In time recommendations through an Associative Classifier and LookBackApriori: a case study

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Abstract

Recommender systems are becoming essential tools in many scenarios, as they help users extract hidden knowledge and useful insights from datasets. In many real domains, the temporal order between events, combined with their contextualization, improves the accuracy of provided suggestions. In this paper, we introduce a framework designed to mine personalized, in time, contextual, and explainable sequential rules useful to provide recommendations for a predefined target parameter. Specifically, this framework is composed of the L^3 Associative Classifier and LookBackApriori, a modification of Apriori algorithm. Our proposal takes historical data and contextual information as input and generates two sets of rules: the first set comprises rules that allow enhancement of the target parameter, and the second makes it worse. The proposed technique is applied to a real-world scenario involving data collected by Fitbit wearable devices to improve the user's sleep score after performing fitness activities in different contexts. The idea has been evaluated on two real datasets, and the results confirm the positive effects of the combination of L^3 with LookBackApriori.

Keywords

Recommendations, Associative classifier, Explanation, Data Mining

1. Introduction

The widespread popularity of sensors and wearable devices, like smartwatches and fitness trackers, has increased the amount of available data that can be leveraged to monitor and enhance various aspects of their users' well-being. Such devices are often equipped with intuitive apps for activity tracking that mainly provide aggregate parameters and trend analysis, thus leaving room for more personalized and insightful suggestions to raise the end-users' awareness about what affects certain monitored parameters and habits.

To achieve advanced insights, historical data, possibly integrated with external information describing the user context, needs to be analyzed for each user to offer tailored and context-aware suggestions to improve their life beyond generic recommendations.

In this work, we propose a framework that aims to give personalized, and in time, contextual suggestions to a specific user to improve a target parameter (e.g., sleep quality) along with an explanation about the provided suggestions. To achieve this goal we integrate monitored data with contextual information, e.g., current weather conditions in the user location and holidays.

More in detail, our use case is based on data gathered with Fitbit and focuses on suggesting the intensity of physical activities and rest periods to carry out during the current day to sleep better. This is done by mining the historical contextualized physical activities during a specified temporal window, which represents the number of consecutive observation days taken into account.

We use two datasets consisting of activity logs from Fitbit wearable devices: PMDataset [1] and a Custom dataset. The latter has been collected from four willing participants in the past two years to integrate more specific information about the user context.

The main aim of this paper is the construction of a novel recommender system that combines the strengths of two algorithms: the L^3 associative classifier [2, 3] and LookBackApriori (LBA) [4, 5, 6]. The first one allows us to predict a specific target parameter based on associative classification. It takes as input all the historical physical activity and the related contextual information (i.e., the context at the time the physical activity was performed) and outputs the predicted sleep score. We leverage the second algorithm to provide an explainable recommendation about what activity to do and what to avoid to increase the predicted sleep quality and not decrease it.

With this framework, we overcome the limitations of the two algorithms and, in particular, the state explosion problems of LBA when managing wide temporal windows are less severe in L^3. In addition, LBA allows the production of explainable recommendations; indeed, since LBA is based on Apriori, it mines sequential rules that contain in their antecedent the explanation of the provided sleep score present in the consequent.

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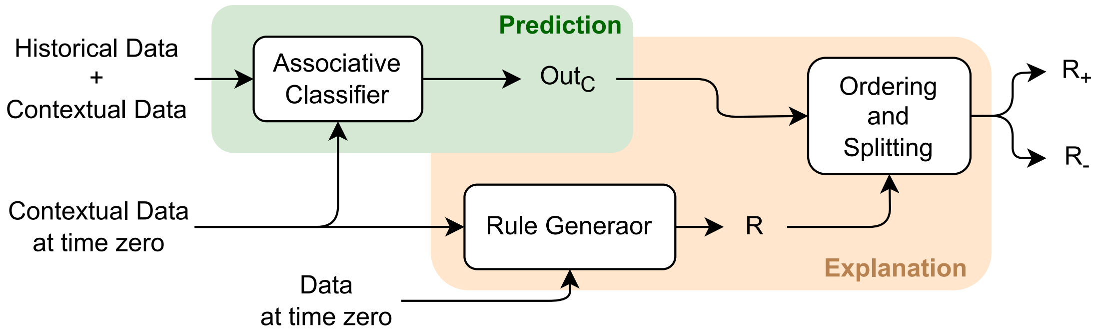

