Leveraging Change Point Detection for Activity Transition Mining in the Context of Environmental Crowdsensing

Hafsa El Hafyani
DAVID Lab
UVSQ - Université Paris-Saclay
Versailles, France
hafsa.el-hafyani@uvsq.fr

Karine Zeitouni
DAVID Lab
UVSQ - Université Paris-Saclay
Versailles, France
karine.zeitouni@uvsq.fr

Yehia Taher
DAVID Lab
UVSQ - Université Paris-Saclay
Versailles, France
yehia.taher@uvsq.fr

Mohammad Abboud
Lebanese University
Beirut, Lebanon
mohammad.abboud.2496@gmail.com

ABSTRACT

The change point detection is a critical problem in time series analysis. Detecting these transitions is gainful to human activities recognition. In this paper, we leverage this method to discover the transition between activities based on data originated from different sensors. We design and evaluate a change point detection process for the environmental crowd sensing data. We detect transitions and integrate the change point detection with multi-dimensional time series to enhance the time series segmentation into separate activities. Experiments on real-world environmental crowd sensing data suggest that combining different dimensions lead to higher performance for the change points detection.

KEYWORDS

Activity Recognition, Change point detection, Segmentation, Data Mining, Mobile Crowd Sensing

1 INTRODUCTION

With the rapid advances of Internet of Things (IoT), along with the widespread use of GPS, and other built-in and external environmental sensors, several applications have emerged to collect geodated data series. One of such applications is the new paradigm of Mobile Crowd Sensing (MCS), which empowers volunteers to contribute data acquired by their personal sensor-enhanced mobile devices. Polluscope[1], a french project deployed in Île-de-France (i.e., Paris region), is a typical use case study based on MCS. It aims at getting insight constantly on individual exposure to pollution everywhere (indoor and outdoor), while enriching the traditional monitoring system with the collected data by the crowd. The recruited participants, on a voluntary basis, collect air quality measurements such as Particulate Matters, NO2, Black Carbon, Temperature and Humidity. Each participant is equipped with a sensor kit and a mobile device which allows for the transmission of collected measurements together with their GPS coordinates as geo-dated data series, and activity annotation through a custom mobile application. This paradigm will allow participants to have personalized insights about their exposures to pollution. It measures indoor and outdoor environments (e.g., Home, Work, Transportation, Streets, Park, etc), and enables participants to gain insights at a higher resolution along their trajectories, thereby, allowing to capture local variability and peaks of pollution, depending on participants' whereabouts.

It is worth mentioning that the ambient air observations strongly depend on the context. More than that, it could be a proxy for an indoor versus outdoor environment. For this reason, there is a great interest of making the analysis context-aware. For this to be done, we need to identify the context automatically from the collected raw data.

Since the context changes with the participants' activity and whereabouts, this also means that we need to detect the changes and segment the geo-data series into non overlapping segments according to participants micro-environments (i.e. Home, Work, Transportation, Streets, Park, etc.). Segmented data is a prerequisite for activity recognition mining task, which assigns to each segment a labeled with a single activity.

In this paper, we propose an approach which combines data pre-preparation, change point detection on individual dimensions, and a post-processing phase to fuse the detection from multiple dimensions. This last phase is based on a supervised learning approach. We implement and test our framework in a real-application setting. The rest of this paper is organize as follows. We introduce the related word in section 2. The formal presentation of our change point detection model is explained in section 3. Section 4 presents the experimental results and evaluation of the change point detection model on real-world data. In section 5, we offer conclusions.

2 RELATED WORK

Existing change point detection approaches in the literature can be classified in term of sensing technology, types of activities, segmentation methods, and online or offline techniques. Offline time series change point detection techniques store the whole data set at once, and look for point locations where the changes have occurred based on a global view of the data. On the other hand, online time series change point detection is an extension of the offline change point detection methods, where an offline change point detection is applied on each newly arrived sequence of data points. [2] enumerate, categorize, and compare methods that have been proposed to detect change points in time series in both batch and online modes.

[1] http://polluscope.uvsq.fr

There is a wide range of change point detection methods that are either based on wearable sensors [9], camera [1], Smartphones GPS logs [16], or Smart Home [3] for collecting information, and understanding and detecting human activities.

