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APPLICATION OF PROCESS MINING IN INSURANCE: A CASE STUDY FOR UTI

Madderi Sivalingam Saravanan[1], Rama Sree .R.J[2]

[1,2]Bharathiar University, Coimbatore
[1] Dept. of IT in VEL TECH, Dr. RR & Dr. SR Technical University, Avadi, Tamil Nadu, INDIA.
[2]Department of Computer Science, Rashtriya Sanskrit Vidyapeetha, Tirupati, Andhra Pradesh, INDIA.

ABSTRACT:
To gain competitive advantage, insurance companies try to streamline their processes. In order to do so, it is essential to have an accurate view of the “careflows” under consideration. In this paper, we apply process mining techniques to obtain meaningful knowledge about these flows, e.g., to discover typical paths followed by particular groups of Insurance holders. This is a non-trivial task given the dynamic nature of insurance processes. The paper demonstrates the applicability of process mining using a real case of Unit Trust of India insurance holder processes in a UTI insurance company located at Chennai in India. Using a variety of process mining techniques, we analyzed the insurance process using the control flow perspective. In order to do so we extracted relevant event logs from the insurance company information system and analyzed these logs using the ProM framework. The control flow perspective algorithm Heuristics Miner (HM) algorithm of the ProM and FPGrowth algorithm of the Weka Library were used to predict the knowledge from the insurance log. The results show that process mining can be used to provide new insights that facilitate the improvement of existing careflows.

Keywords: Process mining, Careflows, Insurance log, ProM framework, FPGrowth, Weka Library.

[I] INTRODUCTION
In a competitive insurance company, the service process for the insurance holder has to be focused on ways to streamline their processes in order to deliver high quality service and care flows while at the same time reducing costs [1]. Furthermore, also on the governmental side and on the side of the insurance control organizations, more and more pressure is put on insurance to work in the most efficient way as possible, whereas in the future, an increase in the demand for care is expected.

A complicating factor is that insurance unit is characterized by highly complex and extremely flexible service processes, also referred to as “control flows”. Moreover, many disciplines are involved for which it is found that they are working in isolation and hardly have many idea about what happens within other disciplines. Another issue is that within insurance unit or insurance sector many autonomous, independently developed applications are found [2]. A consequence of this all is that it is not known what happens in the insurance unit process for a group of services with the same process. The concept of process mining provides an interesting opportunity for providing a solution to this problem. Process mining [3] aims at extracting process knowledge from so called “event logs” which may originate from all kinds of systems, like enterprise information systems or insurance holder processing system or company information systems or automobile repairing process systems, etc. Typically, these event logs contain information about the start or completion of process steps together with related context data for example actors and resources. Furthermore, process mining is a very broad area both in terms of (1) applications and (2) techniques.

This paper focuses on the applicability of process mining in the insurance unit domain. Process mining has already been successfully applied in the healthcare service industry [4]. In this paper, we demonstrated the applicability of process mining in insurance unit domain. We will show how process mining can be used for obtaining insights related to control flows, for example, the identification of control paths and strong comparison between different service methods of services to minimize the processing time. We use several process mining techniques which will also show the diversity of process mining techniques but in this paper we discuss about control flow discovery.

In this paper, we have taken a case study of insurance service processing system to discuss about the control flow aspects of process mining of the UTI insurance unit a big company at Chennai, Tamil Nadu, India. The raw data contains data about a group of 600 insurance holder details and for which all deep analysis and service activities have been recorded to analyze the mined process model and basic performance analysis for better recovery process. Note that we did not use any Apriori knowledge about the control process of this group of services.

Today's Business Intelligence (BI) tools [5] used in the insurance unit domain, like Cognos, Business Objects, or SAP BI, typically look at aggregate data seen from an external perspective (frequencies, averages, utilization, service levels, etc.). These BI tools focus on performance indicators such as the number of tasks or operations of a service, the length of waiting lists, and the success rate of operations. Process mining looks “inside the process” at different abstraction levels. So, in the context of insurance holder, unlike BI tools, we are more concerned with the control paths followed by individual services and whether certain service procedures are followed or not.

