Building Continents of Knowledge in Oceans of Data: The Future of Co-Created eHealth
A. Ugon et al. (Eds.)

doi:10.3233/978-1-61499-852-5-281

Revealing Work Practices in Hospitals Using Process Mining

Felix MANNHARDT[a,1] and Pieter J. TOUSSAINT[a;b]
[a] *SINTEF, Trondheim, Norway*
[b] *NTNU, Trondheim, Norway*

Abstract. In order to improve health care processes (both in terms of quality and efficiency), we do need insight into how these processes are actually executed in reality. Interviewing health personnel and observing them in their work, are proven field-work techniques for gaining this insight. In this paper, we will introduce a complementary technique. This technique, called *process mining*, is based on the automatic analysis of digital events, registered in different information systems that support clinical work. Based on an event log, process mining can help in constructing a model of the process (discovery) or with checking to which extend an actual process confirms to a prescriptive model of it (conformance). This paper will briefly discuss two examples, which illustrate the use of process mining.

Keywords. Clinical processes, Work practices, Patient trajectories, Process mining

1. Introduction

Health care organisations are under strong pressure to make their work processes more effective and efficient. One important driver for this is the need to improve the quality of health care work. In Norway, this has led to attempts to introduce so-called standardised patient trajectories. Another important driving factor for making clinical processes more efficient, is the growing number of people needing care. A Norwegian study has estimated that the sector needs a productivity growth of 3,5-4,0 percent, if we assume that the current situation in which 1 out of 5 working people is employed in health care will not change dramatically [1]. To achieve more effective and efficient clinical processes, we need to have a thorough insight into how clinical processes are actually executed in practice. This helps in standardising best-practices into guidelines or standardised patient trajectories, but also in checking to which extend reality confirms to the prescribed way of working.

In hospitals, processes range from the actual treatment of patients over logistical support processes to financial processes. As Lenz and Reichert have argued [2], clinical processes often consist of combinations of *logistical* and *medical problem-solving parts*. This leads to semi-structured processes that exhibit quite some variation in their enactment. Uncovering how these processes are executed is not a straightforward task. Field work, consisting of interviews and observation studies, has proven to give useful insights into clinical process execution. However, a new source of information that can complement the insights coming from interviews and observations, has become more

[1] Corresponding Author, Felix Mannhardt, SINTEF Teknologi og samfunn, Postboks 4760 Torgarden, 7465 Trondheim, Norway; E-mail: felix.mannhardt@sintef.no.

accessible. Most hospital processes are nowadays supported by information systems that *log events related to the execution of all the activities conducted*. The field of study that considers the use of such event logs to provide insights into the actual execution of processes is called *process mining* [3]. Process mining uses event logs to provide insights that help to identify deviations, workarounds, compliance violations, and inefficiencies. It has been successfully applied in a clinical context in some cases [4,5,6,7]. However, the potential of process mining as a complementary technique to interviews and observations for discovering process model and checking conformance to existing models is enormous. Some of the immediate advantages are:

- Since the analysis is performed on digitally available traces of process instances by automatic tools, a large number of instances can be analysed at a low cost.
- The analysis is based on what *really happened*, and not on what health care workers think they do (interviews), or on how they behave under observation.
- Due to the volume of analysed process instances, we get a better insight into the frequencies of variation. Maybe variations occur only infrequently.

The goal of this paper is to demonstrate the potential of process mining for discovering clinical processes and checking their conformance to prescriptive models. We will do this by highlighting two example applications in hospitals in The Netherlands and in Norway. We will first introduce process mining (Section 2), then elaborate on the two examples cases (Section 3) and present a conclusion.

2. Process Mining

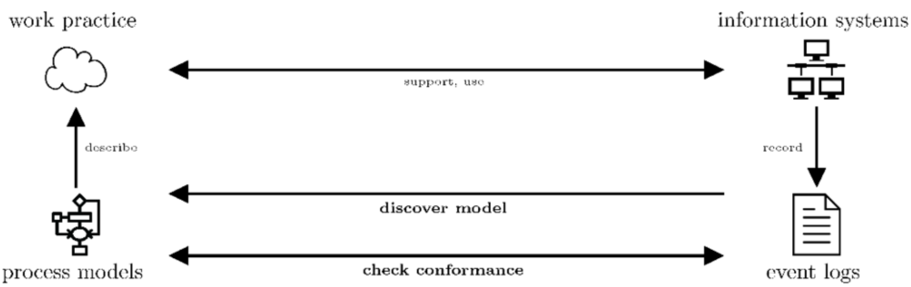

Figure 1. Process discovery and conformance checking, two of the main process mining activities [3].

