The Impact of the Context Interpretation Error on the Context Prediction Accuracy

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Abstract

We study the impact of the context interpretation error on the context prediction accuracy. Benefits and drawbacks of current context prediction schemes are analysed and opposed to a contemporary alternative. We propose a novel context prediction scheme that has the potential to significantly improve the context prediction accuracy. The impact of the context interpretation error on the context prediction accuracy is further analysed in simulations inspired by our analytical considerations.

1 Introduction

Context awareness aims at building applications and services that adapt to the situation of the user. One promising approach to further strengthen this concept is context prediction.

An application situated on a mobile device may for example track user habits and predict future contexts of the user even if they are spontaneous.

However, the prediction accuracy is crucial to the acceptance of any application that uses context prediction methods. Common approaches to context prediction require that the predicted patterns have once appeared in the past [1, 2, 3, 4], which is reasonable since the task of context prediction would otherwise be reduced to mere gambling. A decent overview of context prediction is given by Mayrhofer in [4]. Together with the authors in [1, 2] and [3] he proposes to first interpret the context information into a human readable representation and afterwards to apply the context prediction process. In contrast, in our work we propose to apply prediction before the context interpretation step and study benefits thereof.

1.1 Context Types

We distinguish between high-level context information, low-level context information and raw sensor data. The output of any sensor is considered as raw data since it most probably needs further interpretation. This is due to possibly different encodings of the sensed information or because of a different representation or accuracy.

Afterwards raw sensor data has become low-level context information. The low-level context information of two arbitrary sensors of the same class measured at the same time in the same place is identical with the exception of a possibly differing measurement accuracy, provided that both sensors are in good order.

In order to obtain high-level context information, the low-level context is further interpreted and possibly aggregated with low-level contexts of other sensors. A common application or service expects high-level context information as input data.

1.2 Context Prediction Schemes

Context prediction is usually based on high-level contexts (see for instance [1, 4, 5, 6]). However, the prediction based on high-level context information has vital restrictions due to a reduced knowledge about the context itself.

1.2.1 Reduction of Information

Some of the information contained in a low-level context is lost when transformed to a high-level context since the transformation function is typically not reversible. A time series of observed sensor output values consists of several samples from various sensors. The associated low-level contexts may indicate some general trend. However, the high-level contexts may mask this trend to some extent due to the higher level of abstraction.

1.2.2 Reduction of Operators

The only mathematical operator applicable to high-level contexts is typically the operator '='. All prediction methods that require other operators are not or only with additional computational overhead applicable to high-level context information. Popular context prediction methods therefore implicitly support non-numerical contexts but do not exploit the potential of low-level context information. The number of prediction methods suitable for low-level contexts is therefore larger than the number of prediction methods appropriate for prediction on high-level context information.

1.2.3 Reduction of Accuracy

The prediction accuracy is affected by the order in which the context prediction and context interpretation steps are applied (cf. Fig. 1). Let P_{acq} and P_{int} be the probabilities that no error occurs in the context acquisition and the context interpretation step. We write $P_{\text{pre}}(i)$ if we want to address the probability that the context element at time t_{0+i} is predicted correctly. Assume that the prediction method bases its decision on a context history of k elements. Each of the low-level time series elements is composed of m low-level contexts. For high-level context prediction each time series element is represented by one high-level context. If the prediction is based on the low-level contexts, the probability that the predicted context element at time t_{0+i} is correct is

$$P_{\text{low-level}}(i) = P_{\text{acq}}^{m \cdot k} P_{\text{pre}}^{m}(i) P_{\text{int}} \quad . \tag{1}$$

If the prediction is based on high-level contexts, the corresponding probability is

$$P_{\text{high-level}}(i) = P_{\text{acq}}^{m \cdot k} P_{\text{int}}^{k} P_{\text{pre}}(i) \quad . \tag{2}$$

Comparing these results we obtain

$$\frac{P_{\text{low-level}}(i)}{P_{\text{high-level}}(i)} = P_{\text{pre}}^{m-1}(i) \cdot P_{\text{int}}^{1-k} \quad . \tag{3}$$

Designers of context prediction architectures therefore have to consider the ratio of prediction to interpretation accuracy, the number of low-level contexts involved and the size of the context history considered when deciding on the preferred context prediction scheme.

