An Ontology-based Approach For Conformance Checking of Decision Mining Rules

Sahar Toumia
RIADI Laboratory, Manouba University, Tunisia
High Institute on Management of Sousse, Sousse University, Tunisia
sahartoumia@gmail.com

Asma Mejri
RIADI Laboratory, Manouba University, Tunisia
High Institute of Computer Science of Kef, Jendouba University, Tunisia
mejri.assma@gmail.com

Sonia Ayachi-Ghannouchi
RIADI Laboratory, Manouba University, Tunisia
High Institute on Management of Sousse, Sousse University,Tunisia
sonia.ayachi.ghannouchi@gmail.com

***Abstract*—The decision mining field allows identifying decision points and analyzing rules for each choice depending on the available attributes in the business process. While significant advances have been made in this regard, little attention has been given to the manner of exploring the discovered rules, analyzing them and addressing the issue about their meaning and appropriateness. In order to alleviate this issue, in this work, we explore the possibility of investigating the conformance checking between the discovered rules that are generated by decision mining techniques and the knowledge rules of the corresponding ontology. We propose an Ontology-based approach for Conformance Checking of Decision mining rules (O2CD) in order to discover from event logs the decision models for a given process model and check the conformity between the corresponding discovered decision rules and the rules of an existing ontology. Our approach was evaluated using the COVID-19 case study in the COVID-19 crisis unit of the Farhat Hached University Hospital Center.**

Keywords-Decision mining; DMN; decision rules; ontology rules; conformance.

I. INTRODUCTION

Information systems are becoming more and more intertwined with the operational processes they support. As a result, multitudes of events are recorded by information systems. Nonetheless, organizations have problems when extracting value from these data. In this context, the goal of process mining is to use event data to extract process-related information. It aims to discover, to monitor, and to improve real processes by extracting knowledge from event logs readily available in today's systems [1]. However, the majority of algorithms, which are used for this purpose, produce models that describe the flow of activities, but do not detail how decisions are made along it. In this regard, Decision Mining (DM) is a method of deriving and analyzing event logs with the aim of extracting information from such event logs in order to extract rules, to check compliance to business rules, and to show performance information [2]. In this respect, decision making is one of the most important aspects of Business Processes (BPs) in organizations and making the right decisions during the BP execution is crucial for accomplishing the business goals of an enterprise [3]. Furthermore, due to importance of decision making, many organizations started to address a need for a standardized notation to represent decisions in BP models. Recently, in 2015, the Decision Model and Notation (DMN) [4] standard was published by the Object Management Group (OMG). In addition to that, an ontology is a way of representing a common understanding of a domain [5]. Lately, the scientific communities attempt to explore the decision support in organizations by emerging approaches on different decision ontologies [6]. In this context, the main objective of this paper is to check the conformance checking between decision rule models, elicited using process mining techniques, against the rules of a given ontology. The evaluation of our approach has been done on the basis of a real-life case study, which concerns COVID-19 patients care in the Farhat Hached University Hospital Center (UHC) in Tunisia.

This paper is organized as follows: Section 1 introduces basic background knowledge relative to the different concepts used in our approach. A detailed description of the proposed approach is presented in Section 2, and in Section 3 we illustrate our O2CD approach application and the main results of our case study. In Section 4, we describe briefly the different related works that we consider relevant to our research. Finally, section 5 concludes the paper.

II. BASIC CONCEPTS

In this section, we start by providing short and simple definitions of some important concepts which are decision mining, DMN standard and ontology.

A. Decision Mining

The term of DM was first introduced in process literature in the work of [8]. It was defined as the field that aims at the identification of data dependencies that affect the routing of a case. Moreover, it is based on the idea that a control flow decision can be transformed into a classification problem. Hence, machine learning techniques can be used to discover structural patterns in data based on a set of training instances. In order to solve such a classification problem, there are

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several algorithms, such as C4.5 and support vector machines.

B. DMN

Due to the appearance of decision making and decision mining, several organizations and companies started to address a need for a standardized notation to represent decisions in BP models. In 2015, the Object Management Group (OMG) published the first version of DMN. According to [5], the DMN standard includes two levels; the Decision Requirements level (DRD) and the Decision Logic level (DL). The DRD level shows the structure of decision. It consists of few elements that are used to capture essential information with regards to decisions. The DL defines how decisions are made.

One of the most largely used representations for decision logic is a decision table, which is used in the rest of this paper.

C. Ontology

The term ontology is taken from philosophy, where ontology describes the science of being and, with this, of descriptions for the organization, designation and categorization of existence [9]. Gruber was the first to formulate the term ontology in the field of Computer Science [10] and defined it as “a set of representational primitives with which to model a domain of knowledge or discourse”.

