A Novel Approach to Detect Redundant Activity Labels For More Representative Event Logs

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Abstract
The insights revealed from process mining heavily rely on the quality of event logs. Activities extracted from healthcare information systems with the free-text nature may lead to inconsistent labels. Such inconsistency would then lead to redundancy of activity labels, which refer to labels that have different syntax but share the same behaviours. The identifications of these labels from data-driven process discovery are difficult and rely heavily on resource-intensive human review. Existing work achieves low accuracy either redundant activity labels are in low occurrence frequency or the existence of numerical data values as attributes in event logs. However, these phenomena are commonly observed in healthcare information systems. In this paper, we propose an approach to detect redundant activity labels using control-flow relations and numerical data values from event logs. Natural Language Processing is also integrated into our method to assess semantic similarity between labels, which provides users with additional insights. We have evaluated our approach through synthetic logs generated from the real-life Sepsis log and a case study using the MIMIC-III data set. The results demonstrate that our approach can successfully detect redundant activity labels. This approach can add value to the preprocessing step to generate more representative event logs for process mining tasks in the healthcare domain.

1. Introduction
Process mining (PM) is a technology known to be useful for understanding business processes using event logs captured in information systems [1]. It has shown promising potential in many aspects, including discovering significant insights and improving process performances in the healthcare domain. A typical event log refers to a collection of events, each with a timestamp that records the executed time. An event represents a unique execution of an activity, which is a well-defined step in the process, such as “pay bill”. Cases group these events, also called process instances. For example, a case could be a patient who follows a treatment process in a hospital.

In PM for healthcare, data quality is a critical issue when generating useful process models. Data quality on activity labels in event logs are unique for PM research, as the quality can be affected by discrepancies of labelling in healthcare information systems. A particular issue is synonymous and polluted labels [2], which we refer as redundant activity labels. Additionally, redundant labels do not need to have same semantics as long as they represent the same activity in reality. This type of redundancy can introduce unnecessary complications to event logs and discovered models.

A major contributing factor to such redundancy is the free-text input or human error in providing an initial suggestion in the same system [2] (e.g. “BloodPressure” and “blood pressure” in Figure 1). This example further illustrates the reason why we need to consider all three perspectives (i.e. control-flow relations, numerical data values, and semantic). For instance, suppose we solely rely on semantic similarity between labels, “Release A” and “Release B” would be regarded as redundant. However, these labels represent two different steps before discharge a patient. Additionally, many healthcare information systems only record activities using specific codes instead of their real names. If we only consider control-flow relations, all three tests following “Visit Doctor” would be treated as redundant. By considering the numerical data values (i.e. results for tests), we are able to achieve more accuracy results.

With efforts being made to address redundant activity labels [2, 3, 4, 5, 6, 7], many of these approaches have difficulties in identifying activity labels with low occurrence frequencies, or if invalid labels have been used. However, redundant labels usually occupy a small portion of healthcare event logs. Many of these approaches rely on event logs with categorical resources as attributes instead of numerical
values [2, 3]. However, many activities have such attributes, especially laboratory tests and observations in healthcare logs. Other approaches [6, 7] require domain knowledge to improve the data quality. To summarise, existing approaches achieve relatively low accuracy when redundant activity labels are less frequent and have numerical data values as attributes without domain knowledge.

The goal of this paper is to propose a novel approach to detect both frequent and infrequent redundant activity labels with numerical data as attributes. Our method aims to efficiently incorporate control-flow relations, data values, and label semantic in event logs. For the control-flow perspective (i.e. the ordering of activities), we adopt the statistical method Earth Mover’s Distance (EMD) to compare directly- and indirectly-follows relations of different activity labels. For the data values perspective (i.e. numerical values of recorded activities), activity labels are firstly clustered with Agglomerative Hierarchical Clustering and followed by EMD to compare the data’s distribution. We assess labels’ semantic similarity using Natural Language Processing (NLP) as another perspective. A consensus is guided by a decision-making mechanism to integrate results produced from multiple perspectives. We evaluate our approach using synthetic logs generated from the publicly available Sepsis log [8]. A case study using the MIMIC-III data set [9] has been conducted to further demonstrate our approach’s usability in real-life situations.

