A Survey To Location-Based Context Prediction

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Abstract. In recent years, beginning with the Neural Network Home Project, several approaches addressing context prediction have been published. This paper gives an overview of the conducted research in the field of predicting location-based context information published during the last 14 years. The location of a user or an object offers the most important and common context information and is easy to collect using modern smartphones. Therefore it is likely to be the most relevant and attractive context information new researches might be interested in. Research works discussed in this paper are evaluated with regard to aspects concerning to the data sets the authors used for the evaluation of their prediction approaches. Finally, a comparison of three state of the art context prediction approaches with three popular data mining techniques with respect to their prediction accuracy is presented. The approaches are applied to four different data sets containing location based context information.

Keywords: context prediction, state of the art, overview, location prediction, prediction algorithms

1 Introduction

The prediction of contexts utilising user related information has been an important demand in research for almost 14 years.

Context prediction techniques enable user related systems to act proactive to current actions of the user by utilising recorded behaviour patterns of the user to infer her next action. Therefore, context prediction approaches can make users' live simpler, more comfortable or even more secure.

The first fundamental work in the field of context prediction has been published by C. Mozer during the Neural Network House project [15]. In this project user related information was utilised for the first time to proactively adapt the house to their needs.

Since then, context prediction has been applied to a wide range of application fields like e.g. home automation systems [3], outdoor and indoor location prediction systems [2, 19], the construction of general prediction frameworks [13] or to systems that uses location-based services [32].

Context information of a user combined to a user's context history represent the basis prediction approaches need to make reliable forecasts. Normally, context information is gathered from the following sources: standalone sensors (e.g.

temperature sensors, RFID sensors, movement sensors or cameras); built in ubiquitous environments such as smart homes; sensors built in mobile phones (e.g. GPS sensor, acceleration sensor, gyroscope sensor, etc.); information extracted from electronic devices (calendar information, e-mails, contact information, etc.). But in general every information that can be used to characterize a situation of a person, place or an object [5] can be used by context prediction algorithms.

Compared to the early beginnings of research activities in context prediction when ubiquity of sensor information was still limited by their number, their measurement accuracy and their portability current sensor technologies and the power of external systems to process their information, offers a wide range of possibilities to use context information.

Based on the increasing number of small and inconspicuous sensors that penetrate our living spaces like cars, smart rooms or public facilities, it is likely that the importance of context prediction will increase to provide reliable proactiveness and self-adaptivity of services in these environments. Therefore, the prediction of future contexts is and will be a research field, which is interesting to current and upcoming researchers. This applies particularly for location-based context prediction. This is due to the fact that most available services like e.g. car navigation systems are interested in knowing the future whereabouts of the user in advance.

To the best of our knowledge there does not exist an overview of existing state of the art in location-based context prediction. For this reason this paper gives a motivating overview of past and current research works and projects in this field to help bridge the survey gaps. Further, the presented research works are evaluated with regard to different aspects and state of the art context prediction approaches are compared with machine learning algorithms using different data sets.

The rest of the paper is structured as follows: Section 2 provides a broad overview of existing state of the art in indoor and outdoor context prediction. Further, research works are compared to aspects referred to the data sets the authors used for the evaluation of their prediction approaches. Section 3 compares three state of the art prediction approaches with three well-known data mining techniques using four different data sets containing location-based data. Finally, the conclusion is given in Section 4.

2 State of the Art

Over the past few years there have been published a large number of interesting research works with focus to context prediction techniques in general. These scientific works have covered a wide range of different application fields. The prediction of future vehicular traces [9]. The prediction of pedestrian next paths [33]. The development and the investigation of new suitable approaches to predict next context information [6], [24] and [28]. The examination and the development of so called context prediction frameworks [13]. A framework is able to perform the necessary steps in an automated way that are comprised by a context prediction task like gathering the context data, pre-processing the context data and the prediction process itself. Further, there exist several research works that discusses other aspects that are of concern for context prediction like e.g. its legal effects [31]. The main areas we will discuss in this survey are the predictions of a user's next movement or location based on her current whereabouts in indoor and outdoor locations. We evaluated the presented approaches in these two areas with regard to the aspects presented in Table 1.

abbreviation	aspect
collect own data	did the authors collect their own data?
data extensive	did the authors specified how extensive their used data set is?
used pub. data	did they use publicly available data sets?
used sim. data	did they use simulated data?
prob.	did they mentioned problems they faced during collecting the data?
published data	did the authors publish their data set?
compare approach	did the authors compare the approach to existing approaches?
published approach	did the authors make their approach available for public?

