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PROCESS-MINING USING RULE AUGMENTED WITH CONDITIONAL RANDOM FIELDS ON SEQUENCES FOR EVALUATING THE RESULTS IN HEALTH CARE EVENT ABSTRACTION

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Abstract: Process-mining approaches are geared towards gaining insights into processes by analyzing records of events. Most of the time, the events written down within the event log aren't enough detailed. This causes the software to uncover incomprehensible processes diagrams or processes that do not exactly match the details that are in the log. We demonstrate that when process discovery software can detect an insufficient process model from an event log that is lower level. The general pattern of the event can in certain instances be identified by abstracting the log higher levels of detail. This presents the challenges of creating a bridge between a log that is low-level events and a more detailed view of the log in order to create a more structured and more easily comprehended model of the process is recognized. We have shown that the supervised learning technique can assist in the task of event abstraction for the case that annotations that contain High-level interpretations of low-level events are only available to specific sequences (i.e. trace). We propose a method to create trace features vectors for events dependent on extensions to an event. There is an increasing amount of research about Process-mining in the field of health care, such as oncology, which is the research of cancer. The MIMIC-III dataset contains 16 event tables that can be beneficial in Process-mining. This paper highlights the potential to utilize MIMIC-III to conduct Process-mining in the field of oncology. The findings and the data's quality limitations are reviewed as well as opportunities for further study as well as reflections on the potential of MIMIC-III to facilitate reproducible research on Process-mining.

Keywords—Process-mining, Health Care, Cancer, Rule Augmented, Event Abstraction, Conditional Random Fields, Event Abstraction

1 INTRODUCTION:

Process-mining uses nifty software to monitor and predict the sequence of executions to improve the process for business. It's cost-effective and simple to use. Process-mining gives us an objective way of looking at your company's operations by looking at the data from the back end of your operation. In today's highly competitive market it is essential for companies to have constant and clear feedback. In short, enterprises require an effective analysis tool in order to gain a clear overview of their software processes. Fig.1. Explains how processes actually take place in the real world. It is the main driver behind the advancement and growing applications of Process-mining methods.

The purpose of Process-mining software is to automatize the process models from the transactional logs. From the beginning, these logs are utilized for mining. Every transaction refers to the process or case. In the perspective of a software company every transaction takes the form of a time stamp. These timestamps are extracted and the visual diagram of how the model operates is constructed. The model allows us discover any kind of deviation from normal processes and assists in determining the real reason behind the issue to make the necessary adjustments to ensure that the process is optimal.

The event logs are gathered and then prepared to be mined, which means that the data is cleaned and reformed to make it suitable for a mining tool. Technique flows that are generated by methods of mining are more reliable than those generated by method of interviewing the key stakeholders in the process. This state of affairs in system discovery provides information for future method evaluation

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and development and provides a basis for addition evaluation, including ways of compliance, or forecast of the path taken by the procedure that are based entirely on historical information.
Since event logs are typically not specifically designed to be used in Process-mining, the granularity of the event log on the moment may be at a low in level. Methods for process discovery in cases,where the event log input is not at the appropriate level could lead to a process model that has some undesirable features.

