MINING THE RELATIONSHIPS IN THE FORM OF THE PREDISPOSING FACTORS AND CO-INCIDENT FACTORS AMONG NUMERICAL DYNAMIC ATTRIBUTES IN TIME SERIES DATA SET BY USING THE COMBINATION OF SOME EXISTING TECHNIQUES

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Key words: Temporal Mining, Time series data set, numerical data, predisposing factor, co-incident factor

Abstract: Temporal mining is a natural extension of data mining with added capabilities of discovering interesting patterns, inferring relationships of contextual and temporal proximity and may also lead to possible cause-effect associations. Temporal mining covers a wide range of paradigms for knowledge modeling and discovery. A common practice is to discover frequent sequences and patterns of a single variable. In this paper we present a new algorithm which is the combination of many existing ideas consists of the reference event as proposed in (Bettini, Wang et al. 1998), the event detection technique proposed in (Guralnik and Srivastava 1999), the large fraction proposed in (Mannila, Toivonen et al. 1997), the causal inference proposed in (Blum 1982) We use all of these ideas to build up our new algorithm for the discovery of multi-variable sequences in the form of the predisposing factor and co-incident factor of the reference event of interest. We define the event as positive direction of data change or negative direction of data change above a threshold value. From these patterns we infer predisposing and co-incident factors with respect to a reference variable. For this purpose we study the Open Source Software data collected from SourceForge website. Out of 240+ attributes we only consider thirteen time dependent attributes such as Page-views, Download, Bugs0, Bugs1, Support0, Support1, Patches0, Patches1, Tracker0, Tracker1, Tasks0, Tasks1 and CVS. These attributes indicate the degree and patterns of activities of projects through the course of their progress. The number of the Download is a good indication of the progress of the projects. So we use the Download as the reference attribute. We also test our algorithm with four synthetic data sets including noise up to 50 %. The results show that our algorithm can work well and tolerate the noise data.

1 INTRODUCTION

Time series mining has wide range of applications and mainly discovers movement pattern of the data, for example stock market, ECG(Electro-cardiograms) weather patterns, etc. There are four main types of movement of data: 1. Long-term or trend pattern 2. Cyclic movement or cyclic variation 3. Seasonal movement or seasonal variation 4. Irregular or random movements.

Full sequential pattern is kind of long term or trend movement, which can be cyclic pattern like machine working pattern. The idea is to catch the error pattern which is different from the normal pattern in the process of that machine. For trend movement, we try to find the pattern of change that can be used to estimate the next unknown value at the next time point or in any specific time point in the future.

A periodic pattern repeats itself throughout the time series and this part of data is called a segment. The main idea is to separate the data into piecewise periodic segments.

There can be a problem with periodic behavior within only one segment of time series data or seasonal pattern. There are several algorithms to separate segment to find change point, or event.

There are some works (Agrawal and Srikant 1995; Lu, Han et al. 1998) that applied the Apriori-like algorithm to find the relationship among attributes, but these work still point to only one dynamic attribute. Then we find the association

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among static attributes by using the dynamic attribute of interest. The work in (Tung, Lu et al. 1999) proposed the idea of finding inter-transaction association rules such as

RULE1: If the prices of IBM and SUN go up, Microsoft's will most likely (80 % of time) go up the next day.

Event detection from time series data (Guralnik and Srivastava 1999) utilises the interesting event detection idea, that is, a dynamic phenomenon is considered whose behaviour changes over time to be considered as a qualitatively significant change.

It is interesting if we can find the relationship among dynamic attributes in time series data which consist of many dynamic attributes in numerical form. We attempt to find the relationship that gives the factors that can be regarded as the cause and effect of the event of interest. We call these factors as the predisposing and co-incident factors with respect to a reference variable. The predisposing factor can tell us the event of other dynamic attributes which mostly happen before the reference event happens. And the co-incident factor can tell us the event of other dynamic attributes which mostly happens at the same time or a little bit after the reference event happens.

2 TEMPORAL MINING

An interesting work in (Roddick and Spiliopoulou 2002), they review research related to the temporal mining and their contributions related to various aspects of the temporal data mining and knowledge discovery and also briefly discuss the relevant previous work .

