12m \times 29m$)
    - Meeting room and hallway used as test-bed
  - 2,100 labeled fingerprint in total
    - One scan per point and repeatedly ten times a day with Nexus5 over two days
  - Simulate environmental changes by displacement of AP
    - Four 5m, one 10m, and one 20m displacements
    - Observe how environmental changes affect similarity of vector models

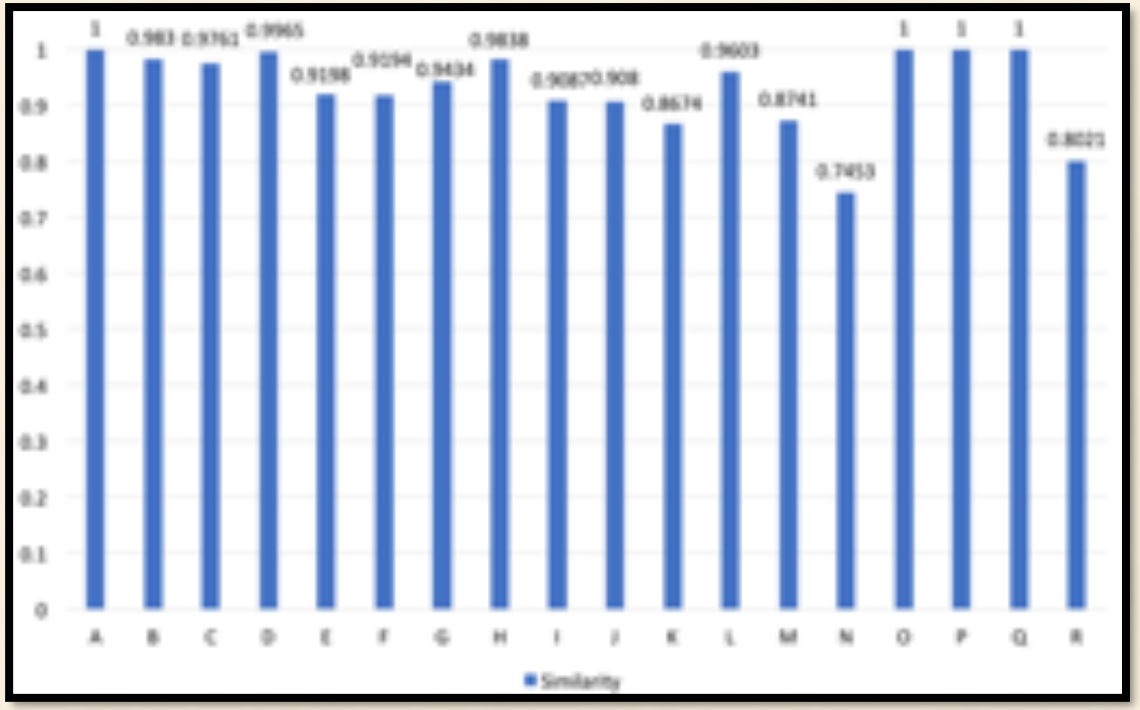