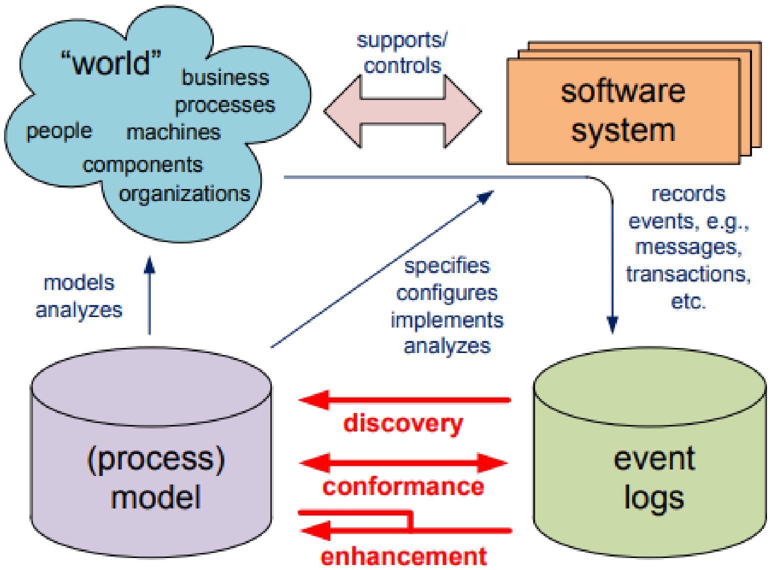

Figure 1 : Overview of Process-mining

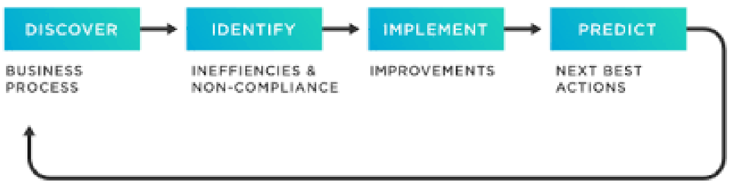

Figure 2 : Process-mining Enterprise System

There are a variety of approaches that have been investigated within the field of Process-mining, which tackle the issue of abstracting low-level events into higher-level events ([7], [8], [9]). The methods currently used to abstract events are based using unsupervised learning methods to transform low-level events into higher-level ones by aggregating groups of events at a lower level to produce events at the highest level. However, the use of unsupervised learning raises two challenges. It isn't easy to classify high-level activities that result from the clustering of low-level events. The present methods call for an analyst of the process or the user to develop labels for high-level events based on specific knowledge of the field or develop long-term labels by combining names of every event of the low-level of the cluster.
However, concatenated long labels can be difficult to read when larger clusters are present and it's difficult for an individual to develop reasonable labels on their own. Additionally methods of learning that are unsupervised for event abstraction provide no instructions regarding the degree of abstraction that is desired. The majority of existing methods of event abstraction use at least two parameters to establish how events will be organized within larger ones. The process of determining the right level of abstraction needed to produce the most reliable results is typically an exercise of trial and trial.
In this paper, we outline the method of supervising event abstraction, which allows process discovery using too finely granular event logs. This technique could be used to apply to any log in which higher-level training labels for low-level events are accessible for a small portion of the traces within the log. We begin by providing an overview of the work in the field of activity recognition in Section II. In Section III, we will introduce the basic concepts and definitions that which will be utilized throughout

the document. Section IV describes the problem and suggests methods to automatically extract the feature vector symbolizing an event. This could be used in conjunction with methods of supervised learning that utilize certain characteristics of the XES the standard description of logs for events.
Process-mining is used to analyze healthcare processes, with the aim to improve the quality of care while also ensuring patient safety optimizing resources [4]. Process-mining can be particularly beneficial to analyze extremely complex and flexible patient healthcare procedures (care pathways) such as those that occur during cancer treatment.
Process-mining has been utilized in the field of healthcare to explain the circumstances that led to it, what was happening, what's going to take place, and highest-quality research studies using Process-mining in the field of oncology were those in healthcare.
Openly accessible datasets are an alternative and this paper outlines the possibility of using MIMIC-III is a Process-mining tool for oncology. This MIMIC-III dataset is an open-access data set from an oncology clinic in the USA with a large number of patient records.
This paper offers a working illustration of how MIMIC-III can do to analyze patient data with the aid of process-mining tools. We describe how specific criteria were applied to create event logs based on the patient's records of treatment, and then examined to get a better understanding of treatment options. The research we conducted is reproducible with MIMIC-III's information and from all SQL queries, graphs along with the process models that resulted and the associated resources have been put up in the GitHub repository.