In addition to that, ontology is composed of a set of elements: (1) Concepts also named terms or classes, which represent the class of entities or things within a domain, (2) Relations between concepts, which describe the interactions between concepts or concept's properties, (3) Properties, which are the set of attributes of the concepts that capture further knowledge about the relationships between concepts, (4) Rules also named predicates are used to constrain values for classes or instances.

III. O2CD APPROACH

One of the main objectives of this paper is to discover from event logs the decision models for a given process model and check the conformity between the corresponding discovered decision rules and the rules of an existing ontology. Therefore, we propose a six-step approach to verify this conformity, as depicted in Figure 1.

- Phase 1: Data extraction

Generally, organizations have the opportunity to store information about their activities that are conducted through information systems. In addition to that, since most BPs are supported by at least one information system, the amount of data being stored about process executions is rapidly growing. As well, the execution of a case results in a sequence of events being recorded. The goal of the data extraction phase is to obtain event log from data that is extracted from the original data source.

However, event data exist but some efforts are needed to extract them. Often, data preprocessing is an important step in process mining. As a result, in this phase, we try to build an event log from the data available within the organization. This step is part of the most crucial steps in the field of process mining. In fact, the different steps that are followed in our proposed approach are based on the event log that is constructed in this step. Thus, this event log will be used to discover a suitable process model. This process model discovery step will be discussed in the next section.

- Phase 2: Process Model Discovery

Based on the results of the previous phase, which is event log the next step is the creation of a process model by means of process mining. Therefore, the field of process mining can be categorized in three categories [1]: discovery, conformance, and enhancement. In the scope of this phase, we only consider the first category, which is process discovery. Its aim is to use the data stored in event logs in order to generate automatically a process model that describes the execution of a process. Moreover, the first step in process discovery is the selection of the algorithm responsible for mining the event log from which process discovery can be done. Over time, many process mining algorithms have been proposed to generate a process [11]. In this paper, we select the inductive Miner [12] algorithm to discover our process model. The main advantage of this algorithm is that it allows to discover models corresponding to hidden transitions and invisible tasks as well as the model always fits, i.e., the model can generate the traces in the log [13].

- Phase 3: Decision Mining Rules Discovery

The input of this phase is event log generated from Phase 1 and process model generated from Phase 2. In this sense, DM is the study of the decision-related characteristics of a process based on a process model of the process and log of previous process executions. It enhances process models with additional data on why specific decisions are made. Therefore, in accordance with [14], in this step, we use the Multi-perspective Process Explorer (MPE) plugin, which is available in ProM tool. In this phase, we are interested in the data discovery mode to express the set of rules. So, in the MPE mode 'Discover Data-Perspective' it is possible to enrich the process model with decision rules discovery based on the event log. Therefore, the output of this phase is a process model enriched with appropriates guards and conditions.

- Phase 4: Ontology selection

Nowadays, there exists a significant and explosion of the number of ontologies, which are available in the semantic web. Therefore, ontology selection is one of the most important steps in order to determine which of the several ontologies would be one of the best ontologies for a specific context or goal. Thus, in this phase, we aim at identifying and selecting the existence of one or more ontologies that are the most appropriate and adequate for a given domain. In this context, several methods have been proposed to select ontologies according to a variety of criteria. For example, more specifically, in this step we have based on the work presented in [15]. The authors proposed a set of elements and criteria that allows selecting the adequate and appropriate ontology. The output of this phase is the selected ontology.

