# Micro-environment Recognition in the context of Environmental Crowdsensing

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# When Mobile Crowd Sensing meets Big Data

1. Widespread use of GPS and other built-in sensors.
2. Emerging portable environmental sensors.

--> Mobile Crowd Sensing (MCS) is a new paradigm for the collection of spatio-temporal data series.

Air quality monitoring is a typical example

POLLUSCOPE

# General Objectives

POLLUSCOPE

**Individual Exposure to Pollution**

**Enrich collected data by the crowd**

**Indoor & Outdoor**

# Context

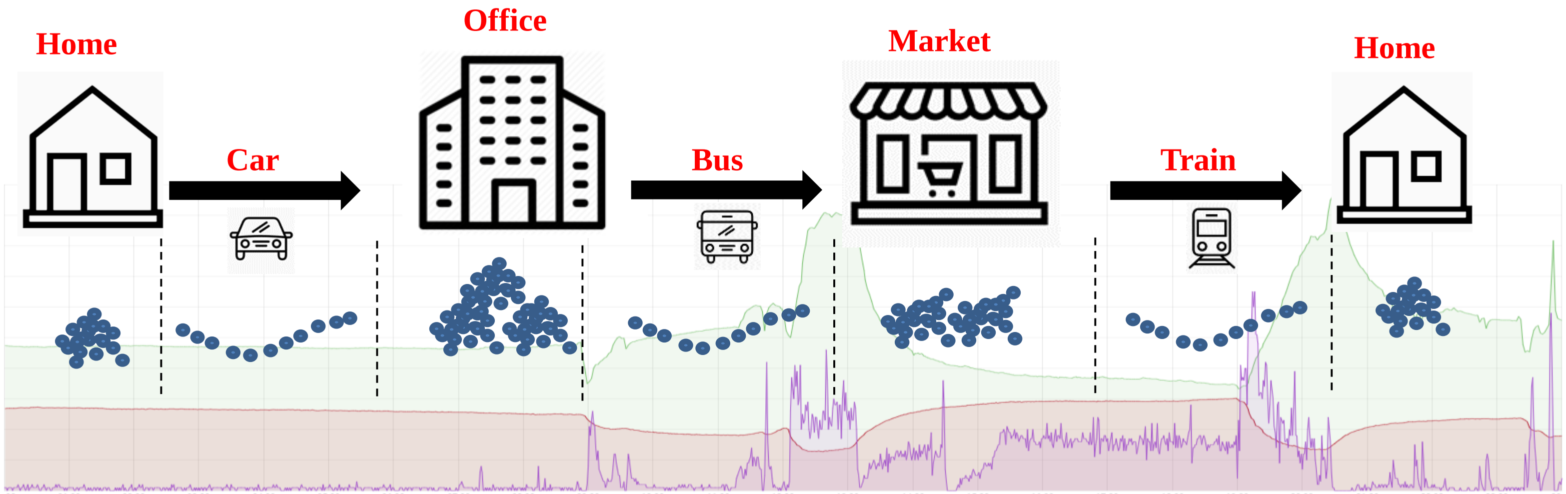
1. The recruited participants collect air quality measurements such as Particulate Matters, NO2, Black Carbon, Temperature and Humidity.
2. Data acquisition is based on a sensor kit and a mobile device.
3. Mobile Apps are used to collect GPS logs and the micro-environment of the participant (also called self-reporting) of the participant

# Problem Statement & Objectives

1. Problems :
   - the context **annotation** is by far the most difficult information to collect in a real-life application setting.
   - Not all the participants thoroughly annotate their **micro-environment**.

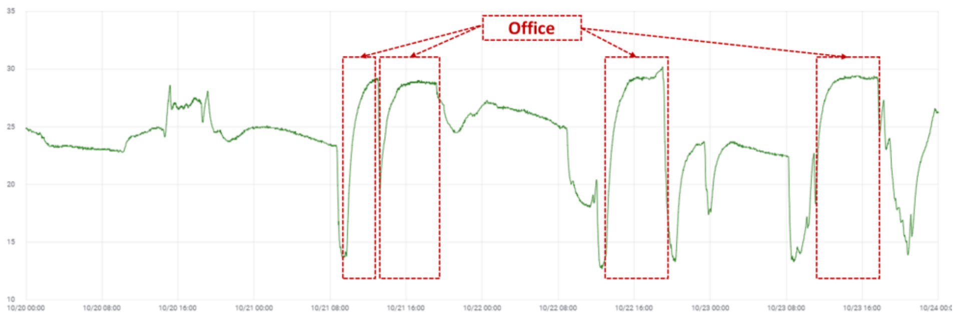
Ambient air observations **strongly** depend on the context.

2. Objective: Automatically detect the participants contexts.

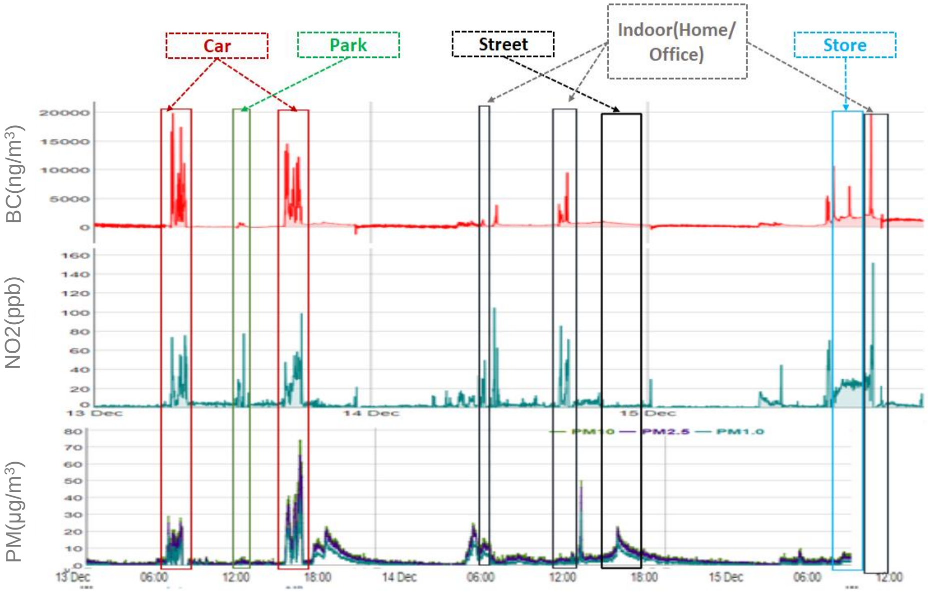


# Problem Statement & Objectives

Micro-environments **preserve** a certain pattern.




