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Abstract

The external environment of an organization is characterized by significant changes that occur in the social, economical, political and technological fields. The organization should know this setting and act effectively. A major challenge is how to define significant information in its diverse contexts. In a business process scenario, context could be defined as the minimum set of variables containing all relevant information impacting the design and implementation of a business process. Although there are a few proposals that deal with context associated to business process (Nunes et al. 2009)(Rosemann et al. 2008)(Saidani and Nurcan 2007), they still miss an explicit method that supports the identification of relevant external contexts that impact on specific activities during a business process execution. In this paper we describe a method for supporting the identification and prioritization of variables to be considered in the context of the external environment that impacts process activities execution.

Keywords

Business Process, External Context, Knowledge Management, Competitive Intelligence, Data Mining.

INTRODUCTION

The external environment of an organization is characterized by significant changes that occur in the social, economical, political and technological fields. For an organization to be able to survive in face of possible adversities, it must know this setting and act effectively (Blanning and King 1996). The organization's continued existence depends on its ability to use information about the environment and adapt itself to external changes and other contingencies imposed. The search for flexibility is linked to the need of promptly implementing changes. Such disruptions in the routine should be reflected in business processes (Recker and Rosemann 2006). This can be done with the support of Knowledge Management and Competitive Intelligence initiatives (Jung et al. 2006).

Knowledge management (KM) and Competitive Intelligence (CI) are interrelated and built on the strategic organization goals. CI focuses on the outside, monitoring and internalizing information from the external environment; in contrast, KM encodes, shares and uses knowledge generated and stored internally in the organization. Considering internal and external environment can help in answering questions such as: How was this business process executed last time the country experienced an economic scenario similar to the current one? Has this process brought positive results? What were the external environmental reasons which caused changes in the process in the past? Unsolved problems within KM and CI are information quality, organization and reasoning. A major challenge is how to define the relevance of information in its diverse contexts.

Context can be defined as any information that can be used to characterize the situation of an entity (Dey 2001). In a business process scenario, context could be defined as the minimum set of variables containing all relevant information impacting the design and implementation of a business process. Context information could be associated to any process element, such as activities, events, actors and, furthermore, its analysis should provide insights to identify problems and learn with the past, besides helping to make decisions. Although there are a few proposals that deal with context associated to business process (Nunes et al. 2009)(Rosemann et al. 2008)(Saidani and Nurcan 2007), they still miss an explicit method that supports the identification of relevant external contexts that impact on specific activities during a business process execution.

To solve this problem, we propose a knowledge management model, which aims to establish an organizational memory with the result of the execution of business processes associated with external contextual information, and a method for supporting the identification and prioritization of variables to be considered in the context of the external environment. The goal of this paper is to describe the method which is based on CI and data mining techniques. An exploratory case study illustrates the application of our approach in a credit analysis process. The remainder of this paper is organized as follows: Section 2 discusses related work; Section 3 presents the solution approach; Section 4 describes the exploratory case study, and Section 5 presents conclusions.

KNOWLEDGE MANAGEMENT ON CONTEXT-AWARE PROCESS

Nunes et al. (2009) proposed a model for context-based KM that deals with the cycle of knowledge representation, capture, storage, comparison and presentation, within the scenario of an activity in a business process. It aims to establish an organizational memory with the outcomes from activities and also the context through which their results were achieved. The authors developed a model to represent context through a formal ontology which includes: (i) information that exist during the execution of an activity (time, artefacts), (ii) information about individuals or groups that perform an activity, (iii) information to spell out the interaction between individuals within the activity performed. The model did not consider external environment context.

Saidani and Nurcan (2007) also discuss the relevance of context in the design of business processes and propose modeling processes including the description of the execution context. Their approach is based on four procedures: context elicitation, context categorization, context adaptation and measure, and business process instantiation. They propose a taxonomy of the most common contextual information (location, time, resource and organization) to support elicitation phase, without providing an explicit method for that.