This paper is structured as follows: Section two provides an overview of process mining. In Section three will show the applicability of process mining in the insurance unit using data obtained for about 600 insurance holder details from the UTI company. Section four concludes the paper.

[II] PROCESS MINING

Process mining is applicable to a wide range of systems. These systems may be pure information systems (e.g., ERP systems) or systems where the hardware plays a more prominent role (e.g., embedded systems). The only requirement is that the system produces event logs, thus recording (parts of) the actual behavior.

Interesting classes of information systems that produce event logs are the so called Process-Aware Information Systems (PAISs) [6]. Examples are classical workflow management systems (e.g. Staffware), enterprise resource planning systems (e.g. SAP), case handling systems (e.g. FLOWer), product data management systems (e.g. Windchill), customer relationship management systems (e.g. Microsoft Dynamics CRM), middleware (e.g., IBM's WebSphere), company information systems (e.g., Chipsoft), etc. These systems provide very detailed information about the activities that have been executed.

However, not only PAISs are recording events. Also, in a typical insurance there is a wide variety of systems that record events. For example, in insurance service process, a system can record the set of processes that undergoes the different procedures to full fill the needs of insurance holder. For a new insurance holder the whole process of service depends on eligibility, age limit etc. This information was recorded till the end of the service process. In order for these systems to work properly, information from different systems needs to be collected, so that it is clear which activities have been performed in the control process of a service. In this way, these systems within the insurance unit can contain information about processes within one department but also across departments. This information can be used for improving processes within departments itself or improving the services offered to customers for various services of the same or different groups.

The goal of process mining is to extract information (e.g., process models) from these logs, i.e., process mining describes a family of a-posteriori analysis techniques exploiting the information recorded in the event logs. Typically, these approaches assume that it is possible to sequentially record events such that each event refers to an activity (i.e., a well defined step in the process) and is related to a particular case (i.e., a process instance). Furthermore, some mining techniques use additional information such as the performer or originator of the event (i.e., the person or resource executing or initiating the activity), the timestamp of the event, or data elements recorded with the event (e.g., the size of an order).

Process mining addresses the problem that most of the processes have limited information about what is actually happening. In practice, there is often a significant gap between what is prescribed or supposed to happen, and what actually happens. Only a concise assessment of reality, which process mining strives to deliver, can help in verifying process models, and ultimately be used in system or process redesign efforts.

The idea of process mining is to discover, monitor and improve the real processes (i.e., not assumed processes) by extracting knowledge from event logs.

We consider three basic types of process mining (Figure 1): (1) discovery, (2) conformance, and (3) extension.

Discovery: Traditionally, process mining has been focusing on discovery, i.e., deriving information about the original process model, the organizational context, and execution properties from enactment logs. An example of a technique addressing the control flow perspective is the α-algorithm [7] which constructs a Petri net model describing the behavior observed in the event log. It is important to mention that there is no apriori model, that is based on an event log some model is constructed. However, process mining is not limited to process models (i.e., control flow) and recent process mining techniques are more and more focusing on other perspectives, e.g., the organizational perspective, performance perspective or the data perspective. For example, there are approaches to extract social networks from event logs and analyze them using social network analysis [8]. This allows organizations to monitor how people, groups, or software or system components are working together. Also, there are approaches to visualize performance related information, e.g. there is an approach which graphically shows the bottlenecks and all kinds of performance indicators, e.g., average or variance of the total flow time or the time spent between two activities.

Conformance: There is an Apriori model. This model is used to check if reality conforms to the model. For example, there may be a process model indicating that purchase orders of more than one million Rupees require two checks. Another example is the checking of the so called "four eyes" principle. Conformance checking may be used to detect deviations, to locate and explain these deviations, and to measure the severity of these deviations.

