Anachronistic Attributes in Temporal Data: A Case Study

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Abstract - The paper is concerned with mining data lacking uniform structure. The data are collected from a number of objects during repeated measurements all of which are tagged by the corresponding time. No attribute-valued machine learning algorithm can be applied directly on such data since the number of measurements is not fixed but it varies. The available data have to be transformed and preprocessed in such a way that a uniform type of information is obtained about all the considered objects. This can be achieved e.g., by aggregation. But this process can introduce anachronistic variables, i.e., variables containing information which cannot be available in the moment when a prediction is needed. The paper suggests and tests a method how to preprocess the considered type of data without falling into the trap of introducing anachronistic attributes. The method is illustrated on a case study based on STULONG data.

Keywords: anachronistic variable, windowing, temporal pattern, trend analysis.

I. INTRODUCTION

Predictive data mining, when working with temporal data [5], must avoid the danger of basing its decisions or recommendations on anachronistic attributes. The anachronistic attribute [8] contains information which is not present in the data when we need it for prediction. As an example let us consider prediction of daily revenue in a shop: certainly, there is a strong relation between revenue and the precise number of customers entering the shop during the day. If this number is known, our prediction of the revenue can be very sharp. But we cannot know in the morning how many people will come during the day - we know this after the closing hour, not before. The precise number of customers is a typical anachronistic attribute, which should not be used for prediction of daily revenue. In this case, the process has to broken into two steps - first, the number of customers from some stored history data is predicted; second this predicted value is used for estimate of the revenue. Prediction of the number of customers can depend on the day of week, part of year, number of customers during the last week or year etc.

Obviously, creating predictive model with anachronistic attributes does not make any sense. But sometimes deep understanding of the considered domain is needed for identification of anachronicity in the data. This may cause serious problems e.g., when treating large input data sets. Moreover, anachronistic attribute can appear not only in the original input data, but it can be added into the data as a result of data preprocessing, for example of data aggregation.

First, we will present this kind of problem on STULONG data. Section II introduces the STULONG project and proposes a naive approach to trend analysis referred as global. At the same time it discusses a danger of anachronicity lying in this approach. Sections II.A and II.B bring another piece of evidence supporting this danger—the global approach deals with anachronistic number of checkups which also relates to the occurrence of cardiovascular diseases. Later, we will combine aggregation with windowing to design a specific type of preprocessing, which is suitable for time series data and which does not enter into the trap of introducing anachronistic attributes. Section III. introduces a windowing method, Section IV. discusses windowing time series with missing values. In Section V. the paper is concluded by an attempt to use these new derived attributes for modelling in STULONG domain.

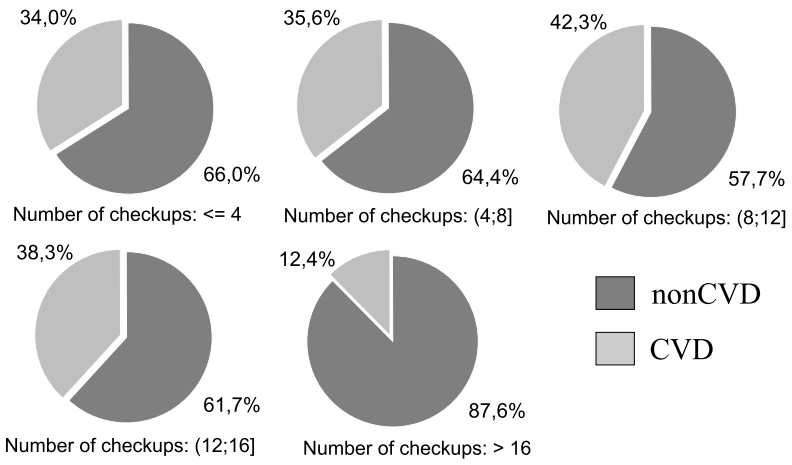

Fig.1. Relation between the number of checkups and the frequency of cardiovascular diseases - pie chart

II. STULONG STUDY

The study STULONG is a longitudinal twenty years lasting primary preventive study of middle aged men. The study aims to identify atherosclerosis risk factors prevalence in a population generally considered to be the most endangered by possible atherosclerosis complications, i.e., middle aged men. It follows the development of these risk factors and tries to discover their impact on the examined men health, especially with respect to atherosclerotic cardiovascular diseases (for further details see acknowledgement).