In majority of time series analysis, we either focus on prediction of the curve of a single time series or the discovery of similarities among multiple time series. We call time dependent variable as dynamic variable and call time independent variable as static variable.

Trend analysis focuses on how to estimate the value of dynamic attribute of interest at the next time point or at a specific time point in the future.

There are many kinds of patterns depending on application data. We can separate pattern types into four groups.

1. Cyclic pattern is the pattern which has the exact format and repeat the same format to be cyclic form, for example, ECG, tidal cycle, sunrise-sunset

2. Periodic pattern is the pattern which has the exact format in only part of cycle and repeat this exact format at the same part of cycle, for example, "Everyday morning at 7:30-8:00 am., Sandy has breakfast", the rest of the day Sandy has many activities which no exact pattern. The cycle of the day, every day the exact format happen only in the morning at 7:30-8:00 am.

3. Seasonal pattern is the pattern which is a sub type of cyclic pattern and periodic pattern. There is a pattern at a specific range of time during the year's cycle, for example, half year sales, fruit season, etc.

4. Irregular pattern is the pattern which doesn't have the exact pattern in cycle, for example, network alarm, computer crash.

2.1 Trend analysis problem

Trend analysis works are normally done by finding the cyclic patterns of one numerical dynamic attribute of interest. Once we know the exact pattern of this attribute, we can forecast the value of this attribute in the future. If we cannot find the cycle pattern of this attribute, we can use moving average window or exponential moving average window (Weiss and Indurkhya 1998; Kantardzic 2003) to estimate the value of this dynamic attribute at the next time point or at the specific time point in the future.

2.2 Pattern finding problem

In pattern finding problem, we have to find the change point to be the starting point and the end point of cycle or segment. Then we try to look for the segment or cycle pattern that is repeated in the whole data set. To see which type of pattern it is, that is, the cyclic pattern of periodic pattern, seasonal pattern or irregular pattern and observe the pattern.

The pattern matching problem is to find the way of matching the segment patterns. Pattern matching, can be exact pattern (Dasgupta and Forrest 1995) or rough pattern matching (Hirano, Sun et al. 2001; Keogh, Chu et al. 2001; Hirano and Tsumoto 2002), depending on the data application. The exact pattern is, for example, the cycle of machine working. The rough pattern is, for example, the hormone level in human body.

Another problem is the multi-scale pattern matching problem as seen in (Ueda and S.Suzuki 1990; Hirano, Sun et al. 2001; Hirano and Tsumoto 2001) to match patterns in different time scales.

One interesting work is Knowledge discovery in Time Series Databases (Last, Klein et al. 2001) . Last et al. proposed the whole process of knowledge discovery in time series data bases. They used signal processing techniques and the information-theoretic fuzzy approach. The computational theory of perception (CTP) is used to reduce the set of extracted rules by fuzzification and aggregation.

Another interesting work done in time series (Keogh, Lonardi et al. 2002) proposed an algorithm that detects surprising patterns in a time series database in linear space and time. This algorithm is named TARZAN. The definition of surprising in this algorithm is general and domain independent, describing a pattern as surprising if the frequency with which we encounter it differs greatly from that expected given previous experience.

3 PROBLEM

We get an OSS data set from http://sourceforge.net which is the world's largest Open Source software development website. There are 1,097,341 records, 41,540 projects in this data set. This data set consists of seventeen attributes include time attribute. The time attribute of each record in this data set is monthly. Each project in this data set is a software. There are many attributes that show various activities. We are interested in thirteen attributes which indicate the number of activities in this data set. The data of these thirteen attributes are all numeric. The value of the Download attribute is the number of the downloads. So the Download attribute is the indicator showing how popular the software is and show how successful the development of the software is. We are interested in the significant change of the number of the Download attribute. Then we employ the idea of the event detection technique proposed by (Guralnik and Srivastava 1999) to detect the event of the Download attribute. The event of our interest is the direction of the significant change of the data which can be up or down.

