Machine Learning for a Context Mining Facility

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***Abstract*—This paper considers generalizing context reasoning capabilities through a context mining facility offered by any Information System application. This facility requires mining context data at the system scale, which raises several challenges for Machine Learning approaches used for such mining. Through a detailed literature review, we analyze these approaches with regard to the requirements of such a context mining facility, pointing the potential and the limitations of this perspective.**

Keywords—context mining, context data, machine learning

I. Introduction

Observing the physical environment and gathering context information is no longer a challenge. The development of IoT technology and smart devices makes it now possible to easily collect multiple information about users and their surrounding environments. In Information Systems (IS), these data can be exploited for decision making as well as for adaptation and automation purposes.

Facing the potential offered by context data, Information Systems might now consider context support as a facility, i.e. as a service offered by the system itself to its applications. Viewing context provision as a facility represents an important shift from the traditional context support paradigm. Instead of considering context data for particular applications with precise goals, it becomes necessary to gather as much data as possible and provide appropriate reasoning mechanisms for current but also future applications (i.e. consumers of the context facility).

This new vision brings interesting challenges for context support. Besides obvious issues related to storage, privacy, security and legal issues, the massive availability of context data also raises some questions regarding Machine Learning (ML) approaches. Indeed, the added value of such context data relies on the capability of extracting knowledge from it, by mining such data for applications, organizations and individuals. Some features of context data, when considered at an Information System scale, may represent a challenge for ML techniques. First of all, context data is uncertain and heterogeneous by nature. Missing and potentially erroneous data from several different formats should be expected. Quality of data cannot be assured, since it depends on unpredictable environment events (e.g. device or network failure, low battery, human intervention, etc.). Besides, context data is evolutive: new sensors and context sources, with different data types and formats, may integrate the system, while others may disappear. Under such conditions, traditional ML tasks, such as selecting features, identifying relevant testing and training sets, labelling data or just training, may become complex.

As mentioned earlier, thinking of context as a facility implied collecting data not only for a precise application, but for several potential consumers, including future ones. Therefore, the use of such context facility being varied, different ML approaches may be considered. For example, extracting indicators (KPI) and tendencies for stakeholders in business organizations will not necessarily use the same approaches as providing context reasoning to applications for runtime adaptation. Different approaches are necessary and it is important to understand the behaviors and drawbacks of ML approaches confronted to evolutive, uncertain and heterogeneous context data at a large scale.

In this paper, we study the opportunity of integrating ML approaches as part of a context mining facility, transforming context support into a service offered by Information Systems to their applications and users.

The remaining of this paper is organized as follows: Section II presents challenges of such context mining facility, while Section III discusses the use of ML approaches on context data. In Section IV, we discuss the applicability of such approaches to this facility view, before concluding in Section V.

II. Towards Context Mining as Facility

Numerous context-aware applications in the literature use ML techniques for reasoning or "mining" context data and for extracting meaningful information from these data. Examples include applications in health care [1], smart cities [2] and IoT [3] [4], just to cite a few. Most of these focus on specific applications, and demonstrate the interest of applying ML approaches to context data. For example, reasoning mechanisms may allow applications to detect or anticipate particular situations and to adapt their behavior accordingly [5] [6] [7].

Moreover, with the growing development of Internet of Things (IoT) and sensing technologies, gathering context data becomes easier, and the potential of mining such data only starts to be foreseen, particularly for Information Systems. In such systems, mining context data may have multiple uses: adaptation of system behavior and applications, recommendation of actions or data, anticipation of user's needs, and decision making [8] [9]. With the availability of context data, we may expect a generalization of this kind of "smart" behavior, built upon mining solutions. For [10], we can already observe a trend toward increasingly sophisticated systems, coined as "intelligent", "context-aware", "adaptive", "situated", etc., for which the notion of 'context' is central: they are aware of the context that they are used in, and intelligently adapt to this context at runtime.

However, generalizing such smart behavior implies generalizing context mining to the whole Information System. Only making available context data for the applications composing such system is not enough, since the cornerstone of this expected smart behavior remains the capability of reasoning (and mining) such data. Instead of collecting and mining context data application by application, such tasks will benefit from being integrated to the Information System as a facility, i.e., as a service offered by the system to whatever application that needs it.