The paper is structured as follows. Section 2 discusses the background. Section 3 introduces the basic concepts used throughout the paper. In Section 4, we explain the main approaches for three different perspectives and the method used to combine results. In Section 5, we describe the evaluations using synthetic logs and the comparisons with the existing approach. A real-life case study is explored in Section 6. The paper concludes with Section 7.

2. Background

Event log quality has been identified as a critical issue that affects PM results from the healthcare domain in both process discovery and improvement [1, 10]. PM manifesto [11] has emphasized the importance of event log quality. The first guideline for PM is to treat event data as first-class citizens. Later on, [12] proposes 11 event log imperfection patterns, including incorrect timestamps and polluted labels. [13, 14] suggest quality frameworks for assessing EMR data in the healthcare domain. Also, [15, 16] raise the concern for the event data quality in PM. Therefore, it is useful to address data quality as early as the event log level.

In order to detect redundant activity labels, relevant works [2, 7] suggest two ways to deal with this issue at the event log level. [2] proposes a contextual approach that takes control-flow relations, resources, time as well as data attributes into consideration. From the control-flow perspective, the method reports the similarity between rows of the footprint matrix, which may not well distinguish the frequency difference between two activity labels and suffers from noisy or infrequent relations. Thus, the method achieves relatively low accuracy when dealing with low occurrence frequency labels. The remaining perspectives largely adopt Probability Density Function (PDF) to assess the value distributions between activity labels. The approach reports relatively poor results if there exists numerical data values as activity attributes, while it is a common phenomenon in healthcare logs because of various laboratory tests. It relies on a weighted clustering method to combine final results, which requires domain knowledge or ground truth to determine the best weight setting. The other method [7] collaboratively and interactively detects problematic activity labels by adopting a gamified crowdsourcing approach, which utilises gamification elements (e.g. badges) to encourage a large group of domain experts to identify and repair redundant activity labels.

Another approach is process matching through the model level [3, 4, 17, 18]. These approaches match two process models from different data sources with
the aim to find similar redundant clusters and activity labels. It is difficult to address redundant labels within the same log since separated logs may have incomplete processes. Hence, they are more widely used in process similarity comparison instead of solving problematic logs. Other approaches [5, 6], look at activity labels themselves while ignoring other information from logs, which may cause erroneous results. For instance, “Release A” and “Release C” will be treated as redundant in the hospital log since they have close string edit distance. However, these two labels represent different ways to discharge patients [8].

3. Preliminaries

Before proposing our novel ideas, this section introduces basic concepts used in Section 4.

An event log is defined as \( L = (E,A,V,N,#,T) \) with: \( E \) is the set of unique event identifiers; \( A \) is the set of activities; \( V \) is the sets of data values; \( N \) is the sets of numerical attribute names; \( #:E \rightarrow (N \cup V) \) is a function that obtains data values recorded for an event \( e \in E \). For example, \( #_{ac}(e) \) gets the activity name for an event, \( #_{n}(e) \) gets the numerical data value for an event. \( T \subseteq \mathcal{E} \) is the set of traces over \( E \). A trace \( t \in T \) records the sequence of events of a process instance. Each event only occurs once in a single trace.

Here are some basic relations in event logs.

- Directly-Follows Relation: \( a \rightarrow_{w} b \) holds if there is a trace \( t \in T \) where \( t(i) = e_i \) and \( t(i + 1) = e_{i+1} \) and \( #_{ac}(e_i) = a \) and \( #_{ac}(e_{i+1}) = b \).

- Indirectly-Follows Relation: \( a \rightarrow_{w} b \) holds if there is a trace \( \pi \subseteq T \) where \( t(i) = e_i \) and \( t(j) = e_{j} \) where \( i < j \) and \( #_{ac}(e_i) = a \) and \( #_{ac}(e_{j}) = b \). Also, it needs to pass a certain threshold using the long distance dependency measurement in [19].

A directly-follows graph defined as \( G = (A, K) \) with: \( A \) is a finite set of activities in the event log (same as Definition 1), \( K \subseteq A \times A \) is a set of directed arcs, which represent directly-follows relations (i.e. \( a \rightarrow_{w} b \) exists if \( (a, b) \in K \)), an example is shown in Figure 2. For any \( a \in A \), \( a \cdot = \{b | (a, b) \in K \} \) represents all the directly outgoing activities from \( a \), e.g. \( A \cdot = \{H, B\} \). Same for \( \cdot a = \{b | (b, a) \in K \} \) represents all the directly incoming activities to \( a \), e.g. \( \cdot C = \{H, B\} \). \( |(a, b)| \), \( (a, b) \in K \) counts how many times the relation \( a \rightarrow_{w} b \) occurs in \( G \) (e.g. \( |(A, H)| = 50 \)).