Figure 1: The main components in our framework

The document is organized as follows: Section 2 outlines the architecture of our recommender system, while Section 3 presents the case study. Section 4 reports the validation of the proposed framework, and Section 5 explores related work. Finally, Section 6 summarizes the main contributions and outlines future directions.

2. Architecture

The framework proposed in this paper combines an associative classifier, L^3, to predict the value of a target parameter (e.g., the sleep score for the current day, the stress level) and an algorithm based on Apriori, called LookBackApriori (LBA), to generate timely and explainable contextual recommendations helpful to suggest what to do to improve the predicted value (i.e. the fitness activities to undertake in the current day to increase the sleep score, whenever it is possible).

Associative classifier The first part of our framework comprises the L^3 associative classifier [2, 3]. L^3 uses a technique of lazy pruning to discard those rules that classify training data incorrectly.

Then, the classification of unlabeled data is executed in two steps: first, by considering a subset of high-quality rules for the classification process, and second, by adding a larger set of rules when it fails to find rules for certain data points.

In the green section of Fig. 1, we show the classifier component, which is employed for predicting the value of a target parameter, represented in our scenario by the sleep score for the current day. It takes historical data (i.e., the user's log of their fitness activities and sleep scores) as input and integrates it with past contextual information, including the context of the current day at the time of the prediction.

LookBackApriori The second part of our framework uses the LBA algorithm, which was initially proposed in [4] and extended in [5, 6]. It is an algorithm based on Apriori that mines totally ordered sequential rules and provides timely and explainable recommendations. More in detail, LBA mines association rules where the antecedent is a sequence of itemsets that represent past events or actions by the user with an explicit relative order w.r.t. the current itemset (representing current day events and actions).

For our specific scenario related to wearable devices, a rule can be formalized as follows:

$$r : I_{-(\tau_w-1)} \wedge \cdots \wedge I_{-2} \wedge I_{-1} \wedge I_0^f \rightarrow I_0^s\ [s_i, c_i]$$

The rule r consists of a sequence of itemsets, each representing either fitness activities (I^f), sleep quality (I^s), or both (I), for a specific day, where 0 represents the current day. The parameter τ_w defines the temporal window, that is, the number of consecutive days that the algorithm can consider and thus may be present in a rule. The antecedent can contain all the itemsets up to I_{-1} (the day before the current one) or some of them (i.e., the sequence may be incomplete), while only the physical activity data is present for the current day. Indeed, this itemset, I_0^f, represents the physical activity suggested to the user by our framework to improve their sleep score for the same night, represented in the consequent as I_0^s.

The associative classifier L^3 is used for historical data processing and prediction to address memory-related issues faced by LBA that stem from the size of the input. After the sleep score prediction step, LBA is used to provide explainable positive and negative recommendations thanks to the form of the mined rules. To this end, the antecedent contains the sequence of events that will lead to the sleeping score in the consequent; thus, it provides an explanation for the recommendation.