Few approaches in the literature point to the importance of external context in process executions. Rosemann et al. (2008) argue that identify, document and analyze contextual issues that might drive changes in processes support the understanding of the interrelationships between changes in the relevant environmental setting of an organization and its process. The authors propose to integrate context in process modeling since it impacts the structure of the process model and define a meta model that considers the structure of a process, its goals, and context. Besides, they describe a context framework in an onion model where diverse context levels are depicted in layers. As the authors state, this framework can be used to identify, classify, understand and integrate relevant context with business process models. A procedure is then applied to use this framework: (i) identify process goals; (ii) decompose process, (iii) determine relevance of context, (iv) identify contextual elements, (v) type context. Our work is directly related to the step 4, which we propose to be an evidence-based rather than an intuitive-based task. Soffer et al (2010) proposes an approach for learning and gradually improving business processes considering three elements: process paths, context and goals. In the same direction as our present work, they argue that the success of a process instance can be affected not only by the actual path performed, but also by environmental conditions, not controlled by the process. Their learning approach is based on an experience base, including data of past process instances: actual path, achieved outcome, and context information.

Similar to the Competitive Intelligence (CI) initiatives (Jung et al. 2006), the achieved outcome is at the process level, and is defined as a combination of goal achievements by a process instance. We propose that context identification be handled at the activity level, thus enabling process stakeholders to dynamically interfere into a specific activity result by applying previously acquired knowledge during the execution of a process. The conditions are defined according to external environment. External contingencies can be considered as opportunities or constraints that influence the structure and internal processes of organizations. Based on (Jung et al. 2006)(Kimball et al. 2002)(Cook and Cook 2000)(Herring 1999), Ramos and Santoro (2010) describe the CI process cycle steps to support the Context-based KM Model (Figure 1).

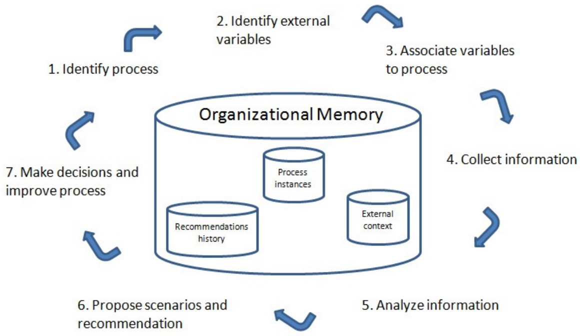

Figure 1: Competitive Intelligence and decision-making process life cycle

First it is necessary to identify process (1), therefore key business processes are chosen from business goals and organization strategy. Then, external variables should be identified and represented (3) and associated to the process model (3) through a Bus Matrix (Kimball and Ross 2002). After doing this, it is possible to start collecting and keeping these information (4) through properly sources (databases, sensors, etc.). All information is maintained in an Organizational memory intended for applying a number of techniques (KDD, inferences) in order to search evidences of their impact in process instances (5). This results in scenarios and recommendations, which might improve the process, either at the instance or at the model level (6). The responsible for the process is able to make decisions based on that outcomes; it could possibly cause process changes (7). Then, the cycle starts in on again. The problem addressed here is related to the external environment context, or the kind of information that generally cannot be captured in transactional systems, but from outside of the organization.

A METHOD FOR IDENTIFYNG EXTERNAL CONTEXT INFORMATION

In order to capture and use context information, it is necessary to specify which context information is to be handled in the organization and then represent this in a format that is understandable and acceptable to all (Nunes et al.2009). We propose a method for identifying new external context variables that may not be part of the organizational memory and that can be very relevant to the organization achieve the process goals. This method also shows which specific process activities are impacted by the external context variables to the organization achieve the process goals. These variables must be relevant to the process achieving its goal.

The knowledge flow during activities execution in the work environment is captured to build the Organizational Memory (OM). In this model, we propose to capture also context of the external environment. The internal and external contexts are associated to the process activities. The internal context of the current activity can be retrieved on performing similar activities. The contexts of the external environment and its association with the business process are retrieved and analyzed to allow the intelligence analyst to define scenarios and recommend actions to give support to the decision-makers. Then, the decision-makers evaluate the previous decisions and make new decisions that can reflect on improving, creating or removing processes.