Inter-sensor correlation



# Main Contributions

1. Multi-variate time series collected by the MCS campaigns not only depend on the microenvironment but could be a proxy of it..

How to combine all these different aspects of the data (geo-location, sensors) to identify the user's context automatically?

How much a model can discriminate the observations in different micro-environments?

**Contribution**: Evaluate different approaches and provide a framework for micro-environment recognition

# Outline

I. State-of-the-art

II. Micro-Environment Recognition Model

II.1 Data Preparation

II.2 Multi-view Approach

III. Experimental Results

IV. Conclusion & Perspectives

# I. State-of-the-art

- Human Activity Recognition
  - Smart Homes Activities [1]
  - Daily Human Activities [2][3]
  - Human Mobility [4][5]
  - Generic MTSC method
    - Multivariate Time Series Classification (MTSC)
    - Multi-view Learning


[1] Aminikhanghahi et Cook 2019. Enhancing activity recognition using CPD-based activity segmentation.
[2] Zhang et Sawchuk 2012. Motion primitive-based human activity recognition using a bag-of-features approach.
[3] Cho et Yoon 2018. Divide and Conquer-Based 1D CNN Human Activity Recognition Using Test Data Sharpening.
[4] Do et Gatica-Perez 2014. The Places of Our Lives: Visiting Patterns and Automatic Labeling from Longitudinal Smartphone Data.
[5] Zheng et al. 2008. Understanding mobility based on GPS data.

# I. State-of-the-art

## MTSC: labelling data segments with the type of activity

- Distance-based methods [6].
- Feature-based methods [7].
- Ensemble methods [8].
- Deep learning methods [9]
  - MLSTM-FCN [10].

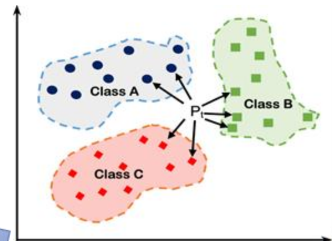
## Multi-view Learning: classify time series data originated from multiple sensors

- Authors in [8] proposed a multi-view stacking generalization approach for fusing audio and accelerometer sensor data for human activity recognition.
- Discriminative Bilinear Projection Approach was proposed by [11].


[6] Berndt et Clifford 1994. Using dynamic time warping to find patterns in time series.
[7] Pärkkä et al. 2006. Activity classification using realistic data from wearable sensors.
[8] Garcia-Ceja, Galván-Tejada, et Brena 2018. Multi-view stacking for activity recognition with sound and accelerometer data.
[9] Fawaz et al. 2019. Deep learning for time series classification: a review.
[10] Karim et al. 2019. Multivariate LSTM-FCNs for Time Series Classification.
[11] Li, Li, et Fu 2016. Multi-View Time Series Classification: A Discriminative Bilinear Projection Approach.

# II. Micro-Environment Recognition Model

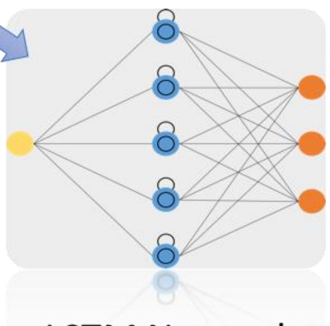
**First-level Learners**




KNN with DTW

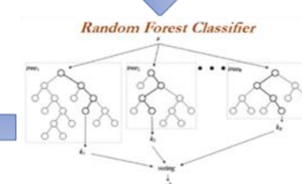
Data Collection

Data preparation

LSTM Network

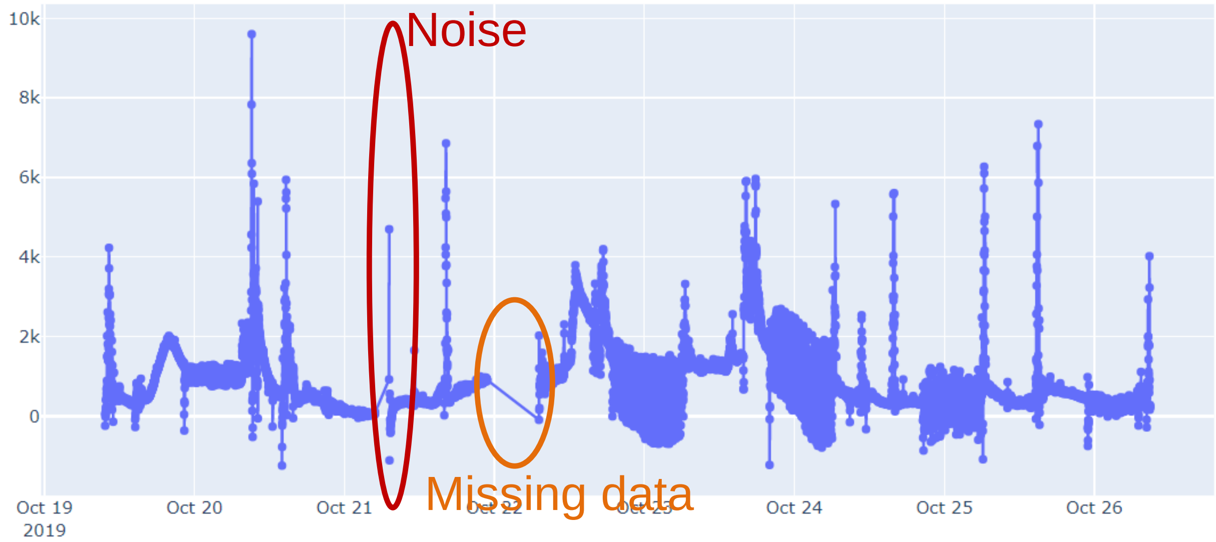
Generating new dataset D’
(using the probabilities and predictions of trained classifiers)