4. Methods

This section describes our proposed novel approach, shown in Figure 3, to detect redundant activity labels. The underlying assumption is that redundant activity labels should share the same patterns on both control-flow relations and numerical data values. We also include semantic similarity as an additional perspective. So, our approach assesses similarities from above aspects using a statistical method Earth Mover’s Distance (EMD) and a NLP library. To this end, we first introduce EMD to compare control-flow relations probability distributions. Then, we demonstrate how to extend EMD to calculate numerical data values similarity. We apply a powerful NLP library in semantic similarity. Finally, we briefly describe how to use the decision-making mechanism to combine results from different perspectives to obtain the final output.

4.1. Earth Mover’s Distance

The Earth Mover’s Distance (EMD) [20] is a method for comparing two multi-dimensional probability distributions over a region. It was first proposed as a matrix to retrieve images in the computer vision domain. However, it has been applied to many other fields [21, 22]. The EMD calculates the lowest costs of transferring one distribution into another, given two distributions indicate different ways of accumulating a certain amount of dirt in a region. A distance function defines the cost needed to move dirt between certain piles. For one thing, it is frequency-aware which considers the magnitude of discovered differences. For another, the difference is determined by the ground distance function that can express different perceptions of similarity [23]. Below we formally introduce the EMD:

Let \( P \) be a probability distribution with \( p_1, \ldots, p_m \in P \) as different clusters and \( \omega_{p_1}, \ldots, \omega_{p_m} \in \mathbb{R}^+ \) as the associated weight for these clusters. Another probability distributions \( Q \) with the same notations \( q_1, \omega_{q_1}, \ldots, q_m, \omega_{q_m} \). A ground distance \( D = \bar{d}(p_i, q_j) \) between cluster \( p_i \) and \( q_j \) is defined. We would like to find a flow \( F = (f_{i,j}) \in \mathbb{R}^{m \times n} \) that minimises the overall costs to transfer \( P \) to \( Q \). The
following constraints should be followed:

- Non-negativity flow: \( f_{i,j} \geq 0, \forall 1 \leq i \leq m, 1 \leq j \leq n \).
- Sent and receive flow should not exceed weights in P and Q:
  - \( \sum_{j=1}^{n} f_{i,j} \leq w_{P, i}, \forall 1 \leq j \leq n \);
  - \( \sum_{i=1}^{m} f_{i,j} \leq w_{Q, j}, \forall 1 \leq i \leq m \).
- All weights possible have to be sent:
  \( \sum_{i=1}^{m} \sum_{j=1}^{n} f_{i,j} = \min(\sum_{i=1}^{m} w_{P, i}, \sum_{j=1}^{n} w_{Q, j}) \)

The optimal flow \( F \) is defined as:

\[
\text{EMD}(P, Q) = \min_{\mathcal{C}} \sum_{i=1}^{m} \sum_{j=1}^{n} f_{i,j} = \min_{\mathcal{C}} \sum_{i=1}^{m} \sum_{j=1}^{n} f_{i,j}
\]

**4.2. Addressing Redundant Labels by Measuring Control-flow Similarity**

*Principle.* Redundant activity labels should share similar control-flow relations or ordering patterns. This similarity means not only identical control-flow relations but also closed distribution patterns.

As shown in Figure 3, the overall idea behind a control-flow perspective is that for each pair of activity labels \((\alpha_i, \alpha_j) \in A\), we adopt EMD to compare the directly-follows and the indirectly-follows relations along with their distributions. Each directly- and indirectly-follows comparison can be further divided into directly-and indirectly-outgoing (i.e. consequence) and incoming (i.e. precedent) relations. Thus, we would get four different values, with the final similarity being the average of these values.