Extension: There is an Apriori model. This model is extended with a new aspect or perspective that is the goal is not to check conformance but to enrich the model with the data in the event log. An example is the extension of a process model with performance data, that is some Apriori process model is used on which bottlenecks are projected.

At this point of time there are mature tools such as the ProM framework [9], featuring an extensive set of analysis techniques which can be applied to real life logs while supporting the whole spectrum depicted in Figure 1.

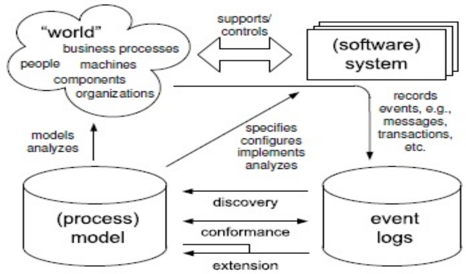

Fig.1 Three Types of Process Mining: (1) Discovery, (2) Conformance, and (3) Extension

[III] INSURANCE UNIT PROCESS

In every process, there should be an input, in the insurance process the insurance holder has taken as input of data to process the insurance holder processes. The insurance holder service process is first start with the registration and then the service type such as simple or complex or moderate, etc. Then this insurance holder is sent to apply for different type of service processes. After identifying the service the insurance holder is sent to identify the method of service to provide to the customer. Hence, the insurance holder is sent for test and then he/ she sent to different service process and finally sent to approval / rejection section. Before approval the insurance holder, the insurance holder is sent to different formalities to complete. If the insurance service centre has the free of cost service, it is treated as separate formulated processes; hence these processes are different from the new insurance holder service. The service process has lot of sub processes; each one of the sub processes is conducted at various departments.

In this section, we want to show the applicability of process mining in insurance unit. However, in this case study, we taken 600 insurance holder service processes, these are the process of service that require for various sub procedures. After the service, insurance holder once again sent to age limit process to approval the insurance holder, hence it has few event logs. It is clear that every insurance holder has different service method to care the insurance holder and at the same time different insurance holder's service process may match for the same service, hence the different services may have a same group of services of different insurance holder in the insurance unit processes need to be identified using clustering technique.

The insurance unit process needs to be compared between different service methods of insurance holders to minimize the processing time and to reduce the service activities and to identify the difference between each group of services of the insurance holder service unit. Consequently, these kinds of systems contain insurance holder process related information of the insurance unit. Hence, these processes are therefore an interesting insurance holder problem or service data collected from the UTI Company to apply various mining algorithms using ProM framework.

To this end, a case study for showing the applicability of process mining in insurance service unit, we use raw data collected by the insurance company for insurance holder of the UTI company insurance unit. This raw data contains information about a group of 600 insurance holder details to approve the insurance process for which all steps of service process have been recorded.

For this data set, we have extracted event logs from the insurance holder databases, where each event refers to a different service of the insurance holder. As the data is coming from a service system, we have to face the interesting problem that for each service of the insurance holder has similar service of fixing and little additional service is identified and recorded using the event logs. These event logs will show how these and process are undergone various steps or activities of same group of service methods of insurance holders.

In additional we have some information about the actual timestamps of the start and completion of the each task or activity of insurance service process. Consequently processing of each of the processes need to be executed as per the event log generated by the system. In this case, the log contains 600 cases, 2648 different events and has 9,200 event logs, which indicate that we are dealing with a non-trivial control flow process.

In the remainder of this section we will focus on obtaining, in an explorative way, insights into the service process of insurance unit process. So, we will only focus on the discovery of process mining, instead of the conformance and extension part. Furthermore, obtaining these insights should not be limited to one perspective only. Therefore, in section three, we focus on the discovery of control paths followed by insurance agents. This also demonstrates the homogenous service process for various services. However, it was discussed in the previous section. Hence, we first need to perform some preprocessing before being able to present information on the right level of detail.