Considering context mining as an Information System facility implies an important switch in the way context support is currently handled, since the system scale changes drastically. We no longer consider single applications, with precise goals and data, but offer service for a full ecosystem of users (stakeholders, employees, customers, etc.) and applications supporting different business processes. When considering a given application, its developers/designers may define precisely what context data will be considered, the processing steps these data need and the most adapted ML technique to apply considering these data and the application purposes. If we consider a service at the Information System scale, we cannot focus on a single purpose, neither predefine the set of context data to be used, since the same service is supposed to be available to many different applications. It is supposed to satisfy the needs of the current applications, considering currently available sources of context data, but also consider future source of data and the needs of future applications and users.

More than ever, context support has to evolve to scale up to the Information System scale. Previous works on context-aware computing have considered the evolution of context sources through middleware and context models allowing new sources, data types and formats to be easily added [11] [12] [13]. However, the same does not necessarily apply to reasoning mechanisms. Indeed, as we will discuss in Section III, ML approaches usually consider specific data, which are formatted and prepared appropriately, according to the algorithms that will be applied. Those algorithms may also vary according to the purpose of the analysis (prediction, classification, etc.).

Thus, considering context mining as a facility involves overcoming such specificities in order to propose a general service, which must also cope with context data characteristics. Context-aware computing literature [11] [14] highlights multiple features of context data, summarized in Table I, which make such data particularly challenging for some ML approaches. Context data is naturally uncertain and incomplete; it may contain errors and be very dynamic; it is heterogeneous, including different formats (numeric and symbolic, structured and unstructured, etc.), types and sources; it may be observed using different frequencies or be pushed up by its sources (i.e. sensors). The sources of these data may also vary, as new sources can integrate the system, while others may disappear (temporarily or definitely). All this suggests new data and potentially new data format for ML algorithms, which may be unable to handle them.

TABLE I. CONTEXT DATA MAIN CHARACTERISTICS

Characteristic	Definition
Uncertainty	Context data may contain errors and imprecisions. Data quality cannot be assured.
Incompleteness	Context data may be missing; we cannot guarantee that 100% of possible observations have been recorded.
Heterogeneity	Context data may be gathered by multiple sources, using multiple formats even for the same data.
Dynamicity	Context data may evolve quickly; new data may arrive frequently, and data may be observed with different frequencies.

Besides, considering context mining as a facility implies other requirements that may also impact different reasoning techniques and notably those based on ML approaches (see Table II).

TABLE II. REQUIREMENTS FOR A CONTEXT MINING FACILITY

Requirement number	Definition
R0	Guaranteeing security and privacy of context data.
R1	Supporting context data characteristics (Table I).
R2	Supporting multiple heterogeneous context data sources.
R3	Supporting the evolution of context data sources and formats; new unexpected or non-predefined context sources and formats should be easily integrated in the system.
R4	Supporting dynamicity of context data sources; these sources may become offline unexpectedly, for small or large periods of time, they may also totally disappear, and other new sources from known and unknown formats and data types may integrate the system.
R5	Supporting online processing; Information System should remain constantly running, and since critical applications may depend on context data, high availability is mandatory for supporting system applications.
R6	Working with no or little human intervention; considering frequent human intervention for keeping the system running, for cleaning or preparing new context data is unfeasible considering the volume of data, the dynamicity of the data set and the need for availability.

As we observe in Table II, these requirements consider a heterogeneous and constantly evolving data set formed by observed context data. Under such conditions, it is difficult to assume a previous knowledge about these data, and stopping the system for pre-treatment or data preparing may be costly or have important consequences for system applications using the service.

Therefore, it is necessary to examine the impact of these requirements on ML approaches in order to generalize the smart behavior promoted by context-awareness at an Information System scale. In order to tackle this issue, we analyzed how ML approaches are currently used for mining context data and their requirements for correctly analyzing these data. Our goal is to evaluate whether our view of context mining facility is possible and which challenges should be tackled for applying ML approaches to context data at this scale.

III. Using Machine Learning for Context Mining

As explained previously, the vision we propose of context as an Information System facility requires the collaboration of several research areas, among which Context-aware Computing and ML. We have therefore considered various research communities for our literature review. We have first studied the articles published at the CoMoRea workshop, as it is dedicated to context modeling and reasoning. The papers we have selected from this conference reflect very interesting contributions. We have however noticed that many of them are application-specific (and therefore context-specific), and we tried to look for more general solutions. Moreover, the justification of choice of the algorithm used for the reasoning part is not always very detailed.