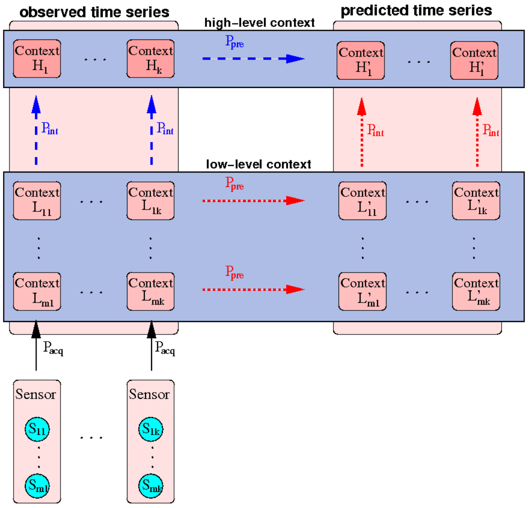

Figure 1: Dotted arrows: Prediction based on low-level contexts. Dashed arrows: Prediction based on high-level contexts.

1.2.4 Reduction of Long Term Accuracy

Provided that a sensor is in good order, the low-level context information reflects the actual situation with respect to the measurement inaccuracy. By interpreting low-level context information to high-level context information we cannot exclude the possibility to misjudge the current context.

A prediction based on high-level context information might therefore be based on erroneous information. This does not only affect the instantaneous prediction accuracy but may also affect the long term prediction accuracy if the context prediction method implements a constant learning procedure in order to adapt to changing user habits. The learning procedure is based on the observed context information which is more likely to be erroneous in case of high-level context information.

1.2.5 Search Space Issues

Let $N \in \mathbb{N}$. The search space S^N of a context prediction algorithm is composed of context patterns of length N. For technical reasons each sensor may produce only a finite number of possible output values. Clearly, if every element in a context pattern can have one out of $|S| \in \mathbb{N}$ values, a maximum number of $|S|^N$ context time series may be unambiguously represented in the search space S^N. For $N, |S| < \infty$ the capacity of the search space S^N is finite.

Int. error	correct predictions	accuracy
0.1 (h-l)	1405	0.964
(l-l)	1310	0.898
0.2 (h-l)	850	0.583
(l-l)	1160	0.796
0.3 (h-l)	649	0.445
(l-l)	1024	0.702
0.4 (h-l)	482	0.331
(l-l)	882	0.605
0.5 (h-l)	25	0.017
(l-l)	693	0.475

Table 1: Context prediction accuracy.

Since high-level time series are derived from low-level time series, the number of elements in the high level search space is lower or equal to the number of elements in the low-level search space. If the number of elements in the high-level search space is lower than the number of elements in the low-level search space, there must exist different low-level time series that are mapped to the same high-level time series. Therefore more information can be expressed by a low-level time series of length N than by a high-level time series of the same length. Consequently, when prediction is based on low-level context elements, a prediction may be possible with less observed context time series elements.

2 Simulation

To experimentally verify the results from section 1.2 we utilise the Foxtrot architecture [7]. We have implemented an alignment-prediction algorithm [8] for low-level and high-level prediction in Foxtrot.

We use four different sensor output patterns with 41 elements each. In the pace of the experiment we repeatedly choose one of these patterns with a uniform distribution and feed it into Foxtrot. In case of low-level context prediction the context interpretation step is applied on the predicted low-level context time series. For high-level context prediction the low-level time series are first transformed to high-level context time series while the prediction is applied thereafter. The context interpretation error is varied in different simulation runs from 0.1 to 0.5.

The results of this simulation are illustrated in Table 1. We observe that with a context interpretation error of 0.1 the high-level prediction accuracy is higher than the low-level prediction accuracy. However, with a context interpretation error of 0.2 or higher the low-level prediction method achieves the better accuracy.