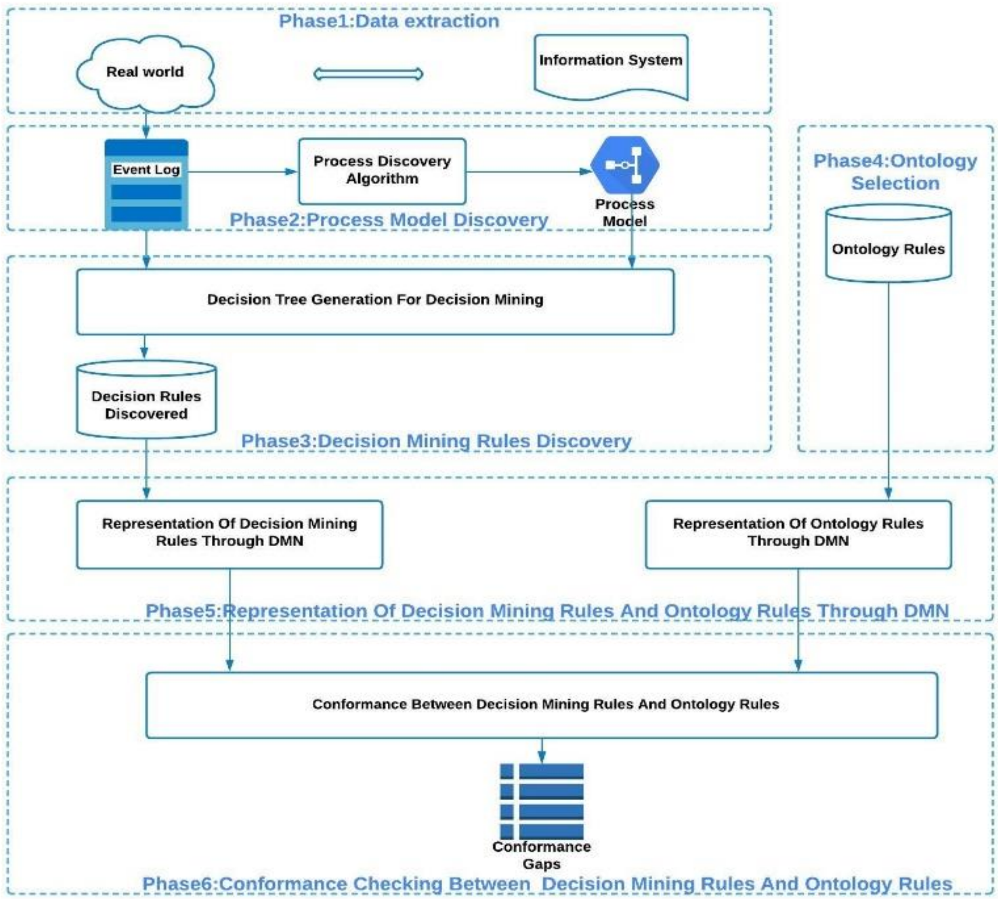


Figure 1. An Ontology-based approach for Conformance Checking of Decision mining rules: O2CD.

- Phase 5: Representation of Decision Mining Rules and ontology Rules through DMN

In this phase, we present how the decisions, which were discovered in process models, can be represented into the corresponding elements of the DMN based on the extraction of both decisions and process model from event log. These important steps were described in the previous phases. Our main idea is that process decision making can be captured and analyzed based on an event log. Further, the development of the proposed approach to transform DM rules into DMN models is inspired by results published by [4]. Secondly, we present the ontology rules through DMN. In this step, we start by extracting from the selected ontology the set of rules corresponding to the represented knowledge. Then, in the same way as we did for DM rules, we expressed them through DMN elements.

- Phase 6: Conformance checking between decision mining rules and ontology rules

In this phase, we try to check the conformity between the rules of ontology which define the acknowledged structured knowledge and those obtained by decision mining. In fact, rules incorporated in ontologies reflect ideal knowledge of a domain, while those from the event log reflect real actual execution. In order to do this, we compare the decision logic presented as tables with each other. The first table references to the corresponding decision tables containing the extracted DM rules and the second one references to the corresponding decision tables containing the extracted ontology rules. Then, we compare them according to a set of output, which are obtained according to a set of input data. In such tasks, the decision maker observes the cases of similarity and differences based on the analysis of the current situation. He/she is able of forming a comprehensive overview of the result and makes decisions using his/her professional experience and intuition, as well as, he /she can review the taken decisions.

IV. O2CD APPROACH APPLICATION AND PROOF OF CONCEPT

This section is dedicated to present the COVID-19 case study and to describe the application of our O2CD approach in a real-life situation.

A. *Context of our exprimentation*

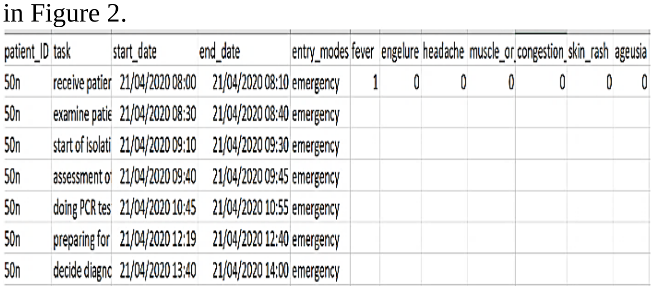
In Tunisia, the coronavirus disease pandemic has officially developed since March 2, 2020. The COVID-19 crisis unit of the UHC has prepared an action plan for the management of COVID-19 patients. However, it has faced many difficulties in federating decisions and actions. Thereby, our aim is to consider the BP of managing covid-19 patients in the COVID-19 crisis unit and to help physicians/stakeholders evaluate their decisions and take the most appropriate ones.

