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Contextual Pattern Discovery in Ambient Intelligent Application

Nayat Sanchez-Pi[1] and Luis Martí[2] and José Manuel Molina[3] and Ana Cristina Bicharra[4]

[1]Instituto de Lógica, Filosofia e Teoria da Ciéncia (ILTC)
Niterói, Rio de Janeiro, Brazil
nayat@iltc.br

[2]Dept. of Electrical Engineering
Pontifícia Universidade Católica do Rio de Janeiro
Rio de Janeiro (RJ) Brazil
lmarti@ele.puc-rio.br

[3]Dept. of Informatics
Universidad Carlos III de Madrid
Colmenarejo, Madrid, Spain
molina@ia.uc3m.es

[4]ADDLabs, Universidade Federal Fluminense
Niterói, Rio de Janeiro, Brazil
cristina@addlabs.uff.br

ABSTRACT

Ambient Intelligence(Aarts, Harwig and Schuurmans, 2001) contributes by enriching the oil and gas environment with technology (mainly sensors and devices interconnected through a network) and built a system to help plant operators to make decisions based on real-time information gathered and historical data accumulated. Ambient Intelligence puts together all these resources to provide flexible and intelligent services to users acting in their environment.

Besides, *Information Fusion* (Llinas, 2002) studies theories and methods to effectively combine data from multiple sensors and related information to achieve more specific inferences that could be achieved by using a single, independent sensor. Information fused from sensors and data mining analysis has recently attracted the attention of the research community for real-world applications. In this sense, the deployment of an ambient intelligent offshore petroleum environment will help to figure out a risky scenario based on the events occurred in the past related to anomalies and the profile of the current employee (role, location, etc.).

In this paper we propose an information fusion model for an ambient intelligent oil environment in which employees are alerted about possible risk situations while their are moving around their working place. The layered architecture, implements a reasoning engine capable of intelligently filtering the context profile of the employee (role, location) for the feature selection of an inter-transaction mining process. Depending on the employee contextual information he will receive intelligent alerts based on the prediction model that use his role and his current location. This model provides the big picture about risk analysis for that employee at that place in that moment.

Keywords: Ambient intelligence, information fusion, context, data mining, ontologies, oil industry.

Computing Classification System: I.2 ARTIFICIAL INTELLIGENCE, J.2 Computer Applications PHYSICAL SCIENCES AND ENGINEERING

1 Introduction

The trend in the direction of intelligent support systems applied to engineering lead us think of Ambient Intelligence (AmI). The hardware cost reduction and miniaturization allows including computing devices in several objects and environments (embedded systems). AmI environments should be aware of the needs of people, customizing requirements and forecasting behaviors. These environmentsare very diverse, from typical environments like homes, offices, meeting rooms, schools, hospitals, to industry. In the aims of Artificial Intelligence, research envisages to include more intelligence in the AmI environments, allowing a better support to the human being and the access to the essential knowledge to make better decisions when interacting with these environments.

In oil industry there is an important effort of oil and gas industry to reduce the number of accidents and incidents.There exists standards to identify and record workplace accidents and incidents to provide guiding means on prevention efforts, indicating specific failures or reference, means of correction of conditions or circumstances that culminated in accident. Besides, oil and gas industry is increasingly concerned with achieving and demonstrating good performance of occupational health and safety (OHS), through the control of its OHS risks, which is consistent with its policy and objectives.

OHS continues to be a priority issue for the offshore oil and gas industry and a determining factor in its overall success. Years passed since community takes into account the implications of oil industry to Health, Safety and the Environment but nowadays industries invest a lot of efforts in accidents prevention. With the advances of communication technologies and the novelty researches in Ubiquitous Computing (UC) and Ambient Intelligence (AmI), is almost a fact to think of a Pervasive Offshore Oil Industry Environment.

In this scenario employees are surrounded of intelligent technology capable of not only interacting in an natural way, but also to intelligently reason on the accidents risk picture in order to alert the employees when an risky event is probable to occur in the place where is located. The process of constructing a dynamic risk picture for accident or incident detection and recognition involves contextual reasoning about past events, dynamic context (location, user, profile, etc), as well as relations between them with respect to particular goals,capabilities, and policies of the decision makers.

In this paper we propose an information fusion model for an intelligent oil environment in which employees are alerted about possible risk situations while their are moving around their working place. The layered architecture, implements a reasoning engine capable of intelligently filter the context profile of the employee (role, location) for the feature selection of an inter-transaction mining process. So, depending on the employee contextual information he will receive intelligent alerts based on the prediction model that use his role and his current location.

