Machine Learning Technologies in Smart Spaces

Somia Belaidouni
MMS Laboratory, Quebec University,
École de technologie supérieure
Montréal, Canada
email :belaidounisoumia@yahoo.fr

Moeiz Miraoui
High institute of applied sciences and technology
University of Gafsa, Tunisia
email: moeizmiraoui@gmail.com

***Abstract*— Context-awareness is a key element for building a smart environment that responds to users needs. The goal of such environment is to provide proactively services according to the demand of users by considering the user's context information. Machine learning techniques can provide several benefits. They can be applied in many context-aware systems to help provide services. They have the possibility to make better prediction and adaptation than other techniques. In this paper, we present the main goals of machine learning and some learning algorithms applied in smart space.**

Keywords-context-awareness; smart environment; machine learning; prediction; adaptation; performance.

I. Introduction

A smart environment can be defined as an environment that is able to acquire and apply knowledge about the environment and its inhabitants in order to improve their experience in that environment [1]. In effect, such environment can perceive the state of the space using sensors, analyzes the state using learning and reasoning techniques and adapt behaviors according to users in order to provide easy daily life by increasing their comfort. Dynamism and complexity are very important characteristics in smart spaces [2]. Indeed, there are different devices networked via an infrastructure of heterogeneous access technologies. Also, the user behaviour or preferences may change at any time.

In addition, the awareness of context is a key feature to develop an adaptable smart system which has the ability to sense and to react according to context modifications. Also, smart space should be able to control and to adapt services automatically with minimum user intervention. Machine learning techniques have been widely used for this objective. Machine learning as a domain capable of supporting the solution of complex problems is able to provide significant help [3]. These algorithms can be applied in a predictive sense or to investigate internal relationships of a dataset [4]. They can be divided into four main groups: supervised learning, unsupervised learning, semi-supervised learning and reinforcing. Each of these groups has their advantages and drawbacks and utilizes different approaches to target different goals.

This paper is organized as follows. Section 2 describes important goals of machine learning in smart environments. Section 3 shows the principal necessary phases in the learning process. Section 4 discusses the different types of machine learning and some techniques applied in smart spaces. Section 5 concludes the paper.

II. Machine Learning Goals

One important feature of smart environments is that they possess a high degree of autonomy, adapt themselves to changing environments, and communicate with humans in an easy way. Application of machine learning in context aware systems can be employed to achieve specific goals. Generally, these goals belong to 4 main classes.

A. Recognition

Several approaches already exist devoted to recognition problem to identify events or activities of users in smart environments. The activity recognition is usually done through two steps: activity pattern clustering and activity type decision [5]. In most cases, recognition problems are processed by supervised learning algorithms which assumes that a training set is consisting of a set of instances that have been properly labeled by hand with the correct output.

B. Prediction

The aim of prediction is to predict what is going to happen in the future. In a smart environment, prediction allows providing information useful for future locations and activities. It helps to predict the most probable event or subsequent activity. This type of problem can be solved by online training approach which can learn from input data over time, to predict the output data [4].

C. Adaptation

Adapting user services according to the current context aims to provide the proper services by considering the user and the environmental information. Machine learning algorithms provide several benefits for context-aware systems. Indeed, it can be applied to support reasoning, inferences and also to deal with complex or fuzzy information [6].

 ISBN: 978-1-61208-505-0

D. Optimization

Optimization is a very important feature in smart environments. It aims to increase their performance and effectiveness. It can be solved by using reinforcement algorithms that can explore idealized learning situations and evaluate the effectiveness of various learning methods [7].

III. LEARNING PROCESS IN SMART ENVIRONMENTS

Machine learning techniques used in smart environments offer major opportunities to provide context-aware services. Context-awareness is about capturing a broad range of contextual attributes (such as the user's current positions, activities, and surrounding environment) to better understand what the user is trying to accomplish, and what services the user might need [8]. In consequence, learning becomes important and indispensable for reasoning and for making the best decision. It is considered necessary for knowledge creation [9]. In addition, artificial intelligence includes several subcategories such as detection, knowledge representation and machine learning, machine perception, among others [10]. In this paper, we focus mainly on four processes namely detection, interpretation, learning and reasoning as illustrated in Fig 1. First, the detection phase is accomplished using different sensors installed in the environment in order to capture current context. After that, interpretation is done in order to interpret raw data to get a useful and significant context. After acquiring the sensed context, learning mechanisms take the useful context and try to classify and to organize the observations according to a specific algorithm. Finally, the reasoning phase allows using the context information knowledge acquired through learning to achieve its objectives.

