From Low-Level Events to Activities:  
A Session-Based Approach  
(Extended Version)

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Abstract. Process-Mining techniques aim to use event data about past executions to gain insight into how processes are executed. While these techniques are proven to be very valuable, they are less successful to reach their goal if the process is flexible and, hence, events can potentially occur in many orders. Furthermore, information systems can record events at very low level, which do not match the high-level concepts known at business level. Without abstracting sequences of events to high-level concepts, the results of applying process mining (e.g., discovered models) easily become very complex and difficult to interpret, which ultimately means that they are of little use. A large body of research exists on event abstraction but typically a large amount of domain knowledge is required to be fed in, which is often not readily available. Other abstraction techniques are unsupervised, which give lower accuracy. This paper puts forward a technique that requires limited domain knowledge that can be easily provided. Traces are divided in sessions, and each session is abstracted as one single high-level activity execution. The abstraction is based on a combination of automatic clustering and visualization methods. The technique was assessed on two case studies that evidently exhibits a large amount of behavior. The results clearly illustrate the benefits of the abstraction to convey knowledge to stakeholders.

Keywords: Event-Log Abstraction · Clustering · Process Mining · Visualization

1 Introduction

Nowadays, complex organizations leverage on well-defined processes to try to carry on their business more effectively and efficiently than their competitors. In a highly competitive world, organizations aim to continuously improve their business performance, which ultimately boils down to improve their process.

The first step towards improvement is to understand how processes are actually being executed. The understanding of the actual process enactment is the goal of Process Mining, which focuses on providing insights by reasoning on the actual process executions, which are recorded in so-called event logs [1]. Event logs group process events in traces, each of which contains the events related
Fig. 1: A model for a very flexible process, which shows an ocean of variability.

to a specific process-instance execution. An event refers to the execution of an activity (e.g., Apply for a loan) for a specific process instance (e.g. customer Mr. Bean) at a specific moment in time (e.g. on January, 1st, 2018 at 3.30pm).

In the realm of process mining, dozens of techniques exist to discover a process model from an event log. Depending on the objective, the process model can be more or less formal and detailed.

While process mining has proven to be effective in a wide range of application fields, it has shown its limitation when the process intrinsically allows for a high degree of flexibility [1] or information systems record executions into logs with events that are a lower-level granularity than the concepts that are relevant from a business viewpoint. Both of problems lead to an “ocean” of observed process behavior. As an example, when trying to discover a process model, this ocean of behavior cannot be easily summarized into a single model, unless the model is very complex and low-level, thus being difficult to interpret.

Extreme complexity and difficulty of interpretation contrasts the initial purpose of process mining: conveying interpretable insights and knowledge to process stakeholders and owners. Typical examples are within the health-care domain [15], in the customer-journey analysis [10] and in the analysis of (on-line) shops. It is worthy noting that the technique is not only beneficial when discovering a model but also in a wider range of application of diverse process-mining techniques.

Similarly to existing related work (see Section [5]), here we advocate the need of abstracting low-level events to high-level activities. However, differently from existing related work, we do not want to rely on the provision of an extensive amount of domain knowledge as existing approaches require: that is not realistic to assume. On the other hand, we want to avoid completely unsupervised approaches, which naturally shows lower accuracy and/or relies on strong assumptions.

To balance accuracy and practical feasibility, we aim at a technique that requires process analysis to only feed in little knowledge that is easy to provide. In a nutshell, the idea is that events of the same trace can be clustered into sessions such that the time distance between the last event of a session and the first event of the subsequent session is larger than a user-defined threshold. Obviously, while clustering, events cannot be shuffled: each trace is transformed
into a sequence of sessions of events. The so-created sessions are encoded into data points to be used as input for clustering techniques; this way, each session is assigned to one cluster. The event log abstraction is such that the entire session is replaced by a high-level event that indicates to which cluster the session belongs. Finally, the high-level events need to be named: The centroids of the clusters provide meaningful information for a process stakeholder to identify the high-level activity that correspond to each cluster. To support stakeholder in this identification, visualization techniques are foreseen, based on heat maps.

The benefit and feasibility of the proposed technique was initially assessed on real-life data related to the usage of the www.werk.nl web site. Results show that overcomplex models can be converted into high-level process models that are accurate and that are simply enough to be able to convey information that has business value. However, the idea of a session-based clustering goes beyond analysing web sites; it certainly applies to other domains, including on-line retailer shops, supermarkets, hospitals, software analysis. In general, one can apply the proposed technique to any domain in which events happen in batches/sessions and clear breakpoints exist between one batch/session and the subsequent. To showcase a wider applicability of the technique, it was also assessed on the event data related to the execution of a process to manage building-permit requests. While discussing this second case study, we also show that the technique is not only beneficial for process discovery but for a broad range of process mining techniques: for instance, the abstract event log was employed to compare how the process is being executed by different responsible resources.