Final Classification Result

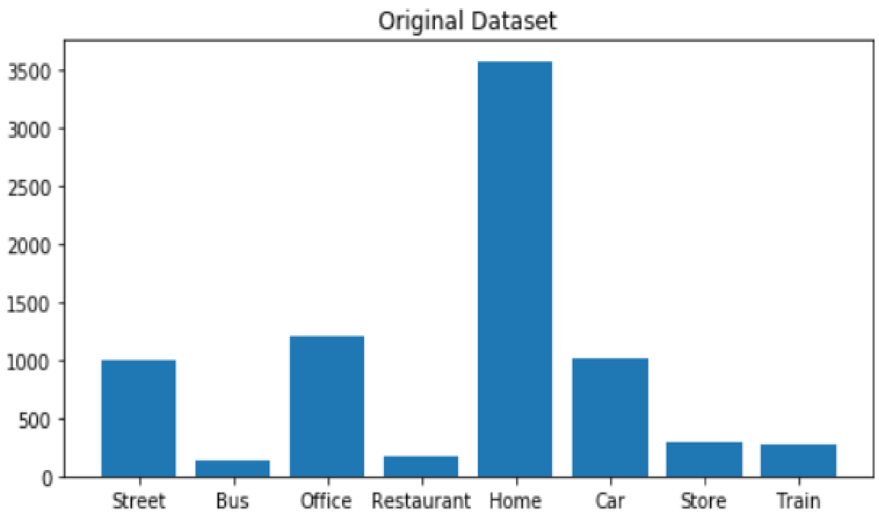
# II.1. Data Preparation

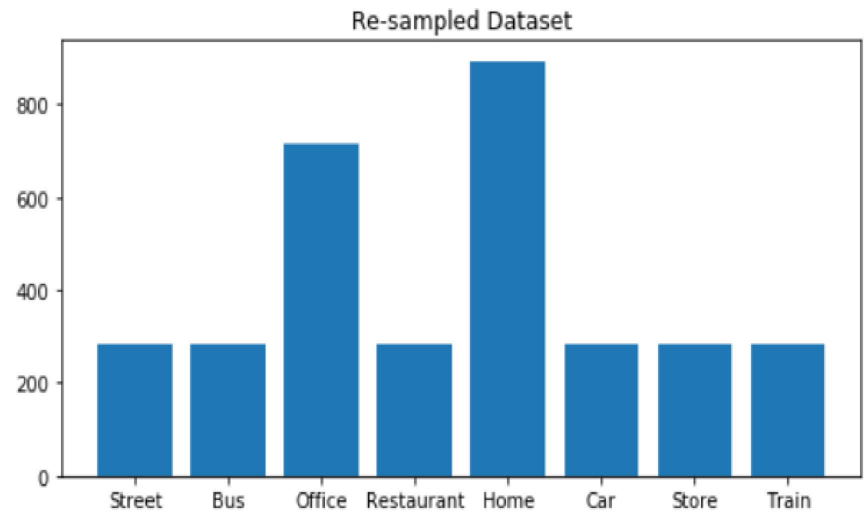
1. Data pre-processing: data **de-noising** (including GPS) & missing data **imputation**.
2. 8 indoor or outdoor activities to recognize : Home, Office, Street, Restaurant, Bus, Car, Store and Train.
3. Splitting data into samples of at most 10 min length.



# Imbalanced Data

1. Indoor activities (mainly "**Home**" and "**Office**") are the **majority classes** (participants spent more time in these micro-environments).
2. Resampling strategy: smooth the imbalanced data using **random over/under-sampler**.



# II.2. Our Approach

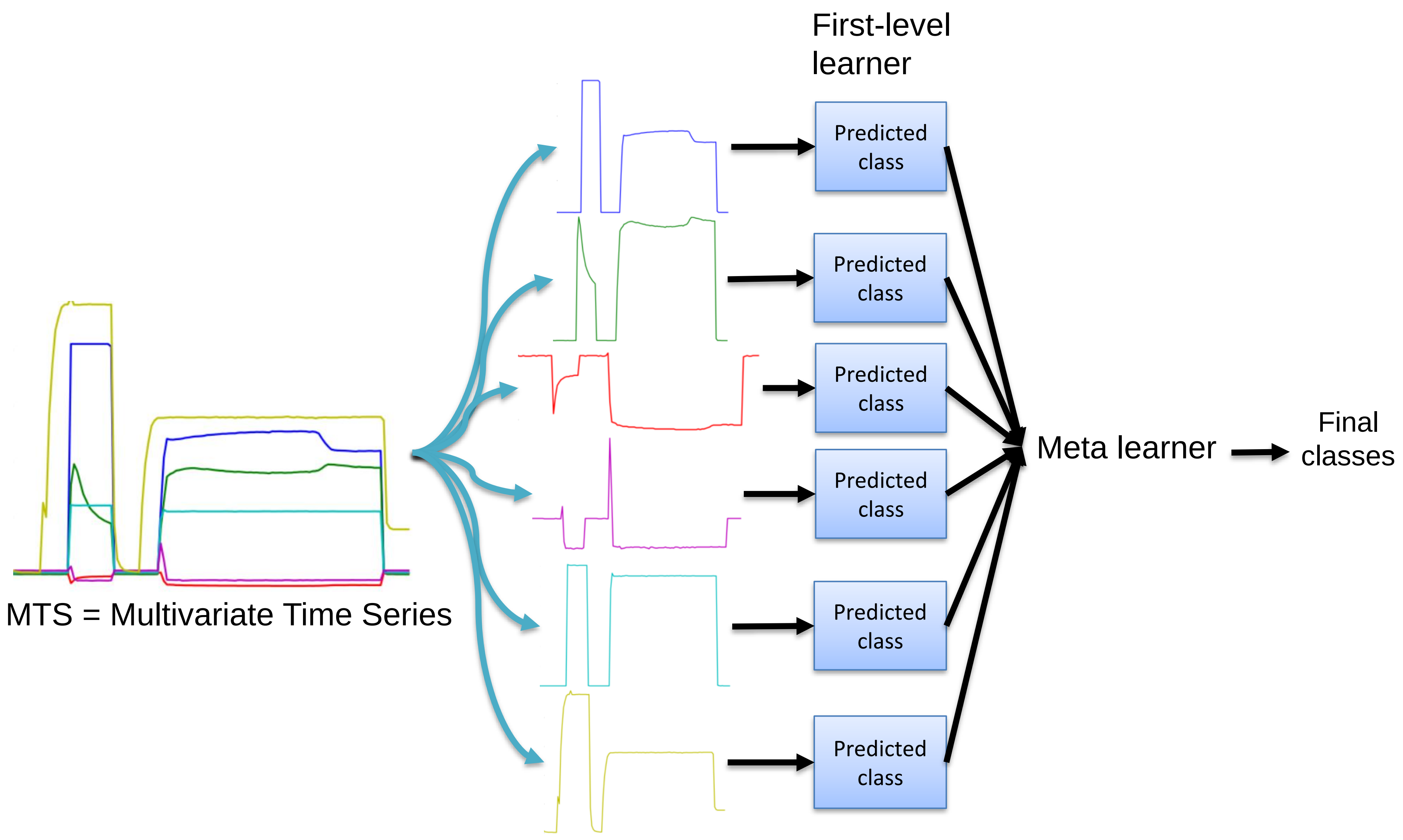
We used a multi-view stacking generalization[8] approach.