The control-flow perspective is separated by directly-follows and indirectly-follows comparisons. We would like to put the most of our effort into explaining the directly-follows comparison, since the indirectly-follows comparison is most likely to be the same, only the relations are indirectly-follows. The reason we also consider indirectly-follows relations is to deal with non-free-choice problems (i.e. whether we choose a task is dependent on what has been executed in the process prior [24]). For instance, both activity \( C \) and \( D \) in Figure 2, have identical directly-follows relations, but \( D >>_{w} G \) (i.e. dashed line) also exists. Thus, \( C \) and \( D \) should not be regarded as redundant.

Algorithm 1 presents our approach for calculating the directly-follows similarity. The starting point is to construct a directly-follows graph obtained from the log (Line 1). Then for each activity label, we calculate its outgoing and incoming activity sets (Lines 2-4). By using Equation 2, the weights are calculated for each element in the activity set (Lines 5-6), (e.g. \( A w = \{ x, x \} \)). Afterwards, for each pair of activity labels, we adopt EMD to calculate the similarity between incoming and outgoing activity sets using the ground distance function \( D_{g} \) from Equation 3 (Lines 7-9). The activities in the sets (e.g. \( A \cdot \)) are clusters. The weights in the

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**Figure 3. An overview of proposed method**

- Control-Flow
- Numerical Data
- Natural Language Processing
- Control-Flow Similarity
- Data Similarity
- Semantic Similarity
- Decision-Making Mechanism
- Final Results
- Domain Knowledge
- Thresholds

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\[
\text{EMD}(P, Q) = \min_{\mathcal{C}} \sum_{i=1}^{m} \sum_{j=1}^{n} f_{i,j} = \min_{\mathcal{C}} \sum_{i=1}^{m} \sum_{j=1}^{n} f_{i,j}
\]
sets (e.g. \( \alpha \)) are the associated weights for each cluster. For instance, suppose we would like to calculate the similarity between outgoing activity sets for \( H \) and \( B \) in Figure 2, the input signatures for EMD would be \( P = \{(C, 0.46), (D, 0.48), (F, 0.02)\} \) and \( Q = \{(C, 0.5), (D, 0.5)\} \). Lastly, the directly incoming and outgoing similarities are averaged to obtain the final directly-follows similarity for each pair of activity labels and added to the set \( S_d \) (Lines 10-11).

**Algorithm 1: Directly-Follows Similarity**

**Input:** Event log \( L = (E, A, V, N, \#, T) \)

**Output:** \( S_d \): Set of Directly Similarities for All Pairs of Activities

1. \( G \leftarrow \text{MakeDirectlyFollowsGraph}(L); \)

2. foreach \( a \in A \)
   
   3. \( a^{\bullet} \leftarrow \text{OutGoing}(a); \)
   
   4. \( a^{\bullet} \leftarrow \text{InComing}(a); \)
   
   5. \( a^{\bullet}w \leftarrow \text{CalculateWeight}(a^{\bullet}); \)
   
   6. \( \cdotaw \leftarrow \text{CalculateWeight}(\cdot a); \)

7. foreach \( a, b \in A \)

8. Outgoing Similarity = \( \text{EMD}(a^{\bullet}, a^{\bullet}w, b^{\bullet}, b^{\bullet}w, D_{cf}); \)

9. Incoming Similarity = \( \text{EMD}(a^{\bullet}w, \cdot aw, b^{\bullet}w, D_{cf}); \)

10. Directly-Follows Similarity = \( \text{Average}(\text{Outgoing Similarity}, \text{Incoming Similarity}); \)

11. \( S_d \leftarrow \text{Directly-Follows Similarity}; \)

12. **return** \( S_d \)

The equation for calculating the weight of a single activity in incoming/outgoing activity sets is defined as:

\[
W = \frac{|(b, a)|}{\{(b, a) | \in \cdot a\}} \quad \text{or} \quad \frac{|(a, b)|}{\{|(a, b) | \in a^{\bullet}\}} \tag{2}
\]

The ground distance function \( D_{cf} \) for EMD between any two clusters \( p_i, q_j \) from activity sets is defined as:

\[
D_{cf} = \begin{cases} 0 & \text{if } p_i = q_j \\ 1 & \text{otherwise} \end{cases} \tag{3}
\]

**Principle.** The same activity label has no cost, and different ones have unit cost. This cost function can be easily extended based on other matrices, e.g. global location for activities. Here, we just show the most basic version for better undesirability.