Three possible rules mined by the LBA Algorithm are the following:

$$r_1 : \{HA : 3, LA : 2\}_{-1} \wedge \{HA : 3, LA : 2\}_0 \rightarrow \{SL : 1\}_0$$

$$r_2 : \{HA : 2, R : 3\}_{-2} \wedge \{LA : 1\}_{-1} \rightarrow \{SL : 3\}_0$$

$$r_3 : \{HA : 2, R : 3\}_{-2} \wedge \{MA : 1\}_0 \rightarrow \{SL : 3\}_0$$

r_1 states that if yesterday the user performed a high level of heavy physical activity ($HA : 3$) and a medium level of light activity ($LA : 2$), and today they perform the same activities, the resulting sleep score will have a low value ($SL : 1$).

r_2 is an incomplete rule since it does not contain information about the physical activity the user should perform during the current day. Although the rule is valid, it is not helpful for making a recommendation to improve sleep quality, as it does not have any itemset labeled 0 in the antecedent.

r_3 is another incomplete rule, but it gives us information about the physical activity the user should do during the current day to sleep well; thus, it can be used to provide a recommendation.

In the orange part of Fig. 1, we show the contribution of LBA to our framework. Firstly, it mines a set of rules R using the Rule Generator, which takes as input the current context, also used by L^3 for the prediction step, and data at the time of the prediction. Secondly, taking advantage of the label produced by the classifier, the rules generated are split into two sets: those that improve the target parameter value w.r.t. the predicted one is labeled R_+, and those that do not are labeled R_-. Then, the rules in both sets are ordered according to the completeness of the rule antecedent, confidence, and support. The rules recommended to the user are the most complete ones with the highest confidence and support.

3. A case study

Our experiments focus on wearable device data: their logs contain information about daily physical activity levels and sleep scores. Whenever possible (i.e., when we have enough data about the user), we integrate such logs with additional information, e.g., holidays, day of the week, and weather conditions related to the user's location, to better contextualize the gathered fitness and sleep quality data.

We consider two datasets for this domain: PMdata [1] and Custom. PMdata consists of logs from 16 users, 13 male and 3 female, all aged 23 to 60 years old. The data was collected for 149 days between November 2019 and March 2020.

The Custom dataset was collected from 4 users specifically for this study, the earliest of which started recording in August 2021 and ended in September 2022. The participants are evenly split between males and females; their ages vary from 16 to 55.

From both datasets, we make use of the logs about "light", "medium", and "heavy" activity, along with rest periods and the sleep score for each day. Fitbit records these features as minutes spent in each activity type; thus, we discretize them to obtain categorical data as described in [4]. During this discretization process, the activity levels and sleep scores are further split into three sublevels according to set thresholds, e.g., a heavy activity (HA) can be encoded into three possible labels: $HA : 1$, $HA : 2$, and $HA : 3$. These represent, respectively, a low level, medium level, and high level of heavy activity, all decided by the amount of time spent undertaking the specific physical activity during the day.

Regarding the context, for both datasets, we also have information on whether a day falls on a weekend (WE) or not (WD).

In addition, for the Custom dataset, we integrate the information about the user's vacations ($VA/noVA$) and the weather conditions. For this last aspect, we have simplified its representation as follows: if there has been rain, snow, fog, or other bad weather conditions, the label is Bad. In all the other cases, it is $Good$. Regarding the temperature, we use the average daily temperature as a feature, and the result is labeled into $Cold$ or Hot, using the yearly average temperature as a threshold.

3.1. Practical example

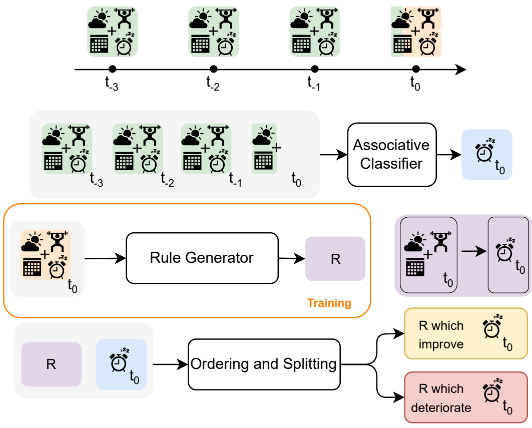

Figure 2: An intuitive workflow of our framework

Fig. 2 shows the workflow of the framework in the specific case of study of this paper.