Section 2 introduces the initial motivating example of the www.werk.nl web site. Section 3 introduces the abstraction technique, while Section 4 reports on the evaluation on the two cases, i.e. the usage of www.werk.nl and the building-permit requests in a Dutch municipality. Section 5 compare with the related work while Section 6 concludes the paper, delineating the avenues of future work.

2 Motivating example

The www.werk.nl web site is a very significant example of customer journey, intended as the product of the interaction between an organization and a customer throughout the duration of their relationship. Gartner highlights the importance of managing the customer’s experience, which is seen as “the new marketing battlefront”\footnote{Key Findings From the Gartner Customer Experience Survey - https://www.gartner.com/smarterwithgartner/key-findings-from-the-gartner-customer-experience-survey/}. The www.werk.nl web site is run by UWV, which is the social security institute that implements employee insurances and provide labour market services to residents in the Netherlands. Specifically, the web site supports unemployed Netherlands’ residents in the process of job reintegration. Once logged in the web site, people can upload their own CVs, search for suitable jobs and, more in general, interact with UWV via messages as well as they can ask questions, file complaints, etc. The www.werk.nl web site is structured into sections of pages and logged-in users can arbitrary switch from one to another. However,
to improve the experience, it would be worthwhile introducing supporting wizards. The starting point for designing such wizards is to gain insights into the typical ways in which the web site is actually used.

Publicly available is an event log that collects the browsing behavior of the logged-in visitors in the period from July, 2015 to February, 2016. The event log is composed by 335655 events divided in 2624 traces. We tried to discover a model of the web-site interaction without abstracting the event log. Figure 1 shows the result obtained through the new Heuristic Miner [14]. Similar results are also obtained through other miners and all show the problems mentioned above: the model is overcomplex, with an “ocean” of activity dependencies. While this is certainly not surprising because of the freedom of visiting the web site, still one wants to discover a model that provides insights for the stakeholders.

3 Session-based Event-log Abstraction Technique

This section introduces the technique of clustering low-level events into high-level activities. This procedure consists of four main steps, as visualized in Figure 2. The starting point is an event log. All the traces of the event log are split into sessions, which can then be clustered; the cluster centroids are visualized on a heat map to provide support to assign a name to each cluster. Finally, the abstract event log is created: each session is replaced by two events (e.g. \( C_1^{st} \) and \( C_1^{co} \) in figure) that are associated with an activity of the same name as the name assigned to the cluster to which the session belongs. The two events refer to the

\[ \text{https://doi.org/10.4121/uuid:01345ac4-7d1d-426e-92b8-24933a079412} \]
start and the completion of the session and, respectively, take on the timestamps of the first and the last event of the session.

3.1 Preliminaries

The starting point of our technique is an event log, which consists of a set of traces, each of which is a sequence of unique events:

**Definition 1 (Event, Trace, Log).** Let $E$ be the universe of events. A trace $\sigma \in \mathcal{E}^*$ is a sequence of events. An event log $\mathcal{L}$ consists of a set of traces, i.e. $\mathcal{L} \in \mathcal{E}^*$.

Events carry on information: given an event $e \in E$, $\lambda_A(e)$ and $\lambda_T(e)$ respectively return the activity associated with $e$ and the timestamp when event $e$ occurred. In the remainder, $e \in \mathcal{L}$ indicates that there is a trace $\sigma \in \mathcal{L}$ s.t. $e \in \sigma$. Given a trace $\sigma' = \langle e_1, \ldots, e_n \rangle$, $\sigma'(i)$ returns the $i$-th event of the trace, namely $\sigma'(i) = e_i$; also, $|\sigma'|$ returns the number of $\sigma'$, namely $n$.

Furthermore, given a second trace $\sigma'' = \langle f_1, \ldots, f_m \rangle$, $\sigma' \oplus \sigma''$ indicates the trace obtained by concatenating $\sigma''$ at the end of of $\sigma'$, i.e. $\sigma' \oplus \sigma'' = \langle e_1, \ldots, e_n, f_1, \ldots, f_m \rangle$.

As mentioned in Section 1, we leverage on existing clustering techniques, while being independent of any specific. In a nutshell, any clustering technique takes a multiset $m$ of $n$-ples, elements of domain $D_1 \times \ldots \times D_N$, and split $m$ into a number of disjoint multisets.

**Definition 2 (Clustering).** Let $\mathbb{M}$ be the set of all multisets of all data points defined over the cartesian product $D_1 \times \ldots \times D_N$. A clustering technique can be abstracted as function $\text{Cluster} : \mathbb{M} \to \wp(\mathbb{M})$ that, given a multiset $M \in \mathbb{M}$, returns a $M$’s clustering into a set $\{M'_1, \ldots, M'_n\}$ of multisets such that $M'_1 \cup \ldots \cup M'_n = M$ and, for any $1 \leq i \leq j \leq n$, $m \in M'_i \land m \in M'_j \Rightarrow M'_i = M'_j$.