We train a model for each view (KNN with DTW).

Combine the results by training a meta-learner classifier.

[8] Garcia-Ceja, Galván-Tejada, et Brena 2018. Multi-view stacking for activity recognition with sound and accelerometer data.

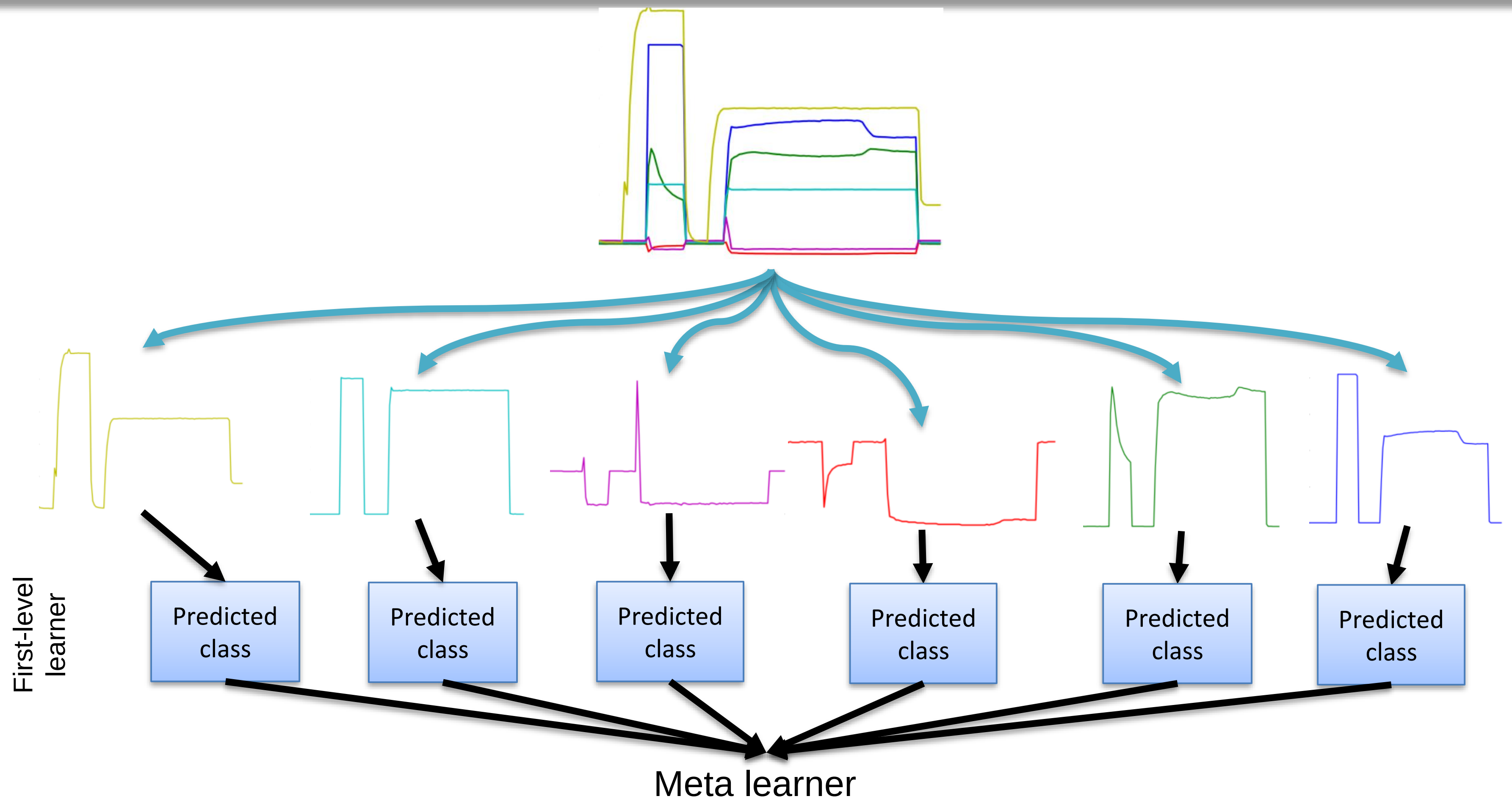
# II.2. Our Approach



# III. Experiments

1. Environmental crowd sensing data collected over 7 days by data six participants who have thoroughly annotated their activities within the campaign.
   – 70% of data is used for training.
   – 30% of data is used for testing.