The study contains data resulting from twenty years of observation of approximately 1400 men in the middle age. The intention of the project is to identify risk factors of atherosclerosis.

The data is inherently multi-relational, consisting of four separate tables. This paper is concerned with two of them - the table *E*ntry describes data collected during the entry examinations of all patients, the table *C*ontrol includes results of a series of long-term observations recording the development of risk factors and associated conditions. By merging these two tables it is possible to obtain a time series of multivariate examinations for each patient. One has to be aware of the fact that data providing the results of various measurements concerning many individual patients has no uniform character. Although the same attributes are being observed during repeated checkups of all patients, there is a significant difference in the number of examinations of individual patients, see Figure 3. Moreover, often the values of some attributes are missing, it means that the total number of patient's checkups is higher than the number of actually measured values. In order to prepare these data for application of any attribute-value learning (AVL) method, it is necessary to create a uniform attribute structure based on the available time series data. This can be achieved by data transformation.

The first idea is to substitute the time series of measurements by one or more aggregated values, for example by the mean or extreme values. This technique is often used in medical domains, see for example [3]. The trends of the observed variables are considered to be one type of risk factors. The trends can be obtained as parameters of the regression line calculated from the input data. But there is a danger in this approach. It can add anachronistic attributes to the data because the equation for calculating trends, see paragraph II.B, uses the total number of all checkups (denoted as n) repeatedly. Certainly, the number of all checkups is an anachronistic attribute, because we do not know in advance, how many times the new patient will come. On the other hand, we do not need all patient's measurements to estimate the development trend of a certain attribute: the parameters of the regression line can do the job and they can be obtained from the first two values already. Is it reasonable to compare regression parameters calculated from the training data with those of new patients calculated from their existing checkups? We will try to answer this question at the end of paragraph II.B.

One of the main goals of the STULONG project is to offer general support for predictive diagnostics of cardiovascular diseases (CVD). In this paper, the CVD label corresponds to occurrence of any of the following diseases: angina pectoris, (silent) myocardial infarction, ischaemic heart disease, silent myocardial ischaemia and claudications. The above-mentioned support can be achieved by creating a model, which differentiates between a patient with CVD and a patient without CVD (nonCVD). In terms of the global approach we are concerned with design of a model which will use the binary attribute CVD as the target function (a possible disease always appears during the last checkup). A more profound temporal definition of CVD is in Section III.A. This paper searches for derived attributes which seem to relate to CVD - they are described and analysed in the paragraph V.

A. Verifying relation between the number of checkups and the occurrence of a cardiovascular disease

Various statistical tests or visualization tools can be applied to verify dependency between number of checkups and CVD. We have used the criterion "area under ROC curve". Receiver operating characteristic (ROC) curves were designed in the 1950's as a by-product of research into making sense of radio signals contaminated by noise [4]. More recently it has become clear that they are remarkably useful in medical decision-making [6]. A ROC curve is a graphical representation of the trade off between the true positive (TP) and false positive (FP) rates for every possible cut-off of the independent variable. In other words, the ROC curve is the representation of the tradeoffs between sensitivity and specificity. By tradition, the plot shows the false positive rate on the x axis (1-specificity) and the true positive rate on the y axis (sensitivity). The area under curve (AUC) quantifies ability of a model to separate two classes under different conditions. A random model shows AUC=0.5, the perfect model shows AUC=1 and the inverse perfect model has AUC=0.

Let us consider a trivial model of CVD based on the number of checkups only. This model does nothing but orders the patients according to the number of their checkups. The model supposes that the more checkups the patient has the more likely he can be struck by CVD in such a way it takes a random checkup threshold which distinguishes between CVD and nonCVD patients (the checkup numbers below and above the selected threshold).

For every possible threshold value of the checkup number, AUC expresses probability that a patient will be correctly classified into one of the two target groups, CVD or nonCVD. By means of the non-parametrical Wilcoxon statistics [9] we have estimated AUC(the number of checkups, CVD)=0.38 (the 95% confidence interval is $[0.33, 0.45]$). In other words, the trivial model based only on the checkup number assigns patients the correct class with probability 0.38. It is evident that the frequency of CVD significantly falls with rising number of checkups (AUC< 0.5). The corresponding ROC curve is shown in Figure 2. AUC can also be used to relate the strength of the studied dependency to the influence of the other variables that are well-known to affect CVD occurrence—e.g., AUC(BMI, CVD)=0.55, AUC(age, CVD)=0.60, AUC(cholesterol, CVD)=0.58. The comparison suggests that the checkup number makes probably the strongest risk factor in the study.