The same process applies to the calculation of indirectly incoming and outgoing similarities. We construct an indirectly-follows graph from the log. We have a set that contains indirectly-follows similarities as well. Then, for each pair of activity labels, the overall control-flow similarity is the average number of directly and indirectly-follows similarities, where there is a value between 0 and 1. The greater the value is, the more significant the effort needed to transfer one distribution into another is, which means the two activity labels have less similarity with regard to control-flow perspective.

The combination of four different scores can be easily extended with other statistical or clustering algorithms, e.g. weighted average or k-means clustering. We would like to show that our approach can achieve desirable results with the most fundamental method and requires no domain knowledge, e.g. weight settings or the number of clusters as input.

### 4.3. Addressing Redundant Labels by Measuring Data Value Similarity

This section introduces the approach used to calculate similarity for the data values perspective, e.g. the numerical results for medical tests. The overall approach, shown in Figure 3, can be divided into two sub-stages. Firstly, we cluster each activity label into different clusters based on value percentiles. Then, we apply EMD to assess data distributions of activity labels within each cluster. Clustering first ensures only activity labels with the same data range are further evaluated. Activities with different data ranges are unlikely to share similar data patterns, which do not need to be further assessed for data distributions.

We describe our approach in Algorithm 2. For each activity, we first assess whether this activity has a data value attribute (Line 2). If not, it has minimal data value similarity with other activity labels (i.e. \( \text{DataValueSimilarity} = 1 \)). If yes, Line 3 finds all events of the attribute \( \#_{ac}(e) = a \) and obtains data values for that attribute \( \#_{nv}(e) \) into a data set (i.e. \( \text{DataSets} \)). Line 4 calculates the 25th and 75th percentile for each data set. We use 25th and 75th percentiles as a 2-D vector and apply Agglomerative Hierarchical Clustering [25] with a threshold \( \theta_e \) for all data sets (Line 5). For example, suppose a activity label has the values 0.3 and 0.5 for its 25th and 75th data value percentiles respectively, then the 2-D vector is \((0.3, 0.5)\). We apply the Euclidean Distance (ED) [26] as the distance measurement between two vectors. Activity labels that are not in the same cluster also have \( \text{DataValueSimilarity} = 1 \). Since there are many unique values in the numerical data, it is hard to directly apply EMD because of the many different clusters in the distribution. As a result, we transfer each data set to a histogram following Sturges’ formula.
[27], where uniform maximum and minimum values are used to ensure two histograms have the same bin number and size when comparing activity label pairs within the same cluster (Line 11). We pick each interval’s left boundary as cluster values (e.g. \( p_i, q_j \)) and lines 12-13 calculate the percentage of each bin as cluster weights (e.g. \( w_{pi}, w_{qj} \)). An example cluster is \((10, 20\%), (15, 30\%), (20, 20\%), (25, 30\%)\). In this way, we transfer each histogram as a cluster and EMD is further used to compare two clusters using distance function \( D_d \) in Equation 4 (Line 14). The DataValueSimilarity function \( D_d \) is normalised [28] to become a value between 0 and 1 and added to \( S_n \). Similar to the control-flow perspective, the greater the value is, the less similarity they have in the data value perspective. The ground distance function

**Algorithm 2:** Data Value Similarity

**Input:** Event log \( L = (E, A, V, N, #, T) \), threshold \( \theta_a \)

**Output:** \( S_n \): Set of Data Value Similarities for all Pairs of Activities

1. foreach \( a \in A \) do
   a. if HasDataValueAttribute\((a)\) then
      b. \( \text{DataSet}_a \leftarrow \text{ExtractData}(a) \);
      c. \( Q_{\alpha a}, Q_{\beta a} \leftarrow \text{CalculatePercentiles}(a) \);
      d. \( \text{Clusters} \leftarrow \text{AgglomerativeHierarchicalClustering}(Q_{\alpha a}, Q_{\beta a}, \theta_a) \);