# III. Meta Learner’s Output




| Temperature Prediction | Humidity Prediction | NO2 Prediction | BC Prediction | PM1.0 Prediction | PM2.5 Prediction | PM10 Prediction | Speed Prediction | Temperature Prediction | Humidity Prediction Probability | NO2 Prediction Probability | BC Prediction Probability | PM1.0 Prediction Probability | PM2.5 Prediction Probability | PM10 Prediction Probability | Speed Prediction Probability | True Label |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | 5 | 5 | 3 | 5 | 5 | 5 | 5 | 0.28 | 0.44 | 0.64 | 0.51 | 0.41 | 0.48 | 0.6 | 0.65 | 5 |
| 5 | 1 | 1 | 8 | 1 | 1 | 1 | 8 | 0.56 | 0.61 | 0.41 | 1 | 0.71 | 0.77 | 0.65 | 0.48 | 8 |

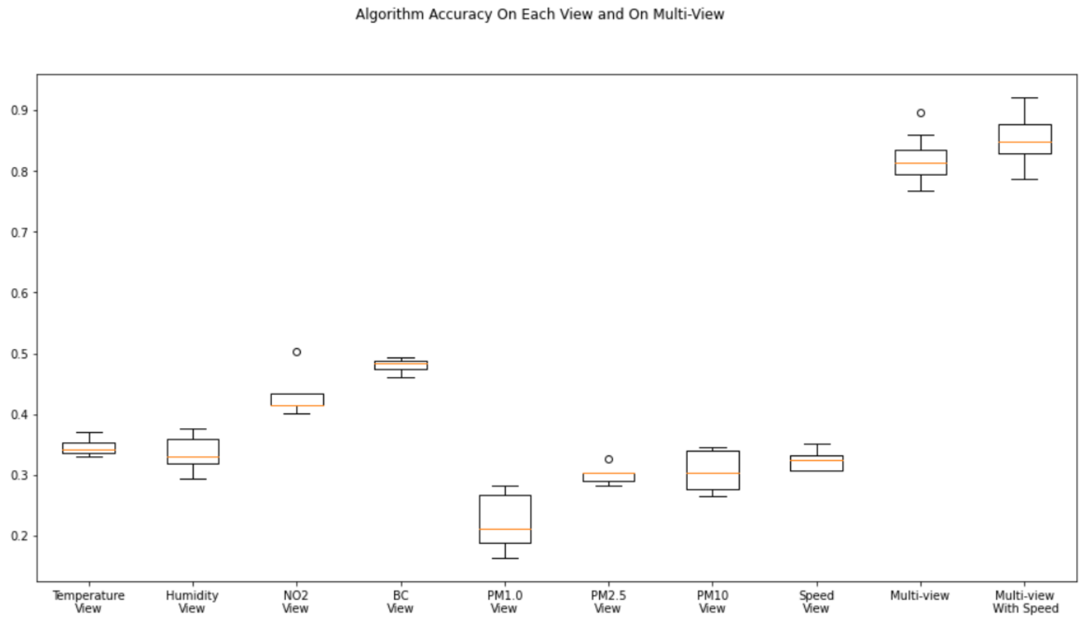
# III. Experimental Results

1. Baselines:
   1. kNN classifier with DTW metric (2NN-DTW), as state-of-the-art technique.
   2. We implemented MLSTM-FCN [10], as it is a multi-variate time series classifier.
2. Multi-view Based: our proposed approach.

| Model | Condition | Accuracy |
|---|---|---|
| kNN-DTW | Speed | 0.450 |
| | No speed | 0.440 |
| | Speed & Re-smp. | 0.587 |
| | No speed & Re-smp. | 0.597 |
| Multi-view Based | Speed | 0.716 |
| | No speed | 0.710 |
| | Speed & Re-smp. | 0.729 |
| | No speed & Re-smp. | 0.640 |
| MLSTM-FCN | Speed | 0.808 |
| | No speed | 0.784 |
| | Speed & Re-smp. | 0.703 |
| | No speed & Re-smp. | 0.691 |

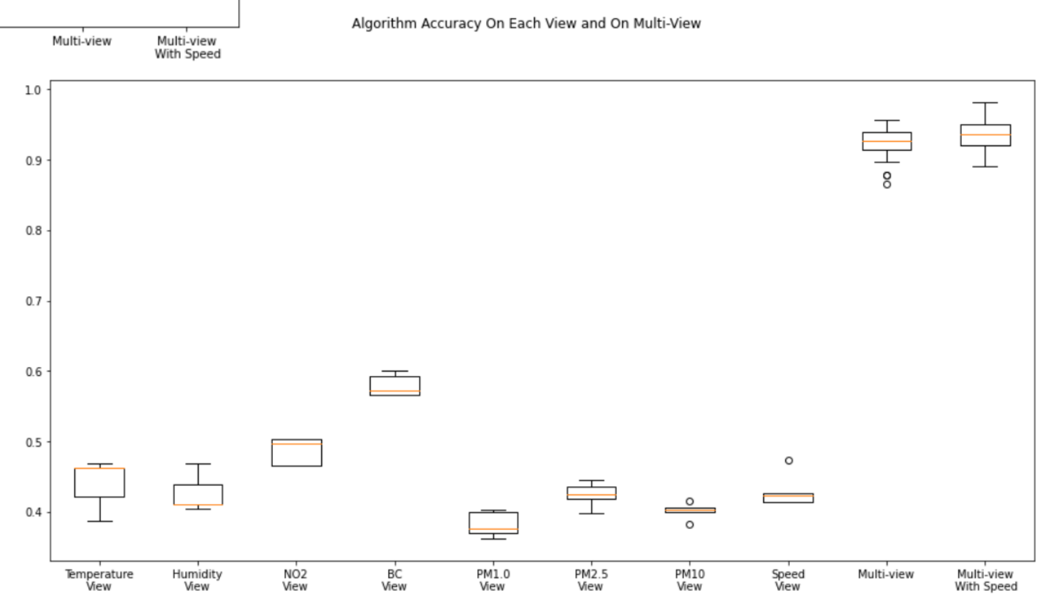
[10] Karim et al. 2019. Multivariate LSTM-FCNs for Time Series Classification.