We have thus widened the spectrum of our literature review in order to include the ML and IoT communities. Instead of focusing on specific conferences, we have performed keywords-based queries like "context prediction" and "context awareness", with a precision on the research area, like "ML", "data mining", or "IoT". We have discarded papers published before 2013 as we wanted to focus on recent works. These keyword-based queries returned more than 200 research papers. We read their abstracts and selected those who went further than merely "provide context data" but also included some reasoning or mining mechanisms. Among the remaining articles, we focused on the approaches that seemed appropriate in terms of scalability and discarded some rule-based or ontology-based solutions, focusing on works using ML approaches.

Following this methodology, we finally selected 30 papers that we analyzed in depth. These papers have been published in various communities, covering a large spectrum of expertise. About 20% come from the context modeling and reasoning community; 23% from sensors and mobile networks area; 20% have been published in ML journals of conferences. Finally, 20% come from generalist computer science sources and about 10% from areas outside the computer science fields, such as biomedicine or social sciences. We therefore met our goal of transdisciplinary study. As mentioned earlier, all papers have been published since 2013; half of them have even been published since 2016.

Whatever the paradigm adopted (supervised, unsupervised, semi-supervised or reinforcement learning [15] [16]), ML is about selecting an algorithm and training it on some data. The effectiveness of a given method depends on various factors, such as the quality of the training data, the chosen algorithm and its hyperparameters. Low quality data may compromise the success of the most powerful ML algorithms [17] [18]. Raw data obtained from heterogeneous sensors can be noisy, scattered and even incomplete. This data may lead to various difficulties such as increased processing time, higher model complexity and overfitting.

In order to address these problems, many studies in context recognition include a pre-processing step. For example, in [7], the authors proposed a general context prediction structure based on a pre-processing phase and a context prediction phase. In [15], the authors presented a framework based on four steps: data processing, feature set generation, model selection and model combination for predicting the consumption of air conditioning in residential buildings. We detail frequently-used pre-processing tasks below.

Data cleaning techniques use one or more filters to identify noisy data and to correct or delete them [19] [20] [21]. They can also process missing values and detect outliers [15] [22].

Data transformation methods modify data representation to make them suitable as model inputs. They involve digitalization and normalization: digitalization encodes qualitative data into numerical data. Indeed, some algorithms can work directly with qualitative data such as K-Nearest Neighbors (KNN), Naive Bayes (NB), Decision Tree (DT), Random Forest (RF), etc. However, many require numerical input and output variables to operate properly. Normalization modifies the values of numerical data into a common scale. In deep neural networks, if numerical data do not have similar ranges of values then they will have a negative influence on gradient descent optimizing methods, with a smaller learning rate [22] [23].

Feature extraction and selection techniques allow the identification of relevant information and help remove as much irrelevant and redundant features as possible from raw data. If there are not enough informative features, the model will not be able to accomplish its task. If there are too many features or irrelevant ones, then the model will be more resource consuming and hard to train; practitioners agree that most of the time in building a ML pipeline is spent on feature engineering [24].

Data augmentation methods create additional training samples since some ML algorithms such as deep neural networks need a huge amount of data to learn effectively [25]. However, collecting such training data is often expensive and laborious.

Unbalanced data processing methods are used to address the problem of class imbalance (i.e. when there is a disproportionate ratio of instances in each class) [26]. In real word problems data sets are generally unbalanced, and the models learned from these data can have good accuracy on the majority class but very poor accuracy on other classes.

These different techniques are used in several research studies for context modelling and recognition. In Table III, we compare the solutions we have found in the selected papers according to the data processing mechanisms implied by each work, as well as the ML approach that has been used. We give special attention to the following steps in data pre-processing: cleaning (*c1*), transformation (*c2*), feature extraction and selection (*c3*), data augmentation (*c4*), and processing of unbalanced data (*c5*). Regarding the ML approach, we indicate the algorithm(s) (*c7*) that have been used. We also report whether or not the authors mentioned hyperparameters tuning (*c6*). Setting hyperparameters can improve the performance of algorithms. Only 67 % of papers appear in Table III as we discarded the survey papers, which did not describe original experimentations.