2. foreach \( C \in \text{Clusters} \) do
   a. if size\((C) \leq 1\) then
      b. continue;
   b. else
      c. foreach \( a, b \in C \) do
         d. \( H_a, H_b \leftarrow \text{MakeHistograms}(\text{DataSet}_a, \text{DataSet}_b) \);
         e. \( H_{aw} \leftarrow \text{CalculateWeight}(H_a) \);
         f. \( H_{bw} \leftarrow \text{CalculateWeight}(H_b) \);
         g. \( \text{Data Value Similarity} = \text{EMD}(H_a, H_{aw}, H_b, H_{bw}, D_d) \);
      h. end
   end
   i. \( S_n \leftarrow \text{Data Value Similarity} \);

\( D_d \) for EMD between any two data value clusters \( p_i, q_j \) from histograms is defined as:

\[
D_d = |p_j - q_j|
\]  \hspace{1cm} (4)

**Principle:** Since both \( p_i, q_j \) are numerical values, it takes less effort to transfer \( p_i \) to \( q_j \) if they are close to each other. We adopt the difference between \( p_i \) and \( q_j \) as the ground distance function.

### 4.4. Addressing Redundant Labels by Measuring Semantic Similarity

In addition to the above two perspectives, we also integrate Natural Language Processing (NLP) into our multi-perspective method. Although simply looking at the semantics of activity labels may lead to false positive results (i.e. labels that are incorrectly detected as redundant), it is still an important factor to consider when detecting redundant labels. We apply a well-known industrial-strength NLP library named Spacy [29] to assess semantic similarity between every pair of activity labels. The results between a pair of activity labels is a numerical number ranging from 0 to 1, where 1 means they are identical and vice versa. However, in order to comply with the same rule setting in previous sections, we subtract the obtained results from 1. In this way, 0 means they are identical in semantic similarity. A threshold \( \theta_s \) is given to determine the final results.

### 4.5. Decision-Making Mechanism to Aggregate Results

For now, each pair of activity labels has three similarities, which are control-flow relations, numerical data values and semantic, if all above information is available in the event log. This section describes a decision-making mechanism to aggregate similarities from the above three perspectives and generate final results. The decision-making mechanism is a set of rules that decide how the results are combined [30]. As shown in Figure 3, rules can either be produced by thresholds or by domain experts to participate in the decision-making mechanism. For threshold rules, users need to determine the threshold for each perspective (i.e. \( \theta_c, \theta_d \) and \( \theta_s \)) to decide whether activity labels are similar in the corresponding dimension along with how many perspectives they want the results are combined from. For instance, activity labels that achieve similarities below \( \theta_c \) and \( \theta_d \) in two perspectives are regarded as redundant. This rule means as long as the activity labels are similar in the control-flow relations and the data values perspectives, they can be regarded as redundant regardless of whether they are similar in semantics. Besides, threshold rules can be easily extended with other features, e.g. label occurrence frequency. To illustrate, activity labels with low frequency can be regarded as redundant if they achieve similarities below \( \theta_c, \theta_d \) or \( \theta_s \) in any perspective; otherwise, they need to satisfy all perspectives. We avoid asking users to determine the weight settings as different settings can significantly impact the final results and are difficult to determine even with domain knowledge.
5. Evaluation

We conducted experiments to evaluate our approach using synthetic logs generated from the publicly available log. We would like to show our method performs well given that exists numerical data value attributes and low-occurrence frequency activity labels in event logs.

5.1. Synthetic Logs Generation

In order to evaluate that our approach can perform well in the healthcare information system, we selected the Sepsis log\(^1\) [8], which records treatment processes of sepsis patients from a Dutch hospital. The details of the log are shown in Table 1. Three labels with numerical data values as attributes are presented in the log, i.e. “CRP”, “LacticAcid”, and “Leucocytes”. We followed the approach in [2] to generate experimental logs. For example, we randomly selected a certain amount of activity labels, and for each activity label, randomly renaming a percentage (i.e. 1% to 30%) of its events to simulate labels with low-occurrence frequency. For example, \(H_{20,1}\) means 20% activity labels are selected and for each label, 1% of its events are renamed. For each setting, 5 logs are generated for more accurate results. In total, 35 different settings are used (i.e. from \(H_{20,1}\) to \(H_{100,30}\)), which lead to 175 synthetic logs. An interesting fact is that the Sepsis log also contains different variants of discharging a patient, which are “Release C”, “Release D”, and “Release E”. They are regarded as redundant labels [2, 8]. So, the ground truth not only contains activity labels which we manually renamed, also consists of any pair of these three labels.