We want to find the predisposing factor and the co-incident factor of the Download event. We employ the same idea about the reference event as proposed in (Bettini, Wang et al. 1998) which is the fixed event of interest and we want to find the other events related to the reference event. So we call the Download attribute as the reference attribute and call the event of the Download attribute as the reference event.

The predisposing factor of the reference event can possibly be the cause of the reference event or the cause of the other event which is the cause of the reference event. And the co-incident factor of the reference event can possibly be the effect of the reference event or the effect of the other event which is the effect of the reference event somehow or be the event happening at the same time as the reference event happens or can be the result from the same cause of the reference event or just be the result from the other event which happens at the same time of the reference event happens. To make this concept clear, see the example as follow

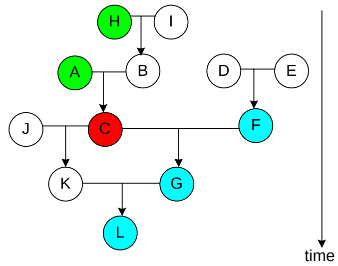


Figure1: The relationships among the events over time

If we have the event *A, B, C, D, E, F, G, H, I, J, K, L* and the relationships among them as shown in Figure 1. That is *H* and *I* give B; *A* and *B* give *C*; *D* and *E* give *F*; *C* and *F* give *G; J* and *C* give *K; K* and *G* give *L*. But in our data set consists of only *A, C, F, G, H, L*. And the reference event is *C*. We can see that *H* and *A* happen before C, we may say that A is the cause of C and/or H is the cause of *C*. But in the real relationship as shown above, we know that *H* is not the cause of *C* directly or it is not because *A* and *H* give *C*. So we call *A* and *H* are the predisposing factors of *C*. And we find that *F* happens at the same time as *C* happens. And *G* and *L* happen after *C*. We call *F* as the co-incident factor of *C*. We can see from the relationship that *G* is the result from *C* and *F*. *L* is the result from *G* which is the result from *C*. And F is the co-factor of *C* that gives *G*. Only *G* is the result from *C* directly. *L* is the result from *G* which is the result from *C*.

We want to find the exact relationships among these events. Unfortunately, no one can guarantee that our data set of consideration consists of all of the related factors or events. We can see from the diagram or the relationship shown in the example that the relationship among the events can be complex. And if we don't have all of the related events, we cannot find all of the real relationships. So what we can do with the possible incomplete data set is mining the predisposing factor and co-incident factor of the reference event. Then the users can further consider these factors and collect more data which related to the reference event and explore more in depth by themselves on the expert ways in their specific fields.

The main idea in this part is the predisposing factor can possibly be the cause of the reference event and the co-incident factor can possible be the effect of the reference event. So we employ the same idea as proposed in (Blum 1982; Blum 1982) that the cause happens before the effect. The effect happens after the cause. We call the time point when the reference event happens as the current time point. We call the time point before the current time point as the previous time point. And we call the time point after the current time point as the post time point. Then we define the predisposing factor of the reference event as the event which happens at the previous time point. And we define the co-incident factor of the reference event as the event happens at the current time point and/or the post time point.

4 BASIC DEFINITIONS AND FRAMEWORK

The method to interpret the result is selecting the large fraction of the positive slope and the negative slope at each time point. If it is at the previous time point that means it is the predisposing factor. If it is at the current time point and/or the post time point that means it is the co-incident factor.

Definition1: A time series data set is a set of records r such that each record contains a set of attributes and a time attribute. The value of time attribute is the point of time on time scale such as month, year.

$$r_j = \{ a_1, a_2, a_3, \ldots, a_m, t_j \}$$

where

r_j is the j^{th} record in data set

Definition 2: There are two types of the attribute in time series data set. Attribute that depends on time is dynamic attribute (Ω), other wise, it is static attribute (S).

Definition 3: Time point (t_i) is the time point on time scale.

Definition 4: Time interval is the range of time between two time points [t_1, t_2]. We may refer to the end time point of interval (t_2).

