Discovering Redundant Activities in Event Logs for the Simplification of Process Models

Qifan Chen, Yang Lu, and Simon Poon
School of Computer Science, The University of Sydney, Sydney, Australia
{qifan.chen,yang.lu,simon.poon}@sydney.edu.au

Abstract. Process mining acts as a valuable tool to analyse the behaviour of an organisation by offering techniques to discover, monitor and enhance real processes. The key to process mining is to discover understandable process models. However, real-life logs can be complex with redundant activities, which share similar behaviour but have different syntax. The existence of redundant activities heavily affects the quality of discovered process models. Existing approaches filter activities by frequency, which cannot solve problems caused by redundant activities. In this paper, we propose first to discover redundant activities in the log and, then, use the discovery results to simplify event logs. Two publicly available data sets are used to evaluate the usability of our approach in real-life processes. Our approach can be adopted as a preprocessing step before applying any discovery algorithms to produce simplify models.

Keywords: Redundant Activity · Model Simplification · Process Mining.

1 Introduction and Motivation

Process mining (PM) is a technology that aims at generating a process model to describe a business process from execution data [17]. Once a model is discovered, the process can be analysed and enhanced for possible improvements. However, an unnecessarily complex process model, which incorporates redundant activities, is often not helpful in analysing the internal process. Redundant activities share the same behaviours but have different syntax, such as “Take Temperature” and “Temperature C” in figure 1. Such activities either occur in data integration from different sources or the system with the free-text nature.

Figure 1 will be used to illustrate the main contributions of this paper. We start from a process with redundant activities due to the free-text nature in the hospital system. This process is unnecessarily complicated because of existences of three pairs of redundant activities (e.g. “Visit Doctor” and “Dr Seen”). Thus, this model is difficult to understand, which further prevents process improvements.
With the efforts being made to simplify over-complicated models through different ways, many approaches sacrifice significant insights by abstracting or removing infrequent activities and relations. However, redundant activities may not meant to be infrequent or outliers. Some infrequent activities and relations are also able to provide useful perception to the process. Nevertheless, many of them have difficulties identifying redundant activities.

The aim of this paper is to present an approach to simplify discovered process models by detecting and integrating redundant activities in event logs. For detection, likely candidates share the same behaviours. So, we adopt a statistical method to compare control-flow relation for each activity. For integration, the activity with the most occurrence frequencies are preserved and replacing the rest of redundant activities. The produced event logs can then be inputted to any existing discovery algorithms. We evaluate our approach using two publicly available event logs.

The rest of the article is organised as follows. Section 2 discusses the background. In Sect. 3, we describe our approach for detecting and integrating redundant activities. Section 4 evaluates our approach using two publicly available event logs, and in Sect. 5, we summarise our findings and suggest future work.

**Fig. 1.** A motivation example (above) and discovered process model after applying our approach (below).

## 2 Background

Diverse methods have been proposed to tackle the simplification of process models. Some existing approaches ignore or remove relations from either models or logs. Skip Miner \[1\] skips a certain percentage of events in logs to ignore some relations in order to discover less spaghetti-like models. Methods \[2,3,6,7,13\] all follow the same idea which is to keep the core behaviour and remove less important ones. In \[28\], infrequent and non-core relations are abstracted by extracting frequent sub-processes, while \[19\] simply removes less frequent traces from logs. \[4\] proposes a collections of log-based simplification techniques where
the importance of places and arcs in the model are ranked first, and more important ones are preserved. In [6,7], processes are presented using Petri net first, then unfolding to retain the central relations and finally folding back into simple process models that contain desired behaviours.

Other technologies [5,9,10,12,15,16] simplify process models through the activity level. [15] identifies and filters out chaotic activities that could happen at any stage within a trace from logs and [5] aggregates activities from different systems using the map-reduce algorithm. Duplicate tasks, which refer to different tasks that have been improperly tagged with the same label, are identified to reduce the complexity of models [12]. Event abstraction technology [9,10,16] abstracts low-level events (e.g. sensor-level) into high-level activities (e.g. daily living) to reduce the number of activities, which is also a way to solve complicated models. [9] abstracts events which have similar or close timestamps based on user defined threshold to different sessions. Then, these sessions are clustered into a branch of activities. In [16], the n-gram analysis is adopted to train an analytical model using a segmented list obtained from domain experts which contains segments of low-level events. Then, the algorithm can cluster low-level events with the pre-trained model. Finally, each cluster is manually renamed to a high-level activity. The pattern-based approach in [10] relies on abstracting sub-processes that frequently occur in logs into high-level activities to produce more representative models.