This model provides the big picture about risk analysis for that employee at that place in that moment. Our contribution is to build a causality model for accidents investigation by means of a well-defined spatio-temporal constraints on offshore oil industry domain. We use ontological constraints in the post-processing mining stage to prune resulting rules.

The paper is organized as follows. After providing an introduction to the HSE problem and the role of information fusion processes in building a risk picture, Section 2 briefly describes the state of the art and some application domains. Section 3 focuses on knowledge retrieval model, its architecture, domain model and reasoning process. Section 4 depicts the formalization of the mining information used by the context based reasoning process for threat detection and recognition. Finally, Section 5 presents some final remarks.

2 Foundations

Ambient Intelligence represents, a new generation of user-centred computing environments aiming to find new ways to obtain a better integration of the information technology in everyday life devices and activities. In order to work efficiently, software running on these devices may have some knowledge about the user, it means that there is an increasing need of improve context awareness and knowledge sharing without interfering with users daily life activities (Sánchez Pi, 2011).

Techniques for using contextual information in high-level information fusion architectures has been studied at (Gómez-Romero, Garcia, Kandefer, Llinas, Molina, Patricio, Prentice and Shapiro, 2010).In the context of oil and gas industry is increasingly concerned with achieving and demonstrating good performance of occupational health and safety (OHS), through the control of its OHS risks, which is consistent with its policy and objectives. In oil industry exist standards to identify and record workplace accidents and incidents to provide guiding means on prevention efforts, indicating specific failures or reference, means of correction of conditions or circumstances that culminated in accident. So, events recognition is central to OHS, since the system can selectively start proper prediction services according to the user current situation and past knowledge.

Knowledge discovery (KDD) is the process of extracting and refining useful knowledge from large databases. KDD stages are: inductive learning, deductive verification and human intuition. Data mining can could be applied to any domain where large databases are saved. Some applications are: failure prediction (BORRAJO, Baruque, Corchado, Bajo and Corchado, 2011), biomedical applications (De Paz, Bajo, López and Corchado, 2013), process and quality control (Conti, Pietro, Mancini and Mei, 2009).

Data mining enables finding interesting patterns in very large databases. It is the most essential part of the knowledge discovery process which combines databases, artificial intelligence, machine learning and statistics techniques. The basic techniques for data mining include: de-

cision tree induction, rule induction, artificial neural network, clustering and association rules.
Association rule learning is a popular and well researched method for discovering interesting relations between variables in large databases. It is intended to identify strong rules discovered in databases using different measures of interestingness. Many algorithms for generating association rules were presented over time. Some well known algorithms are Apriori (Agrawal, Srikant et al., 1994), Eclat (Zaki, 2000) and FP-Growth (Han, Pei and Yin, 2000), but they only do half the job, since they are algorithms for mining frequent itemsets. Another step needs to be done after to generate rules from frequent itemsets found in a database.
There is a need of a fusion framework to combine data from multiples sources to achieve more specific inferences. A fusion system must satisfy the users functional needs and extend their sensory capabilities.
After years of intensive research that is mainly focused on low-level information fusion (IF), the focus is currently shifting towards high-level information fusion (Blasch, Llinas, Lambert, Valin, Das, Chong, Kokar and Shahbazian, 2010). Compared to the increasingly mature field of low-level IF, theoretical and practical challenges posed by high-level IF are more difficult to handle.
Some of the applications that involve high-level IF are:

- Defense (Chong, Liggins et al., 1994; Gad and Farooq, 2002; Liggins, Bramson et al., 1993; Ahlberg, Hörling, Johansson, Jöred, Kjellström, Mårtenson, Neider, Schubert, Svenson, Svensson et al., 2007; Aldinger and Kao, 2004)
- Computer and Information Security (Corona, Giacinto, Mazzariello, Roli and Sansone, 2009; Giacinto, Roli and Sansone, 2009)
- Disaster Management (Little and Rogova, 2005; Llinas, 2002; Llinas, Moskal and McMahon, 2002; Mattioli, Museux, Hemaissia and Laudy, 2007)
- Fault Detection (Bashi, 2010; Bashi, Jilkov and Li, 2009; Basir and Yuan, 2007)
- Environment (Heiden, Segl, Roessner and Kaufmann, 2003; Khalil, Gill and McKee, 2005; Hubert-Moy, Corgne, Mercier and Solaiman, 2002)

But these contributions lack of a well-defined spatio-temporal constraints on relevant evidence and suitable models for causality.(Blasch, Kadar, Salerno, Kokar, Das, Powell, Corkill and Ruspini, 2006).
Our proposed model provides the big picture about risk analysis for that employee at that place in that moment in a real world environment. Our contribution is to build a causality model for accidents investigation by means of a well-defined spatio-temporal constraints on offshore oil industry domain. We use ontological constraints in the post-processing mining stage to prune resulting rules.