B. *Case study: COVID-19 patients care in the departement of infectious diseases*

To evaluate our approach entitled O2CD, we have applied it on a real-life case study, which concerns COVID-19 patients care in the infectious diseases department. For the experimental study, we considered the covid-19 event log, which was extracted from the Electronic Health Record EHR information system. Therefore, we have prepared the log for the application of our proposed approach. Then, we conducted the different steps of our O2CD approach.

- Application of phase 1

First, we need to acquire an event log of the process in this stage. In the context of our case study, the information system records data about its operations in SPSS (Statistical Package for the Social Sciences). Then, we obtained a snapshot of the database that was taken between March 1, 2020 and May 31, 2020. It was converted into CSV extension. In our case, the purpose was to select patients who were suspected to have COVID-19, as shown in the examples in Figure 2.



patient_ID	task	start_date	end_date	entry_modes	fever	engelure	headache	muscle_or	congestion_	skin_rash	ageusia
50n	receive patier	21/04/2020 08:00	21/04/2020 08:10	emergency	1	0	0	0	0	0	0
50n	examine patie	21/04/2020 08:30	21/04/2020 08:40	emergency							
50n	start of isolati	21/04/2020 09:10	21/04/2020 09:30	emergency							
50n	assessment o	21/04/2020 09:40	21/04/2020 09:45	emergency							
50n	doing PCR tes	21/04/2020 10:45	21/04/2020 10:55	emergency							
50n	preparing for	21/04/2020 12:19	21/04/2020 12:40	emergency							
50n	decide diagnc	21/04/2020 13:40	21/04/2020 14:00	emergency							

Figure 2. Screenshot from the Excel sheet.

Then we convert the CSV file into an event log in the form of XES file. This dataset concerns 100 patients in the infectious diseases department which was the unique dataset considered in this phase of our research: 1024 events were recorded involving 18 distinct activities, and 24 data attributes. These attributes encompass the different symptoms of covid-19 such as fever, headache cough,etc and the outcome of test results of coronavirus.

- Application of phase 2

After extracting and preparing the event log, the BP which is mined from the event log, was discovered as a Petri net BP using the “Mine Petri Net with Inductive Miner" plugin which is available in ProM framework as depicted in Figure3.

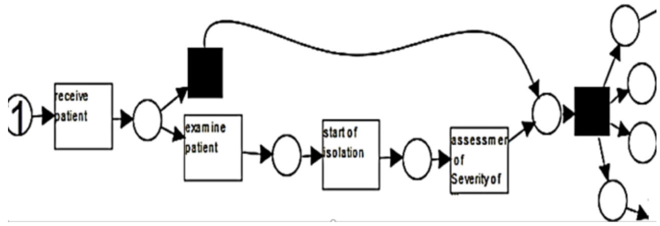


Figure 3. An excerpt of the discovered BP model.

As a result, as shown in Figure 3, the discovered model can be interpreted. We can see that the BP of managing COVID-19 patients starts by receiving the patient. The doctor examines the patient and evaluates the degree of emergency, and then the isolation is started according to clinical documents. Then, a set of activities is activated simultaneously which are: doing Polymerase Chain Reaction (PCR), preparing for hospital stay as well as deciding the appropriate diagnostic protocol and the clinical examination. Then, the PCR test is retrieved by the head of department. However, the patients can have negative or positive PCR test. On the one hand, the patient, with negative PCR result, can be discharged (ending of isolation). On the other hand, concerning patients with positive PCR result, the staff member has to evaluate whether the patient's status is mild, moderate, or severe. As well, the physician proceeds with the “keep isolated” activity and he/she can choose the Covid-19 procedure.

- Application of phase 3

In this phase, the Petri net model and the event log, which were obtained in previous steps, served as inputs for a "Multi-Perspective Process Explorer" plug-in (MPE plug-in). This step was carried out to discover the rules on the Petri net model. Firstly, the value of the "min instances" parameter was modified to the lowest possible value (0.001), which allowed the discovery of very large and complex rules related to some activities. In our case, the process model involved 10 rules base. But in this work, we mainly focused on 3 principal rules. In Figure 4, it is possible to visualize the large and complex discovery rules in the "Discover Data Perspective" mode of MPE found in the position called "p 19" in the Petri net model. These rules, shown in Table I, refer to the arc that takes the transition (activity) " consider case as mild ", " consider case as moderate", and " consider case as severe" transition. The rules, which were discovered in this step, were evaluated and then validated by the hospital staff. The goal was to verify if the discovered rules could be considered as correct and as well, if they are really applied within this process. The hospital staff agreed on the rules. We concluded

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that the applied method may possibly discover correct rules. However, this is not enough in this case to provide insights to the hospital staff. Therefore, we proceeded to explore the discovered rules and check if this information is conformed to acknowledged structured knowledge available in a selected ontology.

