FERRET MINER: A Process Mining Case Study

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Abstract—This project is a process mining case study designed to identify patterns, delays and bottlenecks that obstruct the efficient flow of the process activities. Specifically, our objective is to analyze event data logs from the travel reimbursement process at Eindhoven University of Technology (ETU/c), identify bottlenecks in the process, and seek improvement to its efficiency. We process and filter the event data, and then generate simplified and representative process models to help locate where the most time-consuming and impactful critical tasks are. Our analysis suggests that improvement in the supervisor apppproval and payment handling activities could significantly reduce the time processing the travel reimbursement.

Index Terms—process mining, data mining, conformance, event logs, business intelligence

I. INTRODUCTION

Nowadays, most organizations use information systems to support the execution of their business processes, generating significant amounts of data. Mainstream information systems, such as Enterprise Resource Planning (ERP), Work on Management Systems (WMS), and Customer Relationship Management (CRM), have become vital tools behind the operation of almost any company process [15]. All of these platforms offer rich event logging capabilities, in which an event log is basically a record of an activity performed with a timestamp embedded [6].

As a result, there are plenty of oppportunities, through proper supervision of business behavior, to identify and adjust tasks that are generating problems for the business processes [9]. One important technique to accomplish such goal is process mining, a specialized data analysis technique that reveal core business behavior indicated by activity logs. Process mining would start with these event logs, extracting important information including the chronology of the activities and their execution time registered in each log. Representative models would be built, or discovered automatically, and then be used to detect errors and deficiencies in the process, and to provide insight and suggestions for process enhancement. Process mining is most closely related to data mining amongst business intelligence disciplines. However, data mining concentrates on finding relationships among data, whereas process mining also looks at data from a systematic perspective.

A. Problem Description

In this process mining case study, we are tasked with studying a dataset with real-life event log data from the travel reimbursement process at Eindhoven University of Technology

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(ETU/e). Through analyzing the event logs and mining the business process beneath the events, we seek to identify and suggest remedy to address deficiencies in the reimbursement process. The event logs provide a detailed record of the travel reimbursement process, including important attributes such as identification, resource, timestamp, permits, payment and budgetting information, and event labels. Students or staff would submit their reimbursement application, provide suppport documentation (if traveling internationally), wait for reimbursement decision and subsequent payment, and possibly deal with rejection and resubmission. All of these information is captured in the event log. Collectively, these information provided a substantial amount of detail into the process. The data was obtained from the annual Business Process Intelligence Challenge (BPI Challenge) as part of the 2020 International Conference on Process Mining held in Padova, Italy [2], and has been pre-processed and anonymized for research purpose.

Our approach to process mining is based on the work by Wil Van Der Aalst in his seminal paper titled simply "Process Mining," [16], where process mining guidelines are detailed. A process mining implementation generally covers three main issues: (1) discovery, (2) conformance, and (3) enhancement. Our project focuses on discovery since it is the area that requires more effort and it is the most deterministic for the success of the analysis. That said, we shall also take a cursory look at conformance analysis as an aide to discovery, and to motivate our future work.

B. Motivation

Publications on practical application of process mining are scarce, and our research paper aims to add support to this section. Our goal is to demonstrate the practicality of process mining analysis in practice, in application to the real-life travel reimbursement problem as detailed earlier.

Furthermore, we are very interested in the evaluation and application of a relatively new process mining technique based on the Python-based process mining library called PM4PY developed by Berti, van Zelst, and van der Aalst [1]. According to the authors, PM4PY is a modern, open-source, and emerging platform developed specifically for the data science community. Prior to the turn of the millenium, there were hardly any tooling for process mining, but since then a slew of software tools, both open-source (PROM and APROMORE) and commercial (DISCO, CELONIS, and PROCESSGOLD), have been developed. Yet, many were proprietary, hard to extend, hiding behind graphical user interfaces, or (worst yet) all of the above. The mindset of process mining tooling contrasted

greatly with the modern philosophy of data science R&D, which put significant emphasis on openness and extensibility. PM4PY was developed to bridge the gap between old-style process mining and modern data science capabilities including PANDAS, NUMPY, SCIKIT-LEARN.