Table 1. Describes the different aspects used for the evaluation of the data sets.

2.1 Location Context Prediction

Forecasting the user's possible next locations has been the application field with the highest attention in context prediction over the past few years. Therefore, published research works mostly deal with indoor prediction, outdoor prediction or with a combination of both.

One reason that research has been mainly focussed to next location prediction is that current whereabouts of users or other objects offer the most interesting context information or rather other context information like e.g. humidity, temperature or light intensity are simply not interesting enough.

Another reason why location information has been often used is due to the fact that the location of a person or an object can easily be obtained, using WLAN, GPS, or installed motion sensors. Further, and the most important point why location based information has been so popular is that the possible next location of a user or an object is the most interesting context information that can be used to proactively adapt a service. For example a service that proactively offers information about the next place a user intends to visit.

Indoor Location Prediction So-called smart homes represent a possible applicability for indoor location prediction. Smart homes are self-contained ubiquitous entities that offer the ideal space for observing and collecting persons' behaviours and environmental features. The Neural Network House project directed by Michael C. Mozer [15] was one of the first smart home projects that included a device to forecast user actions based on their collected context information. To achieve this proactive adaption to the needs of the inhabitants an adaptive control home environment system, called ACHE was used. This system monitors the environment, collects specific information on the occupant's lifestyle (e.g. adjusting the thermostat; turning on a particular configuration of lights; preferred sound levels or the inhabitant motion activity) and attempts to find regular behaviour patterns of the inhabitants. The challenges of ACHE was anticipating inhabitants' needs and saving energy costs by automatically adapting light or air temperature or by heating rooms in advance that are likely to be occupied in the near future. The used context predictor to forecast the next actions of the inhabitants was implemented as feed forward neural networks trained with back propagation. The evaluation of the ACHE system showed that the collected behaviour patterns of the inhabitants did not show as much regularities as expected. The authors did not give a exact probability of correctness.

Similar to the Neural Network House project the MavHome project conducted by Diana J. Cook et. al [4, 3] collected environmental context information of its inhabitants. These collected context data contain the movement behaviours of the inhabitants inside the house. Afterwards these histories were used to predict the inhabitants' next location to minimize maintaining costs of the home and therefore maximising the comfort of the inhabitants. The next location predictions were made using the Active LeZi [6] context prediction approach and received an accuracy of 87%. Another approach developed in connection to the MavHome project was the Episode Discovery algorithm [7]. Episode Discovery was used to filter excessive noise from the received context data of the inhabitants. The pre-processed data was used to successfully improve the accuracy of a sequential prediction algorithm and a predictor based on a neuronal network.

In the field of indoor location prediction a vision of smart doorplates within an office building were introduced in [26]. Smart doorplates were used to notify a visitor about the potential return of an absent office owner. Based on the smart doorplates a collection of movement data of four persons over a period of several months was collected and was published in [19]. The so called Augsburger Indoor Location Tracking Benschmark data set is publicly available at the institute for pervasive computing[1] together with other context data sets. The data has been used in [19], [21] and [20] to evaluate and compare several data mining techniques like e.g., Multilayer Perceptrons, Bayesian Network, Markov Models to a State Predictor technique. The State Predictor method was first introduced in [18] and [17]. The State Predictor is motivated by branch prediction techniques of microprocessors. The accuracy received by the State Predictor showed that this new prediction approach is a competitive prediction technique compared to the well-known data mining approaches. Furthermore, the Augsburger data set was used in [27] to evaluate a context prediction technique that bases on neuronal networks. The task of this classifier was also to predict the next room a person will be present based on the history of rooms that have already been visited by this person in the past. The prediction results received by the proposed tech-

[1] http://www.pervasive.jku.at/Research/Context_Database/

niques were quite similar to the results presented in [19], [21] and [20].