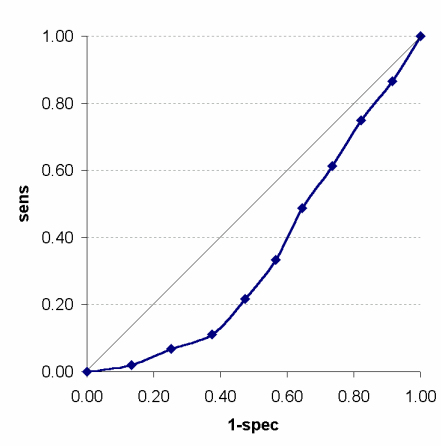

Fig.2. Relation between the number of checkups and the frequency of cardiovascular diseases - ROC curve

Similarly it is possible to reject the independence hypothesis between the number of checkups and CVD whereby χ^2 test (on the level of significance p=0.005). The relation can also be visualized e.g., by the categorization pie chart - see Figure 1. The graph shows the reduced frequency of disease in the patient group with more than 16 checkups.

We can explain the observed relation between CVD and number of checkups as a consequence of the methodology applied when monitoring the patients. Monitoring continued for upto 20 years with some patients. During the project, measurements were taken regularly each year. But monitoring was sometimes stopped earlier because the patient fell to cardiovascular disease and his monitoring was cut. This patient was deleted from the monitored group and transferred into the clinic program of secondary cardiovascular disease prevention. Due to this procedure the patient with fewer checkups is more likely to be struck by a cardiovascular disease than the patient with many checkups.

We have just explained that there is a causal relation between the occurrence of a cardiovascular disease of a patient and the total number of his checkups. Simultaneously, one has to be aware of the fact that the total number of checkups cannot be used to build the predictive model for practical usage in real life since this number is an anachronistic attribute.

B. Using aggregation value for repeating measure

The characteristic values (mean, standard deviation) or parameters of the regression line (curve) are often used as a means for simplification of time series data. How are these values calculated? Let us consider e.g., the expression for estimation of the parameters k, q of the regression line $y = kx + q$, where y stands for values of the observed variable and x for time of measurement or alternatively its sequence number:

$$k = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2},$$

$$q = \frac{\sum_{i=1}^{n} y_i \sum_{i=1}^{n} x_i^2 - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} x_i y_i}{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2}$$

The regression equations refer to basic statistics, we present them mainly in order to emphasis that the number of checkups n re-appears in these expressions. Since this number proved to be an anachronistic attribute, this property can be inherited by the derived attribute, too. Experiments on STULONG data prove that this is indeed the case (see column Global in Table 1.). There is a strong dependency between the values of derived attributes calculated as the regression coefficients and the number of checkups used for their calculation. Consequently the observation that CVD classification is closely related to the values of the regression coefficients can be due to their dependency on the number of checkups n. That is why these aggregation attributes should not be used for building predictive model CVD.

We have to search for more sophisticated transformation of the input data in order to ensure that the predictive result is not influenced by the number of checkups. Only under such conditions the time series data can be replaced by some aggregation values. We will apply windowing for this purpose.

III. WINDOWING

Windowing is a simple and often used method to transform data, see e.g., [1]. Two types of windowing can be distin-

guished. The sequence of data can be either decomposed into several disjunctive windows or a sliding window approach can be applied. The first choice is applied whenever we decide for a 'per partes' linear approximation of the original data. Then the windows correspond to intervals in which data exhibit 'similar', i.e., close to linear behaviour. These intervals can differ in length. On the other hand, the sliding window has a fixed length. It 'slides' over the original series in regular steps generating overlapping sub-series. Both choices lead to a simplified representation of the input sequence, which can result e.g., in a more effective definition of a similarity level for clustering.

Our intention is to find a relation between individual risk factors expressed as time trends and possible development of CVD. For this purpose, the method of the fixed length sliding window seems most suitable. Generally, the sliding window method transforms a time series with n consecutive measurements into a new set of time series. It consists of items with a constant number of measurements, denoted as l. Of course, this approach can be applied to the time series consisting of at least l measurements, only. The shorter series with less than l measurements have to be neglected. The results of this transformation can be safely used in further analyses as the resulting trends are not influenced by the number of controls and the number of considered measurements is constant in the new set of data. The elementary transformation process of a temporal data is illustrated in Figure 3.