# III. Experimental Results

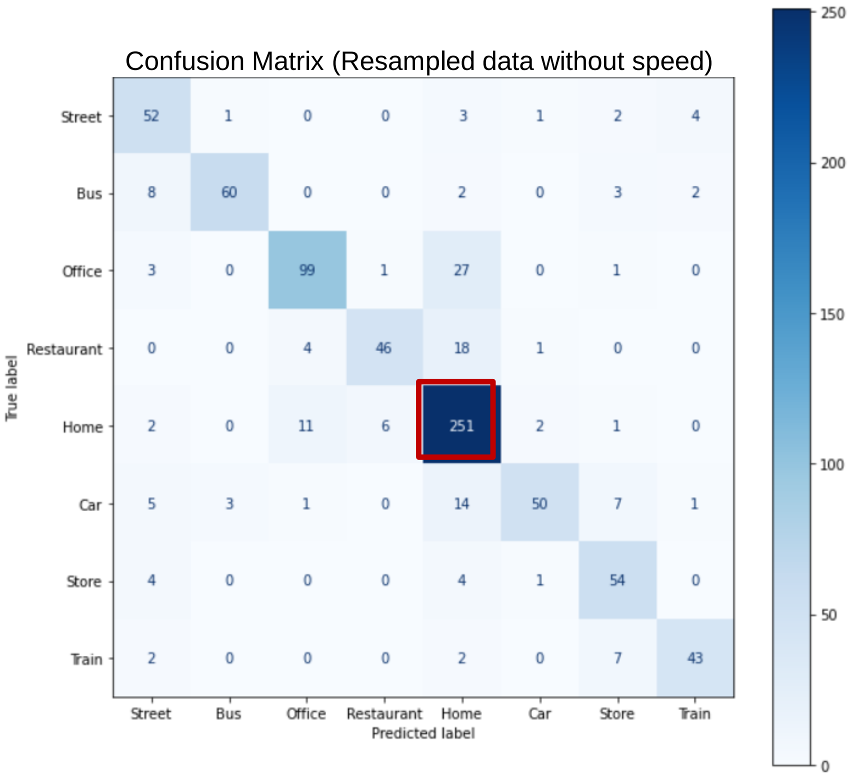


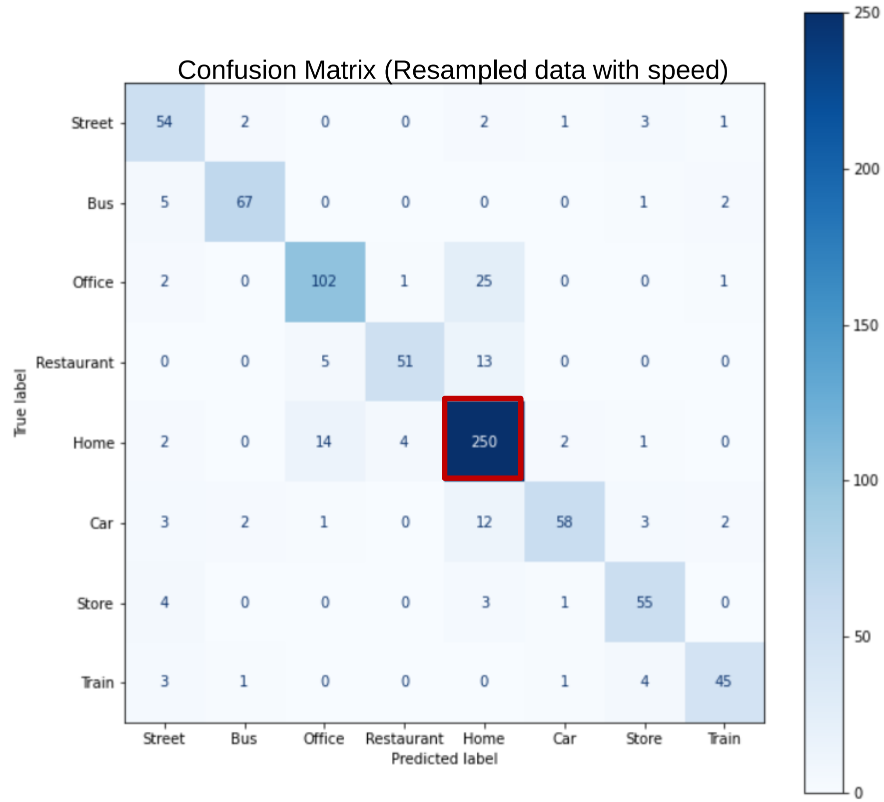

kNN-DTW classifier for the first level learner, and Random Forest for the meta-learner

Random Forest classifier for both the first level learner and for the meta-learner