3.2 Creation of Sessions

The first step of the technique is to identify the sessions. We introduce a time interval $\Delta$. For each trace $\sigma = \langle e_1, \ldots, e_n \rangle$ in an event log, we iterate over its events and create a sequence of sessions $\langle s_1, \ldots, s_m \rangle$. We create a session $s_k = \langle e_i, \ldots, e_j \rangle$, subsequence of $\sigma$, if (1) the timestamp’s difference between $e_i$ and $e_{i-1}$ and $e_j$ and $e_{j+1}$ is larger than or equal to $\Delta$ and (2) the timestamp’s difference between two consecutive events in $\langle e_i, \ldots, e_j \rangle$ is smaller than $\Delta$.

**Definition 3 (Sessions of a Trace).** Let $\sigma = \langle e_1, \ldots, e_n \rangle \in \mathcal{E}^*$ be a log trace. Let $\Delta$ be a time interval. $\bigcup_{\Delta}(\sigma) = \langle s_1, \ldots, s_m \rangle \in (\mathcal{E}^*)^*$ denotes the session sequence of $\sigma$; (1) for any $1 \leq i < m$, $\lambda_T(s_{i+1}(1)) - \lambda_T(s_i([s_i])) \geq \Delta$, and (2) for any $1 \leq i \leq m$ and $1 \leq j < |s_i|$, $\lambda_T(s_i(j + 1)) - \lambda_T(s_i(j)) < \Delta$, and (3) $\sigma = s_1 \oplus \ldots \oplus s_n$.

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3 Given a (multi)set $M$, $\wp(M)$ denotes the powerset, namely the set of all sub(multi)sets of $M$. The operator $\cup$ denotes the union of multisets, namely such that the cardinality of an element in the union is the sum of the cardinality of all elements of the joined multisets.
The third condition states that the session sequence of \( \sigma \) is a sequence of sub-traces that, once concatenated, must result in \( \sigma \). The following example further clarifies:

**Example 1.** Consider a trace \( \sigma = \langle a_1, b_3, c_4, a_{10}, d_{13} \rangle \) of an event log \( \mathcal{L} \). The subscript indicates the timestamp of the event’s occurrence (e.g. \( d \) occurred at time 13). Assume that the time interval \( \Delta = 5 \). One can easily see that the time difference between \( d \) and \( e \) is greater than the given time interval \( \Delta \) (\( \lambda_T(a_{10}) - \lambda_T(c_4) = 6 > \Delta = 5 \)), thus resulting in two sessions: \( \overline{\sigma} = \langle s_1, s_2 \rangle \) where \( s_1 = \langle a_1, b_3, c_4 \rangle \) and \( s_2 = \langle a_{10}, d_{13} \rangle \). Note that the concatenation results in \( \sigma: \sigma = s_1 \oplus s_2 \).

### 3.3 Clustering of Sessions

Once the sessions are created, the next step is to cluster them. To apply clustering techniques, each session needs to be encoded as a point \( p \) in some domain \( D_1 \times \ldots \times D_n \). This encoding can be made using different policies, which leverage on different characteristics. For instance, a session can be encoded into a point that contains one integer component for each activity, and its component for activity \( a \) contains the count of the number of occurrences of \( a \) in session \( s \). Below are two encodings introduced: based on frequency and on activity duration. Here, the encoding is abstracted as function \( \text{Encode}(s, \sigma, \mathcal{L}) \) that returns a tuple that encodes a session \( s \) of a trace \( \sigma \) of an event log \( \mathcal{L} \). Given an event log \( \mathcal{L} \), we create the multiset of data points as follows:

\[
M_{\mathcal{L}} = \bigcup_{\sigma \in \mathcal{L}} \left( \bigcup_{s \in s_{\sigma}(\overline{\sigma})} \text{Encode}(s, \sigma, \mathcal{L}) \right)
\]  

(1)

which are then clustered into \( \{M'_{\mathcal{L}}, \ldots, M''_{\mathcal{L}}\} = \text{Cluster}(M_{\mathcal{L}}) \).

The remainder illustrates two encodings. However, the technique is extensible in the sense that new encoding can be easily plugged in.