Reference point

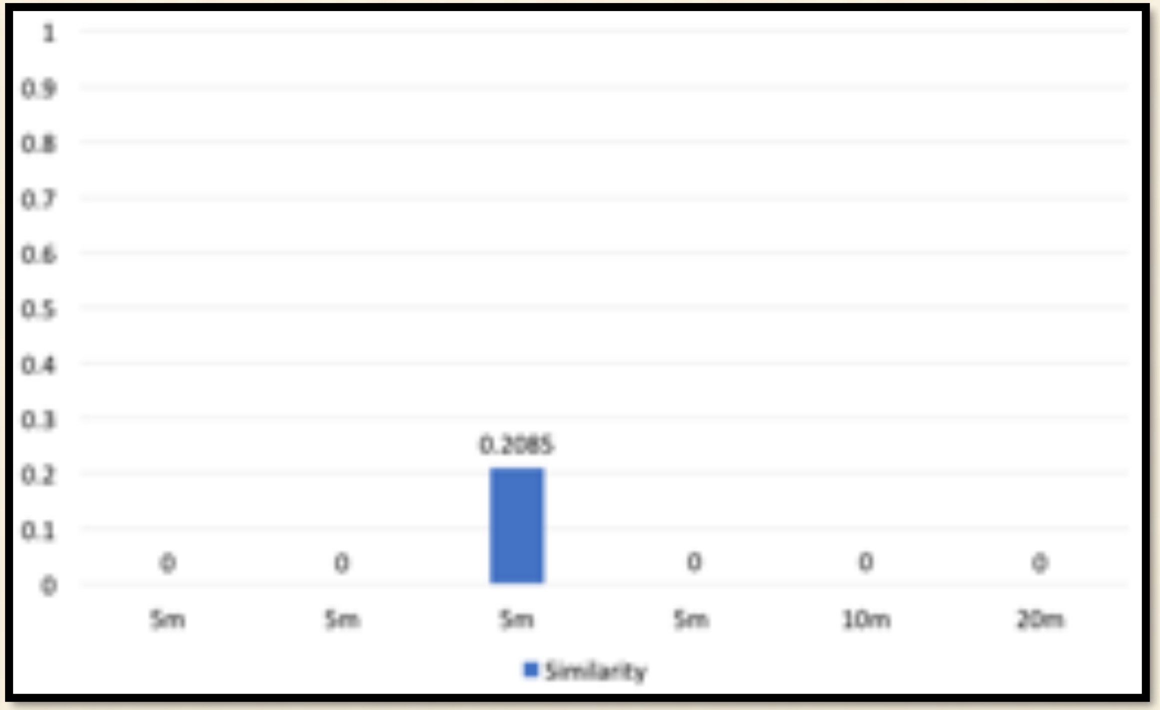


Results – Laboratory Dataset

- 18 vector models were created in both days



Non-distorted 18 AP's similarity



Distorted 5 AP's similarity

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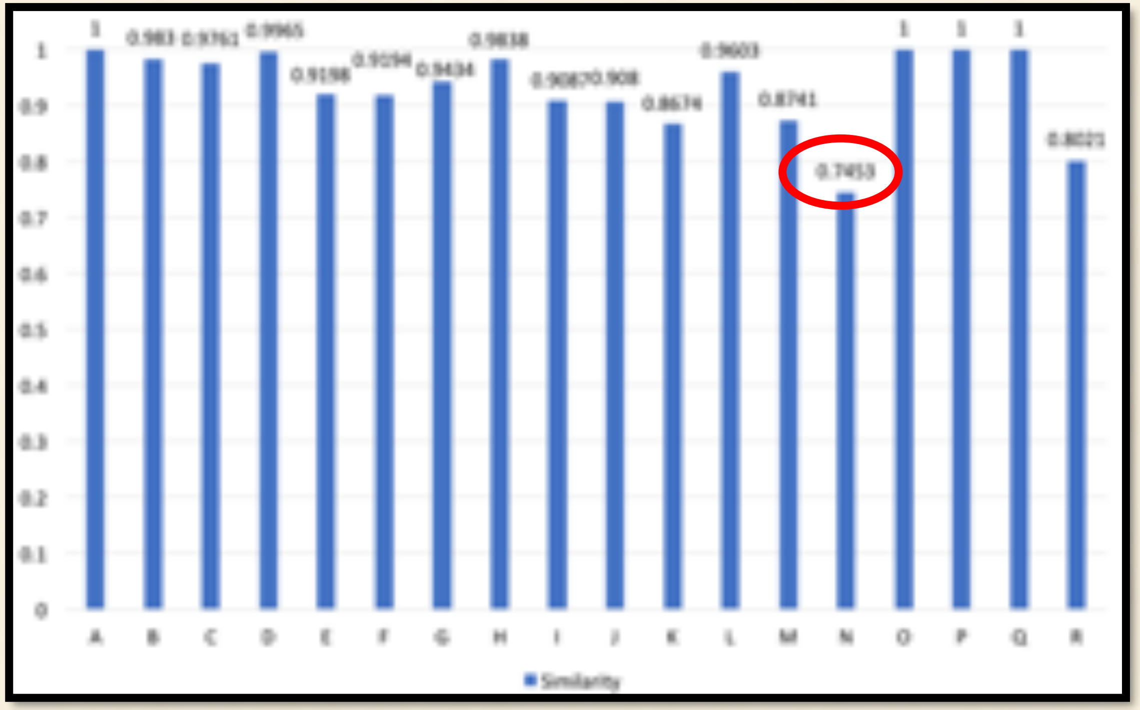

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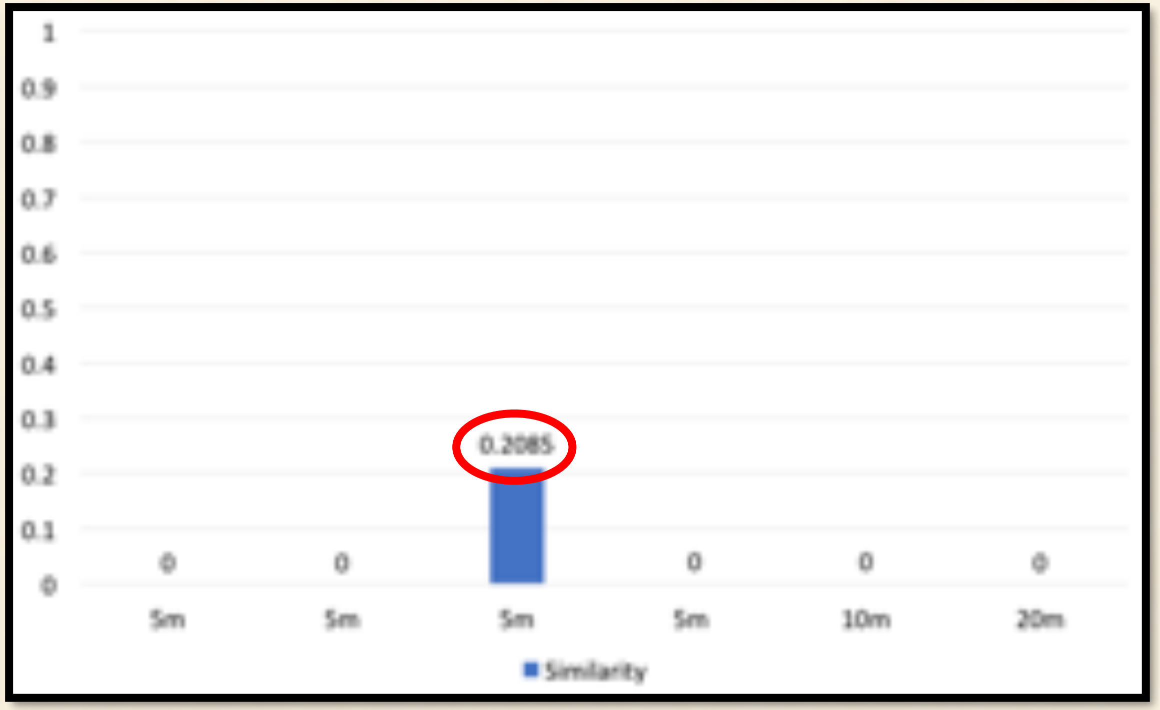