We whole-heartedly agree with the assessment of the authors, and we look further at opportunities that the PM4PY approach brought forward, including the the adoption of modern and rapidly evolving machine learning functionalities to process mining.

C. Approach Summary

The document is structured as follows: Section I provides details about process mining and its fundamentals; Section II presents an overview of our approach and related literature review; Sections III and IV analyzes the outcomes produced from our primary studies and research problem, and section V focuses on the process models we built and the analysis that follows. Section VI refers to our discussion about future work. We will conclude our paper in VII.

II. SURVEY

In this section, we shall offer a very brief review of the literature on process mining, focusing on the development of techniques and algorithms from a control-flow discovery perspective, as well as its applications.

A. Process Mining

Van der Aalst et al. described the discipline of process mining as positioned somewhere between data mining and process modeling [17]. Process mining interacts with the rest of the software ecosystem mainly through the language of event logs (see Figure 1), and the objective is to provides useful information with implication on the business processes, organizations, and people involved.
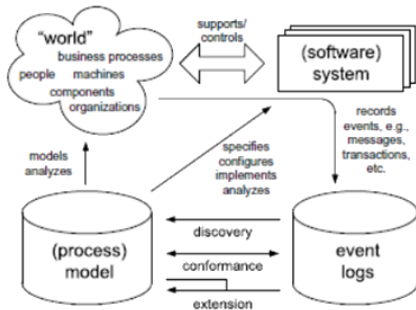

Fig. 1. General outline of process mining approach.

Although information system databases capture important business data in the form of event logs, these systems do not usually provide understanding of the data in a structural or systematic manner. Traditionally, process analysts must search for and retrieve the information directly from the system, and perform manual analysis to accomplish their specific objectives. Another way to put it is that event logs only possess the right information, but not necessarily the right insight, to determine the behavior of the system. Whether or not a process mining implementation is successful or applicable thus largely hinges on what it can do with the event logs [16]. As such, process mining approach must embrace three main actions (Figure 2):

- *Discovery* – to create robust and representative process models through analyzing event logs.
- *Conformance* – to verify and compare newly created models against either the event logs or other predefined models to gain knowledge.
- *Enhancement* – to turn the analysis models into insights and suggestions to overcome previously detected problems.
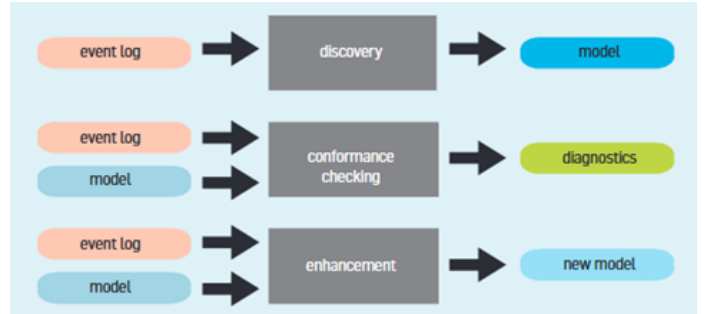

Fig. 2. General outline of process mining approach.

B. Process Models

Many distinct data analysis approaches have been developed to discover processes from event logs. However, Petri nets[1] have become a widely adopted technique over other approaches [4] due to their intuitiveness, mathematical soundness, and ease of analysis. Another approach utilizes Unified Modeling Language (UML) diagrams [14]. In 2004, Van der Wilst et al. described the a novel algorithm called ALPHA MINER [17] which is capable of depicting event data logs into work-flow diagrams, which can be translated to Petri nets. The success of ALPHA MINER has inspired many follow-up publications, including a popular model called FLEXIBLE HEURISTIC MINER [18]. One main characteristic of this algorithm is to be highly permissive in controling statistical levels and threshold adjustment. In order to deal with the massive number of events that actual information systems generate, Burattin et al. [3] developed another extension to HEURISTIC MINER based on lossy counting, as well as a sliding window that effectively analyzes streams of real datasets.

