Context Prediction by Alignment Methods

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INTRODUCTION

Context prediction is the approach to provide applications with information about future contexts. Some work has already been done on predicting future contexts based on the observed context history. The observed context timeline is analysed for typical patterns in the context history. Based on this knowledge the most probable future contexts are forecast.

The authors of [1] and [2] study prediction based on GSM cell location histories. To describe the transition probabilities from one location to the other they use a Markov predictor and a weighted graph respectively. In [3] Unix shell commands are predicted by a simple pattern matching method. The authors in [4] propose a state predictor method which is a variation of a Markov predictor. A decent overview of context prediction is given by Mayrhofer in [5]. Mayrhofer proposes an architecture for context prediction and indicates some of its benefits and challenges. He chooses an approach called growing neural gas to predict arbitrary future contexts. In [4] various context prediction methods that have been mentioned above are compared. Only minor variations in the prediction accuracy have been discovered.

This is not surprising since all these methods suffer from general properties in ubiquitous computing environments. The observed context patterns are highly fluctuating since a user typically not conserves the exact behaviour pattern for several executions of the pattern. A typical behaviour pattern is at most similar to all other repetitions of this pattern. The methods mentioned above are not able to abstract from slight fluctuations in typical behaviour patterns. We propose a context prediction scheme that ignores changes in the user behaviour to some extent.

Another characteristic in ubiquitous computing environments is the weak computational power available. Considering for example a Markov predictor the running time may be estimated as follows. Let k be the number of different context elements known to the algorithm. Each of these is considered a state in the Markov chain. The arcs between the states describe the probability to traverse from one state to another. The future states with highest probability are desired. The time to find the most probable next element is $O(k)$ in the worst case. To find the most probable m/c elements for any constant c the computation time is $O(m^k)$.

We propose a time series based local alignment search method that has a worst case running time of $O(m^2|S|)$ to predict context time series of maximum length m, where $|S|$ denotes the number of typical time series known to the prediction method.

ARCHITECTURE FOR CONTEXT PREDICTION

The context history in our architecture is stored in a rule base. Each typical pattern observed so far is represented by a time series of context elements stored in this rule base. The currently observed context time series is constantly examined for similarities to any time series in the rule base. Due to measurement errors and slight variations in the typical behaviour patterns of the user we expect to find at most similarities instead of exact matchings. Those similarities may be found by local alignment search techniques provided that the representation of the time series elements allows for a similarity metric with a numeric output for any pair of time series elements to be applied.

A suitable rpresentation for arbitrary context elements is created as follows. Let n be the number of different context types in one times series. Context types are for example location, light intensity, humidity or loudness. Each time series element is represented by a real-valued, n-dimensional vector in the hypercube 1^n. Each sensor output is normalised and mapped to one axis of the coordinate system. We define the similarity of two entries in possibly different time series by the Euclidian distance of the corresponding points in the n-dimensional coordinate system.

Local Alignment Prediction Method

The task of the context prediction algorithm is to detect typical behaviour patterns that have been observed in the past and then, based on this information, to provide the most probable continuation of a currently observed set of context elements. Since these contexts can be grouped to a context time series, the actual task is to find typical patterns in the observed context time series that are similar to patterns contained in the typical context times series in the rule base.

The algorithm aligns the observed time series with every single time series in the rule base and computes subseries of these time series that are most similar to each other. These subseries are called the optimum local alignment. The subseries may slightly differ in some time series elements or may contain gaps that are not existent in the other subseries. The context time series directly following the optimum local alignment in a time series in the rule base is predicted by the prediction method, since the time series stored in the rule base are considered typical behaviour patterns.

The prediction process is described in more detail in the following. Let S be the search space of the algorithm containing all possible time series and let $|S|$ be the size of S. We denote the similarity between two time series elements at position i in both strings as $d(t_i, s_i)$. Furthermore we define the cost, if the algorithm does not align t_i and s_i but instead one of the two time series elements to a gap as $d(-, s_i) = d(t_i, -)$.

Let $t = t_1, \ldots, t_n$ and $s = s_1, \ldots, s_m$ be two time series. The optimum alignment between these two time series is found in the following way. First, a $(n+1) \times (m+1)$ matrix M is created. We initialise the Matrix M by $M_{1,1} = \cdots = M_{n+1,1} = M_{2,1} = \cdots = M_{m+1,1} = 0$. All other entries of M ($i \in \{2, \ldots, n+1\}$, $j \in \{2, \ldots, m+1\}$) are created by integer programming:

$$\begin{aligned} M_{i,j} = \min\{ \quad & M_{i-1,j-1} + d(t_i, s_j); \\ & M_{i,j-1} + d(s_i, -); \\ & M_{i-1,j} + d(-, t_j)\}. \end{aligned} \tag{1}$$

Afterwards the ratings of all possible alignments can be found in row $n+1$ of M. The corresponding alignments are computed by backtracking. For a detailed discussion of this method we refer to [6]. All alignments with ratings below a certain threshold value λ are considered important by the algorithm. Let $s'_i \ldots s'_j$ be one of the important alignments found by the alignment method. The sequence $s'_{j+1} \ldots s'_m$ is then predicted by the alignment prediction method (cf. Fig. 1). The length of the predicted sequence is at most m. The running time for filling the matrix is $O(n \cdot m)$, since every entry of the matrix is considered exactly once. Additionally the calculation of the predicted sequences takes time $O(\sum_{i=1}^{m} i) = O(m^2)$ in the worst case when every possible sequence is predicted. The overall running time is therefore $O(n{\cdot}m{+}m^2)$ for the comparison of every two time series. The overall running time of our algorithm is $O((nm + m^2)|S|)$ in the worst case, since the observed time series is aligned to every time series in the rule base. For $m \geq n$ we obtain therefore a running time of $O(m^2|S|)$.

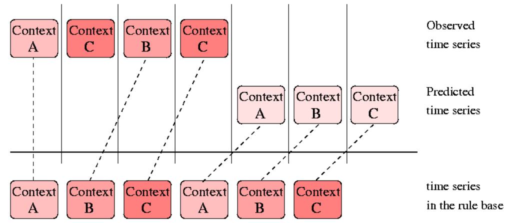

Fig. 1. Context prediction by alignment methods.

Conclusion

We propose a novel local alignment based context prediction method that suits ubiquitous environments due to a high tolerance for slight fluctuations in user behaviour and because it is computationally not expensive. A future task is the comparison of the proposed algorithm to algorithms commonly applied to context prediction in a realistic scenario.

References

[1] K. Laasonen, M. Raento, and H. Toivonen, “Adaptive on–device location recognition,” ser. LNCS, no. 3001, 2004, pp. 287–304.

[2] D. Ashbrook and T. Starner, “Learning significant locations and predicting user movement with gps,” 2002.

[3] B. D. Davison and H. Hirsh, “Predicting sequences of user actions,” in *AAAI/ICML Workshop on Predicting the Future: AI Approaches to Time–Series Analysis*, 1998.

[4] J. Petzold, F. Bagci, W. Trumler, and T. Ungerer, “Next location prediction within a smart office building,” in *1st Int. Workshop on Exploiting Context Histories in Smart Environments (ECHISE’05) at the 3rd Int. Conference on Pervasive Computing*, May 2005.

[5] R. M. Mayrhofer, “An architecture for context prediction,” Ph.D. dissertation, Johannes Kepeler University of Linz, Altenbergstrasse 69, 4040 Linz, Austria, Oktober 2004.

[6] H.-J. Boeckenhauer and D. Bongartz, *Algorithmische Grundlagen der Bioinformatik*. Teubner, 2003, (in german).