Distorted 5 AP's similarity

Validated significant difference in similarity

No-sweat Detective could detect environmental distortion

Evaluation

- Tested in two different situations
  - Laboratory dataset
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  - Underground dataset
    - Testify performance in real world scenario
    - With five-month-long labeled fingerprint and unlabeled fingerprint from Umechika-navi[1)]

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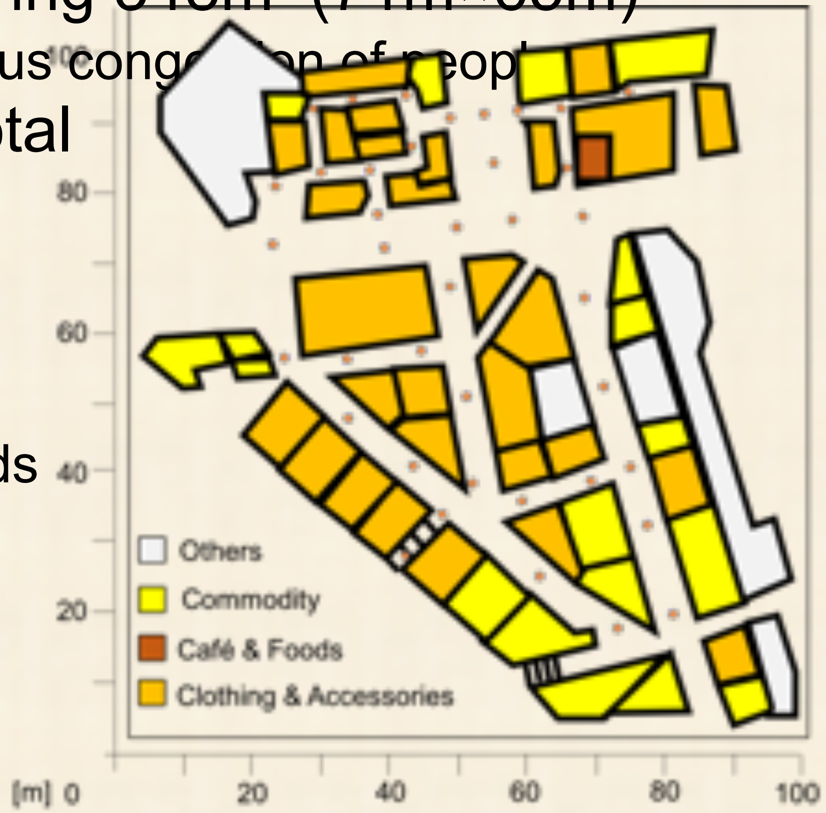
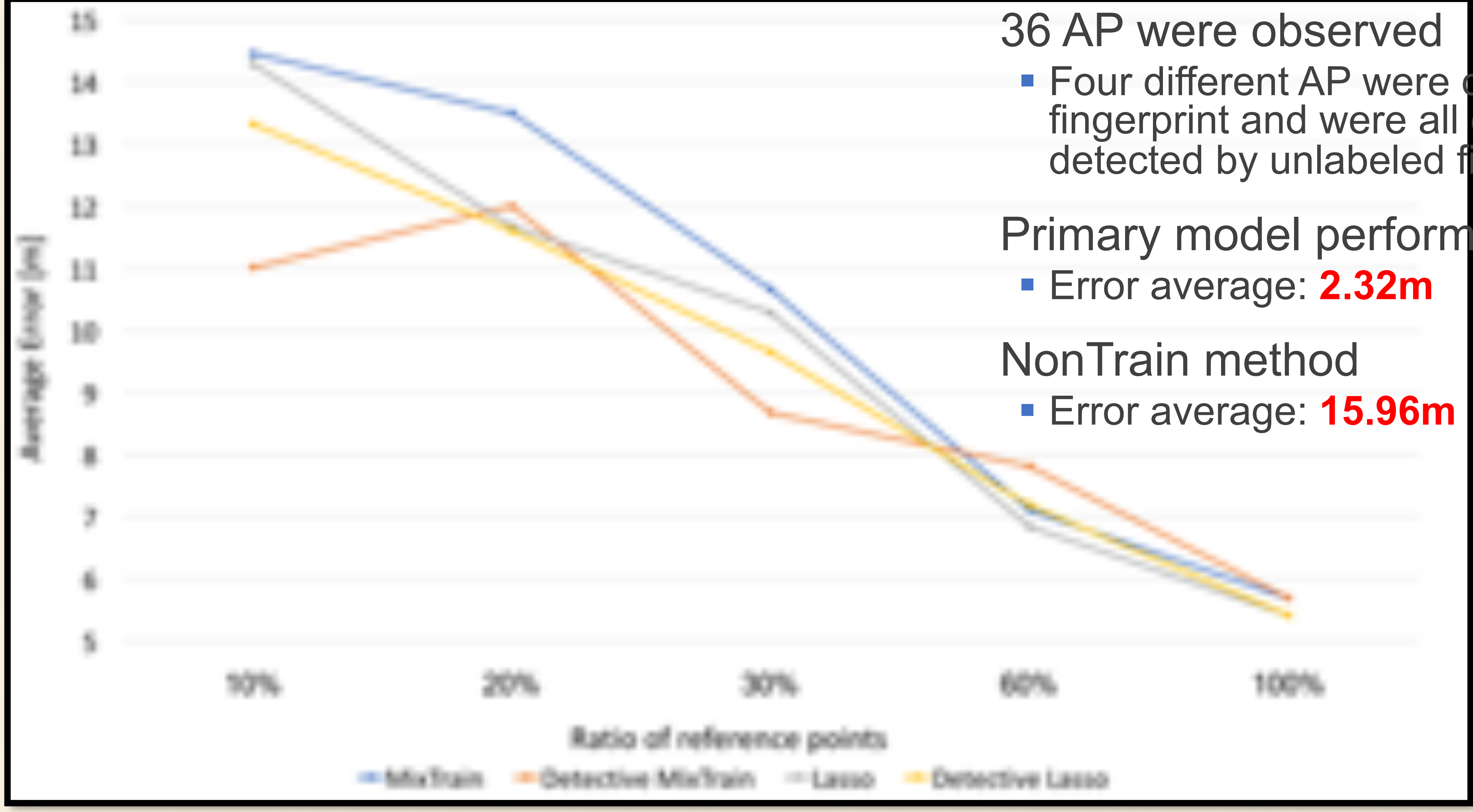
Underground Dataset