3 Knowledge Retrieval Model

In this section more details about the Knowledge Retrieval Model are provided. First a detailed description of the proposed architecture, domain ontology and reasoning process described by means of inductive learning process.

3.1 Architecture

The architecture of our context-based fusion framework is depicted in Figure 1. The context-aware system developed has a hierarchical architecture with the following layers: Services layer, Context Acquisition layer, Context Representation layer, Context Information Fusion layer and Infrastructure layer. The hierarchical architecture reflects the complex functionality of the system as shown in the following brief description of the functionality of particular layers:

- Infrastructure Layer. The lowest level of the location management architecture is the Sensor Layer which represents the variety of physical and logical location sensor agents producing sensor-specific location information.
- Context Acquisition: The link between sensors (lowest layer) and the representation layer
- Context Representation: This is where the low-level information fusion occurs
- Context Information Fusion layer: This layer takes sensor-specific location information and other contextual information related to the user and transforms it into a standard format. This is where the high-level information fusion occurs. It is here where reasoning about context and events of the past takes place. Extended description is given in next section.
- Services Layer. This layer interacts with the variety of users of the system (employees) and therefore needs to address several issues including access rights to location information (who can access the information and to what degree of accuracy), privacy of location information (how the location information can be used) and security of interactions between users and the system.

3.2 Ontology

Normally, ontology represents a conceptualization of particular domains. In our case, we will use the ontology for representing the contextual information of the offshore oil industry environment.Ontologies are particularly suitable to project parts of the information describing and being used in our daily life onto a data structure usable by computers.
Using ontologies provides an uniform way for specifying the models core concepts as well as an arbitrary amount of subconcepts and facts, altogether enabling contextual knowledge
An ontology is defined as “an explicit specification of a conceptualization” (Gómez-Romero, Patricio, García and Molina, 2009). An ontology created for a given domain includes a set of concepts as well as relationships connecting them within the domain. Collectively, the concepts and the relationships form a foundation for reasoning about the domain. A comprehensive, well-populated ontology with classes and relationships closely modeling a specific domain represents a vast compendium of knowledge in the domain.