A. Preprocessing of Logs

The log of the Insurance unit contains a large amount of distinct activities, of which many are rather low level activities, that is events at a low abstraction level. In this study, new insurance holders has preliminary or simple activities are at a too low abstraction level, e.g. determination of age limit process, etc. We would like to consider all these low level process as a single process. Mining a log that contains many distinct activities would result in a too detailed spaghetti-like model that is difficult to understand. Hence, we first apply some preprocessing on the logs to obtain interpretable results during mining. During preprocessing we want to “simplify” the log by removing the excess of low level activities. In addition, our goal is to consider only events at the service methods of the insurance holder. Hence, we can focus on control paths and interactions between different service procedures or methods of the insurance holder.

B. Mining

In this section, we present some results obtained through a detailed analysis of the insurance service processing systems for every event log generated for the service or care flow process. We concentrate on the discovery part to show actual situations, for example control flows in the insurance unit.

1. Converting the raw data into MXML format

In insurance holder process the service first applied to the sample of insurance holder instead of lot of insurance holders, because of service failure of the insurance holders, since the samples are tested by the insurance agents, an expert in insurance unit. So, the sample process is recorded and fed into the system as a data. These data are stored in the form of MS-Access database file format. Then this database information is converted into Mining Extensible Markup Language (MXML) file format using the ProM Import Framework. Finally this converted MXML file is sent as an input to ProM Framework to do different types of mining. In this paper we concentrated to deal with process or control flow of activities or tasks. Hence the view of control flow perspective deal about the mined process model and basic performance analysis to identify and minimize for better process for lot of insurance holders service process, this can be helpful, after the better knowledge discovered from the sampling process.

2. Control flow Perspective

One of the most promising mining techniques is control flow mining which automatically derives process models from process logs. The generated process model reflects the actual process as observed through real process executions. If we generate process models from insurance unit process logs, they give insight into control paths for insurance holder service process. The control flow perspective in process mining has several process mining algorithms such as the α-mining algorithm, heuristic mining algorithm, region mining algorithm, etc [7][10][11].

In this paper, we use the Heuristics mining algorithm, since it can deal with noise and exceptions, and enables users to focus on the main process flow instead of on every detail of the behavior appearing in the process log [10]. Figure 3 shows the process model for all cases obtained using the Heuristics Miner. Despite its ability to focus on the most frequent paths, the process, depicted in Figure 3, is still spaghetti-like and too complex to understand.

Since, processes in the insurance unit do not have a single kind of flow but a lot of variants based on different service methods of the services. Therefore using the figure 3, we can understand the similar services and different services for each service by comparing each service on the insurance holder from event logs.

It is surprising that the derived process model is spaghetti or complex and convoluted. One of the methods for handling this problem is breaking down a log into two or more sub logs until these become simple enough to be analyzed clearly. We apply clustering techniques to divide a process log into several groups (i.e. clusters), where the cases in the same cluster have similar properties. Clustering can be conducted using cluster mining algorithm from ProM framework is used for this case study. Hence, the ProM framework is very useful for mining applications.

The figure 3 has 30 different service methods for a group of insurance holders; each has combination of service process. The service 1 has the insurance holder's age limit and admission, etc. The service 2 has the insurance holder's service sheet allotment, scheme, time limit, benefits, etc. A portion of the service process called "approval" are shown in the process model in figure 3 has 600 insurance holder's service processes. Hence, this model has generated from different combination of services as per the event logs. These event logs are stored in the form of mining extensible markup language (MXML). Then, these logs are converted as the mined process model using different mining algorithms.

The figure 3 shows that the approval is represented as links. These links have the parallel connections or connectors with JOIN and OR operations. The more JOIN operations, identifies the different activity with various combination of service fix. These operations are useful for the benefit of identifying the better service methods, which is used for the parallel activities. The system of insurance holder's service process is always useful for the insurance agents to understand the process using the process model, which is developed using any one of the process mining algorithm using mining tool. A insurance agent in the insurance unit always create the concept of the insurance holder process using his or her experience in the field of insurance holder processes, but even it is not helpful in certain situations, such as complex service process, so the insurance holder process always gives the human thinking or knowledge of process, which is not optimal process model for insurance holder process, because it may consume more time and cost. The service of the process with automation and better mined process model will lead the insurance agent in a better way to proceed.