The objective of activity recognition problem is to recognize participant contexts from different sensors data. The starting point of participants contexts is to detect the transition points and label them with activities. There have been a numerous machine learning algorithms that have been used for change point detection problem [2]. Those include both supervised and unsupervised methods. The supervised methods take a training set to learn a mapping to a target attribute from an input data. In supervised learning, data is already labeled by activity classes collected during data collection or provided by an expert. Unsupervised learning algorithms on the other hand, are used to discover change in pattern within unlabeled data. Since we are dealing with time series data, those approaches can be used to discover transitions based on statistical properties of time series without prior knowledge on class labels or a training set.

[3] used two different unsupervised method to detect the transition in time series on unlabeled data. The first is Relative Unconstrained Least-Squares Importance Fitting (RuLSIF), and the second method is Bayesian Change Point Detection (BCPD). The results show that the best performance for activity transition detection can be achieved when RuLSIF algorithm is used. However, setting appropriate values for RuLSIF parameters has a major influence on the change point detection results. The authors proposed another work a real-time nonparametric change point detection, which uses Separation distance as a divergence measure to detect change points in high-dimensional time series [4]. The goal is to further advance the line of research in density ratio change point detection algorithms, and introduce a new unsupervised algorithm for change point detection in time-series data, called SEP, using the Separation distance metric. The results show that their algorithm exhibits similar behaviour as Kullback-Leibler importance estimation procedure (KLIEP) and uLSIF (Unconstrained Least-Squares Importance Fitting) estimation, which uses Pearson (PE) divergence as a dissimilarity measure.

[11] proposed an offline change point detection method which is based on Information Gain Theory. This method takes the number of change points and detects changes that affect the mean of the time series. The proposed method can also detect changes in the variance of the time series using a moving window. However, setting the number of change points in the whole of the time series affect the change point detection results.

[9] went through two different methods for time series segmentation. The first methodology is an explicit segmentation whereby the data stream is segmented to a set of subsequences using certain window size and sliding length. However, the two parameter affect directly the transition detection precision. The second method is sensor event-based segmentation, which divides the data stream into subsequences containing certain number of sensor events. This approach can dynamically adjust the window size to fit different activities during recognition. However, because two different activities may appear in the same window, detecting the exact change point timestamp may be not possible using a sliding window. [16] used change point detection method based on common sens to segment GPS trajectories into walk and non-walk segments in order to infer the transportation mode. The authors partition a given trajectories into many segments based on the participant velocity and acceleration. Typically, people should stop before changing the transportation mode. However, velocity is very sensitive to traffic conditions and weather. During a traffic jam, the average velocity of driving would be as slow as cycling, and then the change in participant activities may not be captured.

[13] proposed a supervised learning method to reconstruct user's trip information from GPS low data rate collected from mobile phone device. The authors based their work on [15] with adaptation of some parameters, and have used in their approach a trip segmentation based on change point detection. The change point is a GPS point where user changes his/her transportation mode, and segmentation is done by searching change points based on features such as speed and velocity change rate, in each point. Thus if the point matches the criteria of the previous segment then it is grouped to. Otherwise it is marked as a change point and a new segment is created.However, this approach is mono-dimensional change point detection based on GPS points only, and need to be improved to implicated multi-dimensional time series.

[4] state that, compared with other change-point detection methods, density ratio based algorithms offer several advantages for real world problems. One of the direct density ratio change point detection methods that has no limitations on time series data distribution and doesn't require any condition on data stationarity, is the cumulative sum (CUSUM) algorithm [2]. The contribution of this work is a proposed change point detection combination of multi-dimensional time series obtained from real world geo-location and sensors data, where time series dimensions don't contribute evenly in the activity transition detection.

The most current change point detection approaches operate on limited types of time series. Some algorithms, such as kernel-based method or Guassian Process, require the time series to be i.i.d or stationary, and others, such as uLSIF and KLIEP, offer a parametric approach for non-stationary time series [2]. Another issue raises with multi-dimensional data, where not all dimensions may cause the change. These constraints are not coherent with the nature of mobile crowd sensing data, where time series segmentation should not be subject to any constraints. Additionally, the inclusion of weak or irrelevant dimensions should not degrade the performance of the change point detection. To the best of our knowledge, no prior work focuses on the segmentation of human whereabouts using climatic sensors, environmental sensors and geo-location.

3 CHANGE POINT DETECTION MODEL

In this section, we introduce our change point detection approach based on CUSUM algorithm for multi-dimensional time series in environmental crowd sensing. Both the theory and the implementation aspects of the approach will be discussed.

