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Discovery, visualization and performance analysis of enterprise workflow

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Abstract

This work was motivated by a recent experience where we needed to develop enterprise operational reports when the underlying business process is not entirely known, a common situation for large companies with sophisticated IT systems. We learned that instead of relying on human knowledge or business documentation, it is much more reliable to learn from the flow structure of event sequences recorded for work items. An example of work items are product alarms detected and reported to a technical center through a remote monitoring system; the corresponding event sequence of a work item is an alarm history, i.e. the alarm handling process. We call the flow of event sequences recorded for work items, workflow. In this paper, we developed an algorithm to discover and visualize workflows for data from a remote technical support center, and argue that workflow discovery is a prerequisite for rigorous performance analysis. We also carried out a detailed performance analysis based on the discovered workflow. Among other things, we find that service time (e.g. the time necessary for handling a product alarm) fits the profile of a log-mixture distribution. It takes at least two parameters to describe such a distribution, which leads to the proposed method of using two metrics for service time reporting.

Keywords: Business process rediscovery; Data visualization; Queueing system; Mixture model; Cure model

1. Introduction

1.1. Motivation

In this study, we analyze data collected from the ticketing system used to support a business that specializes in the maintenance of communication equipments. Here, the work items are product alarms detected and reported to a technical support center through a remote monitoring system. Our goals are two-fold.

First, we want to understand the structure of the workflow. In other words, we try to discover and reconstruct the underlying workflow by analyzing the event sequence data recorded for the product alarms. It is important to realize that the term workflow often means different things to different people. Here, we take an operational view where the discovered workflow represents how the system is actually used to route work items, whereas workflow in the

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conventional sense often means how it is specified on paper in some business process document. There are always non-trivial discrepancies between the two versions, even for well-implemented systems. Furthermore, processes are often modified or "re-engineered" as the business grows and evolves. It is very difficult, if not impossible, for ordinary users to keep track of all the changes. Through automated workflow discovery, we turn dull data into valuable information and greatly increase our ability to manage the underlying business process. Both the business and its customers can benefit from such an increased level of transparency.

Our second goal is to understand the traffic patterns and to measure business performance based on the discovered workflow. Here, we treat the workflow as a queueing system where work items arrive at random times. After arrival, the work items can be routed to different queues and handled by different groups of human agents. Specifically, we study the stochastic characteristics of the arrival process, as well as the queueing and service time distributions.

The basic points we try to make in this paper are the following: (1) one cannot talk about performance analysis or business measurements without first understanding the business process. During the course of this study, we have encountered many instances where analysts who provide information to management, or even managers who are running the business, often do not have an accurate understanding of the workflow that drives the business; (2) the knowledge of business process often does not come directly from people. In other words, instead of relying solely on human knowledge, as is often the case, we can discover much of the business process by analyzing the system log data; (3) reasonable reporting of business process performance requires understanding the statistical distribution of process times. Conventional process metrics such as "mean-time-to-X" can be very misleading. We argue that two metrics are needed in order to accurately capture time-related statistics.

1.2. Data analysis

In our analysis, we first use directed graphs to visualize the flow structure of the alarm handling processes. This directed graph enables us to learn how most of the alarms are solved and how much time it takes for an alarm to go through various stages (e.g. expert teams of technicians). We can also adapt the graphs for a subset of alarms or/and for a subset of expert teams.

Second, as in Brown et al. (2005), we describe an alarm process through three components: arrival time, service time and waiting time.

The arrival time can be used to measure the traffic volume in a work center. A standard assumption is that the arrival times of random events follow an inhomogeneous Poisson process. Similar to Brown et al. (2005), we adopt a non-parametric test to validate the Poisson assumption. We find that the inter-arrival times for alarms tend to be shorter than what could be produced by a Poisson process. But since the deviation from the Poisson assumption is small, we argue that the Poisson model is reasonable in practice. Once we validate the model assumptions, we further need to model the volume of processed alarms—the arrival alarm rate. For our data, we find that the arrival rate follows a weekly cycle but not a daily cycle. This cycle can be estimated through an additive linear model.

The service time is closely related to the performance of a work center. We find that the log service time for alarms follows a mixture of normal distributions. We identify three mixture components: 70% of the alarms are handled in 22 min, 24% of the alarms are handled in less than a minute, and 6% of the alarms are handled in more than 1 day.

The waiting time can be viewed as a measure of service quality. We find that the waiting time for product alarms follows a log-normal distribution rather than an exponential distribution as predicted in queueing theory. In fact, in terms of waiting time, there are two components: major and minor alarms. One immediate consequence is that the service quality cannot be measured accurately using conventional statistics such as mean-time-to-response. Also, using survival analysis techniques, we estimate that approximately 54% of the product alarms routed to a queue are transient in nature and would clear by themselves given enough time. In reality, we cannot afford to wait forever. Service providers have an obligation to respond when a problem is reported. To improve efficiency, we can leverage technologies such as artificial intelligence since many transient problems can be cleared by automated expert systems.