Uncertain Process Data with Probabilistic Knowledge: Problem Characterization and Challenges

Izack Cohen¹ and Avigdor Gal²

 ¹ Bar-Ilan University, Ramat-Gan, Israel izack.cohen@biu.ac.il, WWW home page: https://izackcohen.com
 ² The Technion - Israel Institute of Technology, Haifa, Israel avigal@technion.ac.il,
 WWW home page: https://ie.technion.ac.il/~avigal

Abstract. Motivated by the abundance of uncertain event data from multiple sources including physical devices and sensors, this paper presents the task of relating a stochastic process observation to a process model that can be rendered from a dataset. In contrast to previous research that suggested to transform a stochastically known event log into a less informative uncertain log with upper and lower bounds on activity frequencies, we consider the challenge of accommodating the probabilistic knowledge into conformance checking techniques. Based on a taxonomy that captures the spectrum of conformance checking cases under stochastic process observations, we present three types of challenging cases. The first includes conformance checking of a stochastically known log with respect to a given process model. The second case extends the first to classify a stochastically known log into one of several process models. The third case extends the two previous ones into settings in which process models are only stochastically known. The suggested problem captures the increasingly growing number of applications in which sensors provide probabilistic process information.

Key words: conformance checking, stochastically known traces, process classification, sensors

1 Motivation and Problem Description

Current times are characterized by increasing amounts of event data that are generated from multiple sources including physical devices and sensors. The source of such data may be video clips from social media [1], multiple sources in a smart city (e.g., the 'Green Wall' project in Tel-Aviv and Nanjing), various medical devices, recording of conversations, and more. The quality of such sources may be low and questionable due to many factors, among them the quality of data capturing devices and quality reduction as part of data processing. The end result of collecting such data into process logs was described in the literature as *uncertain sensor data* [2].

In this work, we focus on the problem of managing uncertain process data whenever event data can be characterised in probabilistic terms. As an illustration, consider the use of a machine learning algorithm to detect activities in video clips.

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Such algorithm typically offers, as a last stage before decision making, a probability distribution over a space of alternatives. The probabilistic information can be utilized to quantify the uncertainty associated with event data, and propagate it to the log to create a stochastic, rather than deterministic, log.

To motivate the problem, consider video cameras as a data source and food preparation as the process domain. Accordingly, think about a restaurant kitchen that is monitored by video cameras. The cook, who prepares drinks and foods, works according to recipes (i.e., process models). We note, in passing, that there are multiple supervised food preparation datasets that can be used for process mining research such as, University of Dundee 50 Salads (50Salads) and the Georgia Tech Egocentric Activities (GTEA). Given a known (or discovered) set of models (e.g., cookbook recipes or histor-



Fig. 1. An illustration of a 12-activity food preparation process.

ical supervised datasets), we wish to automatically identify, based on video clips, a prepared dish (e.g., Figure 1). Such identification can serve various purposes including conformance of a dish preparation with its recipe, informing diners regarding expected dish arrival time or performance improvement by identification of bottlenecks in the kitchen.

The challenge follows from the fact that the predicted trace, which is the result of data processing and learning techniques, is probabilistic (e.g., a softmax layer of a neural network). The matrix below represents a stochastic trace prediction for 12 events $(e_1,...,e_{12})$ and n possible activity classes $(a_1,...,a_n)$:

Assuming a complementary background activity, then for all events j, we can generate a probability space such that $\sum_{i=1}^{n} p_{i,j} = 1$. In practice, we expect the problem to battle a large number of events, much larger than the number of events in the toy datasets (e.g., 12 for Figure 1). The number of events depends on the length of the overall process and the sampling resolution, which may result in a large number of video frames. Also, whenever sampling is performed at a predetermined frequency, time points should be grouped into higher level activities. Therefore, the magnitude of the challenge can be understood by the large number of possible traces that follows from the uncertain trace representation and the fact that to date, no conformance technique was proposed to handle this type of stochastic uncertain traces.

To jump-start the discussion, we present the related literature in Section 2, followed by a taxonomy to characterise the problem dimensions (Section 3), where we also present the challenge in more details.

2 Related Literature

We first review the scarce research about Process Mining (PM) with uncertain data. Then, we add context to the use-case on which we focus – video cameras – by mentioning related computer vision studies.

Data quality and uncertainty in the context of PM have been studied from different perspectives. Several studies focused on data quality and imperfection aspects [3, 4, 5, 6, 7, 8]. These studies have dealt with data quality issues such as wrong event timestamps, a missing linkage between an event and its case-id, and a different description for the same activity. The methodological focus was on preprocessing methods for filtering the affected data or repairing the data values.

Ceylan, Darwiche, and Broeck [9] noted that extracting structured data from knowledge (e.g., images, text and speech) by applying statistical techniques such as machine learning models, necessarily creates uncertain data that include probability values for predicted classes. Therefore, data uncertainty has been researched in the context of probabilistic databases and data mining applications, where attributes and/or records are associated with probability distribution functions (e.g., [10]).