II RELATED WORK

2.1. Process Discovery Algorithms

Many methods for discovering processes were developed during the past decade. The Alpha algorithm was among the many first groupings in process discovery algorithms which could build Petri nets in a way that is automatically based on the logs of events. The initial version [12] of algorithm can ensure the identification of certain behavior in models of processes when the event log used for input is clean and meets certain criteria for completeness. However, the algorithm is not able to identify accurate models of processes with complicated behaviors. The research papers that followed later expanded the alpha algorithm to uncover shorter loops [13], invisibly tasks [14-15] and non-free-choice behavior [14,16] and non-free-choice behaviors . Alpha algorithms provide pleasing results when using data that is noise-free. However, their performance may be severely compromised when trying find processes from actual event logs. The heuristics miners [17-18,19] were proposed on the basis of the algorithms used by alpha to deal with the noises that occur in event logs.
However, all of these techniques depend on the order of events within traces in order to identify processes models. The sequence of events in trace could be wrong if there is a lack of activity labels or events.
The primary goal of the look has been the benchmarking of the overall performance, address differences, and examine the various variations of a bank's client service's name middle info handling calls from its customers and clients. The results showed that the amount of calls that are incoming into the decision middle phase of customer support due to "over card restriction “ problem were the most effective when in comparison to other problems in the name center's event log. However, the outcomes confirmed that approximately 32 percent "Over Card Limit" type problems weren't resolved on the first attempt (i.e. the customers/customers must dial and call the operators to resolve the issue to resolve the problem) eventually, the findings of the study can be utilized can improve and increase the effectiveness of customer support processes with a greener, more quick and efficient manner.
The research demonstrates the successful process of mining methods for regions and transition structures in order to identify, analyze and take an understanding of the customer service methods of the Call Center in a bank in relation to credit card issues, issues such as inquiries and more. Utilizing the top-quality set of guidelines incorporated into the ProM Process-mining, the device allowed us to create and simulate the graphs that resulted in terms from Transition System fashions. The technique

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used in this research and the proposed techniques could be an underlying basis for future and further studies under unique scenarios and conditions. Most of the department of decision-making middle customer support in banks are equipped that give better customer service and data on public members of the family of the organization which can bring more comfort to customers who rely on the issuer principle to improve efficiency in the industrial structure of banks.

2.2. Missing Data in Event Logs

There are a number of research papers that concentrate on the management of events logs that are missing data to aid in Process-mining. In [4, 5] missing data were recognized as one of issues with the quality of event logs. In [6], researchers utilized the generalized stochastic Petri nets (GSPNs) and Bayesian networks to correct the event logs with missing events. Rogge et al. were the first to address the issue of missing data by using Process-mining. However, if the all-stochastic Petri net is not constructed from logs of events (e.g. in the case that many events aren't accessible) the log may not be correctly corrected. Similar to the model in [6], Song et al. [10] utilized process models to correct for the absence of certain events.

The MIEC [9] is a multiple-imputation-based method to repair missing data in event logs. Apart from fixing labels to indicate missing activity in addition, it is also capable of repairing other characteristics that are not present in event logs. It is important to note that the MIEC was based on relationships between attributes of events. For example, certain events can always occur during weekends or by a specific at weekends or by a specific group of individuals. It's sometimes not feasible to restore the logs of events if dependencies aren't present and the event log is comprised of just insufficient attribute information.

2.3 Health Care Process-mining

The procedures during the patient's stay in a hospital are comprised of numerous activities, which include administrative (admission or the discharge process, transfers to hospital ward, etc. as well as clinical (triage tests, scans and triage diagnostic, therapy, etc.) [9].The responsibilities are handled by various roles within the clinical area (doctors or technicians, nurses, specialist and so on.) and vary between different organizations. The healthcare processes are thought of as complex due to being that processes involved are complex and nonlinear, as well as uncertain. These procedures don't follow the conventional order of operations [10].

Many health care institutions utilize EHR (EHR) applications to keep track of details of their administrative and clinical records of their patients and to monitor the procedures they provide. These EHR systems were created from paper-based notes taken by physicians. The requirement to format the records in a more formal manner has increased as health care organizations have increased in size and complexity [11]. The information that patients provide, which includes the demographic data as well as some medical information (e.g. allergies, long-term illness) is supported by records that are time stamped to document the observation, treatment for diagnosis and prescriptions, as well as administrative procedures such as admission and releasing [12]. The data for events is typically comprised of coded variables as well as natural language text that is logged against the time, date of the event, the user ID and the nature of the event. The EHR systems also contain information that is longitudinal which can be examined through Process-mining techniques as EHR systems become more advanced they will have more opportunities to uncover and analyze the process data of the treatment process are increasing.