The aim of process mining is to automatically provide an accurate view on how the process is executed. There are two main artefacts that are used in process mining: event logs and process models. As depicted in Figure 1, we assume that the clinical work practice is supported by *information systems*. These systems record the actual execution of activities by health care workers, which can be extracted in the form of an *event log* containing temporally ordered events that are grouped by process instances. The logging of events may originate from manual data entry by medical practitioners, the financial systems of the hospital, and from medical devices and sensors that are connected to the infrastructure. On the conceptual side, *process models*, e.g., flow charts, BPMN models or Petri nets, are used as representation of the clinical processes.

Against this backdrop, process mining activities can be categorized into: *process discovery* and *conformance checking* [3]. *Process discovery* methods automatically generate descriptive process models that capture the actual execution of a process as recorded in the event log. When analysing the processes of a hospital with little prior knowledge, process discovery is often the initial exploratory step of a process mining analysis. Process models, such as the one shown in Figure 3 can describe the possible sequence of activities, decision rules, resource assignment, and time constraints of a clinical process. *Conformance checking* methods diagnose and quantify the discrepancies between the actual work practice, i.e., the execution of activities recorded by information systems, and normative process models that encode the desired execution of the process. Deviations from the standard execution of the work and performance indicators can be visualized on top of discovered or existing process models and analysed further.

3. Cases

3.1. Analysing the Work Practice of Nurses Using Digital Whiteboards

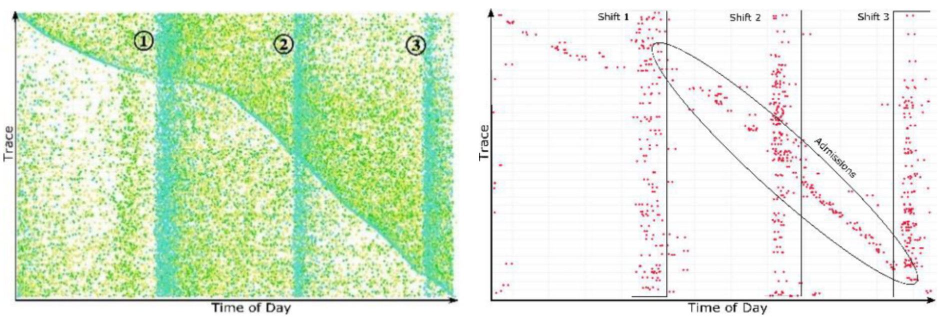

Figure 2. Dotted chart visualization of high-level activity instances and corresponding low-level events [8].

In the first case, we analysed the work practice of nurses in a Norwegian university hospital. The daily work of nurses at an inpatient ward is supported by a digital whiteboard system (Imatis Visi) that gives an overview of all the patients admitted, their location, the nurse responsible for them, the reason for admittance, time slot when they were admitted and treatment plan, in a tabular form. The whiteboard also displays information on patient signals (e.g., which patient calls, from which room, and type of signal). The whiteboards registers events such as: responsible nurse changed; patient admitted; patient signal invoked; nurse attending patient, etc. Our main research question in applying process mining was in discovering how the whiteboard system was used in practice to support the work process of nurses at the ward. We extracted an event log from the digital whiteboard system of the hospital. We considered each stay of a patient in the hospital ward to be a process instance (denoted as trace in the event log) and obtained an event for each modification of the data displayed on the whiteboard. The main challenge in this case was that the events were recorded on a very low-level of abstraction, i.e., a single event did not correspond to an activity in the work process. For example, when responsibility for a patient is shifted (either because the patient is admitted, or because the responsibility is taken over by another nurse), this would correspond to three system level events. First the responsible nurse was registered. After that, in line with the agreed upon procedure, the nurse would visit the patient to introduce him or herself. This induced two system events: nurse in room signal; nurse left room signal.

We developed an abstraction method that could be used to detect the occurrence of instances of certain high-level activities. We refer to [8] for more information on the employed abstraction method. Figure 2 shows two visualizations that are denoted as dotted chart in the process mining field [3]. Each dot refers to an event and is coloured according to the name of the recorded activity. Events are organized according to their process instance (y-axis) and the time of day (i.e., 00:00 until 23:59) of their occurrence (x-axis). Process instances are sorted according to their arrival time. The dotted chart on the left side depicts the three types of recorded system level events that are related to the shift nurse responsibility event. As can be seen from the figure, it does not show very much structure and is therefore not highly informative. The dotted chart on the right side depicts the high-level activity Shift Change detected from the low-level events. Three shift changes ①-③ are visible as vertical lines, corresponding to the three work shifts in day. The events at the diagonal line correspond to shift changes occurring when new patients are admitted. The pattern in the second figure confirms to what can be expected. However, only 405 instances of this high-level activity were captured in comparison to the 8,487 considered process instances. This could indicate that the system is not used as intended.