TABLE III. *COMPARATIVE OVERVIEW OF CONTEXT RECOGNITION APPROACHES BASED ON MACHINE LEARNING*

Ref.	Data criteria					Reasoning criteria	
	c1	*c2*	*c3*	*c4*	*c5*	*c6*	*c7*
[20]	✓	×	✓	×	×	✓	SVM
[27]	×	×	✓	×	×	×	KNN, Gaussian Naive Bayes, DT, RF, RMD
[28]	×	✓	✓	×	×	×	NB, DT, RF, SVM, KNN, Adaptive Boosting, LR, ANN
[29]	✓	✓	✓	×	×	✓	MLP
[30]	✓	✓	✓	×	×	×	NB, ANN, Bayesian Network
[31]	×	×	✓	×	×	✓	KNN
[32]	×	×	✓	×	×	×	KNN, NB, RF
[33]	✓	×	✓	×	✓	×	NB, DT, LR, Adaboost, SVM
[15]	✓	×	✓	×	×	✓	Support Vector Regression, Ensemble tree, ANN
[34]	×	×	✓	×	×	×	RF, SVM, NB, Random Tree, Bayesian Network
[35]	×	×	✓	×	×	×	DT, MLP, LR
[36]	✓	×	✓	×	×	×	MLP, SVM, LogitBoost
[37]	×	×	✓	×	×	×	RF
[19]	✓	×	✓	×	×	✓	RF
[21]	✓	×	×	×	×	✓	CNN+ symbolic model
[25]	×	✓	×	×	×	✓	CNN
[23]	✓	✓	×	×	×	✓	CNN+ LSTM
[22]	×	×	×	✓	✓	✓	CNN
[26]	×	×	×	×	✓	×	RNN
[38]	×	×	×	×	×	✓	CNN

(×) No (✓) Yes

We note that the authors of [20] propose a multi-class Support Vector Machine (SVM) based on features extracted from both an accelerometer and a gyroscope after a pre-processing for noise reduction with a median filter and Butterworth filter. In [27], the authors propose a multi-class classifier to determine the position of smartphones in different contexts of use. They apply KNN, Gaussian Naive Bayes, DT, RF and Random Mixture Model (RMD), and report that KNN provide better performance than the other algorithms. For data pre-processing, the approach is based on a windowing step and a feature extraction step. In [29], the authors suggest a cognitive adopted framework based on genetic algorithm to extract relevant features from IoT raw data and a Multilayer Perceptron (MLP) to classify these data in smart industrial applications.

To obtain better performance, several studies use ensemble methods such as [15] that combines the predictions of three models resulting from Support Vector Regression, Ensemble Tree and Artificial Neural Network (ANN) algorithms for predicting the consumption of air conditioning in residential buildings. To ensure that their data meet the input requirements of the models, they perform a linear interpolation for missing and incorrect data. Then, to select the right feature set, they use a statistical measure. In [34], the authors propose an approach for detecting the current transportation mode of a user from his/her smartphone sensors data. They propose to divide the collected data into consecutive non-overlapping time sequences and to extract four features for each sequence and each sensor. Then, they combine multiple learners to improve their performance. In [35], the authors present an ensemble method that combines the predictions of three models resulting from DT, MLP, and Logistic Regression (LR) for human activity recognition. To determine the class of a new activity, they consider the predictions (i.e. classes) of the three models, and choose the class with the highest number of votes. Their results show that ensemble learning can achieve significant improvements for activity recognition when compared to what each learning algorithm can achieve individually. The same problem is also investigated in [36]; in this case, however, the authors combine the results of other classifiers such as MLP, SVM, and LogitBoost. In addition, they use a clustering method to select 18 relevant features from 24 features and they obtain a good accuracy of 91.15%. In [19], the authors introduce a multi-class classification approach based on ultra-wide band sensor measurements and RF to detect when old people fall down. The pre-processing phase includes filtering, feature extraction, stream windowing, change detection and buffering. The classifier gives the lowest error rate by setting the number of trees at 200.

To extract relevant features without effort and improve their performance, several studies use different deep neural networks architectures. The authors in [22] [25] [38] [39] [40] propose a Convolutional Neural Network (CNN) allowing feature extraction and classification for human activity recognition. The same problem is also investigated in [23], where the authors propose a generic deep framework for activity recognition based on convolutional and Long Short-Term Memory (LSTM) recurrent units. In [31], the authors present a learning deep features for KNN to improve the classification performance. In these works, it is not necessary to extract the hand-crafted features or to use statistical methods or frequency transformation coefficients [31], as deep features can be extracted using deep learning approaches. The first layers of networks extract features that the following layers will combine to form increasingly complex and abstract concepts.