The paper we wrote about is focused on the treatment of cancer patients and the steps involved in the treatment routes. Since we only work on administrative processes we are hoping that the method and information are suitable for use in other areas of.

III. PRELIMINARIES

In this section, we will introduce fundamental concepts that will be utilized throughout the paper. As with all emerging technologies, there are certain mistakes that can be made making use of Process-

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mining in actual situations. We have compiled six guidelines that can be applied to stop users and analysts from making these mistakes.

Event Data Should Be Treated as First-Class Citizens

The most important entry point to any mining event stored. We speak about the collection of events, which are known as event logs but that doesn't mean events have to be kept in distinct files. Events can be recorded in databases, messages logs and transaction logs used for mail archives as well as other sources of information. The most important aspect of the structure of the data kept in this storage device, is the data that is contained in these event logs. The quality of the mining output is greatly dependent on the data input. Therefore, logs of events should be considered as an integral element of systems that enable an analysis process. They can also be utilized as a "by-product" that can be used to debug or profiling.

Log Extraction Should Be Driven by Questions

Process mining must have questions to guide it. Without specific questions, it's very difficult to locate relevant event information. For instance, consider those thousands of tables contained in those databases within an ERP system such as SAP. Without specific data, it's impossible to choose the tables relevant to extracting data.

Concurrency Choice, Concurrency and other basic control-flow constructs Should Be Accepted

There are a myriad of process modeling languages are available Many of these languages offer a variety of modeling components. Control-flow descriptions are the foundation of every process model. The most fundamental workflow concepts (also called patterns) used by the majority. The most common languages are of the mainstream languages are sequence of mainstream languages include sequence (AND splits/joins) and alternatives (XOR-splits/joins) along with loops.

Events Should Be Related to Model Elements

It is a false think processing mining can be restricted to the exploration controls flow. The model that is discovered may be viewed from different perspectives. Methods to check conformance identify and resolve the underlying divergences. Time stamps in the log of events can be used to study the timing of replay. Time variations between events that are In the case of causally linked events, it is possible to determine the expected wait time in the model. These examples show that the causality between the instances of the logs and in the model can be a useful foundation for different types of analysis.

Models should be viewed as a purely abstract representation of reality

Models derived from information about events provide perspectives on the realities. An example of this should offer an accurate abstraction of the behavior recorded in the log of events. If you have an events log, there might be many views that can be beneficial. In addition, the different parties involved may require different perspectives. Indeed, the models uncovered from logs of events should be considered "maps". This principle of guiding principles provides valuable insight, and two are explained in the following.

Process-mining should be a Continuous Process

Process-mining is a great way to create "maps" that directly connect to data from events. Event data from the past along with actual data can project onto the models. Furthermore, processes change as they are analysed. Due to the dynamic nature that processes undergo, it's advised to view the process as one-dimensional. The aim is not to build an exact model, but rather to give life to processes to ensure that analysts and users are encouraged to study them regularly.

IV EVENT ABSTRACTION AS A SEQUENCE LABELING TASK

4.1 Event abstraction

We believe that the methods used in this paper translate (multiple) examples of fine-granular phenomena into instances of coarse-granular phenomena, i.e. they represent an amount in detail close or even greater than the degree of detail at the point at which one is trying to study the process. Our

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research is focused on methods for event abstraction that address the mapping of fine-granular events to coarse-granular ones and connecting them to the activity instances

The concept of event abstraction as discussed in this paper can be seen as part of the larger scope of the larger system that links observations of the physical world to meaningful instances of activity.

