Chapter 7
Process Mining With Semantics:
Real-Time Processing and Application

ABSTRACT

This chapter contains the application of the semantic process mining approach in real-time. This includes the series of analysis that were performed not only to show how the method is applied in different scenarios or settings for process mining purposes, but also how to technically apply the method for semantic process mining tasks. In the first section, the work shows how the authors practically apply the current tools that supports the process mining through its participation in the Process Discovery Contest organised by the IEEE CIS Task Force on Process Mining. In the second section, the chapter shows how it expounds the results and amalgamation of the two process mining techniques, namely fuzzy miner and business process modelling notation (BPMN) approach, in order to demonstrate the capability of the proposed semantic-based fuzzy miner being able to perform a more conceptual and accurate classification of the individual traces within the process or input models.

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FUZZY-BPMN MINING APPROACH

In this section, the work shows how we practically apply the current tools that support the process mining through participation in the First Process Discovery Contest (Carmona, et al., 2016) organized by the IEEE CIS Task Force on Process Mining (IEEE CIS Task Force on Process Mining, 2016; Van der Aalst, et al., 2012). In theory, the IEEE group has introduced the contest to foster scientific research within the area of process mining with the primary aim of promoting the techniques and its main applications in real-world settings. According to Carmona, et al (2016) the process mining contest is dedicated to the assessment of tools and methods that discover business process models from the event logs. Accordingly, a number of event logs were provided for the purpose of the different analysis by the group (Carmona, et al., 2016). Typically, the provided events log were generated from business process models that show different behavioral characteristics. The main objective is to compare the efficiency of the different techniques that can discover fitting process models, that in turn, are capable of providing a proper balance between “overfitting” and “underfitting” models. In other words, the discovered models are seen as *overfitting* (the event log) if it is too restrictive by disallowing behaviours which are part of the underlying process. On the other hand, the model is considered as *underfitting* (the reality) if it is not restrictive enough by allowing behaviours which are not part of the underlying process. Thus:

- Given a trace (t) representing real process behaviour, the process model (m) classifies it as allowed, or
- Given a trace (t) representing a behaviour not related to the process, the process model (m) classifies it as disallowed (Carmona, et al., 2016)

Moreover, each of the test event logs precisely ((*test_log_april_1* to *test_log_april_10*) and (*test_log_may_1* to *test_log_may_10*)) which can be found in (Carmona, et al., 2016) represents part of the original model that was not initially revealed for the purpose of the analysis. Also, the *test logs* with a complete total of 20 traces for each log are considered to consist of 10 traces which are replayable (*allowed*) and another 10 traces which are not replayable (*disallowed*) by the model. Therefore, the total number of traces for the test logs is distributed as follows:

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