In view of time, the figure 3 shows the various service processes taken for each insurance holder is recorded. These processes are recorded using time stamp and originator information for the every event. The minimum and maximum time limit for each activity or event in the insurance holder process will bring better process, instead the normal methods followed by the insurance agents. The figure 2 shows the event log, which is derived from the original insurance holder activity for 262 different service methods among the services with 9,200 event logs or activities. In this figure the process instance represents the case that is each service. Audit trail entry has the four different types of inputs for every event. The first one represents workflow element name, which is "Register" as shown in the figure 2. The Second one represents workflow element type such as "Start" or "Complete". The third one represents the timestamp that is time taken to complete the activity or event. The fourth one represents the originator of the process instance or case, which is known as event creator.

The process instance for every case has the audit trail entry. The audit trail entry is the key component for each entry, because the transaction of every activity will takes place with time and originator. When the instance has completed the event type stores the data in the event log as "complete" or "start". "Start" of the event represents the event starting. "Complete" of the event represents the event ending. Therefore, the service process can be mined for the betterment of insurance units and insurance holder's.

The complex process model generated by the HM process mining algorithm is not easy to understand and to follow. Hence, alternative approaches need to be identified. Therefore, one of the classical data mining technique, association rule mining algorithms were useful to predict the failure of the insurance holder without more age limit and cost. The association rule mining algorithm FPGrowth algorithm is used to simplify the process.

The FPGrowth algorithm has minimum support threshold and the data as inputs. Using these input values the FPGrowth algorithm produce simplified process model with confidence and support values.

The experts or insurance agent in the insurance company can easily identify the perfect or optimal service method. The information recorded for mining the process need to be converted into .AFRR (Attribute Relational File Format). The converted file fed into the Weka library tool. This Weka tool will generate the associator process model as shown in figure 4.


```
<?xml version="1.0" encoding="UTF-8" ?>
<!-- MXML version 1.1 -->
<!-- Created by ProM Import Framework, Version 7.0 (Propeller) -->
<!-- via MXMLib Version 1.9 (http://promimport.sf.net/) -->
<!-- (c) 2004-2007 C.W. Guenther (christian@deckfour.org); Eindhoven Technical
University -->
<!-- This event log is formatted in MXML, for use by BPI and Process Mining Tools.
-->
<!-- You can load this file e.g. in the ProM Framework for Process Mining. -->
<!-- More information about MXML, Process Mining, and ProM:
http://www.processmining.org/. -->
<WorkflowLog xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
xsi:noNamespaceSchemaLocation="http://is.tm.tue.nl/research/processmining/Workflow
Log.xsd" description="This log is converted from the tables &apos;Cases and Events
and CaseAttributes and EventAttributes&apos; at the database
&apos;jdbc:odbc:insurance&apos;">
<Data>
<Attribute name="app.name">ProM Import Framework</Attribute>
<Attribute name="app.version">7.0 (Propeller)</Attribute>
<Attribute name="java.vendor">Sun Microsystems Inc.</Attribute>
<Attribute name="java.version">1.6.0_24</Attribute>
<Attribute name="mxml.creator">MXMLib (http://promimport.sf.net/)</Attribute>
<Attribute name="mxml.version">1.1</Attribute>
<Attribute name="os.arch">x86</Attribute>
<Attribute name="os.name">Windows 7</Attribute>
<Attribute name="os.version">6.1</Attribute>
<Attribute name="user.name">SARA</Attribute>
</Data>
<Source program="MsAccessDB"/>
```

```
<Process id="GLOBAL" description="This log is converted from the tables
&apos;Cases and Events and CaseAttributes and EventAttributes&apos; at the
database &apos;jdbc:odbc:insurance&apos;">
<ProcessInstance id="1160">
<Data>
<Attribute name="Ins_Registration">1160</Attribute>
</Data>
<AuditTrailEntry>
<Data>
<Attribute name="Mr_Saran">Red CA_3gm</Attribute>
</Data>
<WorkflowModelElement>Mr_Sai_Prakash</WorkflowModelElement>
<EventType>complete</EventType>
<Timestamp>2011-01-07T14:00:00.000+05:30</Timestamp>
<Originator>Insurance_Agent</Originator>
</AuditTrailEntry>
```