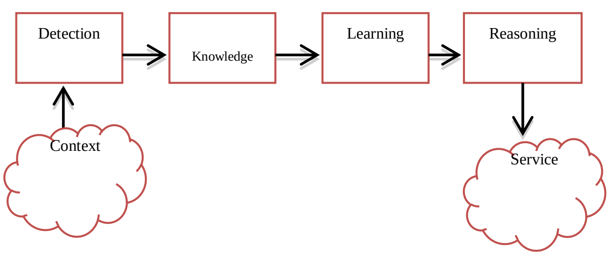

Figure 1. The main steps for learning process in a context-aware system.

IV. MACHINE LEARNING APPLICATION IN SMART ENVIRONMENTS

Diverse machine learning algorithms have been developed to cover a variety of data and problem types in smart environment. Machine learning has branched into several subfields dealing with different types of learning tasks. We give a rough taxonomy of learning paradigm. Mainly, there are four categories: Supervised learning, unsupervised learning, semi-supervised learning and reinforcing algorithms. The next section presents some learning strategies applied for different objectives in smart environment.

A. Supervised learning

Supervised machine learning is the search for algorithms that perform reasoning on externally supplied instances to produce general hypotheses, which then make predictions about future instances [11]. Mainly, supervision is provided in the form of a set of labeled training data, each data point having a class label selected from a fixed set of classes [12]. The use of the supervised activity classification approaches has shown promising results [13].

Supervised learning methods are widely used in smart environments to solve several problems. The ACHE system used neural networks and reinforcement learning to control devices [14]. Bourobou et al. [15] proposed a hybrid approach consisting of the neural network algorithm based on temporal relations and K-pattern clustering to recognize and predict user activities in IoT (internet of things) based smart environments. Neural network was used for inferring the users viewing preferences to develop a personalized contextual TV recommendation system [16]. Fleury et al. [17] used SVM (support vector machine) algorithm to classify the activities of daily living in a Health Smart Home. In [18], authors used Decision tree based on context history to infer the preferences of the user in order to provide personalized services using context-aware computing. A naïve Bayes Classifier was used to learn user activity and availability directly from sensor data according to given user feedback [19].

B. Unsupervised learning

In unsupervised learning no information about the input is given and thus the system cannot know anything about the correctness of the outcome [2]. It tries to directly construct models from unlabeled data either by estimating the properties of their underlying probability density (called density estimation) or by discovering groups of similar examples (called clustering) [20]. The use of an unsupervised approach was applied for different activities recognition in smart spaces when it is difficult to have labels for the data [21]. Authors used a statistical approach based on hidden Markov models in a regression context for the joint segmentation of multivariate time series of human activities. Hidden Markov models (HMM) were also used in [22] for both segmentation and recognition of 3-D Human action to enable real-time assessment and feedback for physical rehabilitation.

C. Reinforcement learning

Reinforcement learning is a learning paradigm concerned with learning to control a system so as to maximize a numerical performance measure that expresses a long-term objective [23]. Q-learning [24] is a model-free reinforcement learning method based on learning the expected utility given a state decision. Li and Jayaweera [25] proposed a Q-learning algorithm to provide a more efficient way for on-line decision making, with more flexibility and adaptiveness with relatively good performance. This algorithm was also implemented in simulation to demonstrate how the performance of the new Markov Decision Process (MDP) representation is comparable to that of a Linear Time-

Invariant (LTI) one on a reference-tracking scenario [26]. Reinforcement algorithms are used in Mavhome project [27] to acquire an optimal decision policy to automate basic functions in order to maximize the inhabitants' comfort and minimize the operating cost of the home.

D. *Semi-supervised learning*

Semi-supervised learning is a learning paradigm concerned with the study of how computers and natural systems such as humans learn in the presence of both labeled and unlabeled data [28]. The goal of semi-supervised learning is to combine a large amount of unlabeled data, together with the labeled data, to build better classifiers [29]. This category requires less human effort as well as building costs.

There are some popular semi-supervised learning models, including self-training, mixture models, co-training and multi-view learning, graph-based methods and semi-supervised support vector machines. Authors in [30] combined between supervised and semi-supervised learning to recognizing ADL (assisted daily life) activities and to provide context-aware services, such as health monitoring and intervention in different smart space.