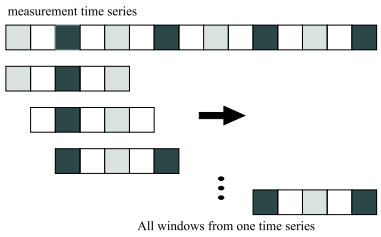

Fig.3. Transformation of a time series using the sliding window method.

The windowing method proposed above is parametrical. The choice of the window length can significantly influence the result, e.g., the fidelity, reliability or predictive ability of a future model. Unfortunately, there is no universal recommendation to choose the appropriate length of the window a priori. This decision is task-dependent, most often based on the estimate of the minimal time period, when one can expect such changes in time series, which allow to predict the result. Consequently, the determination of the optimal window length makes an important step in the proposed preprocessing process.

Because the number of checkups ranges in our case from 2 to 20, the choice of the window length is a trade-off between the amount of data which have to be omitted and the length of observable period. In our case, the window consisting of 5 measurements has been selected first. The histogram and the pie graph in Figure 4 show that with this choice we cannot utilize data concerning about one fifth of patients. The alternative choice can be the length of 8 or 10 measurements. These alternatives give a chance to observe events with higher inertia but simultaneously we are forced to omit nearly half of the patients. As soon as the window length is decided, the data can be transformed. For each patient, a set of $n - l + 1$ new windows is obtained, where n is the number of measurements in the original series of the given patient and l is the window length. Experiments with windows of the length 5, 8 and 10 are reported in the paragraph V.

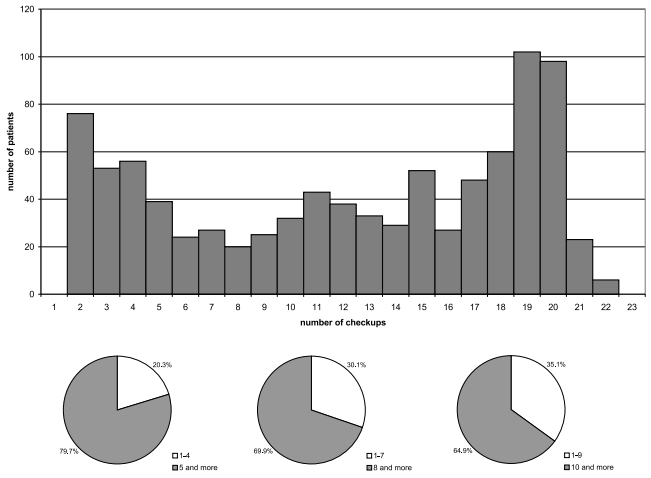

Fig.4. Histogram and pie charts of the number of checkups in the STULONG study

A. Temporal CVD definition

The attribute CVD has been described in Section II. Its value is fixed for each patient. When using windowing method, one should introduce a more sophisticated distinction. No doubt, there is a significant difference between a patient who will show some slight signs of CVD after 20 years in the study and the patient who will prove to be ill during the second or third examination already. The value of the attribute CVD must be related to the considered time of measurement. The best way to achieve this is to replace the original attribute CVD by a new derived attribute CVDi estimating how long will it take before the patient becomes ill (gets CVD)—CVDi expresses a time period between the last windowed checkup and the checkup which diagnosed a cardiovascular disease. When the patient remains healthy, the value of the attribute CVDi has a distinguished value which is interpreted as ”healthy” (CVDi=1000). This attribute is further binned as necessary (see Section V).

IV. WINDOWING AND MISSING VALUES

The windowing method with the fixed window length forms windows (sub-series) that can be concisely represented by the aggregate attributes introduced in Section II.B. Two principal approaches can be applied when considering time series with occasional missing values:

- the first one sticks to the fixed number of checkups — missing values are omitted and the next values in the time series are taken into account: the series of values is shifted,
- the second one insists on the fixed length of the time window — in the later case, reasonable substitutes for the missing values have to be found: the replacement approach is applied.

A. Replacement of the missing value by shifting the series

The direct shift skipping the missing value can cause a severe problem of synchronization. Let us consider an object, which is described by two time series corresponding to development of variables (attributes) A and B, see Figure 5.