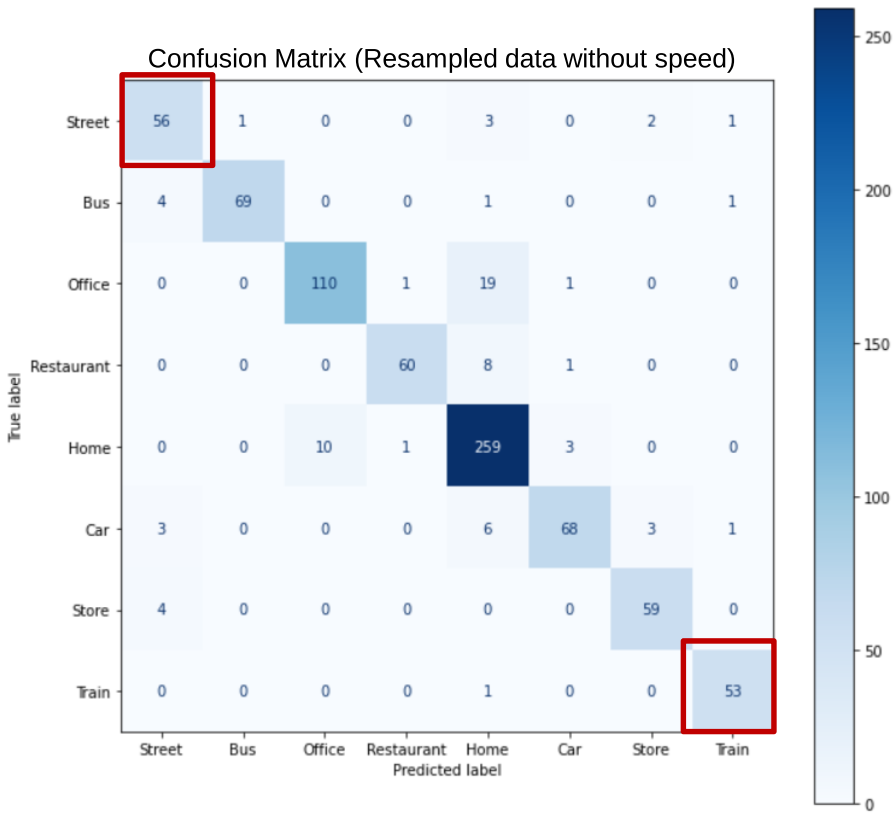


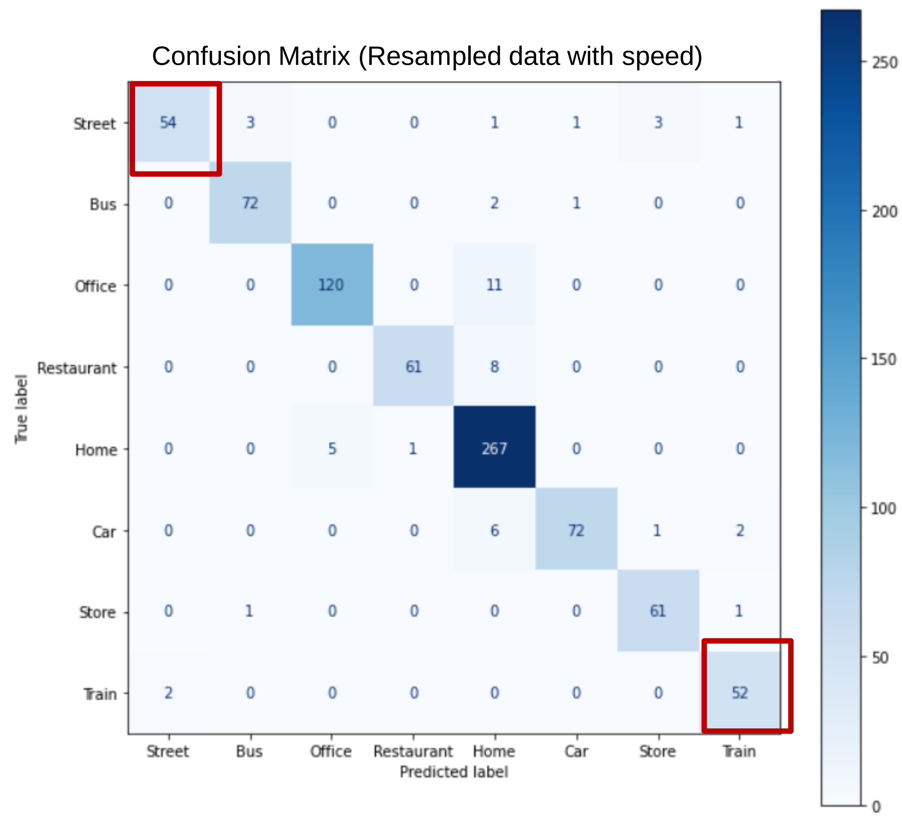
# III. Experimental Results (kNN+RF)



# III. Experimental Results (RF+RF)



# III. Experimental Results

## Without Speed

**Our approach (kNN+RF)**

| Class | Precision | Recall | F Score |
|---|---|---|---|
| Street | 0.684 | 0.825 | 0.748 |
| Bus | 0.938 | 0.800 | 0.863 |
| Office | 0.861 | 0.756 | 0.805 |
| Restaurant | 0.868 | 0.667 | 0.754 |
| Home | 0.782 | 0.919 | 0.845 |
| Car | 0.909 | 0.617 | 0.735 |
| Store | 0.720 | 0.857 | 0.783 |
| Train | 0.860 | 0.796 | 0.827 |

**Our approach (RF+RF)**

| Class | Precision | Recall | F Score |
|---|---|---|---|
| Street | 0.836 | 0.889 | 0.862 |
| Bus | 0.986 | 0.920 | 0.952 |
| Office | 0.917 | 0.840 | 0.876 |
| Restaurant | 0.968 | 0.870 | 0.916 |
| Home | 0.872 | 0.949 | 0.909 |
| Car | 0.932 | 0.840 | 0.883 |
| Store | 0.922 | 0.937 | 0.929 |
| Train | 0.946 | 0.981 | 0.964 |

## With Speed

| Class | Precision | Recall | F Score |
|---|---|---|---|
| Street | 0.740 | 0.857 | 0.794 |
| Bus | 0.931 | 0.893 | 0.912 |
| Office | 0.836 | 0.779 | 0.806 |
| Restaurant | 0.911 | 0.739 | 0.816 |
| Home | 0.820 | 0.916 | 0.865 |
| Car | 0.921 | 0.716 | 0.806 |
| Store | 0.821 | 0.873 | 0.846 |
| Train | 0.882 | 0.833 | 0.857 |

| Class | Precision | Recall | F Score |
|---|---|---|---|
| Street | 0.964 | 0.857 | 0.908 |
| Bus | 0.947 | 0.960 | 0.954 |
| Office | 0.960 | 0.916 | 0.938 |
| Restaurant | 0.984 | 0.884 | 0.931 |
| Home | 0.905 | 0.978 | 0.940 |
| Car | 0.973 | 0.889 | 0.929 |
| Store | 0.938 | 0.968 | 0.953 |
| Train | 0.929 | 0.963 | 0.945 |

# III. Our Approach vs MLSTM

## Without Speed

**Our approach (RF+RF)**

| Class | Precision | Recall | F Score |
|---|---|---|---|
| Street | 0.836 | 0.889 | 0.862 |
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| Store | 0.922 | 0.937 | 0.929 |
| Train | 0.946 | 0.981 | 0.964 |