5.2. Evaluation Settings

The approach is implemented as a Python program\(^2\) for evaluations. For our approach, we only considered the control-flow similarity and the numerical data values similarity because the activity labels were artificially renamed to arbitrary names. As such, including the semantic similarity on those names would lead to meaningless results. We subjectively adopted \(\theta_c = 0.25\) and \(\theta_d = 0.1\) for each perspective. For the baseline approach, we selected the SynonymousLabelRepair [2], which seems to be more capable in handling redundant activity labels than other methods. Since the baseline approach requires domain knowledge to determine the best weight setting, we have no way to obtain it. So, we use its default settings in evaluations, which are 0.7 threshold and uniform weight in all perspectives.

The standard f-score metric for evaluating detection accuracy is used in our evaluation [2] where \(\text{precision} = \frac{TP}{TP + FP}\), \(\text{recall} = \frac{TP}{(TP + FN)}\), \(f - \text{score} = 2\frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}\). TP stands for true positive, FN stands for false negative, and FP stands for false positive. A TP is reported if the detected pair is actual redundant. A FP is reported if the detected pair is actual not redundant. A FN is reported if the actual redundant pair is not detected in our approach.

5.3. Results and Discussion

Figure 4 shows the f-score comparison between our approach and the baseline approach. It is clear that our approach performs better in most logs. For instance, the average f-scores are 0.64 and 0.44 separately. Besides, when the redundant activity labels are less frequent, our approach can still successfully detect most of positive classes while the baseline performs poorly.

The main reason is that the baseline approach only compares directly-follows relations while ignoring their frequency distributions. However, low frequency activity labels rarely contain all directly-follows relations while only maintaining the main one. In this case, frequency distributions are essential to consider in the approach. We also notice that our approach is limited when handling logs that share XOR relations very well if they have identical incoming and outgoing relations. However, this can be differentiated in real healthcare logs since semantic similarity would be taken into considerations. Besides, if domain knowledge is available, the cost function between different labels in EMD can be better defined instead of simply adopting unit cost. Thus, more satisfying results can be potentially achieved by our approach. The baseline approach can perform better when domain knowledge is available to determine the best weight setting. Additionally, distributions of numerical data values are less structured when redundant labels are infrequent. Thus, the baseline achieves relatively low accuracy since it adopts Probability Density Function (PDF) to assess value distributions for numerical data.

6. Case Study

We conducted a case study using the MIMIC-III\(^3\) data set to demonstrate that our approach can be used.

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\(^1\)https://data.4tu.nl/articles/dataset/Sepsis_Cases_-_Event_Log/12707639

\(^2\)https://github.com/GilbertFan/Redundant-Activity-Detection

\(^3\)https://mimic.physionet.org/
in real-life healthcare systems. The MIMIC-III data set comprises of health-related data associated with over 40,000 patients who stayed in the Critical Care Units of a US hospital between 2001 and 2012 [9].

6.1. Data Extraction

Redundant information was found in the form of observation activities, as stated in the MIMIC-III official documentation[^4], due to the free-text nature of data entry in the CareVue system. We would like to analyse the observation process of male diabetes patients (ICD-9 codes [31] are 250.0x -250.9x) in the hospital. We followed the US observation chart in [32] (urine output, consciousness and pain are excluded) to extract observation data. We noticed that there are multiple activity labels representing blood pressure, which could be redundant activity labels. We followed [33] in selection. Eight different observation activities are noticed for blood pressure, four for systolic pressure and four for diastolic pressure. Table 2 shows the observation activities we used in the case study and their corresponding IDs in the MIMIC-III data set. We also extracted other activities such as admission (i.e. admission, ED registration, ED out, discharge and death) and callout (i.e. create callout, update callout, outcome callout and acknowledge callout) following the approach in [34] to make the process not only contain observation information but also general admission information. We utilised tables including ADMISSION, CALLOUT, CHARTEVENT, D_ICD_DIAGNOSES, DIAGNOSES_ICD, D_ITEMS, D_LABITEMS, LABEVENT and PATIENTS.

After extracting the initial data, we filtered out cases where less than one observation activity was presented since they exposed less useful information regarding control-flow relations between different observation activities. Besides, we preserved the results for each observation activity as they represented the numerical data values in the log. The details of the log are shown in Table 1, where a complex log (i.e. 683 cases and 22 activities, which result in over a half-million events) with high variants (i.e. not a single case is the same) is extracted.