TABLE I. THE DISCOVERED RULES RELATED TO THE " CONSIDER CASE AS MODERATE", " CONSIDER CASE AS MILD", " CONSIDER CASE AS SEVERE" ACTIVITIES

Activity Name	Min instances	Guard
Consider case as moderate	0.001	(((respiratory_rate>22.0&& respiratory_rate<=28.0)&&testresult== "positive")&&entry_mode=="urgent medical aid service")
Consider case as mild	0.001	((presence_of_fever>0&& respiratory_rate<=22.0)&&testresult== "positive")
Consider case as severe	0.001	(((respiratory_rate>28.0&& respiratory_rate<=30.0)&&testresult== "positive")&&entry_mode== "urgent medical aid service")

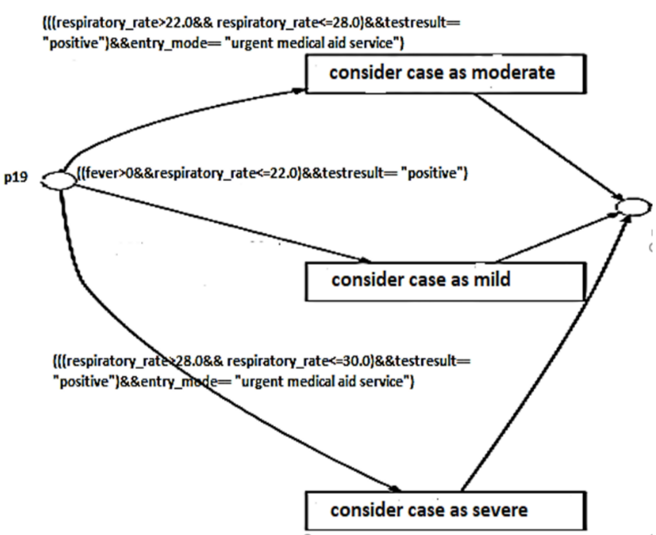

Figure 4. Process fragment representing a set of rules discovered by decision tree algorithm.

- Application of phase 4

In this stage, we try to identify and to select the most appropriate ontology in the context of COVID-19 pandemic. Therefore, we choose COVID-19 ontology for cases and patient information (CODO) [16], in accordance with a set of criteria, which provides a model for the collection and analysis of data about the COVID-19. The ontology already has incorporated real world and has uploaded thousands of cases from data collected by the government of India. As well, the inference rules were written in the Semantic Web Rule Language (SWRL), which is the rule representation language recommended by the Semantic Web community.

- Application of phase 5

After identifying and discovering the decision logic from the process models and the selected ontology, we try to derive a corresponding DMN model according to the proposed approach discussed in previous section. In the fragment process model shown in Figure 4 when place p19 is marked with a token, then, an exclusive choice between the execution of transitions needs to be made: “consider case as mild”, “consider case as moderate” and “consider case as severe”. The doctor evaluates whether the patient's status is mild, moderate or severe. As discussed before, DMN defines two levels: the decision requirements diagram level and the decision logic level. Figure 5 shows the DRD which is based on the fragment in Figure 4 from the health care domain.

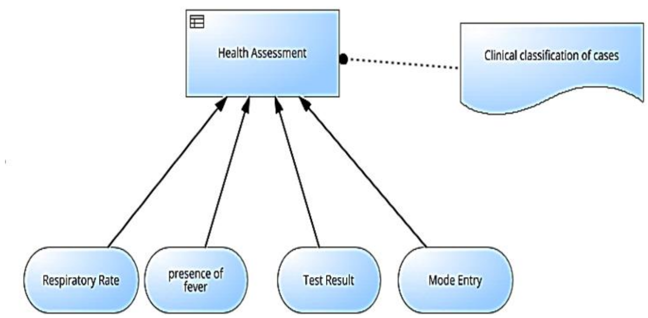

Figure 5. Decision Requirement Diagram of the decision point p19.

The decision to be taken refers to the health assessment and can directly be derived from the input data respiratory rate, presence of fever, test result, and mode entry. We noticed that the decision about how to assess a patient's health depends on the clinical classification of cases, which is a document performed by the staff of Farhat Hached UHC. Moreover, Figure 6 presents the DRD of CODO ontology. Therefore, the decision to be taken refers to the health assessment; can directly be derived from the input data respiratory rate, presence of fever, test result, cough, SpO2, and measured fever.