- Details:
  - Set 39 reference points at 8m intervals covering 348m^2 (71m×65m)
    - Underground district where infamous for murderous conge on of peop
  - 2,693 labeled, 764 unlabeled fingerprint in total
    - Six scans per point with Nexus5 every two weeks
  - Retrain model every two weeks
    - Sliding amount of reference points
      - 10%, 20%, 30%, 60%, 100%
    - Apply No-sweat Detective to conventional methods
      - MixTrain method
      - Lasso method
    - Validate average error of final model
      - NonTrain method (never trained) as base-line



Results – Underground Dataset 2/3



36 AP were observed

- Four different AP were detected by labeled fingerprint and were all covered by 10 AP detected by unlabeled fingerprint

Primary model performance

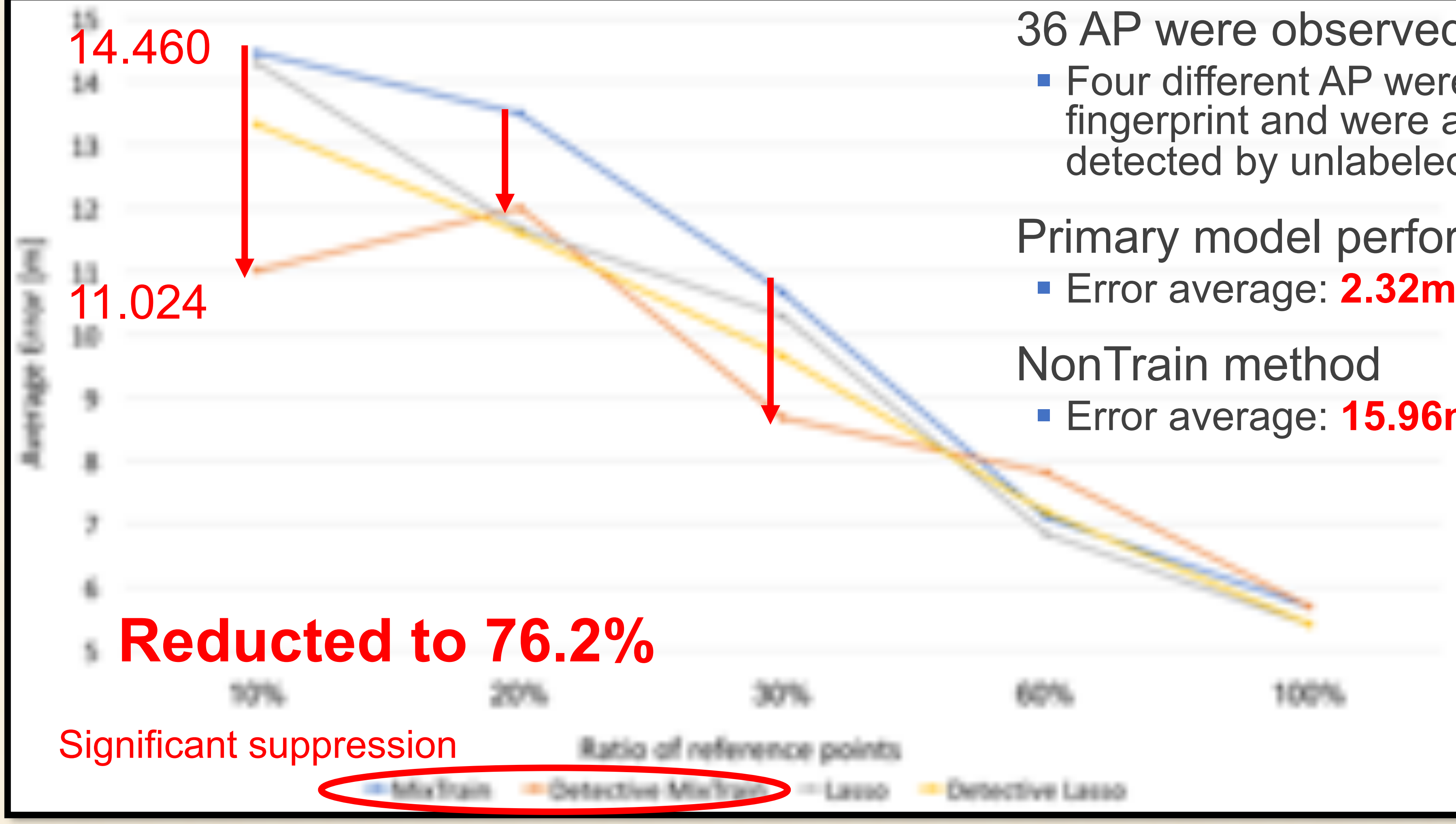
- Error average: **2.32m**

NonTrain method

- Error average: **15.96m**

Average error varying in amount of reference points

Results – Underground Dataset 2/3



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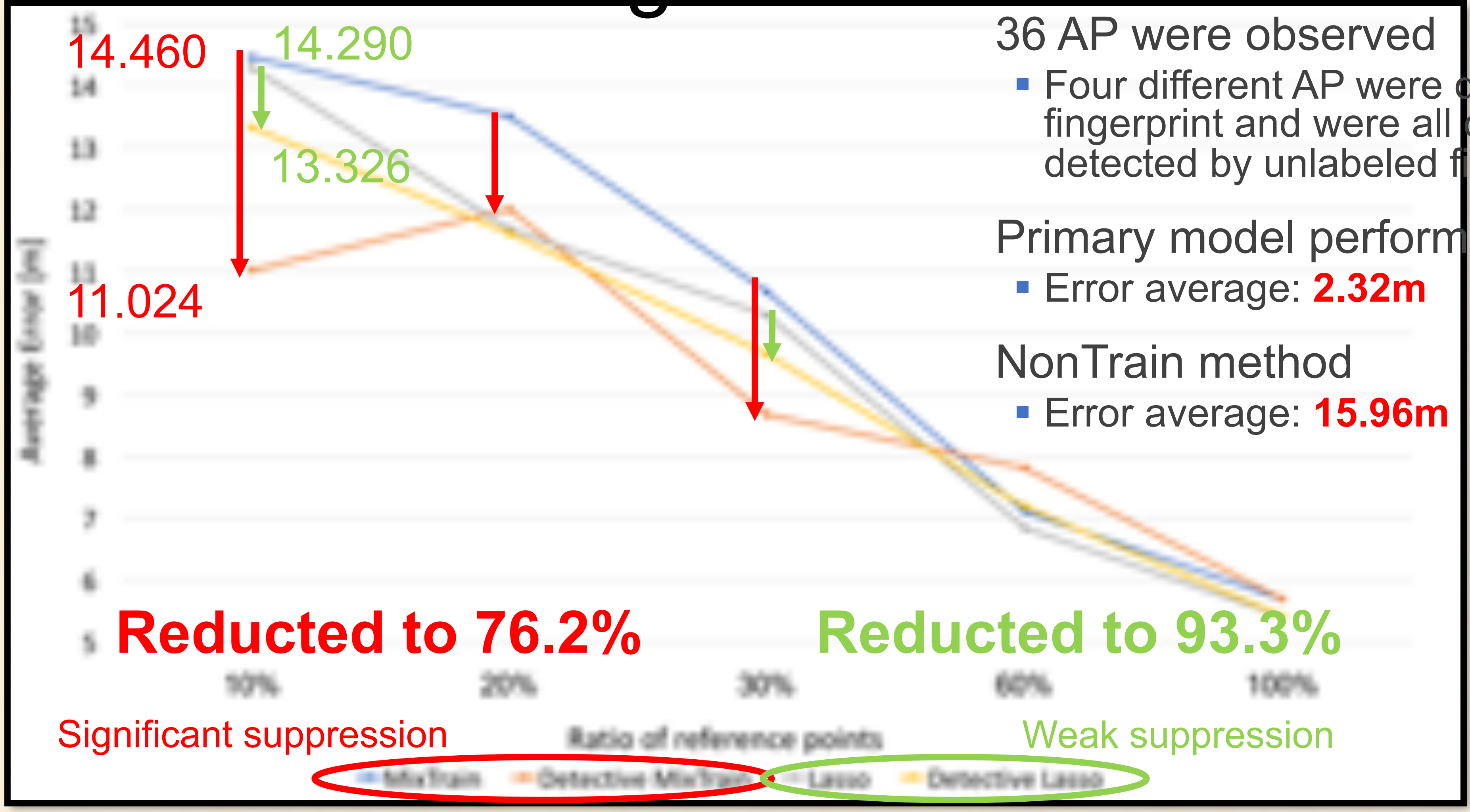
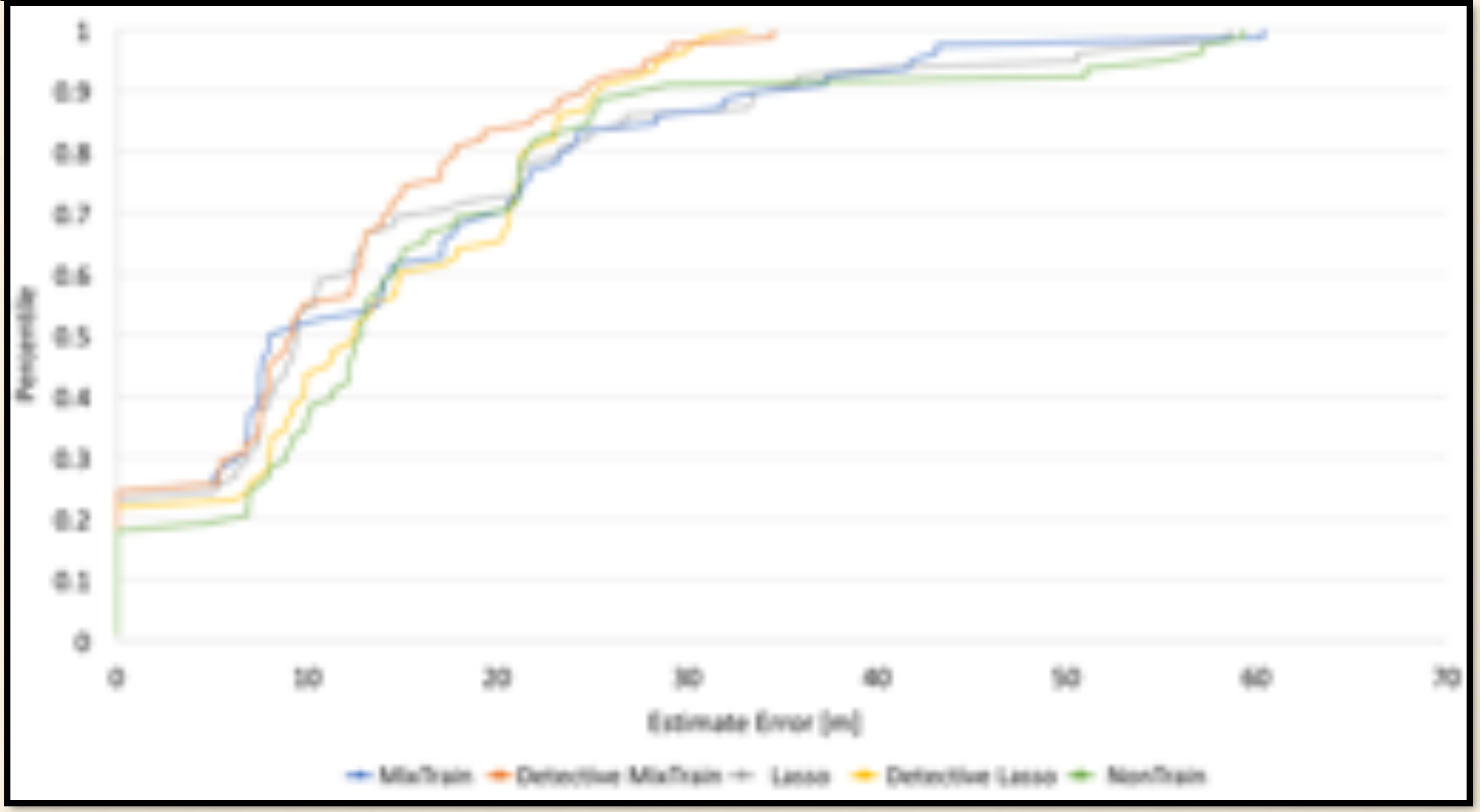