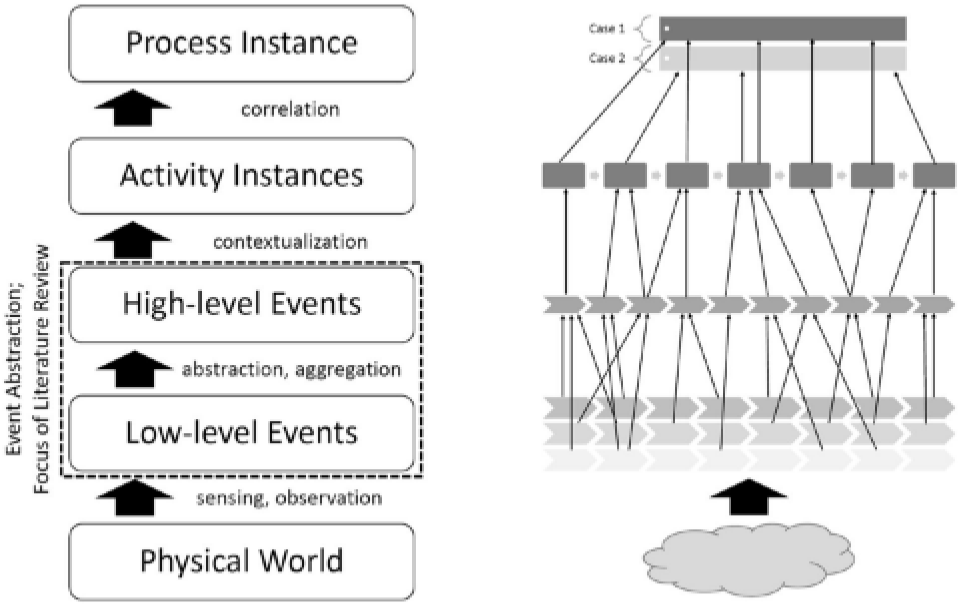

Figure 3: Hierarchy of mappings

4.2 Sequence labeling encoding

If we have the [x1, ..., xn] an n-token sequence which we encode as events as token-level labels [y1 ..., yn] for the purpose of reducing the task to a sequential labeling issue. In the spirit of dependency parsing and coding the label yi associated with each token xi using the tuple h_d h_i, where h_i is the dependent, and is the token's name and the type of its mention (either trigger entity, trigger, or anything else) while the relation is it is used to define the role of the token and head (h) is the name of the specific event that the token is referring to.

To identify event heads of similar types in texts, we encode heads h in terms of the relative head's mention position. For example h = +REG+1 indicates that this head's name is the initial +REGULATION to the right side of d in the relative order of the surface while when h = +REG-2, it means this is the 2nd +REGULATION to the left

4.3 Event Extraction as Sequence Labeling

In essence, we want to discover a function that is f: X-Y which assigns every token xi an organized label yi, i.e. the letters hd, hi, r. The easiest way to solve this problem is to determine the label that yi is an atomic unit (i.e. one label) in an uni-task model.

Based on the above methods, we propose a method to abstract events in a controlled manner is developed using Conditional Random Fields. In addition, we present features functions that can be applied to XES logs of events in a general way making use of XES extension. The method requires two inputs: 1) an annotation of trace, These are trace tracks that show the high-level event incident of low-level status is a part to (the name attribute of the event at the low-level) will be identified by every low-level event 2.) The unannotated sets tracks, which are those which have low-level events that are that are not mapped to high-level events.

Random Fields train using trace annotations in order to build a probabilistic map of low-level events to higher-level events. Once the mapping has been created, it's applied to trace that's not annotated to determine the most high-level event for each low-level event (its distinctive label). Most of the time that low-level events in a sequence within the trace that are identified with high-level annotations will

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share the same label attribute [16, 17]. We believe that a lot of high-level events take place in parallel. This lets us see the specific sequence of attributes and labels as distinct events of an upper-level. To construct a high-level report that's top-level we must divide the sequence of events that have similar value to the attribute's label attributes into 2 distinct events that use this label being the name of the concept. The first is a time-based lifecycle that starts with the other, and it is the complete lifecycle.
We will now demonstrate the case for each XES extension, how it can be transformed into feature functions beneficial to abstract events. We do not restrict our efforts on XES logs that have all XES extensions [17]. If an XES log has one or more extensions, a portion of the features functions will be made available to be used in the supervised learning process. This results in an unspecified feature space size, and could lead to problems because of the issue of because of the problem of. We employ L1-regularized Conditional Fields because of the issue of dimensionality. The regularization of L1 results in the feature vector's weights to become sparse which means that only a tiny portion of the feature weights are featured are given a weight that is not zero and are actually utilized in the model for prediction.