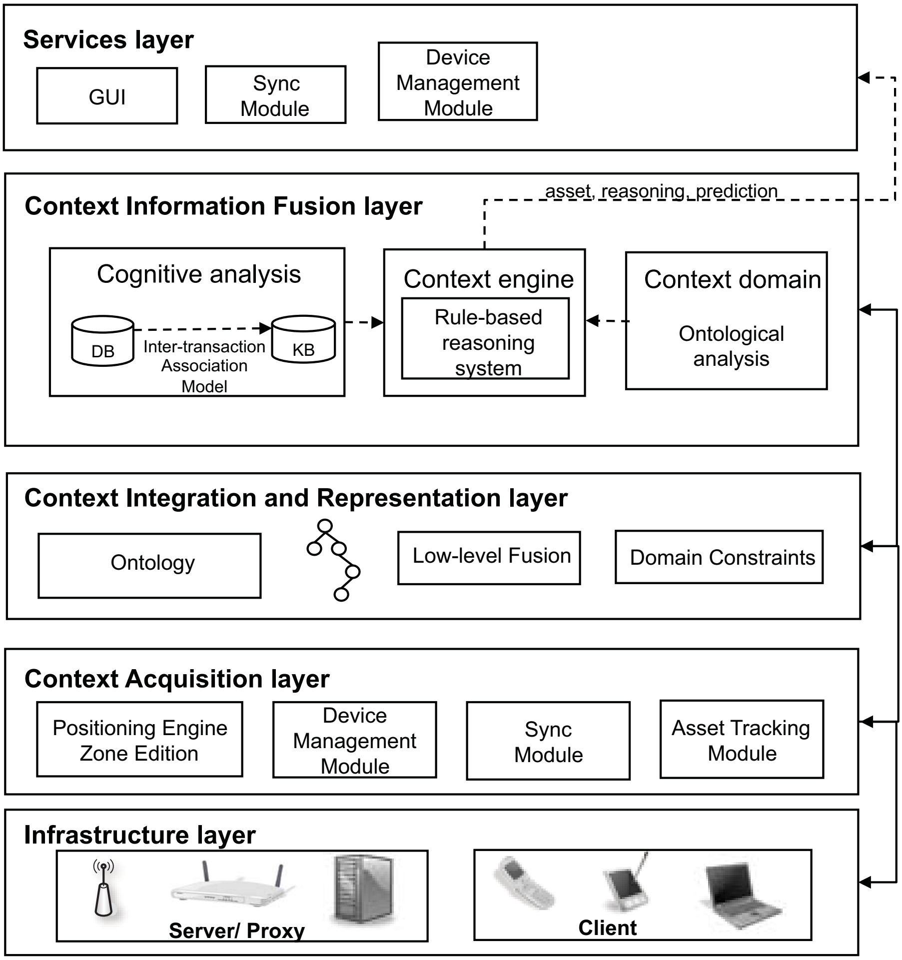

Figure 1: Architecture.

Furthermore, if the concepts in the ontology are organized into hierarchies of higher-level categories, it should be possible to identify the category (or a few categories) that best classify the context of the user. Within the area of computing, the ontological concepts are frequently regarded as classes that are organized into hierarchies. The classes define the types of attributes, or properties common to individual objects within the class. Moreover, classes are interconnected by relationships, indicating their semantic interdependence (relationships are also regarded as attributes).

We built a domain ontology for the Health, Safety and Environment (HSE) of oil and gas domain (Sanchez-Pi, Martí and Garcia, 2013). We also obtain the inferences that describe the dynamic side and finally we group the inferences sequentially to form tasks. Principal concepts of the ontology are the following:

- Anomaly: Undesirable event or situation which results or may result in damage or faults that affect people, the environment, equity (own or third party), the image of the Petrobras System, products or production processes. This concept includes accidents, illnesses, incidents, deviations and non-conformances.
  - Neglect: Any action or condition that has the potential to lead to, directly or indirectly, damage to people, to property (own or third party) or environmental impact, which is inconsistent with labor standards, procedures, legal or regulatory requirements, requirements management system or practice.
    - Behavioral neglect: Act or omission which, contrary provision of security, may cause or contribute to the occurrence of accidents.
    - Non-behavioral neglect: Environmental condition that can cause an accident or contribute to its occurrence. The environment includes adjective here, everything that relates to the environment, from the atmosphere of the workplace to the facilities, equipment, materials used and methods of working employees who is inconsistent with labor standards, procedures, legal requirements or normative requirements of the management system or practice.
  - Incident: Any evidence, personal occurrence or condition that relates to the environment and / or working conditions, can lead to damage to physical and / or mental.
  - Accident: Occurrence of unexpected and unwelcome, instant or otherwise, related to the exercise of the job, which results or may result in personal injury. The accident includes both events that may be identified in relation to a particular time or occurrences as continuous or intermittent exposure, which can only be identified in terms of time period probable. A personal injury includes both traumatic injuries and illnesses, as damaging effects mental, neurological or systemic, resulting from exposures or circumstances prevailing at the year's work force. In the period for meal or rest, or upon satisfaction of other physiological needs at the workplace or during this, the employee is considered in carrying out the work.
    - Accident with injury: It's all an accident in which the employee suffers some kind of injury. Injury: Any damage suffered by a part of the human organism as a consequence of an accident at work.
      - With leave: Personal injury that prevents the injured from returning to work the day after the accident or resulting in permanent disability. This injury can cause total permanent disability, permanent partial disability, total temporary disability or death.
      - Without leave: Personal injury that does not prevent the injured to return to work the day after the accident, since there is no permanent disability. This injury, not resulting in death, permanent total or partial disability or total temporary disability, requires, however, first aid or emergency medical aid. Expressions should be avoided ”lost-time accident” and ”accident without leave”, used improperly to mean, respectively, ”with leave injury” and ”injury without leave.”