There are several methods related to the definition of information needs, e.g., questionnaire, interview and observation that are widely used in different contexts (Vuori 2005). However, the most suitable methods for the definition of information at the strategic level used by competitive intelligence are Key Intelligence Topics (KIT) and Critical Success Factors (CSF). Key Intelligence Topic (KIT) technique was created by Herring (1999) to support specification, definition and prioritization of information needs at the strategic level of the organization. KITs are items that must be constantly monitored to guarantee business success. They should be more detailed in the form of KIQs (Key Information Questions). The KIQs, fundamental questions of intelligence, are items that specify the contents of each KIT. The following item may be an example of a KIT to be monitored, "Strategic Investment Decisions". It consists of several KIQs such as: "What is the involvement of other investors in competitors?" and "What are the critical investments from competitors?".

The KITs are identified through interviews with managers, asking open questions. They fall into three categories: (i) strategic decisions and actions; (ii) topics for early warning, considering threats and issues on which decision makers do not want to be surprised, and (iii) major players in the market, such as customers, competitors, suppliers and partners. The technique also proposes the concept of surveillance areas, which are macroeconomic variables that impact the business sector, and that should be monitored. This paper proposes a method based on KIT, and Dimensional Modeling and Data Mining approaches, through the steps illustrated in Figure 2. The method steps are described as follows.

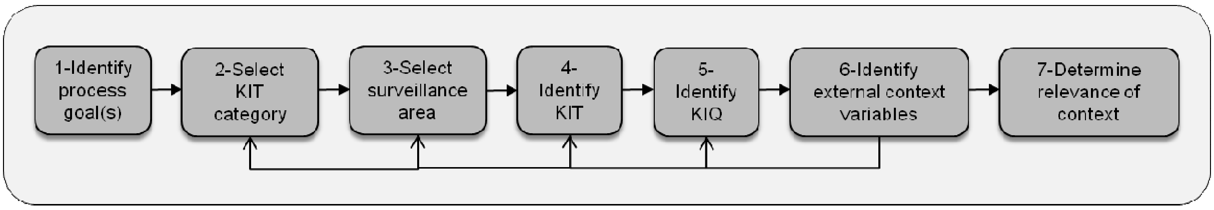

Figure 2: Procedure for external context variables identification

Step 1 – Identify process goal(s). Identify the goal related to a given process and their appropriate measures (Rosemann et al 2008). Repeat this step to identify others goals after concluding the last step.

Step 2 – Select KIT category. Herring (1999) has divided KITs into three categories: 1) Strategic Decisions and Issues, 2) Early-warning KITs, considering threats and issues on which decision makers do not want to be surprised and 3) Key player KITs (such as customers, competitors, suppliers and partners).

Step 3 – Select surveillance area. To define the external context variables, the steps 3 to 6 are part of a top-down approach. Top level areas must be considered to give support to the next step. A model to categorize context information would help to select those areas. The areas can be selected from any framework or a combination of them, such as Five Forces model (Porter, 1979), or SLEPT or STEEP Analysis (The Times, 2010). In general, they are: social, technology, economic, ecology, political, legal and competitors, due to all industries are influenced by them. These forces are continually in a state of change and then should be scanned. Most research about context in business process deal with internal context, i.e. process attributes inherent to the way process is performed, to the organization of activities and internal rules. Few context categories are proposed, such as location, time, and organization environment. Our work focuses on the events that occur external to the process, or ultimately to the organization where it runs, but somehow interfere within this process, provoking some good or bad effects. There are not many proposals to categorize this kind of context information. Rosemann, Recker and Flender (2009) propose that the external layer of their onion model is composed of the following types of context: suppliers, capital providers, workforce, partners, customers, lobbies, states, competitors. Based on the works mentioned before, we propose the categories depicted in Figure 3.

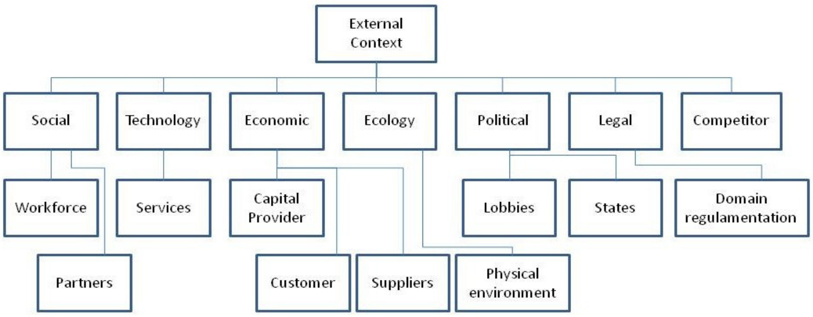

Figure 3 – External Context Categories

Repeat this step for each of the three KIT categories.