**Frequency-based Encoding.** Let \( \mathcal{L} \) be an event log defined over an activity set \( A_{\mathcal{L}} = \cup_{e \in \mathcal{L}} \lambda_A(e) \). Given a session \( s \) of a trace \( \sigma \in \mathcal{L} \), the frequency-based encoding returns a tuple where each of its elements is associated with a different activity of \( \mathcal{L} \) and takes on a value that is the number of occurrence of the respective activity in the event log. For instance, the sessions \( s_1 \) and \( s_2 \) of Example 1 at page 6 are encoded as quadruples where the elements from the first to the fourth component take on values equal to the number of occurrences of respectively \( a, b, c, d \): namely, \( \text{Encode}_{\text{freq}}(s_1, \sigma, \mathcal{L}) = (1, 1, 1, 0) \) and \( \text{Encode}_{\text{freq}}(s_2, \sigma, \mathcal{L}) = (1, 0, 0, 1) \). This encoding is useful when one wants to cluster on the basis of the activities that occur in the session. Consider, for instance, an online retail shop where each log trace contains one event for each item of product that is added to the basket and/or bought by a different customer in different web-site visits. Each web-site visit becomes a session: the frequency-based encoding transforms each session into the vector of the events that occurred, namely the products that were bought and their quantity. More formally:
Definition 4 (Frequency-based Encoding). Let $\mathcal{L}$ be an event log; let $A = \{a_1, \ldots, a_n\}$ be the activities of $\mathcal{L}$, namely $A = \bigcup_{e \in \mathcal{L}} \bigcup_{e \in \sigma} \lambda_A(e)$. Given a trace $\sigma \in \mathcal{L}$ and a time interval $\Delta$, let $s \in \otimes_\Delta(\sigma)$ be a session of $\sigma$. The frequency-based encoding of $s$ is

$$
\text{ENCODE}_{\text{freq}}(s, \sigma, \mathcal{L}) = (c_{a_1}, \ldots, c_{a_n})
$$

such that, for all $1 \leq i \leq n$, $c_{a_i}$ is the number of events $e \in s$ for activity $a_i$, $c_{a_i} = |\{e \in s. \lambda_A(e) = a_i\}|$.

Duration-Based Encoding. Given a session $s = (es_1, \ldots, es_m)$ of a trace $\sigma$ of event $\mathcal{L}$, the duration-based encoding $\text{ENCODE}_{\text{dur}}(s, \sigma, \mathcal{L})$ returns a tuple $(d_{a_1}, \ldots, d_{a_n})$ where, for all $a_i$ in log activity set $A_\mathcal{L}$, $d_{a_i}$ returns the average duration of occurrences of $a_i$ in $s$. In the experiments reported in Section 4 we compute $d_{a_i}$ as the average of all quantities $(\lambda_T(es_{j+1}) - \lambda_T(es_j))$ for all $es_j$ s.t. $j < m$ and $\lambda_A(es_j) = a_i$. The last event has a different treatment because we do not have the timestamp of the event that follows. Hence, the duration can only be approximated: If $es_m$ refers to $a_i$, i.e. $\lambda_A(es_m) = a_i$, the average also considers a quantity equal to the average duration of $a_i$ for those events $\sigma \in \mathcal{L}$ s.t. $\lambda_A(e) = a_i$ when it was possible to compute, i.e. $\sigma$ is not the last of a session. For further clarification, let us again consider the sessions $s_1$ and $s_2$ of Example 1; they are encoded as quadruples where the elements from the first to the fourth component take on values equal to the number of occurrences of respectively $a, b, c, d$: namely, $\text{ENCODE}_{\text{dur}}(s_1, \sigma, \mathcal{L}) = (2, 1, \text{avg}(c, \mathcal{L}), 0)$ and $\text{ENCODE}_{\text{dur}}(s_2, \sigma, \mathcal{L}) = (3, 0, \text{avg}(d, \mathcal{L}))$ where $\text{avg}(c, \mathcal{L})$ and $\text{avg}(d, \mathcal{L})$ respective refer to the average duration of $c$ and $d$ in event log $\mathcal{L}$, to which $\sigma$ belongs. Note that this way to compute is based on the idea that events record the starting of executing an activity, and none records the completion.

The specific choice was driven by the analysis of the [www.werk.nl] web site: events are associated to starting visiting a web-site page and users remain on that page until they start visiting the next. However, new encoding can be put forward, which consider events as the execution’s completion, cross information about resource utilizations and activity executions [17], or which are based on the exactly duration, if derivable/present in the event.

3.4 Visualization of Heat Maps and Creation of Abstract Event Logs

The outcome of the previous phase of session clustering if a set of clusters $\{M_1', \ldots, M_n'\}$ (cf. Equation 1 at page 5).

With the clusters at hand, it is possible to construct the abstract event log. As mentioned, clusters need to be given names. Here, we advocate the use of heatmaps to visualize the cluster centroids and, hence, facilitate the assignment of names to clusters. An example is in Figure 3(a), which refers to the application to the [www.werk.nl] web site. Each row refers to a different low-level event, dimension of the clustering space, and each column does to a different cluster.