Definition 5: An attribute function is a function of time whose elements are extracted from the value of attribute i in the records, and is denoted as a function in time, $a_i(t_x)$

$$a_i(t_x) = a_i \in r_j$$

where

a_i attribute i;

t_x time stamp associated with this record

Definition 6: A feature is defined on a time interval [t_1 ,t_2], if some attribute function $a_i(t)$ can be approximated to another function $\Phi(t)$ in time , for example,

$$a_i(t) \approx \Phi(t) \ , \forall t \in [t_1, t_2]$$

We say that Φ and its parameters are features of $a_i(t)$ in that interval [t_1 ,t_2].

If $\Phi(t) = \alpha_i t + \beta_i$ in some intervals, we can say that in the interval, the function $a_i(t)$ has a slope of α_i where slope is a feature extracted from $a_i(t)$ in that interval

Definition 7: Slope (α_i) is the change of value of a dynamic attribute (a_i) between two adjacent time points.

$$\alpha_i = (a_{i(t_x)} - a_{i(t_{x-1})}) / t_x - t_{x-1}$$

where

$a_{i(t_x)}$ is the value of a_i at the time point t_x

$a_i (t_{x-1})$ is the value of a_i at the time point t_{x-1}

***Definition 8*:** Slope direction $d(\alpha_i)$ is the direction of slope.

If $\alpha_i > 0$, we say $d_\alpha = 1$

If $\alpha_i < 0$, we say $d_\alpha = -1$

If $\alpha_i \cong 0$, we say $d_\alpha = 0$

Definition 9: A significant slope threshold (δI) is the significant slope level specified by user.

Definition 10: Reference attribute (a_t) is the attribute of interest. We want to find the relationship between the reference attribute and the other dynamic attributes in the data set.

Definition 11: An event ($E1$) is detected if $\alpha_i \geqslant \delta I$

Definition 12: Current time point (t_c) is the time point at which reference variable's event is detected.

Definition 13: Previous time point (t_{c-1}) is the previous adjacent time point of t_c

Definition 14: Post time point (t_{c+1}) is the post adjacent time point of t_c

Proposition 1: Predisposing factor of a_t denoted as $PE1a_t$ is an ordered pair (a_i, d_α) when $a_i \in \Omega$

If ${}^{np}a_i\, t_{c-1} > {}^{nn}a_i\, t_{c-1}$, then $PE1a_t \approx (a_i , 1)$

If ${}^{np}a_i\, t_{c-1} < {}^{nn}a_i\, t_{c-1}$, then $PE1a_t \approx (a_i , -1)$

where

${}^{np}a_i\, t_{c-1}$ is the number of positive slope of $E1$ of a_i at t_{c-1}

${}^{nn}a_i\, t_{c-1}$ is the number of negative slope of $E1$of a_i at t_{c-1}

Proposition 2: Co-incident factor of a_t denoted as $CE1a_t$ is an ordered pair (a_i, d_α) when $a_i \in \Omega$

If $(({}^{np}a_i\, t_c > {}^{nn}a_i\, t_c) \vee ({}^{np}a_i\, t_{c+1} > {}^{nn}a_i\, t_{c+1}))$, then $CE1a_t \approx (a_i , 1)$

If $(({}^{np}a_i\, t_c < {}^{nn}a_i\, t_c) \vee ({}^{np}a_i\, t_{c+1} < {}^{nn}a_i\, t_{c+1}))$, then $CE1a_t \approx (a_i , -1)$

where

${}^{np}a_i\, t_c$ is the number of positive slope of $E1$ of a_i at t_c

${}^{nn}a_i\, t_c$ is the number of negative slope of $E1$ of a_i at t_c

${}^{np}a_i\, t_{c+1}$ is the number of positive slope of $E1$ of a_i at t_{c+1}

${}^{nn}a_i\, t_{c+1}$ is the number of negative slope of $E1$ of a_i at t_{c+1}

5 ALGORITHM

Now we present a new algorithm.