Explicit rule addition

Alongside the embeddings of words that are It is fed to the BiLSTM as well as a rule vector through an additional Bi-LSTM are also transferred. Two Bi-LSTMs are provided with word embeddings as well with rule vectors. Hidden layer representations of the hidden layers are jointed to create a combined representation of rules and words [20].
We anticipate that this method will preserve the essential information that rules provide. Comparatively in the concatenation technique that was that was discussed in the previous article, and we expect that it is able can be used to store more pertinent information when the rules are explicitly enacted.

4.5 Word Embeddings

Because of the characteristic of the low-resource languages that out of the vocabulary are often used in the language of low-resources. To address these words, we use trained fastText[18] words that are pre-trained embeddings as well as adjust our corpus.

V RESULTS & DISCUSSION

5.1 Dataset

Medical Information Mart Intensive Care III (MIMIC-III) is an information database which contains EHR details for patients who are admitted to the Critical Care Units [17]. This is an information database that holds data like vital signs, medications lab tests in hospitals (i.e. in-patient) as well as clinics (i.e. out-patient) observation charts during an in-patient's stay in the facility for intensive care. Notes that are not identified about the patient's treatment including nursing notes, medical notes, and discharge summaries.
The study was exploratory with the goal of understanding the treatment of cancer within MIMIC-III as publicly accessible data. The tools used in this study included PostgreSQL (through PgAdminIII graphical interface), Python, and ProM 6.5.1. PostgreSQL was employed for the management of databases which lets SQL-based queries via PgAdminIII to search and select MIMIC III data databases. Python was used to create an organized method of processing data. The ProM offered a set of tools for mining processes for discovering, conformance-checking and enhancement of model of processes. These SQL queries and the resulting models can be reused in the Github repository.

Table 1: Cancer Types

S.No	Description
1	Malignant neoplasm of lip, oral cavity, and pharynx
2	Malignant neoplasm of digestive organs and peritoneum
3	Malignant neoplasm of respiratory and intrathoracic organs
4	Malignant neoplasm of bone, connective tissue, skin, and breast

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5	Kaposi's sarcoma

The extraction of all patient data was achieved by selecting the information from the 16 tables for MIMIC-III events. A list of the records extracted can be found in Table 2.

Table 2. Extracted work

S No	Table Name	Patients	Activities	Rows
1	admissions	7152	9	38547
2	callout	4784	7	27965
3	chartevents	7415	2641	37896541
4	Cptevents	3147	2	19568
5	Datetimeevents	548	157	9215647
6	icustays	7845	3	22987
7	inputevents_cv	3214	845	17415869
8	inputevents_mv	3560	21	665789
9	Labevents	7411	654	6741965

The table that resulted was 51,968,485 rows. The use of This table is directly linked to Process-mining. resulted in a "spaghetti" Process model, which isn't able to be studied and is not included in this paper. The further transformation and the creating an easier version of the data was vital.

