Predictive Process Monitoring for Airport Operational Support

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Abstract

Service quality has become a central focus in the management of airports due to its significance in realizing the fulfillment of travelers and in turn its impact on the desire of travelers to revisit an airport in the future. Information recorded by information systems supporting operations carried out at airports can provide valuable insights which can assist employees of airports to make more informed decisions at the right time. This work provides an analysis of the applicability of predictive process monitoring for supporting luggage handling operations at a large international airport. Multiple iterations of a development cycle for predictive process monitoring were executed to develop an application of a predictive process monitoring technique which performs acceptably when utilized for this purpose. More specifically, a number of novel LSTM based sequence to sequence models were constructed using different feature vectors, including feature vectors which contain inter-case features encoded using a novel inter-case dynamics featurization approach. Finally, a detailed analysis on the applicability of the developed predictive process monitoring application for supporting luggage handling operations at the airport is provided.

Over the past decades, a general paradigm shift can be observed in the nature of airports from being public service organizations towards becoming multiservice business organizations. The same period has seen an incline in the quality of service demanded by passengers, who are prepared to consider alternative modes of transport when not satisfied with the service provided at airports. Correspondingly, business performance indicators, such as customer satisfaction, have become a point of focus in airport management. In fact, airports have become competitive consumer brands which compete to attract travelers (Bezerra and Gomes 2020; Li et al. 2022; Prentice and Kadan 2019). The same period has seen an explosion in the level of recorded information on the day-to-day operations of businesses. This led to important developments in the nature and capabilities of decision support systems. Modern organizations understand the value of processing relevant information in order to support decision making processes, allowing businesses to make more informed decisions about operations at the right time (Shim et al. 2002; Ahmed, Shaheen, and Philbin 2022).

This work will illustrate the applicability of predictive process monitoring for supporting luggage handling operations at a large international airport. By doing so, a number of contributions are made. Firstly, we will illustrate how a development cycle for predictive process monitoring applications can be used to develop an application of a predictive process monitoring technique in the context of a luggage handling system at an airport. Secondly, a novel data aware LSTM based sequence to sequence model will be considered for operational support by providing predictions for the both the future trajectory, i.e., the remaining trace, and the remaining runtime of luggage processed at an airport. Thirdly, a number of sequence to sequence models will be constructed, which differ in terms of the feature vectors used in order to make predictions. A number of different features will be considered, including inter-case features encoded using a novel inter-case dynamics featurization approach. Lastly, a detailed discussion will be provided on the applicability of the final predictive process monitoring application developed for supporting luggage handling operation at an airport.

Development Cycle of a Predictive Process Monitoring Application

After an event log has been extracted from an information system, the development cycle of a predictive performance monitoring application can be initiated. This cycle includes three main phases. First, events are transformed into a suitable format for predictive modeling, and then a predictive model is developed before being evaluated. If the performance of the model is deemed acceptable, it can be applied to provide online decision support by forecasting future attributes or developments of ongoing (i.e., incomplete) cases. The main phases of the development cycle of an application of a predictive process monitoring technique are depicted in Figure 1. A sample containing information on the complete execution history for all luggage (n=432357) processed during a specific time period at the luggage handling system at the airport was extracted from the underlying supporting information system. Multiple iterations of the predictive process monitoring development cycle were executed in order to find a model with an acceptable performance for remaining trace and remaining runtime prediction. Dur-