An approach to infer a user's next position that additional uses future knowledge derived from contextual sources such as a user's calendar was presented in [25]. The proposed approach extends a $O(k)$ Markov predictors that directly operates on states derived from past user movements by adding knowledge of a user's potential presence at a future location. The potential presence time has been extracted from the user's calendar. The extended Markov model was evaluated in comparison with Markov models that only applied the user's movement history using the Dartmouth movement traces[2]. The gained results showed that the proposed extended Markov model outperforms classical Markov models by 6% to 30%.

Another possibility to receive persons' indoor movement data is to make use of existing wireless networks. With the help of received radio-frequency signals of different access points it is possible to identify a person's current position. In [8] the authors used a Nokia E60 mobile device to collect different radio-frequency signals. Afterwards they used a k-Nearest Neighbour (KNN) algorithm and different Linear Discriminant Analysis (LDA) algorithms to predict the user's current position. The prediction task was performed directly on the mobile phone. The results showed that KNN achieved the highest prediction accuracy while requiring the largest training data sets and the longest execution time.

A comparison of the different introduced indoor location prediction approaches with regard to the aspects outlined in Table 1 is presented in Table 2.

ref.	collect own data	data extensive	used pub. data	used sim. data	prob.	published data	compare approach	published approach
[15]	yes	no	no	no	no	no	no	no
[4]	yes	no	no	no	no	no	no	no
[3]	yes	no	no	yes	no	no	yes	no
[6]	yes	yes	no	yes	no	no	no	no
[7]	no	yes	no	yes	N/R	N/R	yes	no
[27]	no	yes	yes	yes	N/R	N/R	no	no
[19]	no	yes	yes	no	N/R	N/R	yes	no
[21]	no	N/R	yes	no	N/R	N/R	yes	no
[20]	no	yes	yes	no	N/R	N/R	yes	no
[25]	no	N/R	yes	yes	N/R	N/R	yes	no
[8]	yes	yes	no	no	yes	no	yes	no

Table 2. Shows the evaluation of the different aspects related to research work in indoor location prediction.

Outdoor Location Prediction One of the first approaches that used GPS data in order to make reliable next outdoor location predictions was presented

[2] http://crawdad.cs.dartmouth.edu

in [2]. The data have been collected for a period of four months using an external GPS receiver. Afterwards the authors used a modified k-means approach to cluster the data to meaningful locations. The location history of the user was used to infer the most likely place the user will go next. For the illustration of a possible next location prediction a partial first order Markov model was outlined. The authors remarked that even with four months of data the creation of a n-order Markov model is limited to $n = 2$.

Another approach that inferred high-level movement behaviours from tracked GPS data was outlined in [16]. The authors created a data file that consists of 12 hours of GPS coordinates collected over a period of three months. This data was used to train a Bayes filter approach combined with an Expectation Maximization approach to learn the parameter of the Bayesian model. The trained model was used to recognize the current transportation mode (driving by bus, driving by car or walking) of a user. Afterwards the information was used to predict the most likely path the user will go next.

One of the first approaches that collected location-based context data in form of GSM data using a mobile phone was developed in [14] during the Context Project. The main focus of the project was the examination and the understanding of the user's current context and the usage of these context data to provide automatic inferences. Kari Laasonen et.al. developed two consecutively arranged approaches for the prediction of user movements within a GSM-Network. The first approach [14] described the automatic recognition of cell transitions, the learning of important locations and the prediction of possible important locations the user is going to enter next. Therefore, the proposed prediction approach took a sequence of recent cell transitions the find the most probable cell the user will enter next. The data were collected for six months with software that runs continuously on a mobile phone. The second approach outlined in [10] extends the first one. Instead of only predicting the possible next important location (cell) the presented approach tries to predict the whole path that a user will probably go next to reach her important place. The gained prediction accuracy varied between 70% and 90%.

While cell-based location prediction is limited to the architecture of the cellular network and therefore can not consider the geometry and the topology of the user's path, network-based location prediction using GPS can detect the user's position more precisely as outlined in [12]. In this paper two prediction approaches that uses synthetic trajectory data sets containing GPS information to predict the next path a user is likely to go were presented. The first approach adopts probabilistic information while the second approach adopts a regression-based classification technique for the trajectory prediction. The results showed that both approaches received better prediction accuracy than random prediction.