First, we need to decide the dimension of the temporal window to consider to make the recommendation. The temporal window shown in Fig. 2 is 4 days, i.e., the three previous days are considered along with the current one.

All the information about the past days is fed to the associative classifier L^3 along with the context. The

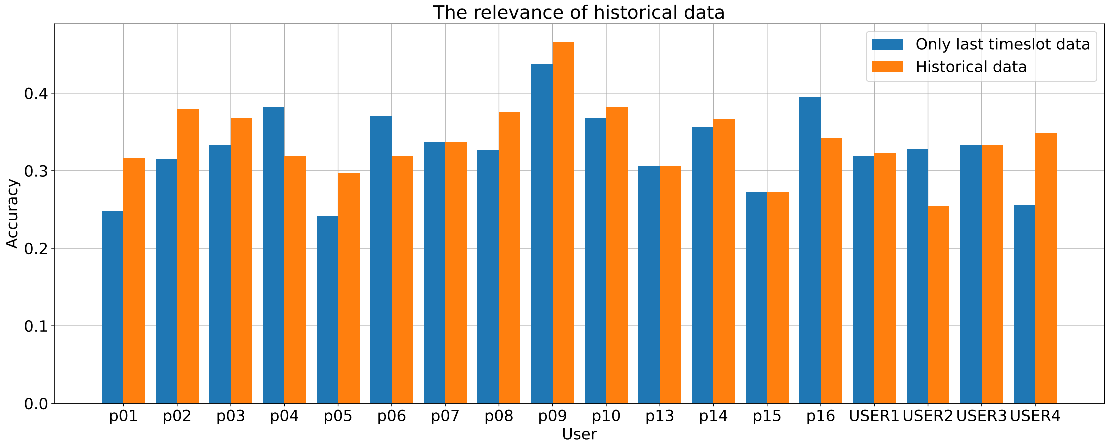

Figure 3: The importance of historical data for each user

classifier then returns a sleep score for the current day.

The rules generated during the training phase state correlations that are only related to the current day, and are in the form shown in the purple rectangle, i.e., contextual information together with physical activity in the antecedent of the rule and the sleep score in the consequent.

Some examples of mined rules are the following:

$$r_1 : \{Cold, Good, WD, HA : 1, LA : 2\}_0 \rightarrow \{SL : 1\}_0$$

$$r_2 : \{Bad, WD, LA : 2, MA : 3\}_0 \rightarrow \{SL : 3\}_0$$

Rule r_1 tells us that on a weekday with clear weather, if the user performs low levels of heavy activity ($HA : 1$) and medium levels of light activity ($LA : 2$), their sleep score for the same night will be low. Whereas rule r_2 states that, in the case of a stormy weekday, the user will sleep well after performing medium levels of light activity ($LA : 2$) and high levels of medium activity ($MA : 3$).

Thanks to the sleep score obtained by the associative classifier, it is possible to split the rules into those that increase or decrease the predicted sleep score. At this stage, the user can explain why their sleep quality may improve or not by looking at the antecedent of the rules.

4. Evaluation

To test the validity of our framework, we have performed several experiments on the following aspects:

- verifying the relevance of historical data and their context in the ability to predict the value of a target parameter, i.e., the sleep score.
- testing the performance of the two algorithms used by the framework w.r.t. execution time and memory consumption.
- testing the efficacy of the proposed framework on L^3 w.r.t. to its ability to predict the value of the predefined target parameter.

For all the experiments, we have reserved the first 80% of the Fitbit logs of each user as a training set and the remaining 20% of the data for testing. Due to the sequential nature of the problem, we cannot randomize the sampling of the two sets. Thus, we maintain the sequential order based on the timestamp of the logs and select the last 20% of the dataset for the tests.