In particular, for each cluster, its respective centroid is normalized between 0 and 1, and the heat map visualizes the coordinates of the respective normalized
centroid through different color intensities, with 0 being white and 1 being the most intense red. The color for a column X and row Y is proportional to the value of the component for low-level event Y in the centroid of cluster X. The normalization of a given centroid is achieved by dividing the centroid’s value of each dimension by the sum of the centroid’s values of all dimensions. This normalization aims to reduce the effect to bring centroids to the zero vector, in those cases in which certain centroids have significantly higher value for some dimensions. The normalization is well explained through the following example:

**Example 2.** Let us assume the following centroids: $(1, 0, 1, 1, 0, 1), (0, 0, 10, 0, 0), (1, 2, 0, 0, 0, 0), (0, 0, 0, 2, 2, 1)$. The normalization produces $\left(\frac{1}{14}, \frac{1}{14}, 1, 0, 0\right), \left(\frac{10}{42}, 0, \frac{10}{42}, 0, 0, 0\right), \left(\frac{1}{14}, \frac{1}{14}, 0, 0\right), (0, 0, \frac{2}{7}, \frac{2}{7}, \frac{2}{7}, \frac{2}{7})$. If we normalized by simply dividing by the largest value, i.e. 42, we would obtain that the first, fourth and fifth centroids would be close to a vector with zero values for all components.

If one obtains an heatmap as that in Figure 3(a), the stakeholder is largely facilitated to assign names to clusters because almost each cluster is characterized by one or two different predominant data-point components (i.e. low-level events). Alternatively, if one does not have domain knowledge, cluster can be given a name that just coincides with the predominant component or with the concatenations of those predominant. As a result, each cluster $M_i$ is given a name $\text{Name}(M_i)$, and the event log can be abstracted. Algorithm 1 illustrates the procedure. For each log trace $\sigma$, the algorithm builds a new trace $\sigma'$ to be added to the abstract log $\mathcal{L}'$ as follows: for each session $s = \langle e_1, \ldots, e_m \rangle \in \mathcal{S}(\sigma)$, the algorithm determines the cluster $M_i$ to which session belongs (lines 5 and
Algorithm 1: Creation of an Abstract Event Log

Input: Event Log \( L \in \mathcal{E}^* \), a set \( M = \{M_1, \ldots, M_n\} \) of clusters with names \( \text{Name}(M_1), \ldots, \text{Name}(M_n) \)

Result: Abstract Event Log

1. \( L' \leftarrow \emptyset \)
2. foreach \( \sigma \in L \) do
   3. \( \sigma' \leftarrow \langle \rangle \)
   4. foreach session \( \langle e_1, \ldots, e_m \rangle \in \bigcirc(\sigma) \) do
      5. \( c \leftarrow \text{Encode}(\langle e_1, \ldots, e_m \rangle) \)
      6. Pick \( M_i \in M \) s.t. \( c \in M_i \)
      7. Create Events \( e_{s}^{\text{start}} \) and \( e_{s}^{\text{complete}} \) s.t.
         8. \( \lambda_A(e_{s}^{\text{start}}) = \lambda_A(e_{s}^{\text{complete}}) = \text{Name}(M_i) \)
         9. \( \lambda_T(e_{s}^{\text{start}}) = \lambda_T(e_1) \)
        10. \( \lambda_T(e_{s}^{\text{complete}}) = \lambda_T(e_m) \)
       11. \( \sigma' \leftarrow \sigma' \oplus (e_{s}^{\text{start}}, e_{s}^{\text{complete}}) \)
   end
3. \( L' \leftarrow L' \cup \{\sigma'\} \)
4. end
5. return \( (L') \)

6) and adds two events \( e_{s}^{\text{start}} \) and \( e_{s}^{\text{complete}} \) to the tail of \( \sigma' \) (lines 7 and 11). Events \( e_{s}^{\text{start}} \) and \( e_{s}^{\text{complete}} \) respectively represent the start and the end of session \( s \) with the corresponding timestamps (see lines 9 and 10), and they refer to the high-level activity \( \text{Name}(M_i) \) (line 8).

4 Evaluation

The abstraction technique introduced in this paper has been implemented as a plug-in named Session-based Log Abstraction in the TimeBasedAbstraction package of the nightly-build version of ProM\(^4\). To this date, the implementation features the K-means and DBSCAN algorithms for clustering and leverages on their implementations available in the ELKI library\(^5\). As discussed in Section 3.3, the cluster centroids are visualized on a heatmap to provide users with the necessary help to determine the high-level activity names: the heat-map visualization is provided via the JHeatChart library\(^6\). The rest of this section illustrates the application to two case studies, for process discovery and behavior comparison.

4.1 Experiments on the \texttt{werk.nl} website

This section focuses on illustrating the successful application to the case study of the \texttt{werk.nl} website.