V. PERFRMANCE COMPARISON OF MACHINE LEARNING ALGORITHMS

Machine learning algorithms that have been used for solving different problems in context-aware smart spaces generally fall into the categories of being supervised, unsupervised, semi-supervised or with reinforcement. Nevertheless, the advantages or disadvantages of each one depend on what learning algorithm wants to solve.

Neural networks are the most widely used supervised learning. Indeed, they offer a number of advantages including requiring less formal statistical training, ability to implicitly detect complex nonlinear relationships between dependent and independent variables, ability to detect all possible interactions between predictor variables and the availability of multiple training algorithms [31]. On the other hand, disadvantages include its "black box" nature, greater computational burden and proneness to over fitting. Decision trees algorithm are non-parametric algorithm and **e**asy to interpret and explain. Their main disadvantage is that they easily over fit. SVMs could work well with an appropriate kernel even when data isn't linearly separable, they have a high accuracy and nice theoretical guarantees regarding over fitting. Whoever, they are hard to interpret.

In unsupervised learning, there is no outcome measure; we observe only the features and the goal is to describe the associations and patterns among a set of input measures [32]. Its major disadvantage is the lack of direction for the learning algorithm and that the absence of any interesting knowledge discovered in the set of features selected for the training. Clustering is a form of unsupervised learning that consists of finding patterns in the data by putting each data element into one of K-clusters, where each cluster contains data elements most similar to each other [33].

Semi-supervised learning is an interesting field. It is a hybrid between clustering and supervised learning, potentially useful on scenarios where labeling effort is not ready available or expensive. These algorithms try to solve a supervised learning approach using labeled data, augmented by unlabeled data. So, by adding cheap and abundant unlabeled data, one is hoping to build a better model than using supervised learning alone.

Reinforcing learning algorithms learn more control policies, especially in the absence of a priori knowledge and a sufficiently large amount of training data. However, they suffer from a major drawback: high calculation cost because an optimal solution requires that all states be visited to choose the optimal one.

VI. CONCLUSION

In this paper, we have discussed the importance of the use of machine learning techniques in context-aware systems. We have presented the major goals of learning methods. We have also shown the main steps to achieve the learning process in context-aware smart spaces. This process must acquire the context of the environment to be able to adapt services to users according to the current context. A discussion of the most important and commonly used learning algorithms was provided to solve different problems in smart environments.

REFERENCES

[1] S. K. Das, D. J. Cook, "Designing and modeling smart environments," Proceedings of the 2006 International Symposium on on World of Wireless, Mobile and Multimedia Networks. IEEE Computer Society, pp. 490-494, 2006.

[2] S. Stenudd, "Using machine learning in the adaptive control of a smart environment," Utigivare, Vuorimiehentie, 2010.

[3] A. Smola and SVN. Vishwanathan, "Introduction to machine learning, " Cambridge University, UK, vol. 32, pp.34, 2008.

[4] A. J. Stimpson, "A machine learning approach to modeling and predicting training effectiveness, ". Thèse de doctorat. Massachusetts Institute of Technology, 2015.

[5] S. T. M. Bourobou and Y. Yoo, "User activity recognition in smart homes using pattern clustering applied to temporal ann algorithm, " Sensors, vol. 15, no 5, pp. 11953-11971, 2015.

[6] V. G. Motti, N. Mezhoudi and J. Vanderdonckt, "Machine Learning in the Support of Context-Aware Adaptation, ". In : CASFE. 2012.

[7] R. S. Sutton, A. G. Barto and G. Andrew, "Reinforcement learning: An introductio, " Cambridge : MIT press, 1998.

[8] WP. Lee, "Deploying personalized mobile services in an agent-based environment, " Expert Systems with Applications, vol. 32, no 4, pp. 1194-1207, 2007.

[9] G. D. Bhatt and J. Zaveri, "The enabling role of decision support systems in organizational learning, ". Decision Support Systems, vol. 32, no 3, pp. 297-309, 2002.

[10] M. Bkassiny, M. Li and S. Jayaweera, "A survey on machine-learning techniques in cognitive radios," IEEE Communications Surveys & Tutorials, vol. 15, no 3, pp. 1136-1159, 2013.

 ISBN: 978-1-61208-505-0

[11] S. B. Kotsiantis, I. Zaharakisand P. Pintelas, "Supervised machine learning: A review of classification techniques," 2007.