Input: The data set which consists of numerical dynamic attributes. Sort this data set in ascending order by time, a_t, δI

Output: ${}^{np}a_i\, t_{c-1}$, ${}^{nn}a_i\, t_{c-1}$, ${}^{np}a_i\, t_c$, ${}^{nn}a_i\, t_c$, ${}^{np}a_i\, t_{c+1}$, ${}^{nn}a_i\, t_{c+1}$, $PE1a_t$, $CE1a_t$

Method:
For all a_i
For all time interval $[t_x , t_{x+1}]$
Calculate α_i
For a_t
If $\alpha_t \succcurlyeq \delta I$
Set that time point as t_c
Group record of 3 time points t_{c-1} t_c t_{c+1}
Count ${}^{np}a_i\ t_{c-1}$, ${}^{nn}a_i\ t_{c-1}$, ${}^{np}a_i\ t_c$, ${}^{nn}a_i\ t_c$, ${}^{np}a_i\ t_{c+1}$, ${}^{nn}a_i\ t_{c+1}$
// interpret the result
If ${}^{np}a_i\ t_{c-1} > {}^{nn}a_i\ t_{c-1}$, then $PE1a_t \approx (a_i , 1)$
If ${}^{np}a_i\ t_{c-1} < {}^{nn}a_i\ t_{c-1}$, then $PE1a_t \approx (a_i , -1)$
If ${}^{np}a_i\ t_c > {}^{nn}a_i\ t_c$, then $CE1a_t \approx (a_i , 1)$
If ${}^{np}a_i\ t_c < {}^{nn}a_i\ t_c$, then $CE1a_t \approx (a_i , -1)$
If ${}^{np}a_i\ t_{c+1} > {}^{nn}a_i\ t_{c+1}$, then $CE1a_t \approx (a_i , 1)$
If ${}^{np}a_i\ t_{c+1} < {}^{nn}a_i\ t_{c+1}$, then $CE1a_t \approx (a_i , -1)$

For the event, the data change direction, we employ the method proposed by (Mannila, Toivonen et al. 1997) that is using the large fraction to judge the data change direction of the attribute of consideration.

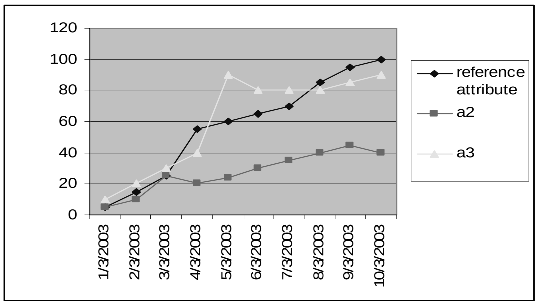
Using the combination of the ideas mentioned above, we can find the predisposing factor and the co-incident factor of the reference event of interest. The steps to do this task are

1. Set the threshold of the data change of the reference attribute.
2. Use this data change threshold to find the event which is the change of the data of the reference attribute between two adjacent time point is equal to or higher than the threshold, and mark that time point as the current time point
3. Look at the previous adjacent time point to find the predisposing factor and the post adjacent time point of the current time point to find the co-incident factor
4. Separate the case of the reference event to be the positive direction and the negative direction

4.1 For each case, count the number of the positive change direction and the number of the negative change direction of the other attributes in consideration.

4.2 Select the large fraction between the number of the positive change direction and the number of the negative change direction. If the number of the positive direction is larger than the number of the negative direction, we say that the positive change direction of the considered attribute is the factor. Otherwise, we say that the negative change direction of the considered attribute is the factor. If the factor is found at the previous time point, we say that the factor is the predisposing factor. If the factor is found at the current time point or the post time point, we say that the factor is the co-incident factor.