To abstract the event log, we used a duration-based encoding (cf. Section 3.3): it is certainly more important to consider how long visitors stay on a web

\(^4\)http://www.promtools.org/
\(^5\)https://elki-project.github.io/
\(^6\)http://www.javaheatmap.com/
page, rather than just which pages were visited. For instance, three very short visits of a page should not be as important as one long visit of a different page. The session threshold $\Delta$ was set to 15 minutes, because it coincides with the timeout set for www.werk.nl before a visitor is considered as automatically logged out.

In the first experiment, the data points that encode the sessions of the log traces were clustered via DBSCAN. The generation of the clusters with DBSCAN took nearly 2 hours on a low-profile laptop with 8 Gb of RAM. The clusters’ centroids were visualized through the heatmap in Figure 3(a). To help stakeholders, the plug-in removes the rows referring to low-level events that, when normalized, are associated with nearly-zero values of all centroids. As sketched, the results are certainly very interesting: the sessions of a certain cluster are characterized by certain peculiar pages, long and often visited. Having no domain knowledge, each cluster was named as the low-level event (i.e. web page) that refers to the component with the highest value in the centroid (the most intense red color). This led to the names in Table 3(b).

Once the names are assigned to clusters, we generated an accordant, abstract event log. To validate the quality of the abstract event log, this was split into a 70% part, which was used for discovery, and a 30%, for testing. The DBScan algorithm naturally computes outliers, namely points that are not assigned to any cluster. Results show that, if those outliers are simply filtered out, the quality of the discovered model is significantly dropped (see discussion below, summarized in Table 1). Therefore, we performed a post-processing where each outlier session is manually inserted into the cluster with the closest centroid. The abstract event log with the manual insertion of outliers was used as input for the new Heuristic Miner [14], and the model in Figure 4 was discovered, using the Causal-Net notation [1].

The same procedure was employed to discover a high-level model with K-Means, using 70% of the traces for discovery and the same temporal threshold and duration-based encoding as for DBSCAN. Note that, compared with DBSCAN, K-Means requires one to explicitly set the number of clusters to create. Our implementation features the Elbow Method to facilitate the setup [12]: when applied to the case study, creating ten clusters seemed to provide a good balancing between minimizing the error and not scattering the sessions among too many clusters (i.e. high-level activities). The resulting model is in Figure 5.

The quality of these models was assessed through the classical process-mining metrics of fitness, precision, generalization and simplicity [1]. Fitness was computed on the 30% of abstract log in order to verify the “recall” on traces that were not used for discovery, in accordance to typical data-mining verification procedures. Conversely, precision and generalization was computed on the entire abstract log. Finally, simplicity was measured as the sum of activities, arcs and bindings of the causal nets. Since fitness, precision and generalization are traditionally defined on Petri nets [1], causal nets were converted to Petri nets using the implementation in [14]. The resulting Petri nets were manually adjusted to ensure soundness while not adding extra behavior. Of course, to keep the comparison fair, all models were discovered by the Heuristic Miner [14], using the same configuration of parameters. This includes the model in Figure 1.
Table 1 illustrates the results of the comparison of the models discovered through abstract event logs, obtained via K-Means and DBSCAN. They equally generalize and are of similar complexity (variation of simplicity is around 10-12%). The abstract model when applying DBSCAN without post processing shows very poor fitness, which is conversely satisfactory when applying K-Means or DBSCAN with post processing. Looking at the precision, the model of DBSCAN with post-processing is characterized by a precision that is 2.25 times than the precision of the K-Means model. The conclusion is that DBScan with post-processing has produced a model that outperforms the others in terms of quality of fitness, precision and generalization.

In conclusion, the model in Figure 4 is the most preferable, and, compared with the non-abstract model in Figure 1, it is definitely more understandable. From a business viewpoint, it illustrates that typical users navigate the werk.nl dataset, clustering via DBSCAN.
Fig. 5: Process model produced by the Heuristic Miner [14] on 70% of the abstract event log of the [werk.nl] dataset, clustering via K-Means.

web site as follows. During the first session, users visit the home page and, also, page taken (Dutch for tasks), where they can see the tasks assigned by UWV (e.g. to upload certain documents). If no tasks are assigned to do via the web site, the interaction with the web site completes. If any tasks are, users look for jobs to apply for (page vacatures_zoeken) and/or amend the information that they previously provided (page wijziging_doorgeven). If information is amended, usually an updated curriculum is uploaded (cf. the branch of the model starting with page mijn_cv) and/or the visitor looks and possibly applies for jobs (cf. the branches of the model starting with pages vacature and vacature_bij_mijn_cv, which are either both executed or both skipped). Looking at statistics, the mean and median duration of the web-site interaction (i.e. the log traces) is around 20 weeks (more than 4 months) and, hence, the visiting sessions are certainly temporarily spread. One can also observe that every session type might be repeated multiple times, probably due to the fact that the corresponding tasks are carried
Fig. 6: Building-permit process model produced by the Inductive Miner without abstraction: overly complex to be insightful.