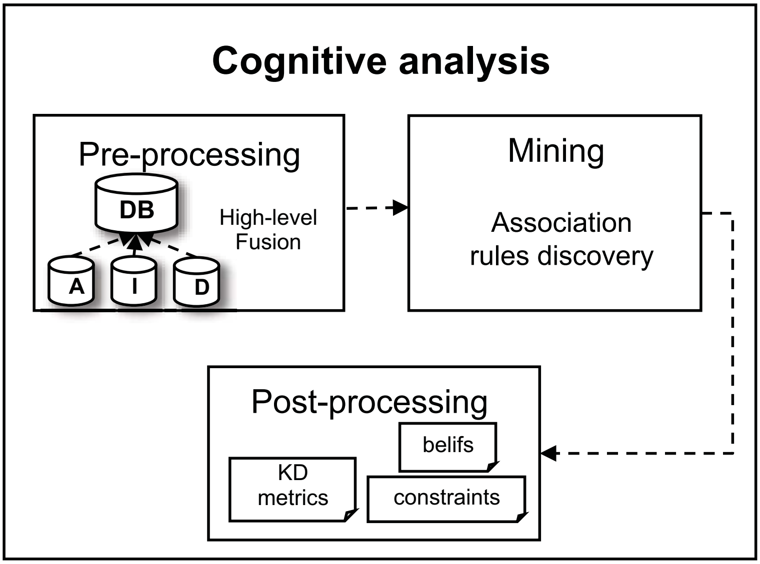

Figure 2: Cognitive analysis

∗ Accident Without Injury: Accident causes no personal injury.

3.3 Reasoning

Standard ontology reasoning procedures can be performed within the ontologies to infer additional knowledge from the explicitly asserted facts. By using an inference engine, tasks such as classification or instance checking can be performed. Figure 2.

Risk prevention is a paradigmatic case of inductive reasoning. Inductive reasoning begins with observations that are specific and limited in scope, and proceeds to a generalized conclusion that is likely, but not certain, in light of accumulated evidence. You could say that inductive reasoning moves from the specific to the general. Much scientific research is carried out by the inductive method: gathering evidence, seeking patterns, and forming a hypothesis or theory to explain what is seen.

In our framework, inductive rules formally represent contextual, heuristic and common sense knowledge to accomplish high-level scene interpretation and low-level location refinement.

Once an employee enters the network, it immediately connects with a local proxy, which evaluates the position of the client device and assign a role to the employee. A pre-processing step begins then filtering the relevant features that are selected to participate in the process of knowledge discovery by type of employee (role). The association rules mining process starts with the selected configuration and the set of resulting rules can be analyzed. Later a post-processing step starts. It is an important component of KDD consisting of many various procedures and methods for pruning and filtering the resulting rules.

The fusion engine implements an association rules model that combines dynamically feature

selection based on the role of the user in order to find spacio-temporal patterns between different types of anomalies (or event sequence, ex. neglects, incidents, accidents) that match with the current location of the user.
Two categories of association mining are employed: Intra-anomaly and Inter-anomaly (Berberidis, Angelis and Vlahavas, 2004). Intra-transaction associations are the associating among items within the same type of anomaly, where the notion of the transaction could be events where the same user participate. However, Inter-transaction describes relationships among different transactions. That meas between incidents, accidents and neglects. Further details are giving in the next sections.

4 Mining anomaly information

As already explained, the task of providing context-based information calls for the processing and extraction of information in the form of rules. One of the possible ways of obtaining those rules is to apply one of the previously described. In this work we employ Aprori and FP-Growth algorithms in parallel in order to mutually validate the results from each other.
As explained in the above section, the fusion engine implements an association rules model that combines dynamically feature selection based on the role of the user in order to find spacio-temporal patterns between different types of anomalies (or event sequence, ex. neglects, incidents, accidents) that match with the current location of the user.
The dataset of anomalies, $\mathcal{S}$, is composed by anomaly instances,

$$\mathcal{S} := \{A_1, A_2, \dots, A_n\}, n \in \mathbb{N}, \tag{4.1}$$

with the instances defined as

Definition 4.1 (Anomaly instance)**.** An anomaly instance can be defined as a tuple,

$$A := \langle t, c, \mathcal{L}, \mathcal{O}, \mathcal{N}, \mathcal{F} \rangle, \tag{4.2}$$

that is composed by:

- t, a time instant that marks when the anomaly took place;
- $c \in \{\text{accident}, \text{incident}, \text{report}\}$, that sets the class of anomaly, and, therefore, its associated gravity;
- $\mathcal{L}$, a set of geo-location description attributes, which describe the geographical localization of the anomaly at different levels of accuracy;
- $\mathcal{O}$, a set of organizational location attributes that represent where in terms of organization structure the anomaly took place;
- $\mathcal{N}$, a group of descriptive nominal attributes that characterize the anomaly with a predefined values, and;
- $\mathcal{F}$, a set of free-text attributes that are used to complement or improve the descriptive power reachable with $\mathcal{N}$ attributes.