We don't use the threshold to find the event of the other attributes because of the idea of the degree of importance (Salam 2001). For example, the effects of the different kind of chilly on our food are different. Only small amount of the very hot chilly make our food very hot. Very much of sweet chilly make our food not so spicy. We see that the same amount of the different kind of chilly creates the different level of the hotness in our food. The very hot chilly has the degree of importance in our food higher than the sweet chilly. Another example, about the number of Download of the software *A*, we can see that normal factors effect on the number of Download are still there. But in case there is a lecturer or a teacher assign his/her 300 students in his/her class to test the software *A* and report the result to him/her within 2 weeks. This assignment makes the number of Download of the software *A* increase significantly in very short time. For the other software, software *B*, is in the same situation or the same quality or the same other factors as the software *A* which should get the same number of Download as the software *A*, but there is no lecturer or teacher assigning his/her 300 students to test it. The number of Download of the software *B* is lower than the software *A*. Or in case there is a teacher or lecturer assign his/her 500 students to test 2 or 3 softwares and report the results to him/her within one month. This event makes the number of Download of many softwares increase in very short time. Such incidental factors have the potential to skew the results. Such factors may have high degree of importance that effect on the number of Download of the software. It is the same as the only small amount of the data change of some attributes can make the data of the reference attribute change very much. So we do not specify the threshold of the event of the other attributes to be considered as the predisposing factor or the co-incident factor. For example, the graph of the data is shown in Graph 1



Graph 1: the data in the graph

We calculate the slope value showing how much the data change and the direction of the data change per time unit.

Then we set the data change threshold as 15. We use this threshold to find the reference event. We find the reference event at the time 4/03. Then we mark this time point as the current time point. Next we look at the previous time point, 3/03, for the predisposing factor, we find that a2 with the positive direction and a3 with positive direction are the predisposing factor of the reference event. Then we look at the current time point and the post time point, 4/03 and 5/03, for the co-incident factor, we find that at the current time point, a2 with the negative direction and a3 with the positive direction are the co-incident factor. And at the post time point, a2 with the positive direction and a3 with the positive direction are the co-incident factor. We can summarize the result in the pattern table as shown in Table 1.

Table 1: the direction of each attribute at each time point

	Previous time point	Current time point	Post time point
a2	Up	down	up
a3	Up	up	up

6 OSS DATA

The OSS data on SourceForge website has been collected over the last few years. Initially some projects were listed with the SourceForge at various developmental stages. Since then a large number of new projects have been added at different time points and are progressing at different pace. Though they are at different developmental stages, there data is still collected at regular intervals of one month. Due to this a global comparison of all of the projects poses many problems. Here we wish to explore local trends at each event.

The main idea is to choose an event in the reference variable as a reference time point and mine the relationship with other numerical dynamic attributes. By using this method, we wish to explore the predisposing and co-incident factors of the reference event of interest in time series data set. The predisposing factor is the factor which can be the cause of the reference event or the factor that has effect on the reference event somehow. The co-incident factor is the factor that can be the effect of the reference attribute or the factor that is also the result of the predisposing factor of the reference event or the reference event effect on it somehow.

7 EXPERIMENTS

We apply our method with one OSS data set which consists of 17 attributes (Project name, Month-Year, Rank0, Rank1, Page-views, Download, Bugs0, Bugs1, Support0, Support1, Patches0, Patches1, Tracker0, Tracker1, Tasks0, Tasks1, CVS. This data set consists of 41,540 projects, 1,097,341 records

7.1 Results

We select the Download attribute to be the reference attribute. And we set the significant data change threshold as 50. The results are separated into two cases. The first case is the data change direction of the Download is positive. The second is the data change direction of the Download is negative. The results are shown in Table 2 and Table 3 accordingly.

7.1.1 Slope direction of the Download is positive

Table 2: Summary of the results in case the slope direction of the Download is positive

	previous	current	post
P/V	Up	up	down
Bugs0	Up	up	down
Bugs1	Up	up	down
Support0	up	up	down
Support1	up	up	down
Patches0	up	up	down
Patches1	up	up	down
Tracker0	up	up	down
Tracker1	up	up	down
Tasks0	down	down	down
Tasks1	up	up	down
CVS	up	up	down

From this finding we can see that the predisposing factors of the number of the Download significantly increases are the number of Tasks0 decreases and the rest of other attributes which consists of Page views, Bugs0, Bugs1, Support0, Support1, Pathces0, Patches1, Tracker0, Tracker1, Tasks1, CVS increase. At the same time interval, the co-incident factors of the number of Download significantly increases are the same as its predisposing factors but after that the number of all of the other attributes decreases.