**MLSTM-FCN**

| Class | Precision | Recall | F Score |
|---|---|---|---|
| Street | 0.93 | 0.89 | 0.91 |
| Bus | 0.93 | 0.99 | 0.95 |
| Office | 0.78 | 0.74 | 0.76 |
| Restaurant | 0.81 | 0.62 | 0.70 |
| Home | 0.84 | 0.90 | 0.87 |
| Car | 0.95 | 0.95 | 0.95 |
| Store | 0.95 | 1.00 | 0.98 |
| Train | 0.96 | 0.96 | 0.96 |

## With Speed

**Our approach (RF+RF)**

| Class | Precision | Recall | F Score |
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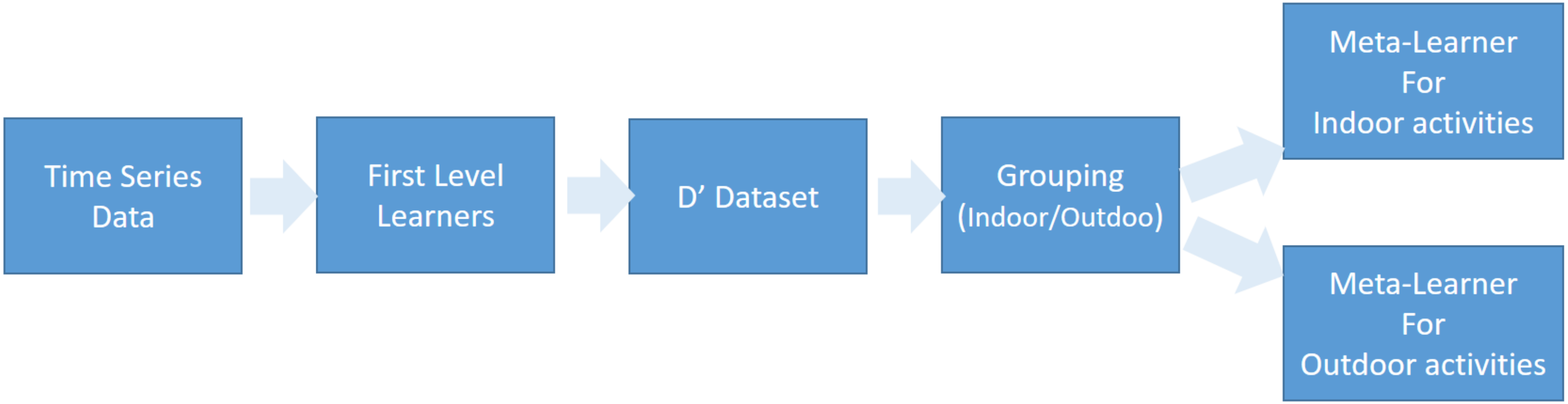
**MLSTM-FCN**

| Class | Precision | Recall | F Score |
|---|---|---|---|
| Street | 0.86 | 0.90 | 0.88 |
| Bus | 0.95 | 0.93 | 0.93 |
| Office | 0.82 | 0.69 | 0.75 |
| Restaurant | 0.80 | 0.62 | 0.70 |
| Home | 0.81 | 0.88 | 0.84 |
| Car | 0.89 | 0.93 | 0.91 |
| Store | 0.94 | 0.98 | 0.96 |
| Train | 0.92 | 1.00 | 0.96 |

# Grouping Step

1. The classifier can strongly discriminate between the types indoor and outdoor but it may fail in classifying the micro-environments.
2. We proposed a **new step**: classify data into indoor and outdoor, and then discriminate between the micro-environments.



# Grouping Step Results (kNN+RF)

1. This approach performed a higher accuracy on resampled data .

Resampled data without speed

| Class | Precision | Recall | F Score |
|---|---|---|---|
| Streer | 0.74 | 0.82 | 0.78 |
| Bus | 0.93 | 0.89 | 0.91 |
| Office | 0.86 | 0.76 | 0.81 |
| Restaurant | 0.87 | 0.72 | 0.79 |
| Home | 0.85 | 0.93 | 0.89 |
| Car | 0.97 | 0.87 | 0.92 |
| Store | 0.93 | 0.95 | 0.94 |
| Train | 0.86 | 0.92 | 0.89 |

Resampled data with speed

| Class | Precision | Recall | F Score |
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| Streer | 0.89 | 0.90 | 0.89 |
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| Store | 0.96 | 0.98 | 0.97 |
| Train | 0.89 | 0.98 | 0.93 |

# Grouping Step Results (RF+RF)

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| Bus | 0.88 | 0.89 | 0.88 |
| Office | 0.94 | 0.92 | 0.93 |
| Restaurant | 1.00 | 0.88 | 0.93 |
| Home | 0.94 | 0.98 | 0.96 |
| Car | 0.98 | 0.90 | 0.94 |
| Store | 0.98 | 0.98 | 0.98 |
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Resampled data with speed

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| Car | 0.98 | 0.98 | 0.98 |
| Store | 0.98 | 0.95 | 0.96 |
| Train | 0.96 | 0.96 | 0.96 |

# Our Approach vs MLSTM

Grouping Step (RF+RF)

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| Car | 0.98 | 0.98 | 0.98 |
| Store | 0.98 | 0.95 | 0.96 |
| Train | 0.96 | 0.96 | 0.96 |

MLSTM-FCN

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| Car | 0.89 | 0.93 | 0.91 |
| Store | 0.94 | 0.98 | 0.96 |
| Train | 0.92 | 1.00 | 0.96 |

# Conclusion

1. We show that the ambient air can characterize the micro-environment.
2. By using the mobility feature, the accuracy improves slightly though the gain is moderate.
3. We have compared the results with kNN-DTW and MLSTM-FCN classifiers which were considered as the baseline.

# Perspectives

1. Use various algorithms for the first level learner and the meta learner, as multi-view learning is flexible.
2. Explore the application of semi-supervised learning to cope with the lack of labels for some classes.
3. Improve the performance of the learned classes by integrating some a priori rules (e.g. the unlikelihood of being in some microenvironment at some time of day).

***Thank you for your attention!***