Step 4 – Identify KIT. Key Intelligence Topics (KITs) are identified by interviewing the key decision-makers and asking them open-ended, non-directive questions (Herring and Francis, 1999). An interview protocol can be very useful to ensure the consistency of results (Herring, 1999). Repeat this step for each of the surveillance area selected.

Step 5 – Identify KIQ. Key Intelligence Questions (KIQs) should be identified for each KIT. KIQs represent the information needs listed in the KIT, i.e. what the manager needs to know to be able to make the decisions. It is possible to have the same KIQ for more than one KIT. Repeat this step for each KIT selected.

Step 6 – Identify external context variables. Each KIQ may reference one or more external variables. These are the external context variables and are identified in this step. It is possible to have the same variable for more than one KIQ. Repeat this step for each KIQ identified in the previous step. For each process goal, the result of all the executions of steps 2 to 6 will be the final Intelligence Tree with the following columns: Process Goal, KIT category, Surveillance Area, KIT, KIQ and External Context Variable.

Step 7 – Determine relevance of context to the process outcome and to the process activity outcome. This step classifies the variables by relevance using data mining (discovering of patterns and evidences). The data mining classification of context variables is the main focus of our approach, and therefore is detailed in the following section. It is not feasible to store all context information that could form part of the Organization Memory. This step is important because it can help prioritize which context to capture and store.

A data mining approach to discover external context variables relevance

The classification of variables by relevance using the data mining approach works as follows: from the external potential variables identified in the previous stage, a data mining technique is applied to discover which of the external variables presents the most relevant results concerning their relationships with the business process. Traditionally, knowledge discovery in databases (KDD) techniques have been used to identify new, valid, potentially useful and understandable patterns in data (Fayyad et al. 1996). More recently, mining approaches have evolved to the discovery of other types of knowledge, such as process models. Process mining extracts information from information systems event logs to come up with business process models (Aalst et al., 2004; Aalst et al., 2005; Aalst et al., 2007; Medeiros et al., 2007) or business rules models (Crerie et al. 2009). Process mining techniques capture how processes are actually implemented on IS through analyzing their output data log. 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. Hence, process mining techniques work well on structured processes with little exceptional behavior and strong causal dependencies between the steps in the process (Aalst et al. 2004).

In our work, we argue that the application of specific mining techniques, such as association rules, will provide managers with evidence-based knowledge about in which circumstances the variation of a given external variable actually related to the moment in which the process was (or should have been) executed in a different way, thus outputting unpredictable results (or preventing the process to achieve better results) towards its goal. This step requires a log of process activities and a history of external environment variables identified in the previous step, and a preliminary selection and classification of data sources available to collect these variables. The data sources can be classified according to their structure, content, reliability and level of access. Structure may be formal or informal, have primary or secondary content; reliability could be high, medium or low, for example.

A CASE STUDY USING REAL DATA FROM A GERMAN BANK

This section illustrates an exploratory case study of our proposed method for identifying external context variables by relevance.

Credit Analysis Process Model

We applied the approach in a scenario on the domain of Credit Analysis. Figure 4 presents this business process modeled in the Bizagi tool (Bizagi t 2010) using BPMN 1.2 notation (OMG 2010).