7.1.2 Slope direction of the Download is negative

Table 3: Summary of the result in case the slope direction of the Download is negative

	previous	current	post
P/V	up	down	down
Bugs0	up	down	down
Bugs1	up	down	up
Support0	up	down	down
Support1	up	down	up
Patches0	up	down	up
Patches1	up	down	up
Tracker0	up	down	down
Tracker1	up	down	up
Tasks0	down	down	down
Tasks1	down	down	down
CVS	down	down	down

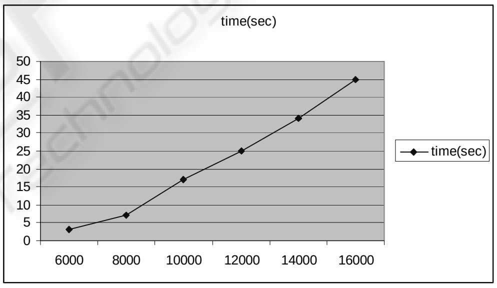
From these results, we find that the predisposing factors of the number of the Download significantly decreases are the number of almost all of the other attributes increases, except only the number of Tasks0, Tasks1 and CVS decrease. And the co-incident factors of the number of Download significantly decrease are the number of all of the other attributes decrease at the same time interval. After that the number P/V, Bugs0, Support0, Tracker0, Tasks0, Tasks1, CVS decrease and the number of Bugs1, Support1, Patches0, Patches1, Tracker1 increase .

8 PERFORMANCE

Our methods consume time to find the predisposing factor and the co-incident factor of the reference event just in $O(n)$ where n is the number of the total records. The most time consuming is the time for calculating the slope (the data change) of every two adjacent time points of the same project which take time $O(n)$. And we have to spend time to select the reference event by using the threshold which takes time $O(n)$. We have to spend time to group records around the reference event (at the previous time point, the current time point and the post time point) which is $O(n)$. And the time for counting the number of events of the other attributes at each time point around the current time point is $O(n)$. The time in overall process can be approximate to $O(n)$, which is not exponential. So our methods are good enough to apply in the big real life data set.

In our experiments we use PC PentiumIV 1.6 GHz, RAM 1 GB. The operating system is MS WindowsXP Professional. We implement these algorithms in Perl 5.8 on command line. The data set test has 1,097,341 records, 41, 540 projects with total 17 attributes. The number of attributes of consideration is 13 attributes. The size of this data set is about 48 MB.

We want to see if our program consume running time in linear scale with the size of the data or not. Then we test with the different number of records in each file and run each file at a time. The result is shown in Graph 2.



Graph 2: Running time (in seconds) and the number of records to be run at a time

From this result confirm us that our algorithm consumes execution time in linear scale with the number of records.

8.1 Accuracy test with Synthetic Data sets

We synthesize 4 data sets as follow

1. Correct complete data set
2. Put 5 % of noise in the first data set
3. Put 20 % of noise in the first data set
4. Put 50 % of noise in the first data set

We set the data change threshold as 10. The result is almost all of four data sets correct, except only at the third data set with 20 % of noise, there is only one point in the result different from the others, that is, the catalyst at the current point changes to be positive slope instead of steady.

9 CONCLUSION

The combination of the existing methods to be our new algorithm can be used to mine the predisposing factor and co-incident factor of the reference event very well. As seen in our experiments, our proposed algorithm can be applied to both the synthetic and the real life data set. The performance of our algorithm is also good. They consume execution time just in linear time scale and also tolerate to the noise data.

10 DISCUSSION

The threshold is the indicator to select the event which is the significant change of the data of the attribute of consideration. When we use the different thresholds in detecting the events, the results can be different. So setting the threshold of the data change have to be well justified. It can be justified by looking at the data and observing the characteristic of the attributes of interest. The users have to realize that the results they get can be different depending on their threshold setting. The threshold reflects the degree of importance of the predisposing factor and the co-incident factor to the reference event. If the degree of importance of an attribute is very high, just little change of the data of that attribute can make the data of the reference attribute change very much. So for this reason setting the threshold value is of utmost importance for the accuracy and reliability of the results.

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