3 Methodology

This section provides an overview of the proposed approach shown in figure 2. First, we describe how our approach detects redundant activities in logs based on control-flow relations. Then, we outline how to obtain and process the discovered results to obtain a simplified log.

3.1 Detecting Redundant Activities Based on Control-flow Relations

The redundant activities are those share similar behaviours, which follow the same control-flow relations patterns. The same patterns mean not only the same control-flow relations but also similar frequency distributions. So, we adopt a statistical hypothesis test (i.e. G-test of independence [14]) to compare control-flow patterns based on the directly-follows graph obtained from the log.

The starting point is event logs. Since we would like to focus on solving redundant activities at the log level, no discovery algorithms are applied to mine a model at this stage. Instead, a directly-follows graph is constructed. An example is shown in figure 3. A directed arc with a number means a directly-follows relation with its frequency in the log (e.g. an arc from $A$ to $B$ with number 50 means activity $A$ has a directly-follow relation to $B$, and this relation occurs 50 times in the log).
Next, control-flow relations comparisons are divided into incoming and outgoing relations. The incoming relation is defined as an activity is caused by the execution of another activity (e.g., activity $H$ has the incoming relation from $A$ since the execution of activity $H$ is caused by $A$). On the other hand, the outgoing relation refers to an activity causes the execution of another activity (e.g., activity $C$ has the outgoing relation to $E$ since the execution of activity $C$ leads to $E$). For each pair of activities, two $2 \times n$ ($n$ is the number of activities in the log) contingency matrices are calculated for the G-test. One for incoming relations and the other one for outgoing relations. An example outgoing contingency matrix is shown in Table 1. The contingency matrix reflects relations along with their frequencies in the log. Then, for each matrix, we perform a G-test. As a result, total $\frac{n \times (n-1)}{2}$ pairs of activities and $n \times (n - 1)$ G-tests are performed. Suppose the resulted $P$-value is smaller than a predefined threshold. In that case, we reject the null hypothesis and reckon these two activities are not redundant due to significant differences in control-flow relations.

### Table 1. An example outgoing contingency matrix for activity $B$ and $D$.

|       | $A$ | $B$ | $C$ | $D$ | $E$ | $F$ | $G$ | $H$ |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|
| Activity $H$ Outgoing | 0   | 0   | 23  | 24  | 0   | 1   | 0   | 0   |
| Activity $B$ Outgoing  | 0   | 0   | 25  | 25  | 0   | 0   | 0   | 0   |

### 3.2 Log Simplification

Each pair of activities now have two $P$-values, which are incoming and outgoing similarities. Since redundant activities need to share similar patterns in

---

1 The typical value of the threshold, i.e. significant level, for the G-test is 0.05 [11].
both incoming and outgoing relations, the activity pair with any \( P\)-value that is smaller than the threshold would not be treated as redundant. However, users can adjust the threshold and rules to determine redundant activities. A \( P\)-value above a predefined threshold accepts the null hypothesis, i.e. control-flow relations distributions of two activities are similar. The frequency of each activity in the log is counted. We preserve the most frequent activity and replace the rest activities in redundant activity pairs (e.g. activity \( C \) and \( D \) are redundant, and all appearances of \( C \) are replaced with \( D \) in the log since \( D \) is more frequent than \( C \)). Thus, we simplify the log before applying any discovery algorithms while maintaining necessary activities and preserving the core behaviour of the process.

4 Evaluation

In this section, we conduct two experiments to evaluate our approach using publicly available logs. The approach is implemented as a Python program\(^2\) for evaluations. Inductive Miner \(^8\) is used to mine models for logs before and after applying our approach.

4.1 Data Sets

Two publicly available real-life logs are adopted to evaluate our approach. BPI challenge 2011 log (BPIC11\(^3\)) records processes from a Dutch academic hospital over three years. BPI challenge 2015 log 3 (BPIC15\(^4\)) contains all building permit applications over a period of approximately four years by five Dutch municipalities. The details of the logs are shown in table\(^2\). The original logs are complex, with hundreds of activities and high trace variants. The process models for the original BPIC11 and BPIC15\(_3\) are respectively shown in figure\(^4\) and \(^5\). The two process models are hard to follow because of redundant activities and complex relations.

| Table 2. Log details before and after applying our approach. |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Log             | #Activity | #Trace | #Events | #Trace vars | Avg trace length |
| BPIC11 - original | 624 | 1143 | 150291 | 981 | 131 |
| BPIC11 - modified | 23 | 1143 | 150291 | 736 | 131 |
| BPIC15\(_3\) - original | 383 | 1409 | 59681 | 1349 | 42 |
| BPIC15\(_3\) - modified | 22 | 1409 | 59681 | 659 | 42 |