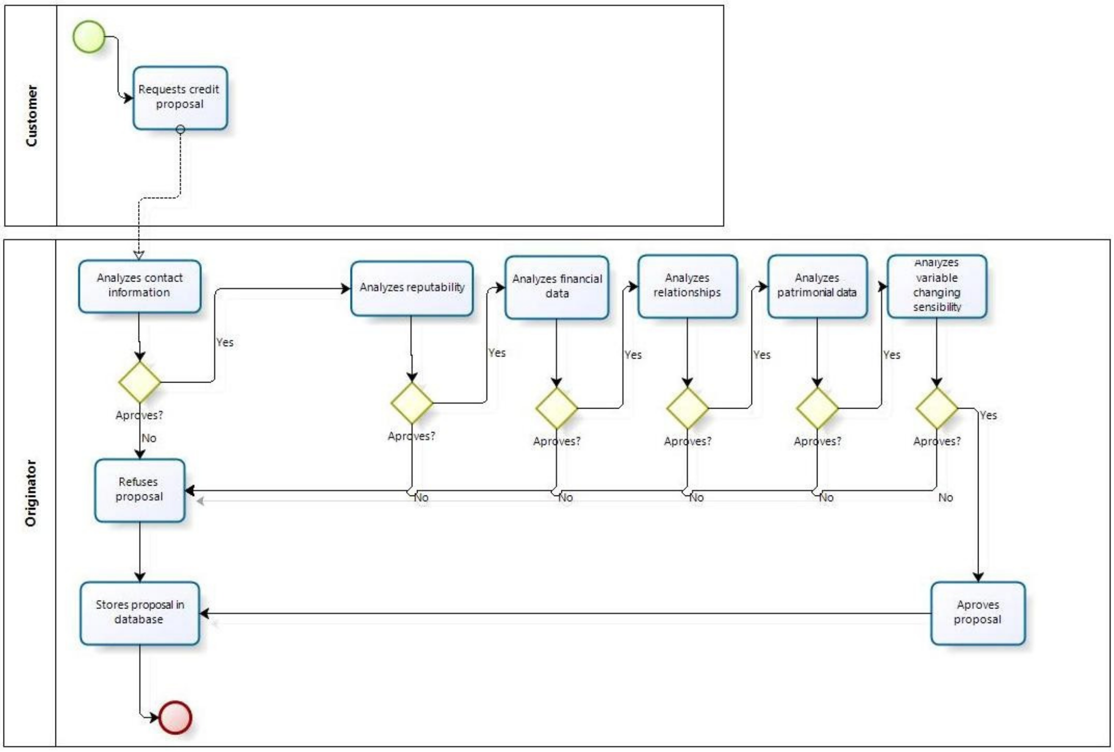

Figure 4: Credit Analysis Process Model

In credit business, banks lend money to consumers, who take the credit for further payment back to the bank. Many credit applicants are "good clients" (meaning that they are "low risky" clients with regard to the probability of not paying the bank back), but some are not. The risk for financial institutions comes from not knowing how to distinguish the good credit applicants from the bad ones. The aim of credit scoring is to model or predict the probability that consumers with certain characteristics are to be considered as potentially "low risky" or "high risky". Credit scoring is the set of decision models and their underlying techniques that help credit analysts in deciding who will get credit, how much credit they should get, and which operational strategies will enhance the profitability of the borrowers to the lenders (Nisbert et al. 2009). In the Credit Analysis process described in Figure 5, the organization is interested in providing support to the following decisions of the banks: granting credit to a new applicant or increasing the credits limits of existing applicants. Other studies discuss which variables must be considered to make a good decision (Fahrmeir and Tutz 1994). However, our focus is on deciding which variables of the external context will support these decisions.

The data set

The proposed method was applied to a real German banking data, publicly available at the University of Munich (German Bank dataset, 2010). This sample data set has 1,000 cases and 20 variables or predictors pertaining to past and current customers who borrowed from a German commercial bank for various reasons, during the early 1980's (Fahrmeir and Tutz 1994) (Lieli et al. 2006)(Nisbert et al. 2009).

For each customer, the binary outcome (dependent) variable "creditability" is available and indicates whether the customers are creditworthy (good customers) or not creditworthy (bad customers). Customers who have missed 90 days of payment can be thought as of being bad, and those that have ideally missed no payment can be thought of as being good (Nisbert et al. 2009). This data set contains 70% of creditworthy (good) customers and 30% of not creditworthy (bad) customers. In addition, some covariates are available for each customer, describing the terms of the loan contract as well as the credit history and socio-economic status of the borrowers.

These variables related to the customers are: basic personal information (age, sex, telephone), family information (marital status, number of dependents), residential information (number of years at current address, type of apartment), employment status (number of year in current occupation, occupation), financial status (most valuable available assets, further running credits, balance of current amount, number of previous credits at this bank), security information (value of savings or stocks, guarantors) and credit information (purpose of credit, amount of credit and duration in months of the loans, installment as a fraction of monthly income). See (German Bank dataset 2010) for a complete description of the data set variables.