The holistic schema of our proposed approach is shown in figure 1. The implementation of our proposed process includes four parts: data collection and preparation, change point detection, post-processing and ensemble method learning.

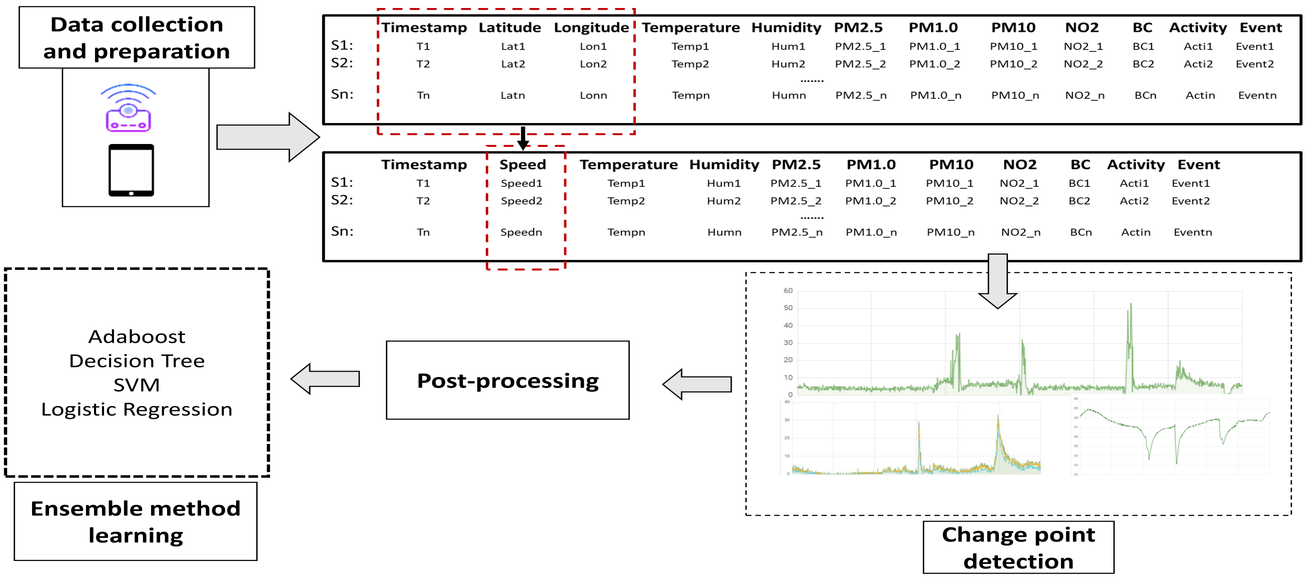

Figure 1: Architecture of our approach

3.1 Data Collection and Preparation

Real-life data are collected within the scope of Polluscope project. A cohort of volunteers is recruited to collect sensory spatio-temporal data series. Participants are equipped with air pollution sensors and tablets empowered with GPS chipsets. The sensors collect time annotated measurements of Particulate Matter (PM1.0, PM10, PM2.5), NO2, Black Carbon, Temperature and Humidity, and the tablet records participants' geo-locations and allows to annotate data with activities and pollution related events. Activities are depicted by micro-environments of participants (e.g., Home, Office, Park, Restaurant, etc.). Events are temporary actions for a brief period (e.g., Start cooking, Open a window, Close a window, Smoking, Turn on a chimney, etc.). Activity and event recognition allow to enrich semantically the collected data with the context. More that 86 volunteers per year participated in the data collection phase. Each participant carries a kit composed of an aethalometer for measuring Black Carbon, a gaz sensor which measures the Nitrogen dioxide (NO2), and a sensor for various size particulate matters (PM) measurements (the sensors have been selected after performing evaluation in [8]) - all bundled with a tablet for seven days with no restrictions on space and time. As such the MCS scheme is opportunistic, aiming at reporting the participants' exposure in accordance with their habits and their daily life. A sequence of these data contains kit ID, timestamp, and values from different sensors. Figure 2 shows an example of sequences collected by tablets and different sensors. This sequence contains a series of logs which include timestamp, kit ID, Latitude, Longitude, ambient air data (i.e., Temperature, Humidity, PM2.5, PM10, PM1.0, NO2 and Black Carbon), activity (e.g., Car) and events (e.g., Close a window).