[12] T. Mitchell, "The role of unlabeled data in supervised learning, " In :Proceedings of the sixth international colloquium on cognitive science. pp. 2-11, 1999.

[13] K. Altun, B. Barshan and O. Tuncel, "Comparative study on classifying human activities with miniature inertial and magnetic sensors," Pattern Recognition, vol. 43, no 10, pp. 3605-3620, 2010.

[14] M. C. Mozer, "The neural network house: An environment hat adapts to its inhabitants," In : Proc. AAAI Spring Symp. Intelligent Environments, 1998.

[15] S. T. M. Bourobou and Y. Yoo, "User activity recognition in smart homes using pattern clustering applied to temporal ann algorithm, " Sensors, vol. 15, no 5, pp. 11953-11971, 2015.

[16] S. H. Hsu, M. H. Wen and M. H. Lee, "A personalized TV recommendation system, " In : European Conference on Interactive Television. Springer Berlin Heidelberg, pp. 166-174, 2007.

[17] A. Fleury, M. Vacher and N. Noury, "SVM-based multimodal classification of activities of daily living in health smart homes: sensors, algorithms, and first experimental results, " IEEE transactions on information technology in biomedicine, vol. 14, no 2, pp. 274-283, 2008.

[18] J. S. E. Hong and J. Kim, "Context-aware system for proactive personalized service based on context history, " *Expert Systems with Applications*, vol. 36, no 4, p. 7448-7457, 2009.

[19] M. Muhlenbrock, O. Brdiczka and D. Snowdon, "Learning to Detect User Activity and Availability from a Variety of Sensor Data, " In : PerCom. pp. 13-22, 2004.

[20] G. T. Chen, S. haxun, X. Tao, "An unsupervised approach to activity recognition and segmentation based on object-use fingerprints, " Data & Knowledge Engineering, vol. 69, no 6, pp. 533-544, 2010.

[21] D. Trabelsi, S. Mohammed, F. Chamroukhi, "An unsupervised approach for automatic activity recognition based on hidden Markov model regression, " IEEE Transactions on Automation Science and Engineering, , vol. 10, no 3, pp. 829-835, 2013.

[22] F. LV and R. Nevatia, "Recognition and segmentation of 3-d human action using hmm and multi-class adaboost, ". In : European conference on computer vision. Springer Berlin Heidelberg, pp. 359-372, 2006.

[23] C. Szepesvari, "Algorithms for Reinforcement Learning (Synthesis Lectures on Artificial Intelligence and Machine Learning, " Morgan and Claypool, 2010.

[24] C. Watkins and P. Dayan, "Q-learning. Machine learning, " vol. 8, no 3-4, pp. 279-292, 1992.

[25] D. Li and S. K. Jayaweera, "Reinforcement learning aided smart-home decision-making in an interactive smart grid, " In : Green Energy and Systems Conference (IGESC), pp. 1-6, 2014.

[26] E. C. Kara and M. Berges and B. Krogh, "Using smart devices for system-level management and control in the smart grid: A reinforcement learning framework, " In : Smart Grid Communications (SmartGridComm), IEEE Third International Conference on. pp. 85-90, 2012.

[27] D. J. Cook, G. M. Youngblood and E. O. Heierman, "MavHome: An Agent-Based Smart Home, " In : PerCom. pp 521-524, 2003.

[28] X. Zhu, A. Goldberg, "Introduction to semi-supervised learning. Synthesis lectures on artificial intelligence and machine learning, vol. 3, no 1, pp. 1-130, 2009.

[29] X. Zhu, "Semi-supervised learning literature survey, ". 2005.

[30] D. j. Cook, "Learning setting-generalized activity models for smart spaces, " IEEE intelligent systems, vol. 2010, no 99, pp. 1, 2010.

[31] J. V. Tu, "Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes, " Journal of clinical epidemiology, vol. 49, no 11, pp. 1225-1231, 1996.

[32] M. Ramon, F. M. Pastor and O. L. G. A. Felipe, "Taking advantage of the use of supervised learning methods for characterization of sperm population structure related with freezability in the Iberian red deer, ". Theriogenology, vol. 77, no 8, pp. 1661-1672, 2012.

[33] B. Wooley, "Scaling Clustering for the Data Mining Step in Knowledge Discovery, ". 1999.