Fig. 2 A Part of MXML log with 30 Cases and 828 Event logs

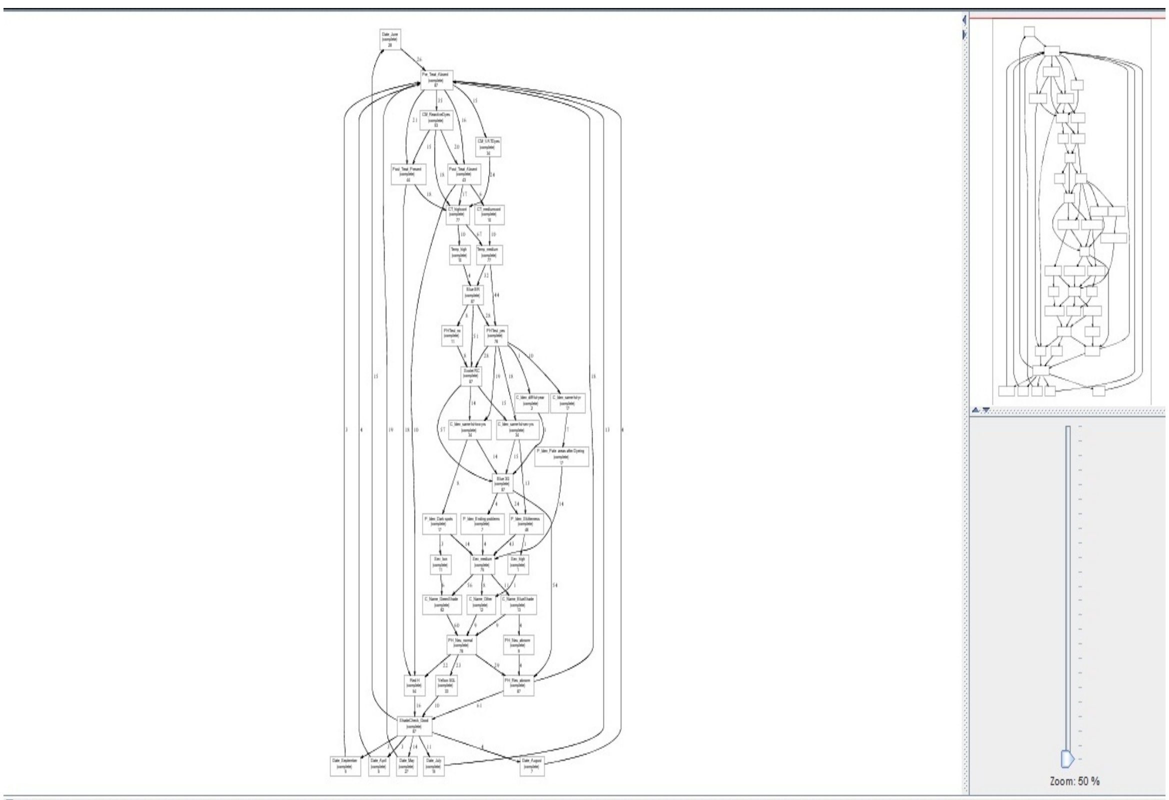

Fig.3 Process model for 600 cases of insurance holder processes with 9,200 event logs using HM algorithm

```
FPGrowth found 20 rules (displaying top 10)

 1. [Ins_Age_Limit=yes, Ins_Registration=yes]: 301 ==> [Ins_Admission=yes]: 297   <conf:(0.99)> lift:(1.17) lev:(0.07) conv:(9.23)
 2. [Ins_Service_Sheet=yes]: 305 ==> [Ins_Scheme=yes]: 299   <conf:(0.98)> lift:(1.11) lev:(0.05) conv:(4.94)
 3. [Ins_Admission=yes, Ins_Service_Sheet=yes]: 294 ==> [Ins_Scheme=yes]: 288   <conf:(0.98)> lift:(1.1) lev:(0.05) conv:(4.76)
 4. [Ins_TimeLimit=yes, Ins_Registration=yes]: 287 ==> [Ins_Admission=yes]: 281   <conf:(0.98)> lift:(1.16) lev:(0.06) conv:(6.29)
 5. [Ins_Registration=yes]: 387 ==> [Ins_Admission=yes]: 376   <conf:(0.97)> lift:(1.15) lev:(0.08) conv:(4.95)
 6. [Ins_ChildScheme=yes]: 339 ==> [Ins_Admission=yes]: 329   <conf:(0.97)> lift:(1.15) lev:(0.07) conv:(4.73)
 7. [Ins_Scheme=yes, Ins_Registration=yes]: 348 ==> [Ins_Admission=yes]: 337   <conf:(0.97)> lift:(1.14) lev:(0.07) conv:(4.45)
 8. [Ins_Approval=yes, Ins_Registration=yes]: 316 ==> [Ins_Admission=yes]: 306   <conf:(0.97)> lift:(1.14) lev:(0.06) conv:(4.4)
 9. [Ins_Scheme=yes, Ins_ChildScheme=yes]: 307 ==> [Ins_Admission=yes]: 297   <conf:(0.97)> lift:(1.14) lev:(0.06) conv:(4.28)
10. [Ins_Scheme=yes, Ins_Approval=yes, Ins_Registration=yes]: 282 ==> [Ins_Admission=yes]: 272   <conf:(0.96)> lift:(1.14) lev:(0.06) conv:(3.93)

=== Evaluation ===

Elapsed time: 0.14s
```

Fig.4 Associator process model using FPGrowth algorithm for insurance holder's service processes

[IV] CONCLUSION

In this paper, we have focused on the applicability of process mining in the insurance unit domain. For our case study, we have used data coming from non-trivial service methods of insurance holder process of the UTI insurance unit. We focused on obtaining insights into the control flow by looking at the control flow perspective. For this