In the Credit Analysis process described in Figure 4, banks are interested in information whether new applicants or existing consumers will pay back their credit or not, i.e. banks must make decisions about granting credit to a new applicant or increasing the credits limits of existing applicants .Some studies (Fahrmeir and Tutz 1994)(Lieli et al. 2006)(Nisbert et al. 2009) that used this dataset discussed which variables of the process must be considered to support this decision. However, our focus introduces also new variables of the external context and relates it to the process activities to support this decision.

Application of the method

We applied the proposed method in Section 3 to define the relevant external variables which influenced the payments of the client's debts with the German Bank to be taken into account in the credit analysis process, and we describe how the use of a data mining technique will support this method.

Step 1 –The goal "Maximize approvals of clients that will pay back all the debt" was considered for the Credit Analysis Process. Of course, it will be also necessary to have the information of the execution of the Credit Payment Process. In this case study, we know for each client that had the credit approved if he paid or not all his debt.

Step 2 to 6 –For each process goal, the result of all the executions of steps 2 to 6 will be a table similar to Table 1 for the process goal "Maximize approvals of clients that will pay all the debt". It is important to note that usually the KIT framework is applied to define variables that will be collected and analyzed in the future. In our proposed method, if there is a process log already, the external variables used are the same but we focus on collecting its past external information to associate with the process log.

Table 1: The Final Intelligence Tree after all the executions of steps 2 to 6

Process Goal	KIT category	Surveillance Area	KIT	KIQ	External Context Variable
Maximize approvals of clients that will pay all the debt for the Credit Analysis Process	Strategic decisions and actions	Economic	Economic recession	Is there any prediction about the economic recession for the next years in Germany?	**Economy Recession Prediction;**
	Early-warning	Economic	Possible causes that prevent a client to pay his/her debt	Did the unemployment rate at the moment he/she did not honor his debt interfere in the client not paying or paying?	**Unemployment Rate** at the moment the client signed the contract ; **unemployment rate** at the moment the client did not honor his debt;
				Inflation rate at the moment the client signed the contract and at the moment he/she did not honor his debt	**Inflation Rate** at the moment the client signed the contract; **Inflation Rate** at the moment the client did not honor his debt;
				Does the client have a new dependent?	**Number of the client dependents** at the moment the client signed the contract; **Number of the client dependents** at the moment the client did

					not honor his debt;
		Ecology	Possible causes that prevent a client to pay his/her debt	Environmental catastrophes	**Hurricane** event, **Vulcan** explosion event;

Step 7 – The relevance of the previous defined external context variables is evaluated. Many techniques can be applied in this step, such as Expert Systems, Fuzzy Logic System or Statistical & Data Mining Systems to select the most relevant external context variables to the process activity outcome activities and to achieve the process goal. Below, we explain how the data mining technique determined that Unemployment Rate was a relevant external context variable to the process outcome and to one of its activities outcome.

In this step, because of difficulties to find all the external context information of the variables obtained in the previous steps, we made a simplification in our case study to just use information about Germany unemployment rate and inflation rate (IndexMundi, 2010) for the period of the loans in this dataset.

The information about the external variables must be associated with the information of the process activities outcomes for the same period. Once this association is done we start running the feature selection to reduce the complexity of the problem transforming the data set into a data set of lower dimensions (Nisbert et al. 2009). In our case study, we used the Feature Selection of STATISTICA Data Miner (StatSoft 2003) to automatically find and rank important predictor variables for predicting the dependent variable "creditability" that discriminates between good and bad customers, as shown in Figure 5. Among these predictors are external variables and process activities outcomes.