6.2. Result and Discussion

In this case study, the thresholds were set to 0.2 for the control-flow perspective, 0.1 for the numerical data values perspective and 0.1 for the semantic perspective. We adopted the decision-making mechanism of: activity labels are redundant if they are similar in all perspectives. We were able to find more pairs of redundant activity labels if we had applied loose thresholds and decision-making mechanism, e.g. four pairs were identified if $\theta_c$ was changed to 0.3. However, since we would like the results to be as rigorous as possible, the most strict thresholds and decision-making mechanism were applied. We sorted and removed the top and bottom 1% of the numerical data values for each activity label in order to reduce the negative effects of abnormal values from extreme cases.

As a result, we found two pairs of redundant activity labels, which were observation activities “Arterial BP [Systolic]” and “NBP [Systolic]”, “Arterial BP [Diastolic]”, and “NBP [Diastolic]”. These two pairs are corresponding in terms of systolic and diastolic blood pressure. They are all common blood pressure

[^4]: https://mimic.physionet.org/mimictables/d_items/
Table 1. Characteristics of event logs used for case study.

| Log                  | #Trace | #Trace variants | #Event | #Avg event/trace | #Activity |
|----------------------|--------|-----------------|--------|-----------------|----------|
| Sepsis               | 1050   | 846             | 15214  | 14              | 16       |
| MIMIC-III Case Study | 683    | 683             | 529688 | 776             | 22       |

Table 2. Observation activities summary with their IDs in the MIMIC-III.

| ID  | Observation Activity |
|-----|----------------------|
| 618 | Respiratory Rate     |
| 50815 | O₂ Flow Rate  |
| 50817 | O₂ Saturation       |
| 51  | Arterial BP [Systolic] |
| 442 | Manual BP [Systolic] |
| 455 | NBP [Systolic]       |
| 6701 | Arterial BP #2 [Systolic] |
| 8368 | Arterial BP [Diastolic] |
| 8440 | Manual BP [Diastolic] |
| 8441 | NBP [Diastolic]      |
| 8555 | Arterial BP #2 [Diastolic] |
| 211 | Heart Rate           |
| 676 | Temperature (C)      |

measurements in the ICU [35], which suggests they are likely candidates to be redundant. Clinically significant discrepancies exist between arterial and manual blood pressure [36], so these two labels should be treated as different (i.e. non redundant), which is consistent with our findings. For “Arterial BP” and “Arterial BP # 2”, there could of been differences in the clinical interpretations, hence both were found to be low in the control-flow similarity measure. Further investigation may be needed.

7. Conclusion

This paper proposes a novel approach to accurately detect redundant activity labels to produce more representative logs for process mining in the healthcare. The method can deal with redundant labels from logs that are generated from a system which uses free-text. By detecting redundant activity labels, more representative logs are produced. Thus, the discovered process model is more intelligible for further improvements. In comparison to existing work, our method adds the following value: First, the detection accuracy is high among all logs even without considering semantic similarity between activity labels. This is useful in the healthcare domain given some systems only record specific codes for certain activities instead of their actual names. Besides, most redundant activity labels have relatively low occurrence frequencies in the log, so, it is critical that the detection method remains reliable and consistent through different frequency levels. Secondly, the method shows good results in healthcare logs which contain numerical data values as activity attributes. It is useful in the healthcare domain, since redundancy happens most among different laboratory tests and observations. These activity labels are usually associated with numerical data value as attributes. However, existing approaches perform poorly when dealing with this situation. Lastly, the NLP technology is integrated into the method, which provides additional insights to the detection results.

As demonstrated in our case study using the MIMIC III data set, two pairs of redundant blood pressure observations were successfully detected. This further demonstrates the utilisation of our approach in reality, especially in the healthcare domain. The approach can be extended to include more perspectives (e.g. resource attributes if certain information exists in event logs).

It has to noted that like other data preprocessing approaches, the detection results still vary under different parameter settings in different logs. Future work includes developing a method to automatically determine thresholds for different perspectives. We would also like to incorporate NLP to automatically repair redundant activity labels by preserving the same contexts and categorising differences according to their closest synonyms.

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