\(^2\)https://github.com/GilbertFan/Model-Simplification

\(^3\)https://doi.org/10.4121/uuid:d9769f3d-0ab0-4fb8-803b-0d1120ffcf54

\(^4\)https://doi.org/10.4121/uuid:31a308ef-c844-48da-948c-305d167a0ec1
4.2 Results

In evaluation, we adopt the typical threshold, which is 0.05 for P-value in G-test. The details of modified logs after applying our approach are shown in table 2. We can see the number of activities is tremendously decrease (e.g. in BPIC11, the number of activities drops from 624 to 23). The number of trace variants also decrease in both logs (e.g. in BPIC15, the number of trace variants becomes half of the original log), making processes more centralised. The discovered models of modified logs are separately shown in figure 6 and 7. The discovered process models are much clearer than before (i.e. process models in figure 4 and 5). These two models are easy to understand with explicit main behaviours of processes, which makes them more suitable for further analysis and improvements.

5 Conclusion

In this paper, we propose an approach to detect redundant activities using the statistical method to compare control-follows relations distributions with the
aim to simplify event logs. The evaluation results demonstrate the approach can significantly reduce the log complexity, which leads to the simpler discovered model. This contribution may be applied to any event logs as a preprocessing step before utilising any discovery algorithms.

Future work can be divided into the following perspectives: 1). Integrating other information from logs (e.g. timestamps, resources etc) for more accurate detection results. 2). Incorporating other technologies such as natural language processing (NLP) to repair redundant activities for more meaningful process models.

References

1. Batista, E., Solanas, A.: Skip miner: Towards the simplification of spaghetti-like business process models. In: 2019 10th International Conference on Information, Intelligence, Systems and Applications (IISA). pp. 1–6. IEEE (2019)
2. Chapela-Campa, D., Mucientes, M., Lama, M.: Simplification of complex process models by abstracting infrequent behaviour. In: International Conference on Service-Oriented Computing. pp. 415–430. Springer (2019)
3. Chapela-Campa, D., Mucientes, M., Lama, M.: Understanding complex process models by abstracting infrequent behavior. Future Generation Computer Systems 113, 428–440 (2020)
4. De San Pedro, J., Carmona, J., Cortadella, J.: Log-based simplification of process models. In: International Conference on Business Process Management. pp. 457–474. Springer (2016)
5. Evermann, J.: Scalable process discovery using map-reduce. IEEE Transactions on Services Computing 9(3), 469–481 (2014)
6. Fahland, D., Van Der Aalst, W.M.: Simplifying mined process models: An approach based on unfoldings. In: International Conference on Business Process Management. pp. 362–378. Springer (2011)
7. Fahland, D., Van Der Aalst, W.M.: Simplifying discovered process models in a controlled manner. Information Systems 38(4), 585–605 (2013)
8. Leemans, S.J., Fahland, D., van der Aalst, W.M.: Discovering block-structured process models from event logs-a constructive approach. In: International conference on applications and theory of Petri nets and concurrency. pp. 311–329. Springer (2013)
9. de Leoni, M., Diündar, S.: Event-log abstraction using batch session identification and clustering. In: Proceedings of the 35th Annual ACM Symposium on Applied Computing. pp. 36–44 (2020)
10. Mannhardt, F., De Leoni, M., Reijers, H.A., Van Der Aalst, W.M., Toussaint, P.J.: From low-level events to activities—a pattern-based approach. In: International conference on business process management. pp. 125–141. Springer (2016)

11. Nuzzo, R.: Scientific method: statistical errors. Nature News 506(7487), 150 (2014)

12. de San Pedro, J., Cortadella, J.: Discovering duplicate tasks in transition systems for the simplification of process models. In: International Conference on Business Process Management. pp. 108–124. Springer (2016)

13. Sani, M.F., van Zelst, S.J., van der Aalst, W.M.: Improving process discovery results by filtering outliers using conditional behavioural probabilities. In: International Conference on Business Process Management. pp. 216–229. Springer (2017)

14. Sokal, R.R., Rohlf, F.J., et al.: Biometry: the principles and practice of statistics in biological research (1995)

15. Tax, N., Sidorova, N., van der Aalst, W.M.: Discovering more precise process models from event logs by filtering out chaotic activities. Journal of Intelligent Information Systems 52(1), 107–139 (2019)

16. Tello, G., Gianini, G., Mizouni, R., Damiani, E.: Machine learning-based framework for log-lifting in business process mining applications. In: International Conference on Business Process Management. pp. 232–249. Springer (2019)

17. Van Der Aalst, W.: Data science in action. In: Process mining, pp. 3–23. Springer (2016)