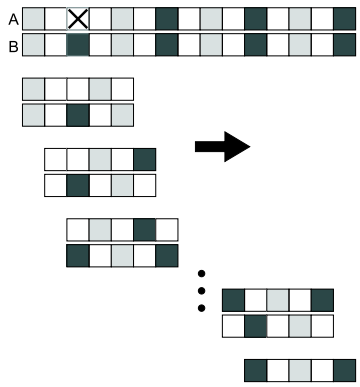

Fig.5. Replacing missing values by shifting

The missing value in variable A is marked by a cross. When we transform the data, we replace this missing value by the next value. We shift only the variable A, because there are no missing values in the variable B—the windows are not synchronized any longer. We have fewer windows for variable A than for variable B and the windows are mutually shifted. The corresponding aggregates are created from the measurements of different time stamps.

The other possibility is to omit those measurements whenever a value of one variable (A or B) is missing. This solves the time shift problem as the window remains identical in time, but we are losing a part of valuable measurements. In our case it means that we would have used only those checkups which are complete (all measurements have been taken for the considered patient). This approach is reasonable only for problems, where only few values are missing.

B. Replacement of the missing value by a new value

The other treatment recommends to denote the place with the missing value by some symbol and replace this symbol cautiously at the end of transformation process. When we consider attributes developing ’relatively slowly and smoothly’, i.e., data exhibiting a certain ’time inertia’, the mean calculated from the former and the future value can be a suitable replacement.

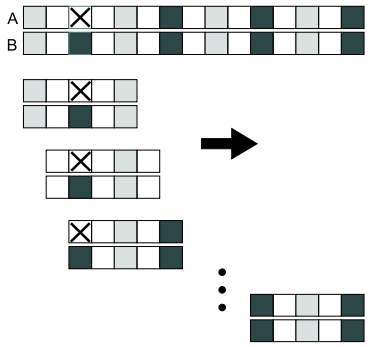

Fig.6. Replacing missing values by a new value

The data transformations related to this solution appear rather time consuming, as they require to implement the corresponding transformations from the scratch for the studied data set. The treatment of data is showed in Figure 6.

V. WINDOWING STULONG DATA

Let us compare the relation between CVD and various types of discussed aggregates: those calculated from all the data denoted as the global aggregates (based on the overall number of checkups) and those from the data created by windowing. We will try to answer the following questions:

a) Is it possible to apply the global approach and compare aggregates based on various number of checkups?

b) If not, what is the optimal window length to reveal true dependencies without influence of the anachronistic number of checkups?

Let us focus on gradients (trends), one of the most interesting and natural aggregate types from the point of view of physicians and patients. The gradients of five important variables will be calculated: systolic and diastolic blood pressure (SYSTGrad, DIASTGrad), cholesterol (CHLSTMGGrad), triglyceride level (TRIGLMGGrad) and body mass index (BMIGrad). For details on the physiological meaning of the variables mentioned above see [12].

First, we apply linear regression to data from all available exams in the approach referred as global. For each variable and patient all the exams are taken and the gradients are calculated. CVD is set as 'false' if no cardiovascular disease appears for the patient during the study, true otherwise, i.e., the patient develops a cardiovascular disease during his exams. Let us recall that the disease was always identified during the last patient's exam.

Second, the gradients are calculated for windows of length 5, 8 and 10 exams (denoted as W5, W8 and W10). The windows are defined by the constant number of exams and not by the constant observation period. For a great majority of patients the exams are taken regularly, e.g., the window of the length 8 corresponds to time period lasting from 7 to 9 years, the influence of different time durations is not studied here. We have mentioned the need for time relativization of the CVD attribute already. For simplicity, we will use a modification of CVDi, namely the attribute CVD1. CVD1 is 'true' if and only if the cardiovascular disease appears at the exam directly following the last windowed exam, i.e., the patient develops a cardiovascular disease in one year from the windowed period.

The table 1 shows the level of significance p of the χ^2 test of independence between CVD1 and the gradients defined above (the gradient variables were discretized into 10 distinct intervals before testing). In the first column, there are results for the global approach. The global approach suggests a strong dependency between all the gradients and CVD. When using windowing, only SYSTGrad, DIASTGrad and BMIGrad seem to relate to CVD1. Moreover, this dependency can be observed for specific window lengths only (SYSTGrad and DIASTGrad when using W5, BMIGrad with W10).