4.1. Relevance of historical data

To conduct this part of the experiments, we use the L^3 associative classifier to predict the sleep label related to the current day t_0.

First, we perform the prediction by selecting only the physical activity and context of the current day as input to the classifier without considering historical data. An example of input data for a Custom user is:

$$(Good\_t0, Hot\_t0, WD\_t0, VA\_t0, LA\_3\_t0,$$
$$MA\_1\_t0, HA\_1\_t0, R\_2\_t0)$$

This can be interpreted as: on clear weather and hot weekdays during a holiday, the user performs a high level of light physical activity, low levels of both medium and heavy activity, and a medium level of rest.

Then, we add the historical data (i.e., physical activity, context, and sleep score of the past days) to the input used for the first set of experiments.

Fig. 3 depicts the recorded accuracies of these two experiments for each user in both PMdata and Custom datasets. These results show that for 77% of users, using historical data instead of only using data from the current day improves the accuracy of the classifier.

Fig. 4 shows that, regardless of the presence of contextual information, having historical data improves the accuracy of most users. The performance of the algorithm decays quickly as the temporal window increases, especially in the absence of contextual data. Thus, it seems clear that sleep quality does not depend on data that is temporally distant from the current day.

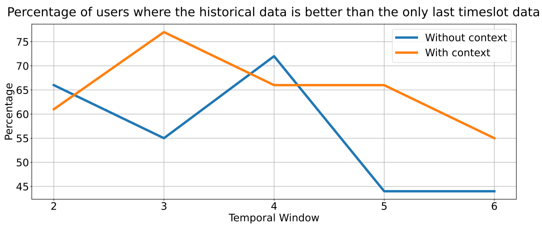

Figure 4: Percentage of users that obtain higher accuracy with the use of historical data, with different lengths of temporal windows, w.r.t. the use of data of the current day

Additionally, the accuracy value obtained by some users increases gradually in the presence of contextual information as the length of the temporal window increases. One example is shown in Fig. 5, where we can also confirm that sleep does not depend on the activities performed six days earlier. We can also observe that contextual information improves the final result.

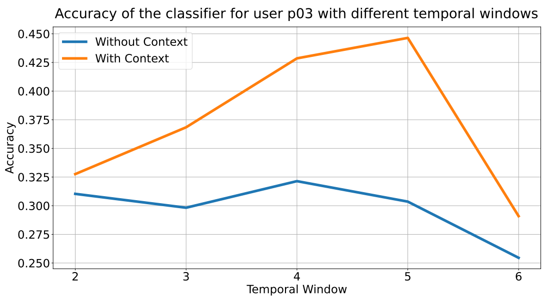

Figure 5: Accuracy trend when we add more historical data, comparison with and without context

4.2. Time and memory performance

Despite LBA's intrinsic capability to provide explainable recommendations for achieving a better sleep score, we still employ the associative classifier L^3 to process historical data. Thanks to the associative classifier, we can process significantly larger volumes of data, e.g., longer sequences of data with their contextual information, without the risk of memory errors. Additionally, L^3 is significantly faster in obtaining the results.

Fig. 6 and Fig. 7 depict the elapsed time and the memory consumption of the framework when using data from one of the users of the Custom dataset, showing the important contribution of L^3. During the experiments, the input is the physical activity log and the available contextual information of the chosen user. We maintain the same support and confidence and gradually increase the temporal windows, i.e., increase the historical data given in input. LBA shows an exponential trend for memory consumption and time elapsed, until its memory allocation fails when the temporal window reaches value 4. On the other hand, L^3 can manage at most a temporal window of 6, maintaining a relatively constant trend.