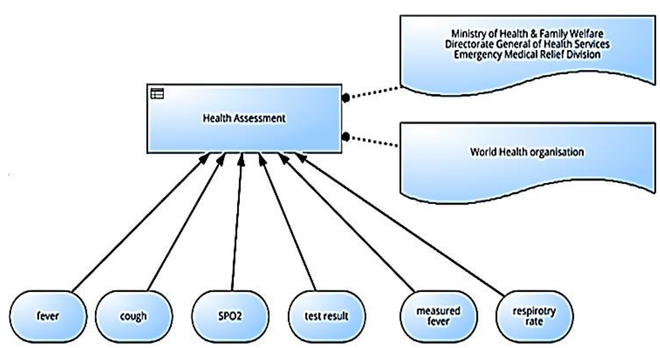

Figure 6. Decision Requirement Diagram of CODO ontology.

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We noticed that the decision about how to control a patient's health depends on the clinical documentation of WHO (World Health Organisation) and a guidance document on appropriate management of confirmed cases of COVID-19 from the ministry of health and family welfare directorate general of health Services EMR (Emergency Medical Relief) Division of India. In addition to that, according to [17], decision logic can be represented in many ways, e.g., by an analytic model or a decision table. In this paper, we used decision tables.

F	Inputs								Outputs
	Respiratory Rate		Fever		Test Result		Mode Entry		case type
	Number		{has symptom fever}		{positive}		{SAMU}		Text
1	≤	22	=	has symptom...	=	positive		-	"mild"
2	∈	[22..28]		-	=	positive	=	SAMU	"moderate"
3	>	28		-	=	positive	=	SAMU	"severe"

Figure 7. Decision table for the rules at place p19 as specified by the DMN standard.

Figure 7 shows the decision rules regarding transitions consider case as mild, consider case as moderate, and consider case as severe, as a decision table. Figure 8 presents the decision rules of CODO ontology as a decision table. It can be seen for example from this figure that if the respiratory rate is between 15 and 30 and the SpO2 between 90 and 94 and the patient has a positive test result then the patient status is considered moderate.

F	Inputs										Outputs
	fever		cough		SpO2		measured fever		respirotry rate	test result	case type
	{has symptom fever}		{has symptom cough}		Number		Number		Number	{positive}	Text
1		-		-	∈	[90..94]		-	∈ [15..30]	= positive	"moderate"
2		-		-		-		-	≥ 30	= positive	"severe"
3		-		-	<	90		-	≥ 30	= positive	"severe"
4	=	has symptom...		-		-		-	-	= positive	"mild"
5	=	has symptom...	=	has symptom...		-	≥	38	-	= positive	"mild"

Figure 8. Decision table for the rules of ontology as specified by the DMN standard.

- Application of phase 6

In this phase, we try to check the conformity and similarity between the discovered rules that were generated by DM technique with the ontology rules, which correspond to acknowledged structured knowledge. For this purpose, we attempt to compare these rules for a specific set of cases. More precisely, for each case, we compared the results respectively obtained by the discovered rules on one hand and the rules from the ontology on the other hand. As a result, in our case study, we used the two decision tables: the first one for DM rules (blue) and the second one for ontology rules (green). In this step, we want also to find out why a test case is producing a certain output and we want to see exactly which rules fire for the input data set. Thus, the formula returns true if the results are exactly the same. If there are any differences, the result returned is false and the decision maker should check his/her result. Thus, the decision maker can observe the cases of similarity and differences and form a comprehensive overview of the result.

CaseId	Respiratory Rat	Measured F	Test Resu	Fever	Cough	SPO2	Result		Name	CaseId	Respirat	Test Resu	Fever	Mode Entr	result		
1	19	38,2	positive	has sympton	has sympt	100	mild		testCases	1	19	positive	has symptom fever		mild	True	Conformance
2	30	37	positive	has sympton	has sympt	100	severe		testCases	2	30	positive	has symp	SAMU	severe	True	Conformance
3	20	38	positive	has sympton	has sympt	96	mild		testCases	3	20	positive	has symp	SAMU	mild	True	Conformance
4	16	39,6	positive	has sympton	has sympt	98	mild		testCases	4	16	positive	has symp	SAMU	mild	True	Conformance
5	16	39,2	positive	has sympton	has sympt	98	mild		testCases	5	16	positive	has symp	SAMU	mild	True	Conformance
6	19	38,2	positive	has sympton	has sympt	93	moderate		testCases	6	19	positive	has symp	SAMU	mild	False	Please check the patient status
7	18	38,1	positive	has sympton	has sympt	98	mild		testCases	7	18	positive	has symp	SAMU	mild	True	Conformance
8	24	37,1	positive	has sympton	has sympt	92	moderate		testCases	8	24	positive	has symp	SAMU	moderate	True	Conformance
9	28	37	positive			92	moderate		testCases	9	28	positive			moderate	True	Conformance
10	24	37,3	positive	has sympton	has sympt	98	mild		testCases	10	24	positive	has symp	SAMU	moderate	False	Please check the patient status
11	24	37	positive	has sympton	has sympt	99	mild		testCases	11	24	positive	has symp	SAMU	moderate	False	Please check the patient status
12	30	36,5	positive			100	severe		testCases	12	30	positive		SAMU	severe	True	Conformance
13	24	37	positive			94	moderate		testCases	13	24	positive		SAMU	moderate	True	Conformance

Figure 9. The result of conformance between decision rules and ontology rules.