	0.1	0.2	0.3	0.4
Iter.				
10	0.11(6)	0.22(10)	0.29(10)	0.43(10)
30	0.11(11)	0.24(29)	0.32(30)	0.5(30)
50	0.14(21)	0.23(49)	0.32(50)	0.6(50)
100	0.14(38)	0.24(94)	0.29(100)	0.62(100)

Table 2: Ratio of erroneously predicted contexts (context history size) with a learning threshold of 0.1 for various interpretation errors.

The same trend is also evident with additional input sensors. Due to space constraints these results are not included in this version of the paper.

We also study the long term influence and especially investigate the interdependence between the context interpretation error and the percentage of wrong predictions with respect to the simulation time. For this second line of simulations we also utilised the learning module of the algorithm. An observed time series that is sufficing different to all time series in the context history is added to the context history. With a learning threshold of $l \in [0, 1]$ the algorithm adds time series with $l\%$ different context elements to the context history.

In our test scenario we use one sensor output pattern consisting of 41 different elements. The algorithm is initially trained to this unique pattern. In different simulation runs the learning rate of the algorithm is varied. Starting with the perfectly trained prediction algorithm we feed the sensor output pattern 100 times into the algorithm and monitor the contents of the context history and the prediction accuracy for various interpretation errors and learning thresholds.

We first consider the ratio of erroneously predicted context elements. The results with a learning threshold of 0.1 are illustrated in Table 2. The figures in brackets represent the number of different time series in the context history. Note that the ratio of erroneously predicted context elements is typically higher than the context interpretation error. This is due to the fact that incorrect time series are added to the context history. If the algorithm decides to base its prediction on one of these time series, many of the predicted context elements are to be erroneous. Since the initial correct time series is

	0.1	0.2	0.3	0.4
Iter.				
10	0.0 (1)	0.0 (1)	0.0 (1)	0.0 (1)
30	0.0 (1)	0.0 (1)	0.0 (1)	0.0 (1)
50	0.0 (1)	0.0 (1)	0.0 (1)	0.0 (1)
100	0.0 (1)	0.0 (1)	0.0 (1)	0.61 (2)

Table 3: Ratio of erroneously predicted contexts (context history size) with a learning threshold of 0.5 for various interpretation errors.

not deleted from the context history, all but one time series in the context history are incorrect. We observe that the ratio of erroneously predicted context elements is not dependent on the number of erroneous time series in the context history. A single erroneous time series in the context history has already significant influence on the context prediction accuracy.

When we increase the learning threshold of the algorithm, the context prediction errors are bounded to some extent. If however, a prediction error occurs, the amount of error is similar to the corresponding value in Table 2. The reason for this is that the number of erroneous context elements in a time series in the context history is relevant to the context prediction error, not the learning threshold of the algorithm.

To stress this point we increase the learning threshold to 0.5. The results of this simulation run are illustrated in Table 3. Observe that the algorithm is now hardly capable of learning new context time series at all. Obviously we do not experience a context prediction error of the algorithm for a context interpretation error up to 0.3. Only with a context interpretation error of 0.4 and after a considerable number of iterations do we observe context prediction errors. With only one incorrect context time series in the context history the ratio of erroneously predicted context elements is at 0.61 right from the start. Few incorrect time series in the context history can therefore have a great impact on the context prediction accuracy.

3 Conclusion

We have studied the advantages of applying context prediction methods to low-level context time series instead of high-level context time series. We were able to derivate various weaknesses of high-level context prediction schemes and further identified guidelines for the application designer that may lead to an improved prediction accuracy. Our proposed architecture for context prediction enables the utilisation of novel context prediction schemes that exploit the additional information provided by low-level context time series. Concluding, we experimentally verified our observations on the different context prediction schemes. We were able to show that high-level context prediction is only to be favoured in case of a low context interpretation error and that further the long term accuracy of the high-level context prediction methods is seriously affected by the context interpretation error.

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