Not the prediction of a pedestrian's next movement or location was the objective in the following paper [9], but the prediction of a driver's possible next destination. Therefore, the authors collected GPS waypoints from about 200 drivers about a couple of weeks. Beyond only considering previously visited destinations the proposed Bayesian algorithm, which was performed, to run directly on a vehicle's navigation system considered also trends in the data. The prediction accuracy of the algorithm improved the closer the driver comes to his desired destination.

A comparison between different machine learning approaches for outdoor location prediction was presented in [1]. The authors compared a spatial context model with a Bayesian Network, a Decision Tree, a Rule-Induction and Instance based classification algorithm and further combined them by using voting, bagging and boosting mechanisms. The best prediction result with regard to accuracy was achieved by applying the voting approach to the spatial context model.

In most cases, existing approaches to outdoor location prediction try to forecast only the next behaviour or the next important place of a user. Therefore, they do not try to look further into the future. In [22] an approach called NextPlace is described that uses nonlinear time series not to only predict the next location but to predict the user's arrival and residence time at the next location also. To evaluate the NextPlace approach the authors used 4 different data sets. Two contain GPS-based data and two contain registration patterns of WiFi access points. The proposed approach first extracted the significant locations from the GPS data and the WiFi data. Afterwards, two time series were derived, one that contains all start times and one that contains all duration times related to visited significant locations. Subsequently, these two histories were used to prediction a user's next place, her arrival time and her residence time with an overall prediction accuracy up to 90%.

A comparison of the different introduced indoor location prediction approaches with regard to the aspects outlined in Table 1 is presented in Table 3.

ref.	collect own data	data extensive	used pub. data	used sim. data	prob.	published data	compare approach	published approach
[2]	yes	yes	no	no	yes	no	no	no
[16]	yes	yes	no	no	yes	no	yes	no
[14]	yes	yes	no	no	N/S	no	no	no
[10]	yes	yes	no	no	N/S	no	no	no
[12]	no	yes	no	no	yes	no	no	no
[9]	yes	yes	no	no	N/S	no	no	no
[1]	no	N/R	no	yes	N/R	N/R	yes	no
[22]	no	yes	yes	no	N/R	N/R	yes	no

Table 3. Shows the evaluation of the different aspects related to research work in outdoor location prediction.

Interpretation of the aspects The different indoor and outdoor location prediction approaches presented in this Section have been examined with regard to the aspects outlined in Table 1. The results are shown in Table 2 for the indoor location prediction approaches and in Table 3 for the outdoor location prediction approaches. The most interesting fact that can be noticed is that neither in the indoor prediction area nor in the outdoor prediction area a newly collected data set or a developed approach have been made publicly available.

Although existing and publicly available data set have been used in research works [19, 21, 20] to the best of our knowledge data sets which have been proposed in a paper for the first time have not been published by the authors. If an author used a data set that has previously been published to evaluated her proposed approach the aspect "published data" in Table 2 and in Table 3 has marked as not required.

Hence, it could be possibly quite difficult for interested researchers to evaluate the presented results of the different context prediction approaches. Due to this, it is also hardly possible to compare own results with already gained results in other research works. The only data sets that are publicly available and that have been used in the presented research work are the Augsburger Location Tracking Benchmark data set, the data set created during the Context Project and the data sets used in [22]. Additional data sets with regard to context prediction can be found at the so-called Context Database.

3 Evaluation

In this section we compare three context prediction techniques with three common data mining classification techniques. The reason is to evaluate on the one hand which technique performs best and on the other hand to evaluate if common and well-known classification techniques outperform algorithms specifically used in the field of context prediction. As context prediction algorithms we used the Alignment approach introduced in [23] and [24], the ActiveLeZi approach introduced in [6] and the Collaborative Context Prediction (CCP) technique presented in [28] and [29]. As data mining techniques we used a J48 tree classifier, a Bayesian Network classifier and a classifier based on Decision Tables. The context prediction approaches have been implemented by our own in Java and Matlab. The data mining algorithms have been used from the Weka Data Mining Software.