perspective, we presented some initial results. We have shown that it is possible to mine complex insurance unit service processes giving insights into the process. In addition, with existing techniques we were able to derive understandable mined process models for large groups of services to identify the same and different insurance holder process. The results are not derived by human thinking, it goes as per the recorded information and hence the automated mined process model helps the insurance agent, well sufficient for the better insurance holder process.

Furthermore, we compared our mined process model with a process model before mining of the insurance unit process. Normally a top down approach had been used for creating the process model and obtaining the logistical data [12]. With regard to the before mining process model, comparable results have been obtained. These types of knowledge help in many ways for the insurance agent in the insurance service unit process. However, a lot of effort was needed for creating the process model and obtaining the logistical data, where with process mining there is an opportunity to obtain these kind of data in a semi automatic way.

Unfortunately, traditional process mining approaches have problems dealing with unstructured processes such as insurance holder applications and insurance etc. Future work will focus on both developing new mining techniques and on using existing techniques in an innovative way to obtain understandable, high level information instead of "spaghetti-like" models showing all details. Obviously, we will plan to evaluate these results in insurance unit organizations such as the UTI insurance unit.

REFERENCES

[1] Bingsen Zhang , Hanchun Li, Research on Application for Service Matching in Textile Insurance holder Based on Numerical Analysis. International Conference on Computer Science and Software Engineering, Volume 01, publisher IEEE Computer Society, Washington, DC, USA, 2008, ISBN: 978-0-7695-3336-0.