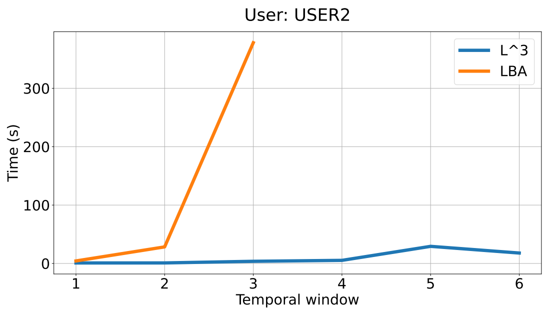

Figure 6: Execution time with different temporal windows for USER2 of Custom dataset.

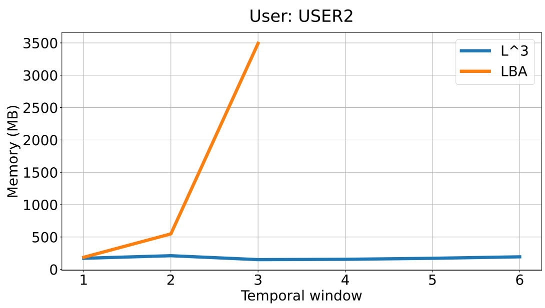

Figure 7: Memory usage with different temporal windows for USER2 of Custom dataset.

4.3. Evaluation of the framework

The last set of experiments performed is on the complete framework, as explained in Sec. 3.1. The idea is to validate, on real user logs, the prediction of L^3 enriched with the recommendation produced by LBA. In order to validate the results of the whole framework, the best approach would be to ask for inputs directly from the users. Due to time constraints, the evaluation of the framework is strictly empirical.

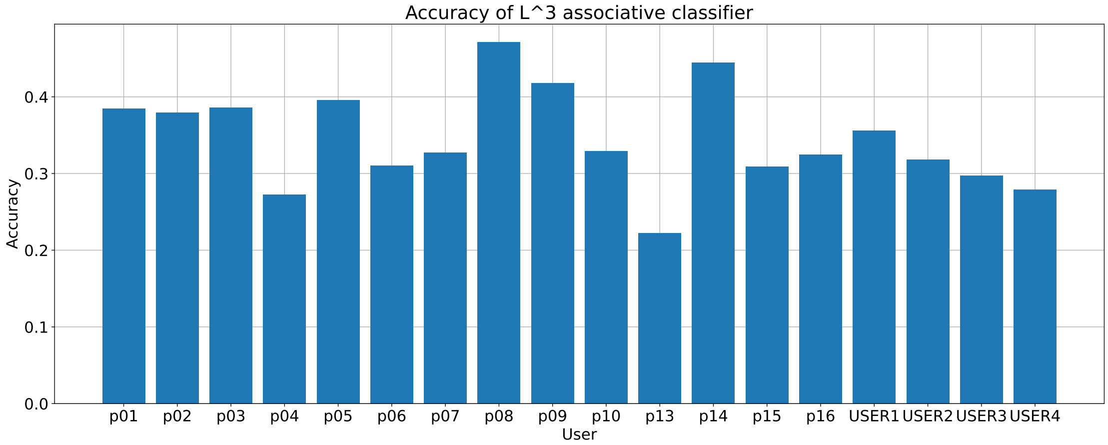

Figure 8: Accuracy of the L^3 associative classifier

As before, we use the first 80% of the dataset to train both L^3 and LBA. The first step is setting the length of the temporal window, which is done empirically by analyzing the experiments in the previous case study. The input of the classifier is composed of the physical activities, contextual information, and sleep score of the past days and the contextual information of the current day. The classifier then predicts the sleep score on the current day.

Separately, the rule generator produces a set of rules correlating the physical activities and contextual information for the current day (antecedent) and the related sleep score (consequent).

At this point, a trained classifier and a set of rules exist for each user. To test the complete framework, we take from the remaining 20% of the dataset a temporal window of observation at a time: all the past data, together with the current context (i.e., the contextual information of the current day), are used by the associative classifier to predict the sleep score.

In Fig. 8, we report both the accuracy of the classifier, without any knowledge about physical activity for the current dayIt can be noted that the accuracy of L^3 for most users is less than 0.45.

