Process-To-Text: a framework for the quantitative description of processes in natural language

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Abstract. In this paper we present the Process-To-Text (P2T) framework for the automatic generation of textual descriptive explanations of business processes in natural language. P2T integrates three AI paradigms: process mining for extracting temporal and structural information from a process, fuzzy linguistic protoforms for modelling uncertain terms and natural language generation for building the explanations. A real use-case in the medical domain is presented, showing the potential of P2T for providing natural language explanations addressed to cardiology specialists.

Keywords: Process mining · Natural Language Generation · AutoAI · Explainable AI

1 Introduction

Processes constitute a useful way of representing and structuring the activities in an organization information systems. The Process mining field offers techniques to discover, monitor and enhance real processes from the event logs generated by processes execution, allowing to understand what is really happening in a business process, which may be different from what designers thought [3].

Process models are usually represented with different notations that represent in a graphical manner the activities that take place in a process as well as the dependencies among them. Usually process models are enhanced with properties such as temporal information, process execution-related statistics, key process indicators trends, interaction between the resources involved in the execution of the process, etc. Information about these properties is shown to users through visual analytic techniques that help to understand what is happening in the process execution from different perspectives. However, in real scenarios process models are highly complex, with many relations between activities, which make them nearly impossible to be interpreted and understood by the users [2]. Furthermore, the amount of information that can be added to enhance the process description is also very high, and its correlation with the process model is quite difficult to establish for users. It is also very useful to define additional analytics which summarize quantitative relevant information about the processes, such as frequent or infrequent patterns, that make it easier to focus on finding usual or unexpected behaviors. Nevertheless, correct interpretation of is usually difficult for users, since they need having a deep knowledge about processes modelling. In this regard, some approaches have been described to automatically generate natural language descriptions of a process aiming to provide users with a better understanding of the process. These descriptions aim to explain in a comprehensible way, adapted to the user information needs, the most relevant information of the process model. In general, textual information is complementary to process visualization, which is the usual way of conveying the information to the users.

Natural Language Generation (NLG) [11] provides different methods for generating insights on data through natural language. Its aim is to provide users with textual descriptions that summarize the most relevant information of the data that is being described. Natural language is an effective way of conveying information to humans because i) it does not rely on human capability to identify or understand visual patterns or trends and ii) it may include uncertain terms of expressions, which are very effective for communication [10]. Research suggests that knowledge and expertise are required to understand graphical information [9] and that users in some domains can take better decisions from textual descriptions or explanations than from graphical displays [6]. With the integration of NLG and process model and analytics visualization, users with limited expertise on process modeling and analysis are provided with an AutoAI tool that will allow them to understand the relevant information about what is really happening within a process.

In the state-of-the-art, techniques for process description focus on two perspectives. On one hand, the Control-Flow perspective aims to align the graph-based representation of a process model with its textual description [1, 8, 12]; that is, every relation between the activities of the process model has a textual description, which is usually enhanced with references to the resources that perform these activities. The aim of these proposals is to, first, facilitate users to understand the process model structure and the dependencies between the activities, and, second, detect inconsistencies in the process model such as missing activities, activities in different order, or misalignments. The main drawback of these approaches is that they focus mainly on processes with a well-defined structure, preventing its application to unstructured process models with many relations between the activities, including frequent loops, parallels and choices. On the other hand, Case Description techniques focus on generating textual descriptions about the execution of single activities or activity sequences that have been registered in an event log (a case is a particular execution of a process) [5]. The main drawback here is that the process model structure is not considered neither the relations between activities. Therefore, they do no provide a global description of what is happening in the process execution.

In this extended abstract, we present the Process-To-Text (P2T) framework, a process mining-based framework for the automatic generation of natural language descriptions of processes, including information from both the control-flow

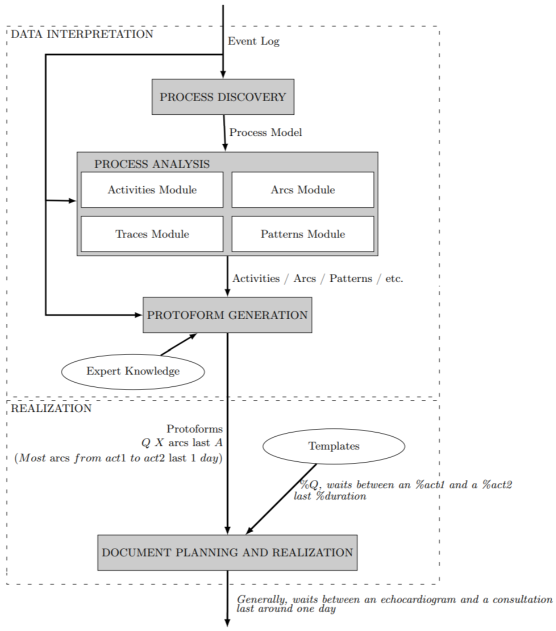

Fig. 1: Framework for the linguistic description of processes

and case perspectives. P2T is based on a Data-to-Text architecture [11] using fuzzy quantified propositions (as a way to handle imprecision) that will be generated into natural language texts with a template-based realization approach.

2 P2T: a framework for textual description of processes

Fig. 1 depicts the Process-To-Text (P2T) framework, for the automatic generation of textual descriptive explanations of processes. This framework is based on the most widely used architecture for Data-To-Text (D2T) systems [11], which defines a pipeline composed of four stages: signal analysis, data interpretation, document planning, and microplanning and realization. P2T includes the (*data interpretation* and *realization*) stages, since signal processing and document planning are not needed because, respectively, data input are not numerical, but event logs, and planning is subsumed in the realization stage.