3.2. Analysing Trajectories of Patients from Emergency Admission to Dismissal

In the second case, we analysed patient trajectories from admission to discharge in a Dutch hospital. We focused on patients that were screened for one of the SEPSIS criteria [9]. By focussing on one patient group, for which a specific trajectory is to be expected, we aimed to avoid some of the alleged complexity of clinical processes [4]. As a starting point, we obtained a flowchart-like description of the expected patient trajectories from the hospital stakeholders. This document served as starting point for the process mining analysis. Based on the document we identified several questions and extracted an event log from hospital IT-systems. We refer to our previous work in [7,10] for a more detailed discussion.

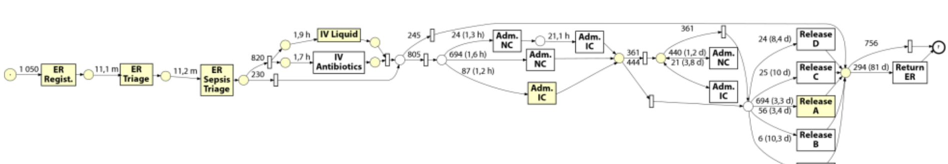

Figure 3. Process model with conformance statistics discovered based on patient trajectories [10].

Here, we aim to highlight how we obtained an automatically discovered process model and applied conformance checking. The stakeholders were interested in three different trajectories: (1) patients admitted directly to the normal care ward, (2) patients admitted directly to the intensive care ward, and (3) patients first admitted to the normal care ward and, only then, transferred to the intensive care ward. The last trajectory points to potential problem in the triage process in the emergency department, since the severity of the condition was not detected. Figure 3 shows the discovered process model (as described in [10]) and the frequencies and waiting times compute by using an open-source conformance checking tool [11]. As described in [10], we could determine that 2.9% of the admitted patients are of the problematic category: They are first admitted to the normal care ward and, then, re-admitted to the intensive care ward. Moreover, when looking only at the trajectory of problematic patients, we revealed that 56.5% of these patients return to the emergency room within one year (i.e., activity Return ER occurs). Among the other patients only 27.4% return. Thus, patients of the problematic category return more often. The hospital could, e.g., monitor these patients more closely.

4. Conclusion

Process mining offers an extra method to get insight in the execution of health care processes. As we have shown in the two examples, these insights can be used to analyse the process performance and/or to check whether the actual performance confirms to the prescribed one. It complements other methods used, such as interviewing health personnel, observing their work practice and doing document analysis. Two major challenges for process mining in practice are: the data quality of the log file; and the level of granularity of events in the log file. The process mining community has developed tools and techniques to help inspecting and cleaning log files to cope with the first challenge. The second challenge can be coped with by using the abstraction technique illustrated in the first example above, where digital events from the log are combined in a pattern that corresponds to an event that gives meaning in the organisational context.

References

[1] H. Midt-Norge, Strategi 2030, Technical report, 2016.
[2] R. Lenz and M. Reichert. IT support for healthcare processes – premises, challenges, perspectives. *Data Knowl Eng*, **61**(1) (2007), 39–58.
[3] W. M. P. van der Aalst, *Process Mining - Data Science in Action*, Second Edition. Springer, 2016.
[4] A. Rebuge and D. R. Ferreira, Business process analysis in healthcare environments: A methodology based on process mining. *Inf Syst*, **37(2) (**2012), 99–116.
[5] R. S. Mans, W. M. P. van der Aalst, and R. J. B. Vanwersch, *Process Mining in Healthcare*. Springer, 2015.
[6] E. Rojas, J. Munoz-Gama, M. Sepulveda, and D. Capurro. Process mining in healthcare: A literature review, *Journal of Biomedical Informatics*, **61**(2016),224–236.
[7] F. Mannhardt and D. Blinde, Analyzing the trajectories of patients with sepsis using process mining, CEUR WS, **1859 (**2017), 72–80.
[8] F. Mannhardt, M. de Leoni, H. A. Reijers, W. M. P. van der Aalst, and P. J. Toussaint, From low-level events to activities - A pattern-based approach, *BPM* **9850** (2016), 125–141.
[9] A. Rhodes et al., Surviving sepsis campaign: International guidelines for management of sepsis and septic shock, *Intensive Care Med*, **43(3)** (2016), 304–377.
[10] F. Mannhardt, M. de Leoni, H. A. Reijers, W. M. P. van der Aalst, and P. J. Toussaint, Guided process discovery - A pattern-based approach, *Inf Syst* (2018).
[11] F. Mannhardt, M. de Leoni, and H. A. Reijers, The multi-perspective process explorer, BPM, *CEUR WS* **1418** (2015), 130–134.