As can be seen in the Figure 9, the formula compares the two tables, identifies cells with differences or finds similar values and displays the differences and similarities in corresponding cells. In our cases, we have around 75% cases of conformance and 25% cases of *divergence*, which are highlighted with the red color.

V. Related works on decision mining and ontolgy

In this section, we present the reviewed literature that we considered relevant to our research. The related works can be divided into two groups. The first group refers to the works dealing with the using of decision mining technique in processes. The second group is related to approaches that incorporate ontology in the field of decision-making. In fact, in recent Business Process Management (BPM) literature, DM appears as a frequent term [18]. In literature of DM, we identify three approaches: The first category focuses on improving decisions without considering DMN. The term of DM was first introduced in process literature in the work of [8]. The work identifies and describes the routing and choices in Petri nets by using a decision tree algorithm. However, De Leoni et al. [2] stated that the technique proposed in the work of [8] has several limitations, such as the technique cannot discover conditions associated with XOR-splits and many loop. To address these problems, the authors proposed a new approach, which was implemented by De Leoni et al. [2]. Later on, this plug-in was reused and integrated into the Multi-perspective Process Explorer plug-in for ProM introduced by [14]. The second category is dedicated to different approaches to derivate DM within DMN standard. In fact, in [19], the authors proposed an approach, which is based on using information about decisions incorporated implicitly in the process execution data. Furthermore, they proposed a technique to rebuild decision trees and to identify the dependencies between the discovered decisions. Recently, in [20], the authors proposed a new approach to produce DMN models from BPMN process models while focusing on the data perspective of process models. The third category is dedicated to Decision-aware control-flow discovery approaches. In [18], the proposed approach revised the way in which the decision and the process model can be retrieved in holistic manner. This work considered process activities as the drivers of decisions, whereas in our work we assumed that the decision drivers were control flow decision points and data attributes. In the second group of the related work have been proposed works dedicated to conceptual decision ontologies complementary to BPM techniques. The literature shows that few works addressed the relationship between discovering decision models from process and ontology. For example, in [7], the authors presented a decision ontology for supporting decision-making in information systems. This work derived components to decision processes and created independent decision-making ontologies. In [21], the investigated problem is whether a DM technique allows to identify business rules in Knowledge-Intensive Processes points. More specifically, in this work, the authors were interested in exploring the decision making associated to business rules of KIPO (Knowledge-Intensive Process Ontology), which is an ontology proposed in [22].The literature shows that the most studied works relies on the presentation and the discovery of decisions in process models on the one hand. On the others hand, a few academic works proposing their own decision-making ontology exist. However, those works are more conceptual and do not provide means for operationalizing of the decision-making ontologies. Moreover, we concluded that there is no existing works that try to check the conformity and similarity between the discovered rules that are generated by decision mining techniques with the ontology rules. So, what distinguishes our work from the existing works, is that we aim to check this conformity.

VI. Conclusion and future work

In this paper, we presented our ontology-based approach for conformance checking of DM rules using ontologies. Our approach deals with discovering from event logs the decision models for a given process model and checking the conformity between these discovered rules with ontology rules, which are already existing. The proposed approach was evaluated using a real-life case study. We concluded that the proposed approach provided valid and accurate conformance gaps that can serve for improving the organization's decision making and hence its overall performance. In the future, we plan to extend our approach. We can improve our approach by considering more data from the various information systems to ensure the diversity of data. We can also collect data during a long period in order to examine more cases and check the correctness of the results. With more data and for a long period, more specific scenarios can be encountered which favors obtained better conclusion. Moreover, we aim to create an automatic tool for extracting the divergent cases when comparing DM rules and ontology rules. Recent technologies, such as reinforcement learning [23] and deep learning [24] algorithms, could be helpful for achieving this purpose. In addition to that, in future work, we will rely on similarity metrics specifically dedicated to semantic similarity such as semantic cosine similarity [25] and we will use different data sets for training and testing. Besides, in this work, the assessment stage and the accuracy evaluation are still based on a limited test case selection. In future work, we will plan for more test cases.