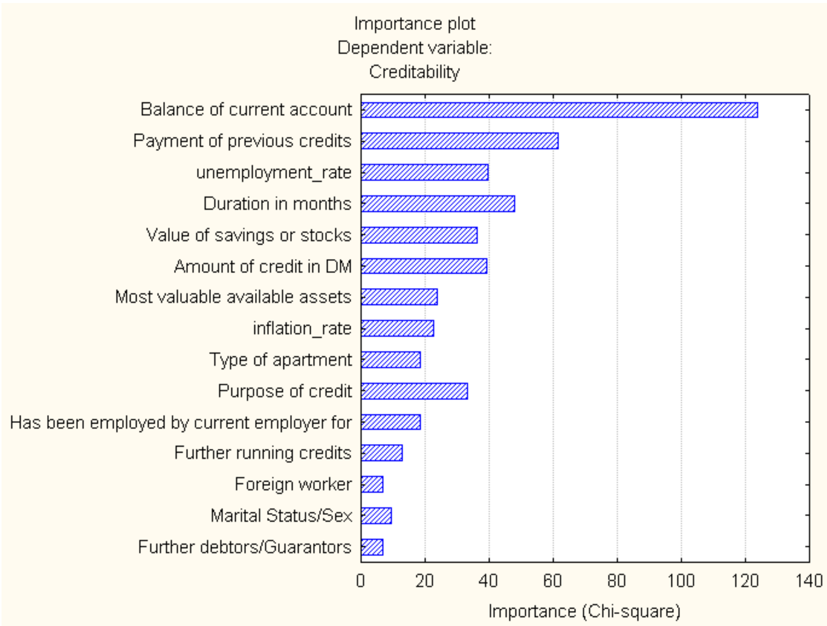

Figure 5: Creditability bar chart

Figure 5 shows that among the 22 variables (2 external context variables and 20 process activities outcomes) there are 7 variables that stand out as the most important predictors: 1-Balance of current account, 2- Payments of previous credits, 3- Duration in months of the loan, 4-Unemployment rate, 5-Amount of credit in DM, 6-Value of saving or stocks and 7-Purpose of Credit. Among these 7 relevant variables to achieve the process goal, the fourth most relevant is from the external context. All the others 6 come directly from the process activities outcomes.

Our goal is not just to find the relevant variables of the external contexts to achieve the process goal, as we just did, but is also to find the relevance of these variables of the external contexts to the process activities. Below we show that the unemployment rate is also a relevant external context variable to the "Payments of previous credits" variable that is an outcome of the "Analyze Relationship" process activity. For this, we used a decision tree (CHAID) shown in Figure 6. CHAID stands for Chi-squared Automatic Interaction Detector and detects interaction between variables in the data set.

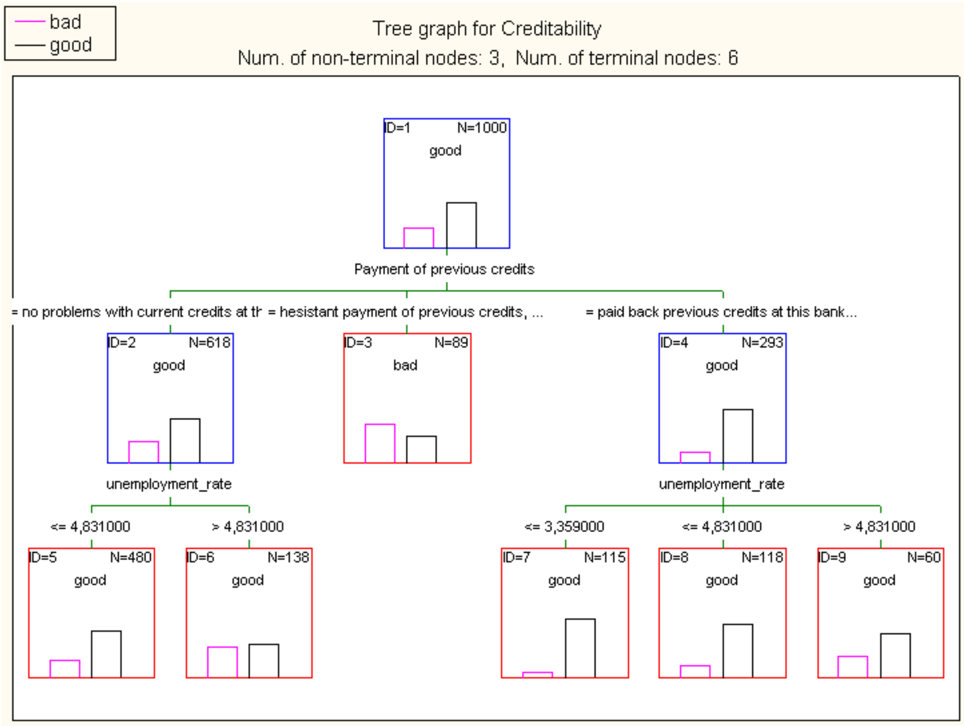

Figure 6: A decision tree (CHAID) for the credit risk data set considering some of the most relevant variables for predicting the dependent variable “creditability”

Decision trees are powerful tools for classification and prediction. The decision tree of Figure 6 was run using STATISTICA Data Miner (StatSoft 2003) considering the following relevant variables for predicting the dependent variable “creditability”: Duration in months of the loan, Unemployment rate, Payments of previous credits and Purpose of credits.