Participants geo-locations are collected as GPS logs. As shown in the upper part of figure 1 by dotted rectangle, each GPS log is a sequence of GPS points that contain latitude, longitude and timestamp. We drive the velocity time series from GPS coordinates.

time	kit_id	lat	lon	Temperature	Humidity	PM2.5	PM10	PM1.0	NO2	BC	activity	event
2019-10-20 12:52:57	57	48.766292	2.032283	26.2	51.5	2.0	2.0	1.0	10.0	1027.0	Voiture	Fermeture De Fenêtre
2019-10-20 12:53:28	57	48.766292	2.032283	26.5	50.7	2.0	2.0	2.0	0.0	921.0	Voiture	Fermeture De Fenêtre
2019-10-20 12:53:59	57	48.766292	2.032283	26.5	50.7	2.0	2.0	2.0	0.0	921.0	Voiture	Fermeture De Fenêtre
2019-10-20 12:54:30	57	48.764743	2.034910	26.6	50.2	2.0	3.0	1.0	0.0	888.0	Voiture	Fermeture De Fenêtre
2019-10-20 12:55:01	57	48.762178	2.038895	26.8	49.7	3.0	4.0	1.0	3.0	885.0	Voiture	Fermeture De Fenêtre
2019-10-20 12:55:32	57	48.762240	2.044100	26.8	49.7	3.0	4.0	1.0	3.0	885.0	Voiture	Fermeture De Fenêtre

Figure 2: An Overview of data collected in the context of MCS

It is important to emphasize that not all data are thoroughly annotated with participants contexts. Also most sensor data are noisy, and require a prepossessing phase to clean them from irrelevant measurements. We have observed this especially in the GPS data, BC, and some PM data. The sensors for climatic parameters do not show such defect. Therefore, the data preparation is twofold. From one hand, a de-noising process is applied to clean the data. From another hand, the highest quality sample of annotated data is selected as a baseline to validate the process of data segmentation. The idea is to generalize the change point detection to all participants data, by using the model derived from a good-quality dataset.

3.2 Change Point Detection

The change point detection problem is the process of detecting abrupt changes in time series data. The change points are detected when the probability distribution of time series changes abruptly between two consecutive intervals.

In this work, we propose a multi-dimensional time series segmentation to discover activities and events boundaries in the context of mobile crowd sensing. The main contribution is precisely the combination of different dimensions in the change point detection, when not all dimensions may cause or contribute evenly in discovering the change in participant's activities or events.

The overall question is: how to combine all these different aspects of the data (geo-location, sensors, partially annotated activities and events) to segment and discover the context of the user, and to discriminate the observations in different micro-environment? This is called a holistic approach of activity recognition [6].

The segmentation phase consists mainly in splitting spatio-temporal data into coherent segments. Each segment represents a micro-environment. One way to do this segmentation is to detect the changes either in the ambient time series, or in the geo-location. The former corresponds to the problem of change point detection (CPD) in time series. Many solutions exist in the literature when it comes to mono-variate time series. As for the the GPS data, it is related to the so-called stop & move detection in trajectories. In this paper, we use the change point detection in time series for both problems, simply by adding the velocity dimension, which is easily derived from geo-location data.

The CUmulative SUM (CUSUM) is one of the main CPD techniques in mono-dimensional time series. It has no limitation on time series data distribution and does not require any condition on data stationarity [2]. First introduced by [10], CUSUM algorithm is a sequential analysis technique, and it is the most familiar change point detection algorithm. The CUSUM proposed by [10] uses the Sequential probability ratio test (SPRT) to detect change points. The algorithm performs by comparing probability distributions of two time series intervals. As the two intervals are moving, the test issues an alarm of a change point when the probability distributions of the two intervals are significantly different.

One form of implementing the cumulative sum test is given by the expression 1, which detects changes in the positive and negative direction (g_j^+ and g_j^-) in the data (x) [7]. The decision rule is: if g_j^+ and g_j^- exceeded a user defined **threshold (h)**, then an alarm is given (t_{alarm}), a change point has been detected, and the test statistic is reset ($g_t^+ = 0$ and $g_t^- = 0$). This algorithm depends also on another parameter called ***drift*** **(v)** for drift correction to avoid false alarm or slow drift. The CUmulative SUM (CUSUM) test is given by:

$$\begin{cases} s_t = x_t - x_{t-1} \\ g_t^+ = max(g_{t-1}^+ + s_t - v, 0) \\ g_t^- = max(g_{t-1}^+ - s_t - v, 0) \end{cases} \tag{1}$$

$$if \quad g_t^+ > h \quad \text{or} \quad g_t^- > h : \begin{cases} t_{alarm} = t \\ g_t^+ = 0 \\ g_t^- = 0 \end{cases}$$

The CUSUM test accuracy depends on tuning the parameters h and v. Both parameters present a trade-off between faster detection of true alarms and allowing more false alarms. High values of v allow false alarms at the cost of obtaining a delayed detection [7]. As soon as the CUSUM test exceeds a threshold h, the change is detected. The accuracy of this algorithm is often computed by indicators such as false positive rate.