on through similar sessions in consecutive days. It is, however, remarkable that the model does not contain larger loops involving different session types. This means that, once visitors stop accessing certain pages, they will no more come back to those: the web site is visited in phases, which justifies the introduction of wizards. We acknowledge that some information is lost in the abstraction. However, the model provides comprehensible, remarkable insights for the stakeholders. We showed this model to one UWV’s stakeholder, who literally said “this is the most understandable analysis of the web-site behavior that I have seen, certainly beyond the results seen for the BPI Challenge”.

4.2 Evaluation on a Building-Permit Process

This section illustrates a second case study to illustrate the applicability of the technique beyond werk.nl. This case study refers to the execution of process to manage building-permit applications in a Dutch municipality. There are 304 different activities denoted by their respective English name as recorded in attribute taskNameEN. The event log spans over a period of approximately four years and consists of 44354 events divided in 832 cases. Figure 6 shows the model discovered with the Inductive Miner - Infrequent Behavior [13], using the default configuration. The model exactly shows the same problems as that in Figure 4, it is overly complex to provide useful insights because of the large amount of different behaviour (e.g. the large OR split around the area highlighted by a red circle in the picture). We applied the abstraction technique to the event log, using the frequency-based encoding (cf. Section 3.3) and the DB-SCAN clustering algorithm with post processing, which proved to perform better for

\footnote{Indeed, the BPI challenge in 2016 was based on the same event data - \url{https://www.win.tue.nl/bpi/doku.php?id=2016:challenge}}

\footnote{The event log is available at \url{http://dx.doi.org/10.4121/uuid:63a8435a-077d-4ece-97cd-2c76d394d99c}}
Fig. 7: The heat map of the cluster centroids for the building-permit process (part a) and the names given to the clusters (part b)

the first case study reported in Section 4.1. Even though the timestamps have the granularity of seconds, the events within the same day are always recorded with the same timestamp. Therefore, a session threshold of, e.g., one hour guaranteed that the events of the same day were put in the same (work) session.

The clustering step resulted in the heatmap in Figure 3(a) where, similarly to the previous case study, infrequent activities are filtered out, and each cluster centroid has large values for the component of one low-level activity, possibly along with lower values, but significantly non-zero, for one/two additional low-level activity/ies. Clusters were again given the name of the activity associated with the larger value, possibly concatenated with the names of the additional activities associated to a non-negligible value for the additional component (see Table 7b).

The abstract event log was then generated and used as input for the Inductive Miner - Infrequent with default values for the parameters, namely the same as for the model in Figure 6. This yielded the model in Figure 8. This model is greatly simplified, thus really enabling learning how the process is being executed.
Fig. 8: Building-permit process model produced by the Inductive Miner with abstraction, clustering via DBSCAN.

Via this case study, we also showcase that is the event-log abstraction technique not only meant for process-model discovery, but also it enables a fruitful application of several other techniques. For instance, each case/trace of the event log is associated with a resource who is responsible for the specific building-permit request: The executions under the responsibility of certain resources can be compared wrt. the others to seek for statistically-significant differences in process behavior. To achieve this goal, we leveraged on the technique proposed in [5], which firstly made us find out that the executions under the responsibility of resource 560458 are remarkably different. The result is given as a transition system where nodes are the event’s activities and an arc between nodes A and B indicate that, in some traces, events for activity A are followed by events for B. Figure 9 shows the results: some nodes and arcs are coloured with different shades of blue and orange to indicate that respectively that state or transition is statistically more frequent for 560458 or for the others. The thickness of arcs and node’s borders signifies the frequency of occurrence. The colour’s darkness is proportional to the average difference. In Figure 9 e.g., the node `entersend date procedure confirmation` stands out: the procedure occurs in 67% of the cases of resource 560458 versus 13.7% of the cases of any other responsible resource. Similar proportions are also observed in node `enter senddate procedure confirmation`. Conversely, node `register deadline` is colored orange, showing that it is statistically more frequent for the cases in which resources other than 560458 are responsible. It follows quite naturally that, without abstraction, the behavior complexity represented in Figure 6 would generate such a complex transition system that no fruitful insights could be derived. The same holds for other process-mining techniques, such as decision mining, bottleneck or root-cause analysis [1].
Fig. 9: Comparison of the building-permit process behavior between executions when resource 560458 is responsible and when others are.

5 Related Work

Research work has been conducted on log abstraction. It can be grouped in two categories: supervised and unsupervised abstraction. The difference is that supervised abstraction techniques require process analysts to provide domain knowledge, which is not leveraged on by unsupervised techniques.