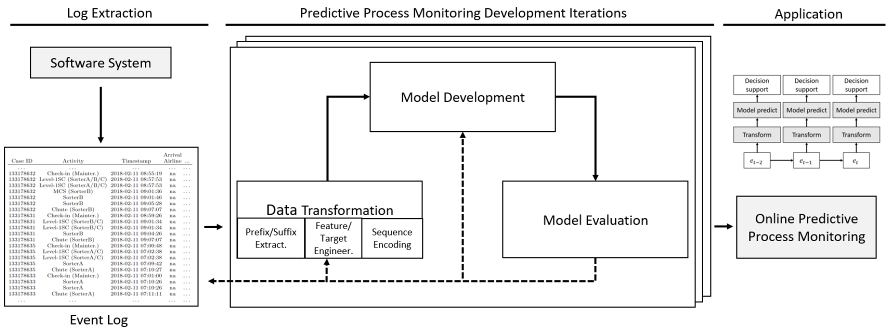

Figure 1: Development cycle of an application of predictive process monitoring techniques. After an event log is extracted, this cycle can be initiated. The cycle includes three main phases. First, events are transformed into a suitable format for predictive modeling, and then a predictive model is developed. Finally, the performance of the model is evaluated. If the model's performance is deemed acceptable, it can be applied to provide online decision support by forecasting future attributes or developments of ongoing cases.

Table 1: Evaluation of the performance of models constructed at different iterations of the development cycle. When evaluating the models for remaining trace prediction, the normalized Levenshtein similarity between the predicted and the actual trace was considered. The mean absolute error (MAE) was considered to evaluate models for remaining time prediction.

	Remaining trace	Remaining time
Act. + Time	0.7166	526
Act. + Time + Inter	0.7276 (+1.1%)	520 (+1.1%)
Act. + Time + Flight	0.9070 (+19.0%)	233 (+55.7%)
Act. + Time + Flight + Inter	0.8980 (+18.1%)	306 (+41.8%)

ing each iteration, additional features were extracted from the underlying information system and incorporated into the modelling setup in an attempt to improve the performance of the developed predictive process monitoring application for both prediction tasks. An evaluation of the performance of models constructed at different iterations of the development cycle are given in Table 1. As can be seen, a considerable performance increase was observed when the model is allowed to incorporate flight information, in addition to time information and activity labels (i.e., Lev.: +19.0% and MAE:+55.7%). Other attempts to expand this model architecture further, e.g., by additionally incorporating inter-case features, did not lead to further performance gains.

Detailed Analysis of the Performance of the Developed Model for Online Decision Support

A detailed analysis of the performance of the developed model was then carried out in order to investigate its applicability for supporting luggage handling operations at the airport. Here, the performance of the model for different groups of luggage, i.e. departing, transferring, early and late luggage, was analysed. Additionally, to obtain a relative view of the performance of the developed model, the performance of the model was compared to the performance of two baseline models, namely a transition system (remaining trace prediction) and a random forest (remaining time prediction).

A number of conclusions can be drawn from this analysis. First, the developed LSTM based sequence to sequence model consistently and comfortably outperforms considered baselines for both prediction tasks. Second, the model shows a strong performance when predicting both the remaining traces and remaining runtimes of departing and transferring luggage. A large majority of remaining traces for these groups of luggage are for example perfectly predicted when the model has not observed a single actual event in the traces of luggage. Similarly, remaining time predictions made for around half of the departing and transferring luggage has an absolute error (AE) lower than one minute at this prediction point. As expected, the performance of the model drops when evaluated for the two other groups of luggage, namely early and late luggage. This is to be expected given the high variability in the processing of these groups of luggage and relatively high average processing times. That being said, the average normalized Levenshtein similarity of remaining trace predictions made by the model are in general still quite high for early luggage, and a large majority of early luggage is correctly identified as such at an early prediction point. Additionally, the performance of the model when predicting the remaining runtime of late luggage is quite acceptable, e.g., around a third of remaining runtime predictions made for late luggage have an AE which is lower than two minutes at an early prediction point.

As detailed, the model performs strongly for both prediction tasks. Consequentially, the model can be used to identify deviations based on the predicted remaining traces and remaining runtimes. As an example, luggage that has a predicted remaining runtime which exceeds its scheduled departure time could be identified. This would allow for the execution of preventive measures, e.g., an escalation process, in order to counter the potential loss caused by deviations.

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