2.1 Data interpretation

This stage is composed of two modules: *process analysis*, which extracts the process-related information from the input data, and *protoforms generation*, which obtains the instances of an intermediate language that is the input of the realization stage.

Process Analysis. The input of the data interpretation stage is an *event log*, defined as a multiset of traces. A trace is a particular execution of a process (i.e., a case), and it is represented as an ordered sequence of events, being an event the execution of an activity. An event contains context information about the execution of the activity (e.g. timestamp, the case it belongs to, the resources involved in performing the activity, the variables modified in the activity execution, ...).

However, the event log itself cannot be used as a direct input to generate the descriptions. Process mining techniques are used to extract useful information from the log. Firstly, the process model is discovered from the event log by applying a mining algorithm (e.g. the inductive miner [7]). Once the process is mined, the log is replayed [3] over the extracted model, this gives us both temporal and frequency-based information about activities, arcs (relations between activities) and traces such as temporal relations and frequency of relations, that can be used to extract frequent and infrequent behavioral patterns [4].

Then, this information is "summarized" into indicators (e.g. average duration and frequency of the temporal relation between two activities, average and mode duration of a trace, changes of mean duration of an activity in a time period, etc.) which are computed in the modules depicted in figure 1 in the data interpretation phase.

Protoform generation. A protoform [13] is an abstracted linguistic prototype usually expressed as a fuzzy quantified statement. In P2T, protoforms include fuzzy temporal references for providing information about the temporal dimension of activities, arcs, or traces. There are also protoforms related to activities, arcs, and traces. For example, *Q B activity lasts A* is an activity-related protoform that might be used as an input to the generate the textual description *Most executions of activity α_1 last ten minutes in average more than those of activity α_2*. Note that behavioral patterns can be expressed through relations between activities, meaning that pattern-related protoforms are compositions or arcs-related protoforms.

2.2 Document planning and Realization

Its objective is to generate the natural language descriptions of the process, taking the protoforms, templates, and expert knowledge as inputs. Template-based realization is a good solution for cases where natural language sentences are simple or mostly static, as in our case. Since the focus of a process analysis is rather similar disregarding the application domain similar linguistic structures are used in realization. In order to cope with specific realization aspects related with the application domain some domain expert knowledge is needed.

3 Case study

We have applied our framework in a real case study in the health domain: the process related to the patients' management in the Valvulopathy Unit of the Cardiology Department of the University Hospital of Santiago de Compostela. In this Unit, consultations and medical examinations, such as radiography, echocardiogram or CAT, are performed aiming to understand the patient's state in order to better decide its treatment (including surgery).

Medical professionals have a real interest in applying process mining techniques to this process, since it allows them to extract valuable knowledge about the Unit, like, among others, relations between age, sex, admittance (emergency or normal admission) and the number of successful surgeries, delays between process activities (such as the admission of a patient and its surgery) due to tests like CATS or echocardiograms, the improvement of the process from year to year. This information is helpful for improving the process for future patients (e.g. reducing waiting times, adding additional medical consultations or resources, taking into account certain patient characteristics for choosing tests or treatments, as this could potentially increase the number of successful surgeries).

The model that describes this process (Fig. 2) has been discovered from an event log with data on 588 patients. It is a very complex model, since patients' management depends on their pathological state, which means that the frequency trace is very low (increasing the number of relations between activities). This makes it difficult for medical professionals to understand what happens within the process even when it is graphically represented. However, linguistic descriptions of the main process analytics, as shown in Table 1, facilitate this understanding of temporal relations and delays between activities and traces.

Table 1: Textual descriptions generated for the valvulopathy process

Between 01/01/2018 and 30/06/2018 52% less Surgical Interventions were registered compared to the 01/07/2018 - 31/12/2018 period.
In the process 78% less Surgical Interventions than Coronographies were registered.
Waiting time between Consultations is around 5 weeks and 6 days in average.
Waiting time between a Coronography and a CAT is around 6 weeks and 2 days in average.
Around 7 weeks and 3 days after the Medical-Surgical Session a patient undergoes Surgical Intervention.
6% of times, after the First Medical-Surgical Session, a Second Session is held around 5 weeks and 3 days later. On the contrary, 33% of times, patient undergoes Surgical Intervention around 7 weeks and 3 days later.
Patients who go through Assessment, Medical-Surgical Session and Surgical Intervention stay for 114 days in average at the cardiology service.

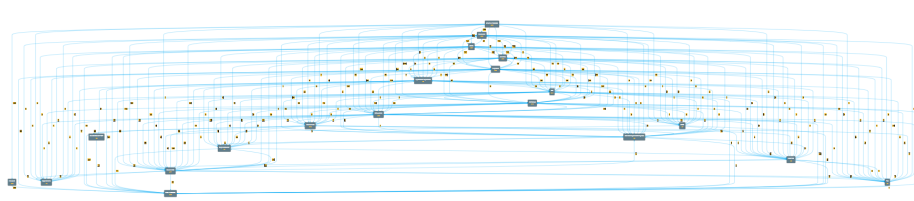

Fig. 2: Model of the valvulopathy process

4 Conclusions

We have presented the P2T framework, which integrates the process mining, natural language generation and fuzzy linguistic protoforms paradigms for the automatic generation of textual descriptive explanations of processes. Descriptions include quantitative information related to the process execution extracted through process mining techniques, such as frequent and infrequent behavior extracted from the replay of the traces over the model, temporal distances between events and frequency of the relationships between events. A real use-case in the medical domain is presented, showing the potential of P2T for providing natural language explanations addressed to cardiology specialists about consultations and interventions of the patients of the valvulopathy unit.

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