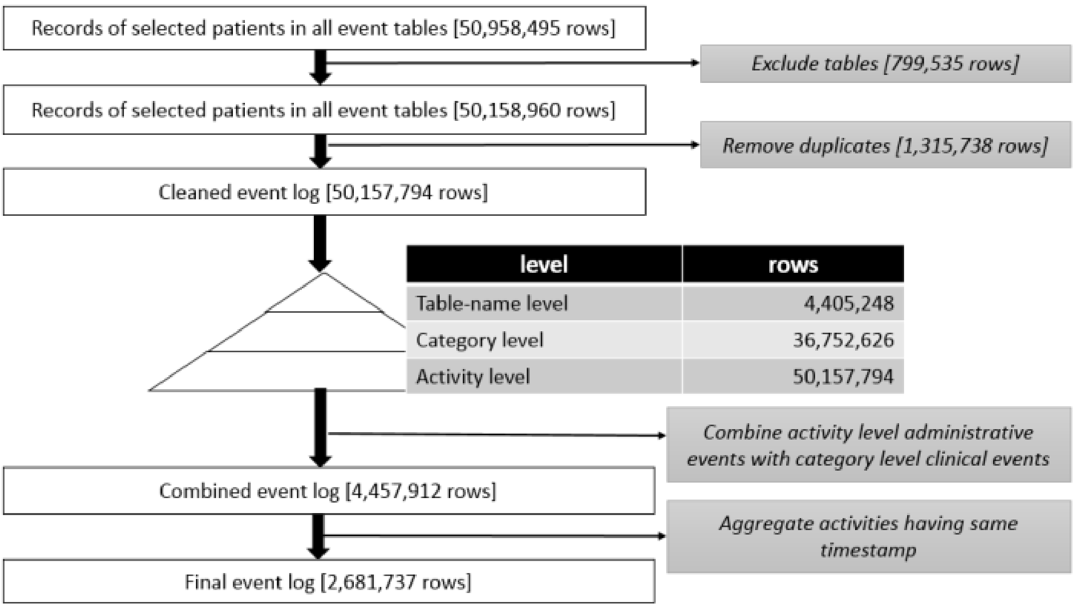

Fig. 1. Data extraction, transformation and sequence Stage 1

In addition, the log is enhanced by building three levels of information by using three different labels of activity. They is the initial name of a task (activity stage) and categories from the D_labitems and d_items table (category level) and also table names (table-name the levels). The three levels are essential in order to let you analyze the data in three different levels of detail based on the information contained within the data.

Views were developed by selecting the amount of detail required in the next stage. The procedure took into account two types of events that that were recorded in tables, which are administrative and clinical events. In MIMIC-III, administrative events are recorded in admissions, ICU stays as along with services and transfer tables. An overall suggestion for obtaining an overall model of the process of all events within an individual patient group is to include activities of administrative events with the middle or high levels in clinical activities.

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Create control flow model and connect event log

The model in Fig. 4 was created using the "BPMN Miner" plug-in (23) within ProM that is an admission to 10,843 patients with cancer who had complete pathways. The test was performed on the model developed using the "Replay log to verify the conformance" plugin in ProM. The model was evaluated using accuracy and fitness measurements. The extremely high performance (0.971) as well as the high precision (0.8808) suggest that the theory proposed could be used to explain the behavior observed in the log of events, but it's not able to explain the behavior that isn't linked to the events that are recorded within the event log.

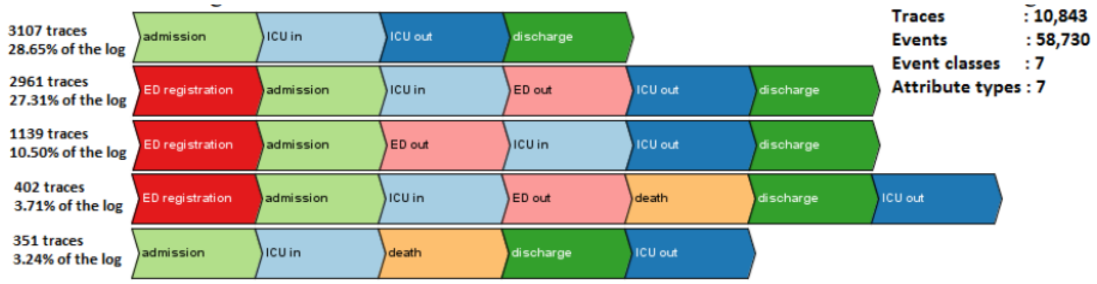

Fig 2: The five most common trace variants representing 73.41% of traces

VII CONCLUSION

This paper proposes an approach that is a mix of Automatic extraction of events and arguments. We present a brand-new data set for the field of disasters for five languages, which is comprised of a large numbers of tags that are not found in typical data sets. We present a variety of variations of a rule-based system to improve deep learning models. Numerous experiments show that our method of rule-based augmented models outperform deep learning models using less annotated data as well as low resource languages. Further, this paper examines the use of process-mining to the health care field, specifically the cancer pathology with the MIMIC-III data. MIMIC-III is a representation of ICU as well as hospital data and is able for reproducible research because it is accessible to researchers. This research paper focuses on getting insights into the flow of patients through the implementation of L* lifecycles using control-flow perspective and the time perspective. It was demonstrated the possibility to extract complicated hospital processes using current methods to find and analyze process models.

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