Context-Aware and Self-Learning Dynamic Transport Scheduling in Hospitals

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Abstract. The increase in available ICT infrastructure in hospitals offers cost reduction opportunities by optimizing various workflows, while maintaining quality of care. In this demonstrator-paper, we present a self-learning dashboard, for monitoring and learning the cause of delays of hospital transports. By identifying these causes, future delays in transport time can be reduced.

1 Introduction

Due to the financial pressure on the healthcare system, many hospitals struggle to balance budgets while maintaining quality. These hospitals are therefore investigating ways to optimize care delivery processes. Since organization of logistic services in hospitals may account for more than 30% of all hospital costs [6], it is certainly an area of interest. More specifically, huge opportunities exist in the transport of logistics of patients and equipment in terms of efficiency and cost reduction.

In previous work [3,5], we introduced the AORTA project[3], where we exploit the advent of the Internet of Things and intelligent decision support systems to automatically assign the most suitable staff member to a transport based on all the available information about the context (e.g. location of staff and patients and how crowded the hospital is), the staff (e.g. competences), the patient (e.g. physical condition) and the specific transportation task (e.g. pick-up location and priority). In this work we present a self-learning dashboard that is able to monitor and learn why hospital transports were late. By identifying the cause of these delays, future delays can be avoided. To give the hospital management control over what is learned, the learned causes are presented and converted to human readable sentences. The learning is performed on the historical data from a context layer that captures all information regarding the hospital. This context layer also provides data to a dynamic scheduler, that optimally dispatched transports to the staff-members. Once the learned delays have been inspected and approved by the management, the context layer is updated and more accurate data can be provided to the scheduler, minimizing transports delays.

[3] www.iminds.be/en/projects/2015/03/10/aorta

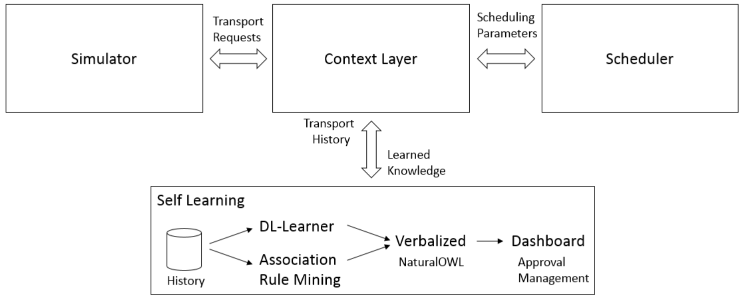

Fig. 1. The architecture of the simulation part of the AORTA system

2 Architecture

The overall architecture of the simulated AORTA system is visualized in Figure 1. This work uses a *Simulator* to represent the information within the hospital, more information regarding the real components that are being simulated in this work can be found in Ongenae et al. [5]. The simulator enables easy demonstrator purposes. Note that the simulation is based on realistic data captured from two Flemish hospitals.

The **Context Layer** integrates data resulting from various sources within the hospital, such as the floor plan of the hospital, the pathology of the patients, the capabilities of the staff, their locations captured by the IoT infrastructure, information about the tasks within the hospital, etc. To integrate all this heterogeneous data, a semantic model is utilized. This allows us to perform reasoning to automatically extract implicit statements, e.g. whether staff-members can perform specific tasks based on their capabilities. Since the *Context Layer* has a view on the current context within the hospital, it can provide accurate data to the scheduler.

The **Dynamic Scheduler** constructs an optimal transports schedule such that all the requests can be handled in a timely manner with an optimal use of resources [7]. To achieve this optimal rostering, the scheduler requests the dynamic context information from the Context Layer, e.g., the locations, availability, competences, work load & average walking speed of the staff, busy areas and possible causes of delay. This allows the scheduler to take the current situation into account when scheduling tasks. It constantly maintains an overall optimal schedule and updates this schedules as new requests and status updates of on-going transports come in. When a staff member indicates that a transport has been finished, the Context Layer will communicate this to the Dynamic Scheduler, which will then assign a new task to this staff member based on this overall optimized schedule.

The **Self-learning Module** keeps a historical overview of the context represented in the *Context Layer*. This information contains all the information regarding the executed transports, e.g. who executed the transport, what was the source and destination, what kind of transport mode was used, what were the pathologies of the patient, etc. Based on this historical context, the *Self-Learning Module* learns why transports in the past were delayed, such that these delays can be prevented in the future. For example, the module could learn that certain transports during the visiting hour on Friday are often late and more time should be reserved for them. The incorporation of the knowledge, modeled in the ontology, allows to learn more accurate rules. Furthermore, learning semantic rules allows to understand and validate the learned results. Once the rules have been learned, they can be inspected and approved by the management. Upon approval, the learned rules update the *Context Layer*, such that more accurate information can be provided to the *Dynamic Scheduler*.

3 Implementation

This section details the implementation of the previous presented components, with specific focus on the *Context Layer* and the *Self-Learning Module*.

To model all the hospital domain knowledge, an ontology was constructed by extending the Task Model Ontology[4], the Ambient-aware Continuous Care Ontology[5] and the Amigo Location Ontology[6]. Currently RDFox[7] is supported as triple store to capture all the context information. Semantic reasoning is implemented by defining rules. There is also support for graph databases such as Neo4j[8], however lacking the reasoning capabilities.