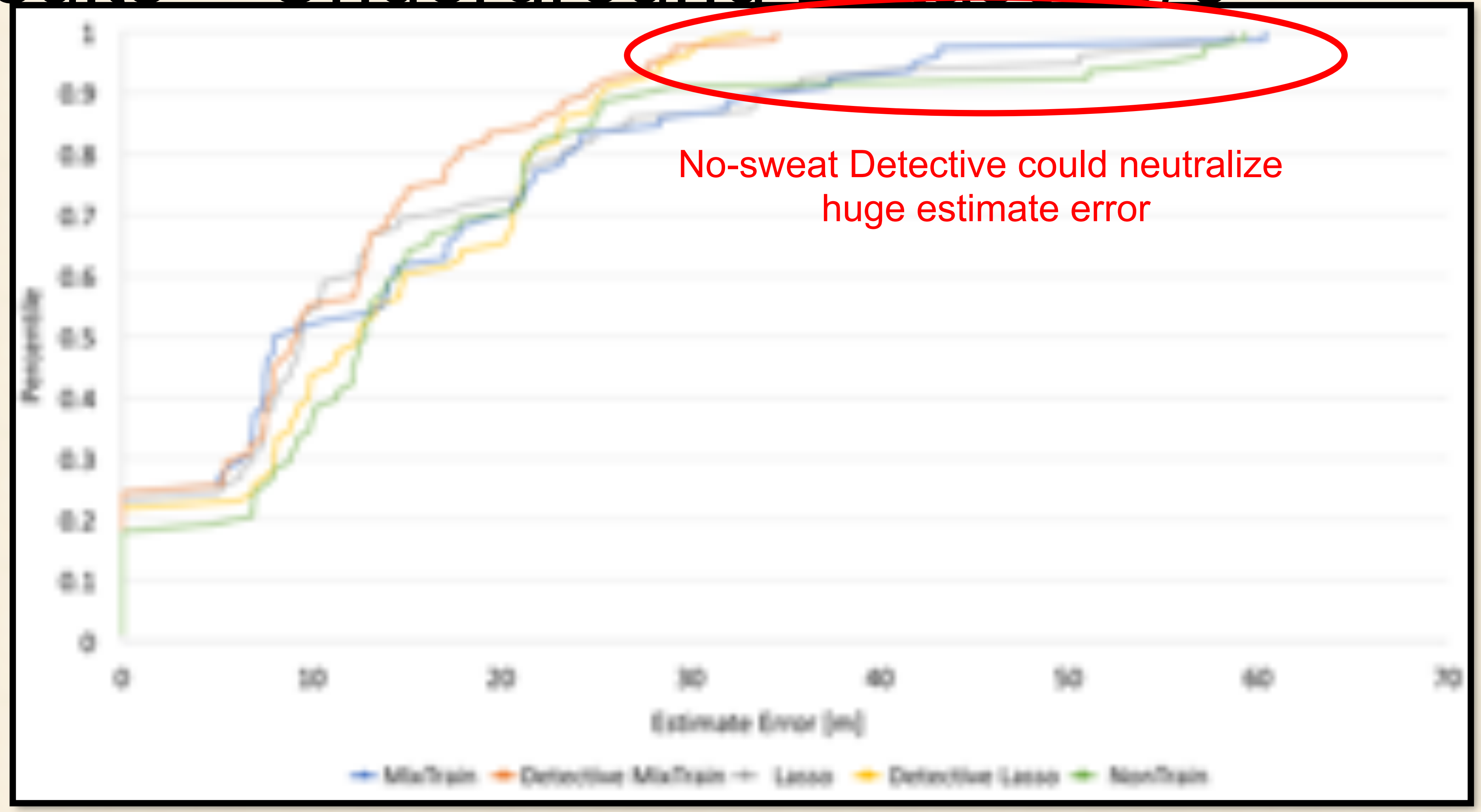
Average error varying in amount of reference points