[2] Lenz, R., Elstner, T., Siegele, H., and Kuhn, K., A Practical Approach to Process Support in Health In-formation Systems. Journal of the American Medical Informatics Association, 2002, 9(6), pp 571–585.

[3] van der Aalst, W., van Dongen, B., Herbst, J., Maruster, L., Schimm, G., and Weijters, A., Workflow Mining: A survey of Issues and Approaches. IEEE Journal of the Data and Knowledge Engineering, 2003, 47(2).

[4] van der Aalst, W., Reijers, H., Weijters, A., van Dongen, B., de Medeiros, A. A., Song, M., and Verbeek, H., Business process mining : an industrial application. Journal of the Information Systems, 2007, 32(5).

[5] Snezana, S., Violeta, M., Business Intelligence tools of Statistical Analysis. 32nd International Conference on Information Technology Interfaces (ITI) by the University of St.Kliment Ohridski Bitola, Bitola, Macedonia and published in IEEE Journal, 2010, Vol: 21-24 June, pp 199-204.

[6] Dumas, M., van der Aalst, W., and ter Hofstede, A., Process-Aware Information Systems: Bridging People and Software through Process Technology. Published by Wiley & Sons, 2005.

[7] van der Aalst, W., Weijters, A., and Maruster, L., Workflow Mining: Discovering Process Models from Event Logs. IEEE Transactions on Knowledge and Data Engineering, 2004, 16(9), pp 1128–1142.

[8] van der Aalst, W., Reijers, H., and Song, M., Discovering Social Networks from Event Logs. Published in Computer Supported Cooperative Work, 2005, Vol 14(6), pp 549–593.

[9] van der Aalst, W., van Dongen, B., Gunther,¨ C., Mans, R., de Medeiros, A. A., Rozinat, A., Rubin, V., Song, M., Verbeek, H., and Weijters, A. ProM 4.0: Comprehensive Support for Real Process Analysis. In Kleijn, J. and Yakovlev, A., editors, Application and Theory of Petri Nets and Other Models of Concurrency (ICATPN 2007), Published by Springer-Verlag, Berlin, 2007, Vol 4546 of Lecture Notes in Computer Science, pp 484–494.

[10] Weijters, A. and van der Aalst, W., Rediscovering Workflow Models from Event-Based Data using Little Thumb. Published in Integrated Computer-Aided Engineering, 2003, Vol 10(2), pp 151–162.

[11] van Dongen, B., Busi, N., Pinnaand, G., and van der Aalst, W., An Iterative Algorithm for Applying the Theory of Regions in Process Mining. BETA Working Paper Series, WP 195, Eindhoven University of Technology, Eindhoven, 2007.

[12] Elhuizen, S., Burger, M., Jonkers, R., Limburg, M., Klazinga, N., and Bakker, P. Using Business Process Redesign to Reduce Wait Times at a University Company in the Netherlands. The Joint Commission Journal on Quality and Insurance holder Safety, 2007, Vol 33(6), pp 332–341.

AUTHORS

Saravanan. M.S received B.Sc degree in computer science from Madras University in 1996, the MCA degree from Bharathidasan University in 2001, the M.Phil degree from Madurai Kamaraj University in 2004, M.Tech degree from IASE University in 2005. And now pursuing PhD degree in Bharathiar University. His current research interests include Process Mining, Business Process modeling, Workflow management systems and Exception handling etc. He is an Assistant professor in the Department of Information Technology in VEL TECH Dr, RR & Dr. SR Technical University, Avadi, Chennai, India. M.S. Saravanan has published twenty six international publications and presented ten research papers in international and national conferences, having 13 years of teaching experience in various institutions in India.

Rama Sree. R.J received M.S degree in computer science from BITS Pilani University in 1996 and PhD degree in S.P. Mahila University, Tirupati. She is a Reader in Department of Computer Science in Rashtriya Sanskrit Vidyapeetha, Tirupati. Dr. Rama Sree has published three books and thirty three international publications and ten national publications, having 19 years of teaching experience.