Acknowledgment

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References

[1] W. Van Der Aalst, "Data science in action," in *Process mining*, Springer, 2016, pp. 3–23.
[2] M. De Leoni and W. M. P. Van Der Aalst, "Data-aware process mining: Discovering decisions in processes using alignments,"

Proc. ACM Symp. Appl. Comput., no. January, pp. 1454–1461, 2013, doi: 10.1145/2480362.2480633.
[3] S. Leewis, K. Smit, and M. Zoet, “Putting Decision Mining into Context: A Literature Study,” *Lect. Notes Inf. Syst. Organ.*, vol. 38, no. September, pp. 31–46, 2020, doi: 10.1007/978-3-030-47355-6_3.
[4] E. Bazhenova, “Discovery of Decision Models Complementary to Process Models.” University Potsdam, 2018.
[5] D. Model, “Notation (DMN). Version 1.1,” *Object Manag. Group, Inc*, 2016. Available at: http://www.omg.org/spec/DMN/1.1/, 2016.
[6] R. Kishore and R. Ramesh, *Ontologies: a handbook of principles, concepts and applications in information systems*, vol. 14. Springer Science & Business Media, 2007.
[7] E. Kornyshova and R. Deneckère, “Decision-making ontology for information system engineering,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 6412 LNCS, pp. 104–117, 2010, doi: 10.1007/978-3-642-16373-9_8.
[8] A. Rozinat and W. M. P. Van Der Aalst, “Decision mining in ProM,” in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2006, vol. 4102 LNCS, pp. 420–425, doi: 10.1007/11841760_33.
[9] M. Rebstock, F. Janina, and H. Paulheim, *Ontologies-based business integration*. Springer Science & Business Media, 2008.
[10] T. R. Gruber, “Toward principles for the design of ontologies used for knowledge sharing?,” *Int. J. Hum. Comput. Stud.*, vol. 43, no. 5–6, pp. 907–928, 1995.
[11] E. Gupta, “Process mining algorithms,” *Int. J. Adv. Res. Sci. Eng.*, vol. 3, no. 11, pp. 401–412, 2014.
[12] S. J. J. Leemans, D. Fahland, and W. M. P. van der Aalst, “Discovering block-structured process models from event logs-a constructive approach,” in *International conference on applications and theory of Petri nets and concurrency*, 2013, pp. 311–329.
[13] R. Ghawi, “Process Discovery using Inductive Miner and Decomposition,” *arXiv Prepr. arXiv1610.07989*, 2016.
[14] F. Mannhardt, M. De Leoni, and H. A. Reijers, “The Multi-perspective Process Explorer.,” *BPM*, vol. 1418, pp. 130–134, 2015.
[15] M. Sabou, V. Lopez, and E. Motta, “Open Research Online,” *Choice Rev. Online*, vol. 51, no. 06, pp. 51-2973-51–2973, 2014, doi: 10.5860/choice.51-2973.
[16] B. Dutta and M. DeBellis, “CODO: An Ontology for Collection and Analysis of Covid-19 Data,” no. November, pp. 76–85, 2020, doi: 10.5220/0010112500760085.
[17] K. Batoulis, A. Meyer, E. Bazhenova, G. Decker, and M. Weske, “Extracting decision logic from process models,” in *International conference on advanced information systems engineering*, 2015, pp. 349–366.
[18] J. De Smedt, F. Hasić, S. K. L. M. Vanden Broucke, and J. Vanthienen, “Towards a holistic discovery of decisions in process-aware information systems,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 10445 LNCS, pp. 183–199, 2017, doi: 10.1007/978-3-319-65000-511.
[19] E. Bazhenova, S. Bülow, and M. Weske, “Discovering decision models from event logs,” in *International Conference on Business Information Systems*, 2016, pp. 237–251.
[20] E. Bazhenova, F. Zerbato, B. Oliboni, and M. Weske, “From BPMN process models to DMN decision models,” *Inf. Syst.*, vol. 83, pp. 69–88, 2019, doi: 10.1016/j.is.2019.02.001.
[21] J. Campos, P. Richetti, F. A. Baião, and F. M. Santoro, “Discovering Business Rules in Knowledge-Intensive Processes Through Decision Mining: An Experimental Study,” 2018.
[22] J. B. S. França, F. A. Baião, and F. M. Santoro, “Towards characterizing knowledge intensive processes,” in *Proceedings of the 2012 IEEE 16th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, 2012, pp. 497–504.
[23] R. S. Sutton and A. G. Barto, *Reinforcement learning: An introduction*. MIT press, 2018.
[24] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
[25] F. Rahutomo, T. Kitasuka, and M. Aritsugi, “Semantic cosine similarity,” in The 7th International Student Conference on Advanced Science and Technology ICAST, 2012, vol. 4, no. 1, p. 1.