Table 1: Overview of time spent in every micro-environment for four participants

Micro-Environment	Mean	SD	Min	Median	Max
Office	03:58:36	02:32:04	00:02:00	03:58:30	09:19:00
Bus	00:08:02	00:05:09	00:03:00	00:06:00	00:18:00
Cinema	02:00:00	0	02:00:00	02:00:00	02:00:00
Home	04:30:26	05:48:49	00:00:00	01:10:00	23:16:00
Store	00:19:25	00:26:53	00:01:00	00:10:00	01:39:00
Metro	00:25:07	00:09:10	00:15:00	00:23:30	00:40:00
Park	01:20:00	0	01:20:00	01:20:00	01:20:00
Restaurant	00:43:52	00:27:12	00:24:00	00:37:00	01:50:00
Street	00:07:53	00:09:05	00:00:00	00:05:00	00:55:00
Train	00:22:42	00:13:20	00:01:00	00:20:30	00:48:00
Car	00:26:12	00:37:32	00:01:00	00:08:30	02:52:00
Bike	01:08:00	00:44:27	00:14:00	01:12:00	02:22:00

3.3 Post-Processing

In multi-dimensional time series, some dimensions may contribute more in the explanation of the change, while others may be considered as irrelevant. Participants' context is very highly correlated with ambient air temperature and humidity more than, for example, speed. Because, first, the temperature and humidity indoor are different than outdoor. When participant changes their micro-environment, temperature and humidity change abruptly. Second, speed is very sensitive to traffic conditions. During a traffic jam, using a transportation mode such as Car or Bus, participant's speed drops frequently without indicating a change in micro-environment.

The application of the CUSUM algorithm on different dimensions of time series may generate numerous false alarms. Post-processing the CUSUM algorithm results will improve the change point detection accuracy by merging the detected change points into one change point if a certain condition is verified. The condition, in this work, is the time difference between two consecutive detected change points should be less than 5 minutes. If the time difference between two consecutive detected change points is less than 5 minutes, then the detected change points will be merged into one detected change point. As shown in table 1, participants don't stay in the same micro-environment for a short period of time. The least time spent in one micro-environment are found to be 8 minutes. The 2 minutes spent in "Home" correspond to the time spent in the micro-environment "Home" before the participant start a pollution related event (e.g., Cooking, Open window).

3.4 Ensemble Method Learning

One of the contribution of this work is the combination of multi-dimensional sensory time series data and geo-located data (i.e. GPS data) to detect the changes boundaries of participants micro-environments when some dimensions may be considered irrelevant to the change detection or not all dimensions cause the change. In order to enhance the accuracy of the change point detection, many ensemble methods [17] have been proposed to further enhance the algorithms accuracy by combining learners rather than trying to find the best single learner.

There are different types of combination methods, among which, the most popular are: **Averaging**, **Voting** and **Combining by Learning** [17]. *Averaging* is the most popular and fundamental combination method for numeric outputs. Regression is an explicit example of how *Averaging* works. *Voting*, on the other hand, is the most popular and fundamental combination method for nominal output. Classification is an explicit example of how *Voting* works. There are four types of voting [17]: (1) *Majority Voting* is the most popular voting method. Here, every classifier votes for one class label, and the final output class label is the one that receives more than half of the votes. (2) *Plurality Voting* takes the class label which receives the largest number of votes as the final winner. (3) If the individual classifiers are with unequal performance, it is intuitive to give more power to the stronger classifiers in voting and this is realized by *Weighted Voting*. These three voting methods are suitable for classifiers that use *crisp class labels*. However, if individual classifier produce class probability outputs (such as Naive Bayes, Logistic Regression), *Soft Voting* is the choice.