We have further analyzed the obtained dependencies. As for the global approach, all the gradients seem to relate to the occurrence of the disease in the same way:

Table 1. Dependencies between CVD and selected gradients (p values < 0.1 are in bold)

10 intervals	**Global**	**W5**	**W8**	**W10**
SYSTGrad	**0.065**	**0.005**	0.703	0.571
DIASTGrad	**0.078**	**0.072**	0.114	0.683
CHLSTMGGrad	**0.005**	0.497	0.487	0.950
TRIGLMGGrad	**0.002**	0.321	0.183	0.624
BMIGrad	**0.007**	0.804	0.746	**0.061**

when the gradients are strongly increasing or decreasing, CVD is more likely to develop. Conversely, if the gradients are stable, CVD is less likely to appear.

Although this potential dependence may have physiological explanation for some risk factors, the influence of the anachronistic number of checkups seems to be very important. The gradients tend to be extreme when the patients have fewer exams. At the same time, the patients with fewer exams are exactly those patients for which the suspicion for appearance of a cardiovascular disease is stronger as these patients are always removed from the study before its end.

The results obtained by the windowing suggest a weaker influence of the studied gradients. For SYSTGrad and DIASTGrad (and W5) it holds that the more blood pressure increases the more likely CVD is. The influence of SYSTGrad is shown in Figure 7. There are 122 windows of the length 5 being classified as CVD1='true' out of the 'pool' of 4837 windows, i.e., there is about 2.5% of the positive instances. Within the lowest SYSTGrad group, the rate of the positive instances decreases to 1.8%, while in the opposite group their relative frequency increases to 3.4% (SYSTGrad is partitioned by the equi-depth binning). A similar kind of dependency was observed for BMIGrad and W10, the more BMI increases the more likely CVD is.

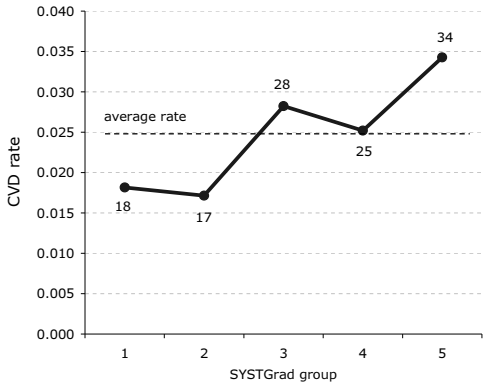

Fig.7. Relative frequency of CVD in various SYSTGrad groups

The above-mentioned dependencies make sense and we find windowing as a reliable way for their retrieval. On the other hand, the experiments show that especially when searched dependencies may be weak, various window lengths should be tried. For example, BMI tends to oscillate reasonably between the exams. Some patients show great short time changes of their weight. These changes do not seem to influence their health as much as slow but long term weight gain. A long time window is needed to distinguish between these changes and therefore BMI has to be followed for 10 exams at least. On the contrary, the blood pressures for the persons who came down with a cardiovascular disease in the study tend to decrease first and then increase back or even more. These changes cannot be identified with longer windows, which tend to average both trends.

Let us notice that multivariate analysis may have proven a higher influence of the defined gradients. It is very likely that increasing BMI is more risky for a fat person than for a slim one which is not considered here. Although the study deals with more than 1400 of men, we can identify only 27 men who came down both with a CVD and the obesity risk. This group is not large enough to study influence of BMIGrad.

The obtained results support the causality doubts mentioned in the introductory theoretical analysis, i.e., the global approach cannot be utilized and windowing has to be applied. The influence of the number of checkups was erased and consequently the relationship between the trend values (gradients) and CVD occurrence has significantly changed and weakened. The optimal window length is given by the physiological nature of the observed events and can be different for different variables. When analyzing the data created by windowing, specific development patters seem important in the considered data, e.g., the trend pattern which can be described as "down-up". The corresponding derived attributes should be designed and analyzed with respect to CVD1 later.

VI. CONCLUSION

We have used the STULONG data to point to the danger of introducing anachronistic attributes during the data preprocessing phase of the data-mining process. Windowing described in the section IV.B proved to be a reasonable approach which can help to escape this danger. The main handicap of this approach is that it requires demanding coding of transformations which has to be done from the scratch for each new considered problem. We believe that windowing is a robust transformation which can find its place in many tasks. That is why we have decided to include a windowing module in the original data preprocessing system and transformation tool SumatraTT, which is ready to report efficiently all future experiments [13].

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