Research about performing PM tasks with uncertain data emerged during the last couple of years, by a small group of researchers that included Pegoraro, Uysal, and Aalst and their associates. Pegoraro, Uysal, and Aalst [11] and Pegoraro and Aalst [12] introduced a taxonomy of uncertain event logs and models. They defined two types of uncertainty: strong uncertainty and weak uncertainty; strong uncertainty refers to unknown probability distribution values for attribute values while weak uncertainty assumes complete probabilistic knowledge (i.e., a probability distribution). The authors suggested a conformance checking technique for a strong uncertainty setting and a way to transform a weakly uncertain log into a strongly uncertain one. Such transformation, however, results in an information loss. Pegoraro, Uysal, and Aalst [13] suggested a discovery technique over strongly uncertain logs. Uncertain activities and arcs in the discovered model can be filtered based on upper and lower bounds on the occurrence frequency of activities and direct relationships between activities. Another stream of research focuses on developing efficient ways to construct behaviour graphs from strongly uncertain longs. These graphs, which consist of a graphical representation of precedence relationships among events [14, 15], form the foundations for model discovery by using methods based on directly-follows relationships such as the Inductive miner [13].

Computer vision literature typically refers to process discovery as 'complex activity recognition', which similarly to PM, consists of a set of sensor-detected temporallylinked lower-level events. Thus, computer vision based process discovery is dependent upon automatically recognizing *simple* activities from which the process is composed such as 'walking', 'jumping', 'meeting' and the temporal links between them; and this task poses a challenge for current machine learning techniques [16, 17].

In this paper, we focus on the challenge of weakly uncertain logs that were only mentioned casually in past research [11]. We believe that weakly uncertain settings, which are increasingly common in many applications, need (and can) be explicitly dealt with. While data uncertainty may extend across several attributes we focus on the control-flow aspect which implicitly accommodates the aspect of time.

3 Taxonomy, Challenges and Initial Solution Ideas

To characterize environments of interest, we define two terms, namely Deterministically known (DK) and Stochastically known (SK). The former refers to a process model or an event log that are given and deterministic (e.g., a supervised dataset of video movies). The latter refers to a known probability distribution of event attribute values in an observed event log (e.g., to a testing dataset of video movies). Accordingly, for a SK trace within a dataset, the probability distribution of each event to be classified as one of the possible activities is known.

Model (Dataset) \rightarrow Single process			Multiple processes	
\downarrow Observation (Log)	DK	SK	DK	SK
Deterministically Known (DK)	1	2	3	4
Stochastically Known (SK)	5	6	7	8

Table 1. Eight cases according to the characteristics of the process and observed log

Table 1 accommodates the spectrum of conformance checking using the SK term. Case 1 is the standard conformance checking where process realizations are compared to a process model. Case 3 uses conformance for classification where several processes are given and the observation is classified to the process model with which it conforms the most. Thus, conformance checking is performed with respect to each of the known processes. Cases 5 and 7 relate to weakly uncertain observed logs. Case 5 may represent a setting in which one wants to check, for example, the conformance of a surgical procedure with its model (e.g., for educating surgeons or debriefing purposes). Such a case poses the challenge of developing a conformance technique that explicitly accommodates the probabilistic information. In such a case, an example observation may be modeled by the following probability matrix:

where rows correspond to activities (e.g., a-d), columns to timestamps (e.g., e_1-e_4), and entries represent the probability of an activity to occur in a time point. The matrix can be the outcome of a softmax layer of a neural network; the probabilities associated with the first event e_1 , for example, are p(a)=0.50, p(b)=0.30, p(c)=0.20, and p(d)=0.00. We note that the presentation implicitly captures time uncertainty; for example, consider events that represent the sensor sampling time – that is, e_1, e_2, \dots represent time moments in which probabilistic information about activities was gathered. Thus, an activity duration may be represented by a time interval between events, e.g. $t(e_j)-t(e_i), e_j \succ e_i$, with some probability.

In Case 7, an observed process needs to be classified into one of the process models using a conformance measure. A representative use-case may include a dataset of food preparation DK models (e.g., latte, tea, scrambled eggs, and cheese sandwich) and a SK log based on a video recorded dish preparation that needs to be automatically classified as one of the models. In such a case, we suggest conformance checking of the observation with respect to each of the models—the best conforming model is selected as the prepared dish. The challenge is to develop the conformance checking procedures for the probabilistic setting.

In Cases 2,4,6 and 8, the models are SK. Such settings may arise when creating a fully supervised dataset is too costly. A natural way to discover the models is to apply neural network techniques on videos of known dishes, which would result in a SK trace for each historical video with a deterministically known label (i.e., the dish name is known). Cases 6 and 8 in which both models and the log are SK, are the most challenging. We expect that it would be extremely hard to distinguish between two types of stochasticity. The first reflects variations across process realizations (e.g., in 60% of the realizations $a \rightarrow b$ and in the rest $a \rightarrow c$) and the second type reflects quality discrepancies induced by sensors and statistical data processing techniques (e.g., the second event is b with probability of 0.6 or c with probability of 0.4).

To recapitulate, we introduced a set of challenging conformance and classification problems one needs to address when logs use uncertain data that were generated by devices, sensors and data processing algorithms. The difference with respect to related work is both in the taxonomy and the explicit way in which we model and deal with uncertainty. Modeling and solution methods will require extending conformance methods (e.g., alignments) or developing new ones based on probabilistic measures (e.g., Frobenius norm, Cross-entropy) and new cost structures.

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