However, CUSUM algorithm produces the timestamp when the change has occurred. Some dimensions (such as Temperature and Humidity) are more important and correlated to the change in participants activities than others. The most suitable for that type of multi-dimensional time series would be the *Weighted Voting*. The key here is to assign weights in proportion to the performance of individual learners. Assigning inadequate weights has a major effect on the learning accuracy.

To assign automatic weights to single learner, *Combining by Learning* method is a procedure where individual learners are trained for the *first level learners* and combined by a learner for the *second-level learner*. **Stacking** introduced by [14] [12] [5], can be viewed as a generalization of many *Combining by Learning* methods.

In this work, we propose a model that integrates the CUSUM change point detection algorithm with multi-dimensional time series to achieve a strong combination abilities. The model works as follows: (1) the change point detection algorithm is applied on each time series dimension separately; (2) each dimension generates a set of detected change points, with a certain accuracy to the ground truth; (3) the weights of every dimension are then learned from the gold set data annotated by activities and events of participants. The model used in this experiment include: *AdaBoost* with Decision Tree, *Decision Tree* (DT), *SVM* and *Logistic Regression*. The proposed model allows to understand which dimension is affected by the changes in participants micro-environments and pollution related events.

4 EXPERIMENTS AND RESULTS

The above-mentioned segmentation model was implemented in Python using scikit-learn (0.22.2) for *Combining by Learning* method, and tested on real environmental crowd sensing data to detect boundaries transition in activity and pollution related events.

4.1 Experiments

We evaluate our change point detection model to segment participants' daily activities and pollution related events. We use for the experiment phase environmental crowd sensing data collected over

Table 2: Cumulative Sum parameters optimization for each dimension

Dimension	Threshold	Drift	Precision	Recall
Temperature	0.6	0.05	0.72	0.78
Humidity	4	0.05	0.70	0.82
PM 2.5	25	0.03	0.87	0.30
NO2	15	15	0.66	0.26
Black Carbon	900	500	0.22	0.65
Speed	1	0.1	0.12	0.52
Post-processing	-	-	0.45	1

7 days by two participants. Each participant is equipped with three sensors that record ambient air data (i.e. Temperature, Humidity, Particulate Matter: PM2.5, PM10, PM1.0, NO2 and Black Carbon) and a tablet for geo-location and data annotation.

From geo-location data, speed of participant every minute is calculated. Then, our multi-dimensional time series has six dimensions: *Speed*, *Black Carbon*, *NO2*, *Temperature*, *Humidity*, and *Particulate Matter PM2.5*.

4.2 Parameters optimization

Sitting *Cumulative Sum* algorithm parameters, **threshold** h and **drift** v, depend on each dimension. Several parameters combinations has been tested to chose the one that yields the highest performance. The parameters that have been used in this experiment are given in table 2. To evaluate the overall performance of the algorithm, we compute the precision to measure the ratio of true positive change points to total points classified as change points. The recall (true positive rate) is also computed to measure the portion of change points that was correctly detected.

To evaluate the performance of the change point detection, we consider as a true positive every detected change point that belong to a buffered interval of 5 minutes before and after the actual change.

Overall, **Temperature** and **Humidity** have the highest *precision* and *recall* at the same time. However, **Speed** generates the highest number of false positives. Thereby, *Temperature* and *Humidity* should be assigned with more power than the rest of dimensions.

After post-processing the results, the recall, the true positive rate, records a score of 100%, which means that all the change points have been detected successfully. However, the precision indicates that many false alarms are still being detected due to some weak dimensions

4.3 Ensemble learning performance

For the ensemble learning step, a second data set is generated. This data set contains the output of the CUSUM algorithm results. In other words, the output of the first-level learners is considered as input for the second-level learner. The response vector is the vector of the actual change points. This vector is binary re-coded and takes 1 if there is a change point, and 0 if not.

We study the performance of different classifier model as predictor of the response vector. We divided the first participant data into two sets. 70% of the data is for training the models, and the rest 30% for testing the models. In order to validate our approach and generalize it on other un-annotated data, we use the second participant data of one day and compare it with our ground truth. The results of the change point detection (CPD) experiment are summarized in figures 3,4, 5 and 6.