For the evaluation of the algorithms we used four different data sets. The first data set is the Augsburger data set introduced in [26]. The second data set is a slightly modified version of the Augsburger data set we call Augsburger_2. In this modified version we used a sliding window approach with a window size of four to add additional data to the data set. The third data set consists of different movement behaviours of a person. This data has been recorded using an acceleration sensor in a modern android-based smartphone [11]. The recorded data has been classified afterwards into the five different movement behaviours sitting, standing, walking, going upstairs and going downstairs of a person. The fourth data set we used for the evaluation consists of different movement paths of a pedestrian on a pavement presented in [30]. The movement paths consists of a string that represents the different coordinates of the pavement the pedestrian walked through. The movement paths have been classified using a mobile phone a pedestrian was wearing in her left trouser pocket. With the help of build-in and software sensors like gravity, accelerometer, gyroscope and orientation the direction and location changes of a pedestrian on the pavement were detected and automatically mapped to the corresponding coordinate of the pavement.

To apply the CPP approach we must use context histories of different persons because CCP only can be applied if it can take advantage of relations between the histories of at least two persons. For this reason, every data set consists of four different context histories of four different persons. For the Augsburger data set we merged the summer and the fall data of a person to one history. Altogether, the Augsburger data set also consist of four different context histories.

For the evaluation process the different context histories of a data set have been concatenated to one history that was segmented into several instances which consist of four contexts. The fourth context of the instance symbolizes the respective context that should be predicted after seeing the first three context of the instance.

All algorithms except of the CCP approach used the concatenated history. To evaluate the prediction accuracy of the different approaches we randomly picked 30% from a data set as test data. This draw was performed five times in order to obtain a mean and variance on the result. The rest was used to train the algorithms. The received averaged prediction accuracies of the algorithms are presented in Table 4.

The first three rows present the results of the data mining techniques. The second three rows the results of the context prediction approaches and Θ presents the similarity coefficient of the related data set. This coefficient specifies the similarity of the different user context histories of a data set.

	Augsburger	Augsburger_2	Movement	Pedestrian
BayesNet	55.6%	60%	69.5%	65.1%
DecissionTable	44.9%	57.5%	70%	69.8%
J48 Tree	54%	58%	70%	70%
ActiveLeZi	55%	13%	71%	72%
Alignment	55%	11%	70%	72%
CCP	28%	63%	82%	80%
Θ	0.6%	32%	23%	66%

Table 4. Prediction accuracies of the different tested prediction approaches.

The results show that the three evaluated context prediction approaches Alignment, ActiveLeZi and CCP achieved results that are slightly higher than those received by the well-known data mining approaches. Except from the Augsburger data set the CCP approach receives the best prediction accuracy. This is due to the fact that the Θ coefficient is quite low for this data set and therefore

CCP could not find existing direct or indirect relations between the histories of this data set. The modified Augsburger_2 data set which has a higher Θ coefficient because of adding data using a sliding window approach increased the prediction accuracy of almost all algorithms. Only the prediction accuracy of the Alignment and the ActiveLeZi approach drops drastically. In our opinion this might be due to the fact that using the sliding window approach comes along with adding ambiguous information to the data set which leads to a problem for algorithms that try to match a given context pattern in the user's history exactly. Overall, the results showed that prediction algorithms, which are specifically designed and used for context prediction are at least as good as the tested data mining techniques. They received even slightly better results in this evaluation.

4 Conclusion

In this paper we have given an overview of existing indoor and outdoor location-based context prediction approaches. We focused to next location prediction approaches because current whereabouts of users or other objects are the contexts that have been most frequently used by researches, since the beginning of context prediction. The presented approaches have been evaluated with regard to different aspects. The different applied aspects are related to the data sets the authors used for the evaluation of their prediction approaches. The analysis of the aspects resulted that the collected data and the proposed approaches have not been made publicly available in most cases. Therefore, it is not easy for new researchers that are interested in location-based context prediction to evaluate presented results and to make them comparable to their own results. Subsequently, we compared three state of the art context prediction approaches to three well-known machine learning algorithms using four different data sets. The results showed that the prediction approaches slightly outperformed general machine learning approaches.

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