To ensure the performance of deep learning networks, the authors of [23] pre-process sensor data to fill in the missing values by linear interpolation and to perform channel normalisation at the interval [0,1]. For [22], a normalization step is required for the raw signal extracted from the accelerometers to have a common scale. They propose to apply a mean-zero normalisation. In [25], the authors use data augmentation methods such as Gaussian noise to artificially create new training data from existing learning data. In [26], the authors present a Recurrent Neural Network (RNN) based on a windowing approach for human activity recognition. They apply a synthetic minority over sampling technique to deal with the class imbalance problem.

In the next section, we analyze lessons learned from these ML approaches face to the challenges proposed by a context mining facility.

IV. Machine Learning Approaches face to Context Mining Challenges

The comparative table we proposed above (Table III), based on our literature review, allows us to make several observations. We observe that the authors from context and from sensors/mobile networks communities are up to date with regard to the state of the art in ML solutions. Indeed, there is no striking difference in the algorithms used in those communities as compared to the ML one. However, we notice that most of these “non machine learning experts” used the algorithms without mentioning any hyperparameters tuning phase. This may suggest that they could benefit from experts help in this area to better use existing ML solutions, notably considering the use of hyperparameters. Besides, we can note that deep learning solutions (among which CNN, frequently seen in Table III) are becoming more and more popular. Indeed, one of their strengths is that they allow skipping the feature extraction and selection step. Moreover, these approaches can handle large volumes of data, which is one of the requirements for context data.

Another observation we can make is that very few works consider the variety of context data and take into account all their features. The approaches we have reviewed apply ML techniques to subsets of very specific data, such as a predefined set of sensors.

As we may observe in Table III, ML approaches illustrated by our literature review heavily rely on data pre-processing phases. The quality of these approaches depends on these phases, which may be mandatory in some cases. Focusing on precise context data allows the execution of these pre-processing phases, since data types and formats are known in advance. However, when considering requirements highlighted on Table II, we may note that the execution of such phases cannot be guarantee. Since new context data sources and formats can join the system at any moment, these pre-processing phases can be put in question. On the one side, if these phases are not reconsidered, new relevant data may remain ignored and context data unexplored. On the other side, stopping the facility for re-executing those may also present an important drawback since critical applications may depend on it.

TABLE IV. Estimation of the Impact of context mining facility requirements on ML data criteria

ML Data criteria	Context mining facility requirements					
	R1	R2	R3	R4	R5	R6
Cleaning	😐	😐		😐	😐	😐
Transformation	😐	😐	😐		😐	
Feature extraction		😐	😐	😐	😐	😐
Data augmentation	😐		😐	😐	😐	
Proc. unbalanced data	😐		😐	😐		

(😐) Negative impact estimated

Table IV confronts context mining facility requirements summarized in Table II, and ML practices reported in Table III (since we do not analyze security and privacy aspects here, requirement R0 is not considered on Table IV). We may observe that requirements on Table II make harder the applications of some steps preconized by most of the approaches previously discussed. For instance, processing unbalanced data can be challenging when considering context data characteristics (R1), and notably uncertainty and incompleteness. Similarly, feature extraction and selection can be complex without human intervention or previous knowledge about the data. To sum up, Table IV highlights the fact that, although ML algorithms proved to be useful for mining precise context data, the overall process necessary for applying those can be challenging when considering a large scale.

V. Conclusions

Recent advances in middleware solutions allow to integrate new context data sources at runtime [41] [42]. The availability of such data raises relevant questions: how can ML algorithm exploit these data? How to make available such reasoning capabilities to whatever application on an Information System? How to make ML approaches scale up to a system (and not a precise application) scale?

In this paper, we proposed a literature review of works applying ML techniques to context data. By analyzing these works, we could observe that several approaches are not enough general and often focus on precise kinds of context data, ignoring all the heterogeneity of such data. Most of these works considers context data as a “traditional” data, and do not take enough into account the characteristics of such data. Besides, the scale involved on a context mining facility also imposes some requirements, since we cannot keep thinking on a precise application, but open the possibility of an evolving set of applications/customers and context data.

All these points highlight the challenges of applying traditional ML process in the case of a context mining facility. Although challenging, the use of ML for reasoning on such facility is not impossible. The potential of generalizing such reasoning capabilities is huge on different domains, such as Smart cities and Industry 4.0. We are convinced that a stronger collaboration between ML experts and context specialists could help make ML solutions more flexible and adapted to context data, and further helping reaching the full potential of context data on large Information Systems.

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