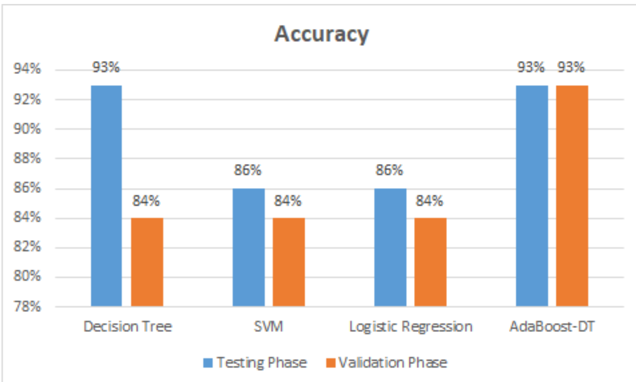

Figure 3: Accuracy of CPD for testing and validation phases

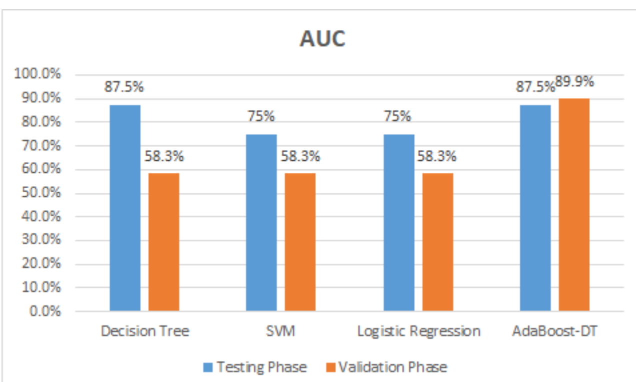

Figure 4: AUC scores of CPD for testing and validation phases

The experience conducted on real world data shows that our approach outperforms the traditional cumulative sum algorithm. During the testing phase, when comparing the combining learning algorithms' precisions to the overall precision of the traditional CUSUM algorithm in figure 5, *Decision Tree*, *SVM*, *Logistic Regression* and *AdaBoost* with Decision Tree base learner outperform the CUSUM algorithm. Considering the recall of the CUSUM after post-pras shown in figure 6, *Decision Tree* and *AdaBoost* show a good recall scores with 75% each.

When comparing the performance of the combining learners algorithms, considering the accuracy in figure 3, all the algorithms perform well during the testing phase, and *Decision Tree* and *AdaBoost* outperform the other algorithms with 93%. When considering the validation phase, *AdaBoost* outperforms all the other algorithms with an accuracy of 93%. Considering the *Area Under the ROC Curve* (AUC), during the testing phase, *Decision Tree* and *AdaBoost* outperform the other algorithms with 87.5%. However, during the validation phase, *AdaBoost* outperforms the other algorithms with 89%.

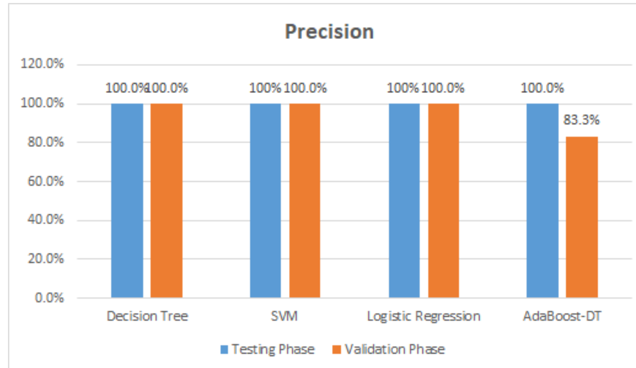

Figure 5: Precision scores of CPD for testing and validation phases

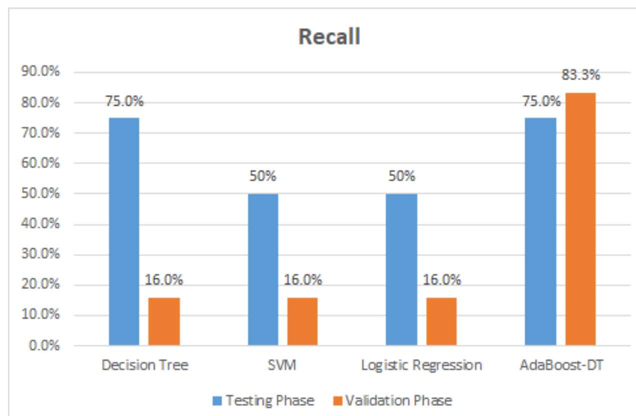

Figure 6: Recall scores of CPD for testing and validation phases

5 CONCLUSION

Change point detection segmentation can provides insights about on human behaviour's transition. Participants' whereabouts can be learned after segmenting the the collected multi-dimensional time series, and discover insights about individual exposure to pollution.