Supervised Abstraction Methods. Baier et al. provide a number of approaches that, based on some process documentation, map events to higher-level activities [2,3,4], using log-replay techniques and solving constraint-satisfaction problems. The idea of replaying logs onto partial models is also in [15]: the input is a set of models of the life cycles of the high-level activities, low-level events are considered as life-cycle transitions. Ferreira et al. [9] rely on the provision of one Markov model, where each Markov-model transition is a different high-level activity. In turn, each transition is broken down into a new Markov model where low-level events are modelled. Fazzinga et al. [8] assume one to provide a probabilistic process model with the high-level activities, along with a probabilistic mapping between low-level events and high-level activities. It returns an enumeration of all potential interpretations of each log traces in terms of high-level activities, ranked by the respective likelihood. In [18], authors propose a supervised abstraction technique that is applicable in those case in which annotations with the high-level interpretations of the low-level events are available for a subset of traces.

Unsupervised Abstraction Methods. In [16], Mannhardt and Tax have proposed a method that is based on the discovery of local process models (i.e., model fragments) of the most common behavioral patterns, which are then used as process-model inputs for the supervised abstraction technique in [15]. However, the technique relies on the ability to discover local models that are accurate and cover most of low-level event activities. In [11], Günther et al. cluster events looking at their correlation, which is based on the vicinity of occurrences of events for the same low-level activity in the entire log. Clustering is also the basic idea of [6] to cluster events through a fuzzy k-medoids algorithm. Both [6] and [11] share the drawback that the time aspects are not considered and, thus, they can
cluster events that are temporarily distant (e.g. web-site visits that are weeks far from each other). Also, work [6] only aims to discover a fuzzy high-level model, instead of abstracting event logs to enable a broader process-mining application, whereas [11] assumes that, e.g., if events for activity A are correlated with those for activity B and those for activity C, then B and C are also correlated. This is not necessarily always true, as illustrated by Figure 3(a): cluster 3 shows a correlation between Visit page werkmap and Visit page vacature\_bij\_mijn\_CV and cluster 4 shows a correlation between Visit page werkmap and Visit page taken, while no correlation exists between Visit page vacature\_bij\_mijn\_CV and Visit page taken. Finally, van Eck et al. [7] illustrates a technique to gather observations from sensor data, encode and cluster them in a similar way as our approach does. However, their purpose is to create event logs from sensor data, instead of abstracting an already-existing event log. Also, the setting is different: the input data is a continuous stream of observation that is sampled as constant rate (i.e., no concept of session is present), and they do not leverage on visualization techniques to help process analysts.

6 Conclusion

Abstracting and grouping low-level events to high-level activities is a problem that is receiving a lot of attention. Often, event logs are not immediately ready to be used because they model concepts that are not at the right business level and/or they exhibit a too broad variety of behavior to be summarized into accurate models, yet not overcomplex. Here models are intended in a broader sense, not only such process models as BPMN, Petri Nets or EPCs.

Section 5 illustrates how supervised methods often require vast domain knowledge, which is not always possible to provide, and how unsupervised methods have their limitations, related to the lack of any external knowledge. This paper reports on a third way where very limited domain knowledge is necessary, easy to provide through visualization techniques. The basic idea is that a single execution can be regarded as a sequence of sessions each of which terminates when no low-level events occur within a user-defined time interval.

We acknowledge that the vision of executions in terms of sequences of sessions is not always possible. However, the paper discusses two case studies where this is possible. Similarly, the technique is applicable to other domains, such as when customers purchase goods in on-line or physical retailer shops (e.g. through Amazon) or, also, in healthcare where patients visit hospitals “in sessions”. The case-studies results showcase that the log abstraction enables the provision of valuable insights for process owners and stakeholders, even when the event data show an “ocean” of potential behavior. The building permit case study also illustrate that the application is beyond the sole process discovery.

This work is just the first of a potential series on session-based clustering. The technique is entirely independent of the clustering algorithms employed. In fact, we intentionally decide not to mention the actual clustering algorithms until the evaluation to highlight this independence. We plan to explore hierarchical clustering because it would allow one to tune the level of aggregation that is achieved through the log abstraction. Furthermore, the number of low-level ac-
activities is generally large. Therefore, it is worth investigating the benefits, if any, of reducing the components to consider, before applying clustering. Currently the sessions do not consider the entire event payload, namely the data points do not incorporate additional information beyond the sole activity names; for instance, for the *werk.nl* case study, one could add data-point components related to the customer age, gender, geographic locations, etc. The use of the entire payload might lead to a more accurate clustering of the sessions. Last and not least, it would be worth analyzing the structure of the sessions within each separate cluster: they consist of sequences of events and, hence, they can be used to discover small (fragments of) models, to be combined with the models discovered via abstract event logs.

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