The output of L^3 produced is used as a threshold to separate the rules mined by the Rule Generator in the two sets R_+ and R_- of positive and negative recommendations, respectively. Due to the nature of the problem at hand, it would not be accurate to use historical data to check whether the recommendation given by the framework will actually result in a change in sleep score.

5. Related Work

With the spread of smart devices and the availability of their large datasets, we have the possibility to extract both explicit and implicit knowledge about monitored parameters. For this reason, there are many intelligent techniques proposed in the literature to improve the customization of data exploitation. Recommender Systems (RS) offer suggestions on items, services, or news that may interest users and affect their decisions based on their profile, history, and preferences [7]. For instance, in [8], the authors develop an RS that can suggest activities targeted to specific users to improve their health conditions starting from data collected by a Fitbit wearable device. The physical activity information collected by Fitbit is also used in [9] to correlate daily physical activity levels with predictions of sleep quality. Neither of the mentioned works considers contextual information.

In the literature, there are many methodologies for sleep prediction. In particular, [10] introduces an explainable sleep model that exploits the correlation between daily activities and sleep quality, providing recommendations to improve sleep quality. While the outcome of this framework aligns closely with our proposal, the approach does not account for sequences of events that occurred in the days leading up to the prediction intended for the user. Furthermore, the model presented fails to incorporate external contextual information beyond sensed humidity and temperature. As highlighted in Subsection 4.1, historical data are important to improve the quality of provided predictions.

In the state of the art, contextual information is often integrated into RS to improve the precision of recommendations. In general, user preferences may vary depending on the environment and the situation in which they are acting [11, 12]. Therefore, Context-Aware Recommender Systems (CARS) use contextual information, such as time, location, and social situation, to add knowledge during the recommendation process, thus improving the personalization and the relevance of the suggestion [13]. A systematic literature review is proposed in [14], where the authors describe the integration of the context in RS, the main categories of contextual features, and the validation mechanism with respect to datasets, properties, metrics, and evaluation protocols.

In a lot of real scenarios, the history of events and their order is important and can be leveraged in the process of knowledge extraction. Sequential pattern mining aims to extract hidden sequential patterns in sequential databases. These patterns can be used as a first step to extract frequent sequential rules, usually formalized as $X \rightarrow Y$ [15, 16, 17]. These algorithms propose partially ordered sequential rules where the antecedent X is composed of events that happened before the consequent Y and do not consider the relative order of the events. For this reason, we develop our approach where the antecedent is a sequence of events with a relative temporal label.

In general, when using algorithms based on Apriori to predict a target parameter, the dimension of sequences one can manage is limited. For this purpose, an analysis of classifiers is mandatory. In the literature, there are several associative classifiers, such as CBA [18], DeEPs [19], CMAR [20], CPAR [21], and iCAEP [22]. However, these present two main drawbacks: either a loss of useful information due to an overpruned set of rules or, conversely, a significant growth of the rule set in case of limited rule pruning. For these reasons, we decided to use the L^3 associative classifier [2, 3], which addresses both problems.

It has also been recognized that when users understand why certain items have been recommended, the suggestion becomes more persuasive. Hence, in recent years, explainable RSs have been applied in real-world scenarios [23]. However, explanation techniques are often not compatible with some machine learning or deep learning approaches due to their black-box nature [24]. Although there exist some studies on the explainability, interpretability, and trustworthiness of deep learning techniques [25, 26], data mining techniques remain more effective in offering comprehensive explanations for the nature of the rules they are able to infer.

6. Conclusion

In this paper, we have combined the L^3 associative classifier and the LBA algorithm to provide explainable recommendations. Such an approach helps give insights to users who desire to know what affects their sleep score and how to improve it when fitness and sleep parameters are monitored through wearable devices. As future work, we are extending the proposal to other domains, like the correlation of fitness activities with blood glucose levels.

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