Results – Underground Dataset 3/3



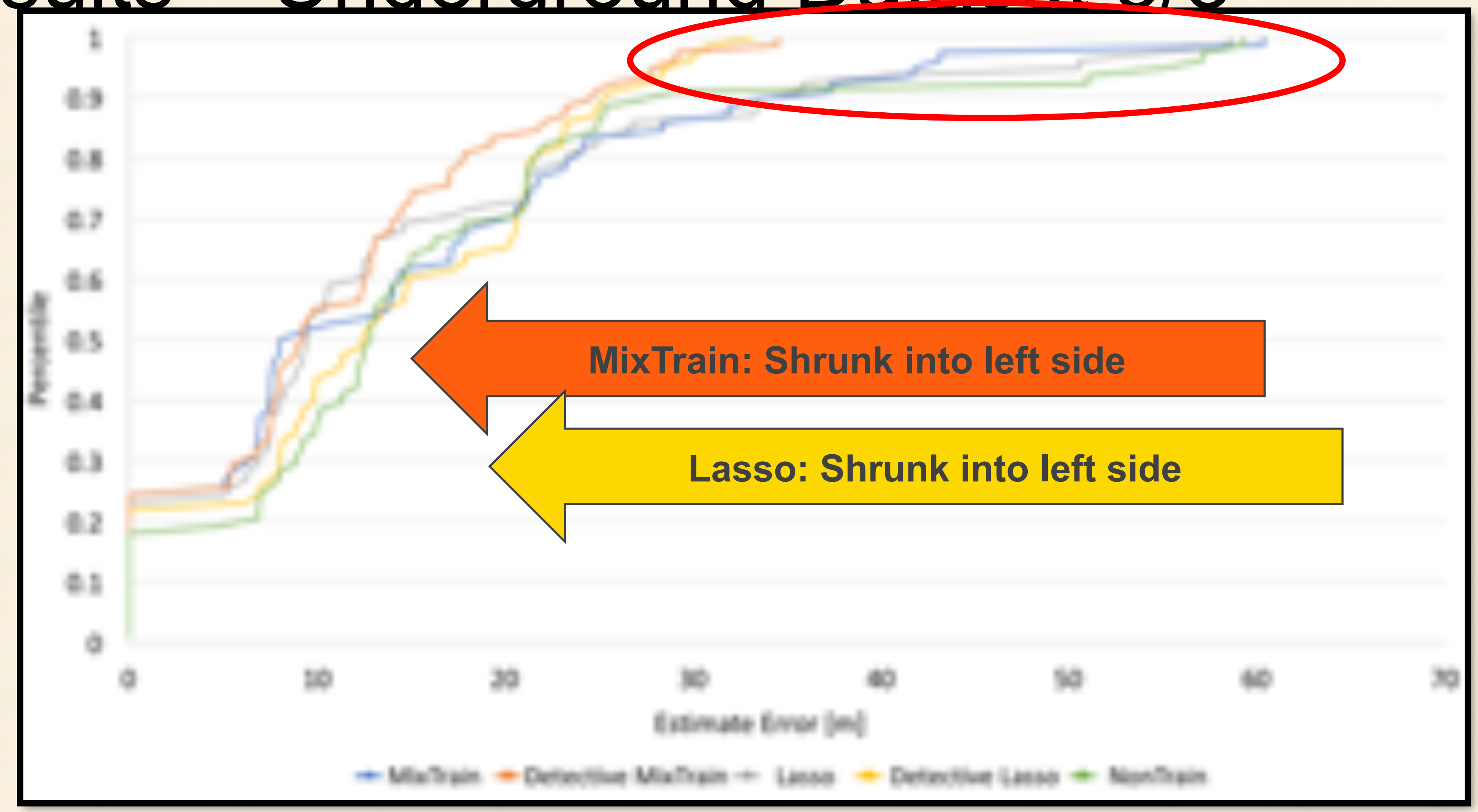
Cumulative distribution of estimate error