In order to make the rules produced interesting for the user the mining dataset, $\mathcal{S}$, must be preprocessed to meet the her/his needs. Using the above described problem ontology, the set of anomalies relevant for mining can be (i) filtered and (ii) its attributed selected.
For the first task we defined a function $\texttt{filter\_anomalies}\,(u, \mathcal{S}) \rightarrow \mathcal{S}'$, $\mathcal{S}' \subseteq \mathcal{S}$, which determines the subset, $\mathcal{S}'$, of the anomalies dataset, $\mathcal{S}$, that are of interest for a given user, u. For the second task we created the function $\texttt{filter\_attributes}\,(u, \mathcal{S}') \rightarrow \mathcal{S}^*$, where $\forall A' = \in \mathcal{S}'$, $\exists A^* \in \mathcal{S}^*$ such that $t^* = t'$, $c^* = c'$, $\mathcal{L}^* \subseteq \mathcal{L}'$, $\mathcal{O}^* \subseteq \mathcal{O}'$, $\mathcal{N}^* \subseteq \mathcal{N}'$ and $\mathcal{F}^* \subseteq \mathcal{F}'$.
Relying on the $\mathcal{S}^*$ dataset customized to the user profile two classes of data mining operations can be carry out to extract knowledge rules. The first mines for rules regarding the relations of different attribute values in anomalies, and hence was called *intra-anomaly rule mining*. The other, more complex one, mines for relationships between anomalies, that take place in a same location —either geographical or organizational— and in similar dates. Because of that this operation was denominated *spatio-temporal* or *inter-anomaly rule mining*. In the subsequent sections we describe both mining processes.

4.1 Mining for intra-anomaly information

In this case the data pre-processing before mining is pretty straightforward, as the interest is to discover relationships between the values of different attributes and the possible presence of probabilistic implication rules between them. In particular, each anomaly in $\mathcal{S}^*$ is treated as a transaction whose items are the non-null values of the corresponding $\mathcal{N}^*$. The results of applying the rule mining algorithms are post-processed to eliminate cyclic rules and to sort them according to an interestingness criterion.

4.2 Spatio-temporal causality mining

Mining spatio-temporal rules calls for a more complex pre-processing. As the most relevant anomalies are the accidents mining is centered around them. In this case, transactions will be constituted by anomalies that took place in the same location (deduced from the user profile) and with a given amount of time of precedence.
More formally, having the set of all accidents $\Lambda = \{A \in \mathcal{S}^* | A.c = \text{accident}\}$, for each element $\lambda \in \Lambda$, we construct the set of co-occurring anomalies, $\mathcal{C}(\lambda)$ as,

$$\mathcal{C}(\lambda) := \{\lambda\} \cup \{\kappa \in \mathcal{S}^* | \lambda.t - \kappa.t \leq \Delta t; \mathrm{loc}(\lambda, u) = \mathrm{loc}(\kappa, u)\}, \tag{4.3}$$

with $\mathrm{loc}(\cdot)$, a function that for a given anomaly an user returns the value of the location attribute of interest for that user according to her/his role, and Δt, a time interval for maximum co-occurrence.
The set of co-occurring anomalies $\{\mathcal{C}(\lambda) | \forall \lambda \in \Lambda\}$ is used as transactions dataset for the mining algorithms. However, anomalies can not be used as-is, as it is necessary to express them in abstract form, in order to achieve sufficient generalization as to yield results that not are excessively particular or refined.
For this task, again depending on the user profile, a group of elements of each $\mathcal{N}^*$ is selected to create the abstract anomaly. This reduced set of attribute values are then used to construct the transactions.

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with $\operatorname{loc}(\cdot)$, a function that for a given anomaly an user returns the value of the location attribute of interest for that user according to her/his role, and Δt, a time interval for maximum co-occurrence.

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5 Final Remarks

In this work we have discussed an information fusion framework for providing context-aware services related to risk prevention in offshore oil industry environment. We made an innovative use of rule mining for provisioning knowledge for assessing and decision making regarding risk an accidents prevention. The solution presented here is currently deployed and in use by a major oil extraction and processing industrial conglomerate of Brazil. Future work will focus on dealing with uncertainty data and unstructured data

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