Each box in the tree of Figure 6 shows the number of instances at that node and information about the distribution of the dependent variable values (credit risk). The root node contains 1000 instances, i.e. all the instances of the dataset. Below the root node is the first split that splits the data into 3 new nodes based on the predictor variable “Payments of previous credits” that is one outcome of the “Analyze Relationship” activity. The node in the center resulting from this split contains 89 instances associated with bad credit risk. This node will not be split further because most of the instances have the same value of creditability: bad. The other 2 nodes further split based on the predictor variable “Unemployment rate” that is an external relevant variable to the process outcome. These split resulted in more 5 nodes (nodes 5 to 9). Node 6 clearly shows the relevance of the external variable to the process activity. It evidences that, unlike all other tree leaves in which good clients occur more frequently than bad clients, when the unemployment rate raises above 4.831 then bad and good clients occur with almost the same probability. This may fire a change during the process execution, for example requiring the analyst to ask the consumers for more guarantees or reducing the credit amount to maximize the probability that he will pay all his debt in the future.

Analysis and discussion

The vital point to use this proposed method is to have a very large sample of the process log associated to the external contexts. It is important to note that external variable relevance is discovered based on the process log. As with any data mining approach, the discovered knowledge depends on the amount of detailed information available in the log. Therefore, when our approach discovers that a specific external variable is not-so-relevant, it does not mean that it is not relevant at all; instead, it means that the process log did not include enough evidences pointing to the relevance of this external variable to the historical process log, when compared to other variables. In our exploratory study, for example, inflation rate (which is usually a very relevant external variable for the bank domain) showed to be less relevant than unemployment rate for the German Bank.

Therefore, it is important to take into account a process log with enough information to run our method and to consider other methods and the experience and feelings of the specialists and of the decision makers when deciding which external variables are relevant to be scanned. At least, it must contemplate the relevant variables found in our proposed method.

Our method differs from existing approaches in the literature (Rosemann, Recker and Flender 2009)(Soffer et al 2010) since it suggests new external context variables that may not be part of the organizational memory and that can be very relevant to the organization achieve the process goals; and shows which specific process activities are impacted by the external context variables to the organization achieve the process goals. Of course, it may not always be easy to collect data from external variables. This problem is less relevant when we look for more recent information, once there is much information available in the Internet and there are many others ethical ways suggested by Competitive Intelligence to discover it.

CONCLUSIONS AND FUTURE WORK

Successful organizations are those able to identify and answer appropriately to changes in their internal and external environments. The organizations´ decision makers need to make important decisions in order to carry this out.

Although there are a few proposals that deal with context associated to business process (Nunes et al. 2009)(Rosemann et al. 2008)(Saidani and Nurcan 2007), they still miss an explicit method that supports the identification of relevant external contexts that impact on specific activities during a business process execution. In this paper we described a method for supporting the identification and prioritization of variables to be considered in the context of the external environment that impacts process execution and that may not be part of the organizational memory. This method also shows which specific process activities are impacted by these variables to the organization achieve its process goals.

An exploratory case study illustrated the application of our method in a credit analysis process using real data from a German Bank. This method is based on CI and data mining techniques and provides the process manager with a fact-based understanding on which are the most relevant external variables that really influenced previous process executions, among the several variables that could be taken into consideration unnecessarily. This case study showed that changes in relevant variables of the external context may cause an undesired effect during process execution, and that it may fire a decision of the decision maker to quickly responding to these changes, by adapting the process specification, or creating other business rules to be followed by the business process.

The vital point to use this proposed method is to have a very large sample of the process log associated to the external contexts and to consider the experience and feelings of the specialists. As future work we are conducting case studies to validate the proposal, both in fictitious scenarios and in real organization.

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