In this paper, we present a change point detection approach based on the *Cumulative Sum* algorithm to discover transition points in multi-dimensional time series using real world data collected in the context of environmental crowd sensing.

The experiment conducted in multi-dimensional time series, where not all dimensions may cause the change, shows that our approach outperforms the traditional CUSUM algorithm, using *AdaBoost* as a combining learner algorithm.

ACKNOWLEDGMENTS

This work is supported by the grant ANR-15-CE22-0018 Polluscope of the French National Research Agency (ANR). This work has also received a co-financing from DIM Qi^2 with the support of the Ile-de-France region.

REFERENCES

[1] Anjum Ali and Jake K. Aggarwal. 2001. Segmentation and recognition of continuous human activity. *Proceedings IEEE Workshop on Detection and Recognition of Events in Video* (2001), 28–35.

[2] Samaneh Aminikhanghahi and Diane J. Cook. 2016. A survey of methods for time series change point detection. *Knowledge and Information Systems* 51 (2016), 339–367.

[3] Samaneh Aminikhanghahi and Diane J. Cook. 2017. Using change point detection to automate daily activity segmentation. *2017 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)* (2017), 262–267.

[4] Samaneh Aminikhanghahi, Tinghui Wang, and Diane Joyce Cook. 2019. Real-Time Change Point Detection with Application to Smart Home Time Series Data. *IEEE Transactions on Knowledge and Data Engineering* 31 (2019), 1010–1023.

[5] Leo Breiman. 1996. Stacked regressions. *Machine learning* 24, 1 (1996), 49–64.

[6] Hafsa El Hafyani. 2020. Big Data Series Analytics in the Context of Environmental Crowd Sensing. *The IEEE International Conference on Mobile Data Management* (2020).

[7] Fredrik Gustafsson. 2001. Adaptive Filtering and Change Detection: Gustafsson: Adaptive.

[8] Baptiste Languille, Valérie Gros, Nicolas Bonnaire, Clément Pommier, Cécile Honoré, Christophe Debert, Laurent Gauvin, Salim Srairi, Isabella Annesi-Maesano, Basile Chaix, and Karine Zeitouni. 2019. A methodology for the characterization of portable sensors for air quality measure with the goal of deployment in citizen science. *Science of The Total Environment* 708 (11 2019), 134698. https://doi.org/10.1016/j.scitotenv.2019.134698

[9] Li Liu, Yuxin Peng, Sungsune Wang, Ming Liu, and Zigang Huang. 2016. Complex activity recognition using time series pattern dictionary learned from ubiquitous sensors. *Inf. Sci.* 340-341 (2016), 41–57.

[10] E. S. Page. 1954. CONTINUOUS INSPECTION SCHEMES. *Biometrika* 41 (1954), 100–115.

[11] Amin Sadri, Yongli Ren, and Flora D. Salim. 2017. Information gain-based metric for recognizing transitions in human activities. *Pervasive Mob. Comput.* 38 (2017), 92–109.

[12] Padhraic Smyth and David Wolpert. 1998. Stacked Density Estimation. In *Advances in Neural Information Processing Systems 10*, M. I. Jordan, M. J. Kearns, and S. A. Solla (Eds.). MIT Press, 668–674. http://papers.nips.cc/paper/1353-stacked-density-estimation.pdf

[13] Apichon Witayangkurn, Teerayut Horanont, Natsumi Ono, Yoshihide Sekimoto, and Ryosuke Shibasaki. 2013. Trip reconstruction and transportation mode extraction on low data rate GPS data from mobile phone. (2013), 1–19.

[14] David H Wolpert. 1992. Stacked generalization. *Neural networks* 5, 2 (1992), 241–259.

[15] Yu Zheng, Yukun Chen, Quannan Li, Xing Xie, and Wei-Ying Ma. 2010. Understanding Transportation Modes Based on GPS Data for Web Applications. *TWEB* 4 (01 2010). https://doi.org/10.1145/1658373.1658374

[16] Yu Zheng, Quannan Li, Yukun Chen, Xing Xie, and Wei-Ying Ma. 2008. Understanding mobility based on GPS data. In *UbiComp*.

[17] Zhi-Hua Zhou. 2012. Ensemble Methods: Foundations and Algorithms.