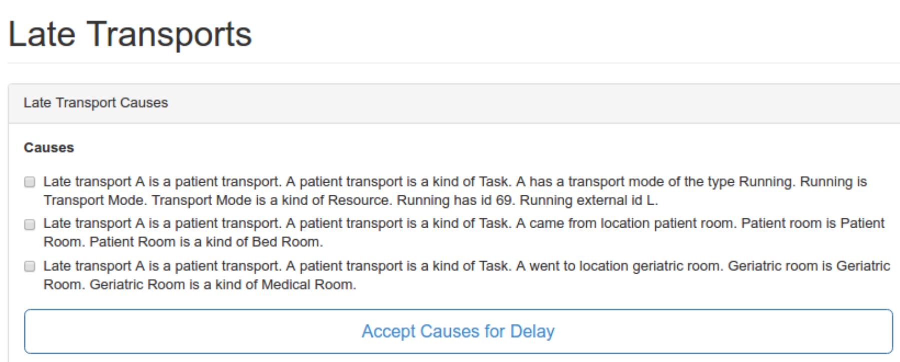

Fig. 2. An overview of the learned rules in human readable format

Two implementations [2, 3] of the Self-Learning component have been researched: one utilizing Inductive Logic Programming by the use of DL-Learner [4] and one using extensions of Association Rule Mining to enable mining over semantic data. Both are capable of learning the causes of various transport delays.

[4] www.semanticdesktop.org/ontologies/2008/05/20/tmo/
[5] users.intec.ugent.be/pieter.bonte/ontology/accio.htm
[6] gforge.inria.fr/projects/amigo/
[7] www.cs.ox.ac.uk/isg/tools/RDFox/
[8] https://neo4j.com

Each of these techniques has its pro's and con's, e.g. by exploiting the knowledge in the ontology the ILP technique is more accurate, however the association rule mining technique scales better. The learned rules are presented to the management for final confirmation through a visual interfaces, as depicted in Figure 2. The semantic learned rules are converted to human readable text through the use of NaturalOWL [1] that can convert OWL Axioms to sentences. By defining how the classes and properties in the ontology should be verbalized, NaturalOWL can generate fluent human readable text. This makes it easier for the management to interpret the learned rules.

Once one or more learned rules are verified by management, the *Context Layer* is updated with the newly learned knowledge. This is done by calculating the average delay for the identified late transports and this delay is then added by the *Context Layer* when a new transports needs to be scheduled that adheres to the learned rule. Furthermore, a dashboard provides management a real-time

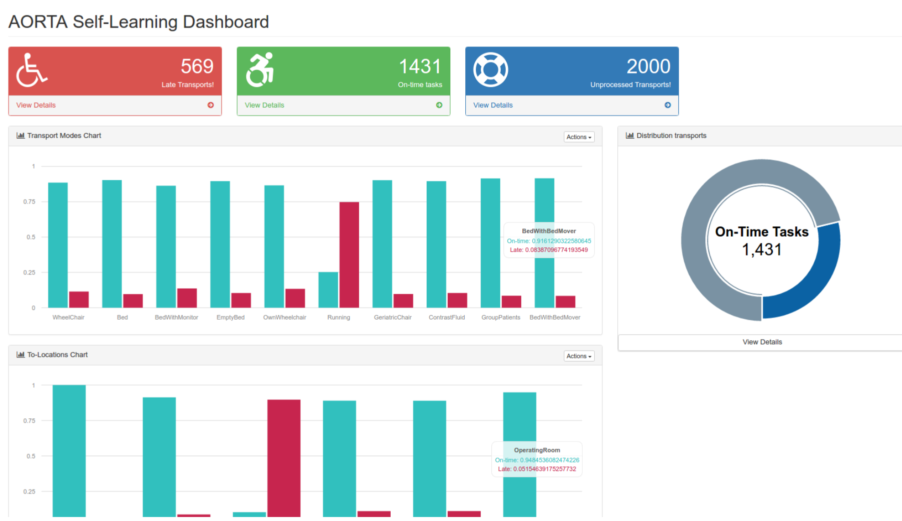

Fig. 3. The dashboard visualizing the transport distributions.

overview of the distribution of transports that are on time and those that are late. As shown in Figure 3, a few straightforward delay causes are already presented in the dashboard, i.e. the percentage of transports that are late or on time for each of the transports modes (i.e. bed, wheelchair, running,etc.), the type of room the transport came from and the type of destination.

4 Demonstrator

In the demonstrator we show a simulation of a hospital setting where a number of staff-members are dispatched to perform various transports. The dynamic scheduler will optimally schedule the transport. The simulator can be manipulated to introduce various sources of delay, allowing the self-learning module to detect these problems and update the context-layer such that more time is taken in the future for these kinds of transports and less delays occur. The demonstrator shows that after taken into account the learned rules, less transports are late. A short video presenting the described functionality can be found on http://pbonte.github.io/aorta/.

5 Conclusions

In this paper we presented a self-learning dashboard for the AORTA system that is able to learn and optimize hospital transports. By integrating data generated in the hospital in a semantic enabled context layer, intelligent decisions can be made. Furthermore, a dynamic scheduler can optimally dispatch transports and a self-learning module can identify the delays of late transports and take steps to eliminate these delays in the future. The dashboard present the learned causes of transport delay in readable text, allowing management to easily inspect and approve the learned knowledge.

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