Results – Underground Dataset 3/3



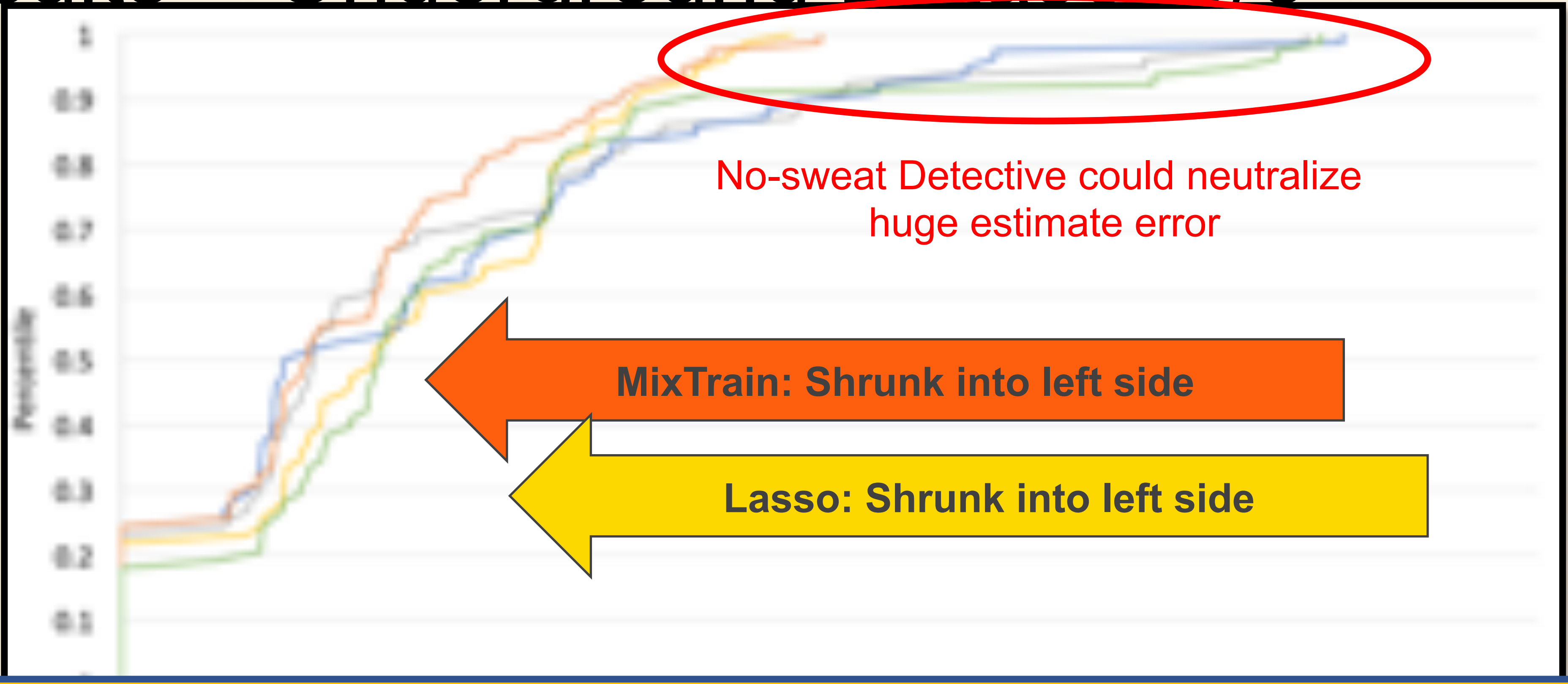
Cumulative distribution of estimate error

Results – Underground Dataset 3/3



Cumulative distribution of estimate error

Results – Underground Dataset 3/3



No-sweat Detective can be applied to existing transfer learning methods to maintain higher accuracy over long time operation

Cumulative distribution of estimate error

Summary and Outlook

- Fingerprinting localization mode deteriorates over time
- Transfer learning employed majorly
  - But additional dataset are randomly sampled
- Propose No-sweat Detective
  - To identify reference points where environmentally changed
  - With no effort using unlabeled fingerprint from user of location services
  - Could detect environmental distortion
  - Achieved higher recovery with same amount of additional dataset
    - With five-month-long observation
- Outlook
  - Validate performance recursively
  - Substitute unlabeled fingerprint as labeled fingerprint to let No-sweat Detective be autonomous