C. Applications

Most process mining publications are dedicated mainly to the enhancement of novel methodologies and algorithms with significant emphasis on the control-flow discovery area [17]. However, the public services area has been fruitful ground for process mining development research. For instance, a Genetic Miner approach was tested by Alves de Madeiros et al. [5] in

[1]and the equivalent BPMN models and process trees

Dutch municipalities. Additionally, van del Aalst et al. [12] applied an analysis of organizations in another municipality process. Rozinat et al. [13] evaluated process models in two different case studies on the public sector. Nonetheless, all these research applications are focused to validate and assess rather than enhance the process.

Implementation of process mining approaches have also been deployed in the private domain. Distinct discovery approaches were deployed by Goedertier et al. [7] in the field of telecommunication. Mans et al. [10] and Rebuge et al. [11] both evaluated process mining methods to resolve the tracking of patients within the healthcare industry.

III. TECHNICAL APPROACH

We shall briefly describe our approach to answering the questions of where the bottlenecks are. We would start with a thorough analysis and cleaning of the event logs, and then build a model that best captures the behavior of the process, making the proper tradeoff between robustness (does the model capture the intent of the process), and coverage (what fraction of the use cases are captured). Then, we will use the chosen model to answer the questions we have in mind.

We shall note that process mining is a relatively new techniques, and as such we spent a disproportional amount of time ramping up the project. While we fully believe in the full potential of PM4PY due to its focus on algorithmic discovery and availability on Python, it is essentially still an academic software in its nascent stage, and hence suffers from instability. There is still plenty of room for improvement in areas such as lack of control in visualization and presentation, scanty documentation, and signs of immaturity in API design.

IV. METHODOLOGY

In this section we will discuss about data, how we preprocessed the data, which model we used, and how we reach the result and disscuss about the result.

A. Description of the Dataset

After a thorough review of what our tasks entail, we decided to focus exclusively on the domestic and international travel event logs in order to identify the process bottleneck. Both event logs were provided to us in XES format, an XML-based standard for event logs [8], which can be easily parsed using PM4PY. The events are organized as a two-level hierarchy as follows: An event log is made of a collection of cases (also known as traces in technical term), and each case is made of a collection of events. Both cases and events are extensible constructs to allow for maximum flexibility in modeling events for different needs.

The event logs provide a detailed record of the travel reimbursement process, including important attributes such as identification, resource, timestamp, permits, payment and budgetting information, and event labels. Students or staff would submit their reimbursement application, provide support documentation (if traveling internationally), wait for

As we imported the logs into Python via PM4PY, in their simplest form the log is organized into a Python dataframe, a key construct of PANDAS, the popular Python Data Analysis Library. However, as dataframes are not hierarchical, PM4PY flattene the log such that the cases, and case attributes, become attributes of events. Therefore, if there are A_c case attributes in the case, and A_e event attributes in the XML specification, after PM4PY import, we obtain a dataframe with N observations, a total of $A_c + A_e$ attributes.

In our project, the domestic process log is organized differently than the international process log. For domestic trip, an employee would first complete the trip and then ask for reimbursement. On the other hand, the policy for international trips mandates that employees first obtain travel permits from the supervisor prior to commencing the trips.

As a result, we are dealing with a more complex process in the case of international travel, and the formal specification that describes international cases also contain more fields. Specifically, domestic cases have 5 attributes each, and international cases have additional 13 attributes, together with the 5 attributes shared with domestic cases (id, concept:name, BudgetNumber, DeclarationNumber, Amount), for a total of 18 attributes. In either case, the raw event in the XES hierarchy has the same 5 attributes (id, org:resource, concept:name, time:timestamp, and org:role). After flattening, we have the domestic dataframe with 56437 events and $5 + 5 = 10$ attributes, and the international dataframe with 72151 events and $18 + 5 = 23$ attributes. To avoid namespace collision, all case attributes were prefixed with case: by PM4PY (for example, the id field of a case became case:id after flattening). Please refer to Tables I, II, and III for a complete list of attributes:

TABLE I
XES EVENT ATTRIBUTES (5 TOTAL)

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id, org:resource, concept:name, time:timestamp, org:role

TABLE II
XES DOMESTIC CASE ATTRIBUTES (5 TOTAL)

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id, concept:name, BudgetNumber, DeclarationNumber, Amount

TABLE III
XES INTERNATIONAL CASES (18 fields)

Permit travel permit number, DeclarationNumber, Amount, RequestedAmount, Permit TaskNumber, Permit BudgetNumber, OriginalAmount, Permit ProjectNumber, concept:name, Permit OrganizationalEntity, travel permit number, Permit RequestedBudget, id, Permit ID, Permit id, BudgetNumber, Permit ActivityNumber, AdjustedAmount
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B. Data Preprocessing I – Missing Values

Prior to process mining, we performed a thorough evaluation of the domestic and international dataframes to ensure the best possible starting point for analysis. There were three categories of modification we applied to the datasets:

While we did not find any missing value per se (as far as what PANDAS is concerned), we did find columns with values of the form "UNKNOWN" or "MISSING" as string. We carefully evaluated what to do with these attributes on a case-by-case basis. For example, we could drop the column (attribute), drop the row (event), fill the missing values, or simply ignore the column.

In the case of international reimbursement, we decided that we should drop events without a permit number. The permit number is actually a concept of the case, and hence we were removing traces without permit number in their entirety. This would turn out to be the most significant modification to our international dataset. We believe this is justified, because a trip without any associated permit violated the very fundamental assumption about the international reimbursement process, that there is a permit associated with the trip. Note that the decision to drop these entries was not "lossy", because international reimbursement request without a permit number should have been rejected and not entered into the system in the first place.

C. Data Preprocessing II – Duplicated Attributes

Perhaps due to prior inconsistency between versions of the enterprise software, there are fields that are similar or duplicate of each other. For example, Permit ID, Permit id, and Permit travel permit number may refer to the same thing. Moreover, it is more than likely that exactly one of the three fields were filled, while the other two had missing values (or reported as "MISSING"). We combined these similar fields into one, picking out the value from the non-missing column, and dropped the duplicates. Note that we performed this duplicate analysis prior to future treatment of missing values.

As a result of these cleaning procedures, the size of the the international dataframe was reduced from 72151 to 43707 (a 60% drop), with the missing permit accounting for 95% of such reduction. The number of columns was reduced from 23 to 19, having dropped several permit-related columns that are duplicates.

The domestic dataframe was also modified to a much small extent. The number of events was reduced from 55087, a mere 2% drop.

D. Data Preprocessing III – Infrequent Events

Process models that can explain all possible event traces could be arbitrarily complex. For example, obviously we would expect reimbursement to be paid out only after the request was approved. But what if there is a trace with a missing approval due to erroneous logging? A process model built to handle 100% of traces must then be able to handle a flow with payment before request. Not only would the model be complex and clumsy, it would also fail our objective.

A naive approach is to remove events that are uncommon, but doing so may not be sufficient. For example, using the previous example, while REQUEST APPROVED that happened after PAYMENT HANDLED might be a rare sequence, neither of these events were rare.

In PM4PY terminology, the variants of an event log is the union of all possible sequences of event execution. For example, there are 68 variants in the domestic log, and 464 variants in the international log. In fact, the above example points to the need to remove traces that are uncommon. Clearly, it could be beneficial to have the choice to build the process model based on only the most popular traces. In fact, this was an important part of our methodology and we shall take a closer look in the next section.

V. MODELS AND RESULTS

With the event logs new well understood and properly prepared, we are now ready to consider building the actual process model.

A. Choice of Models

We must first answer the question of what formal model to use. Our choices include BPMN[2] model, process tree, Petri net, and Directly-Follows Graph (DFG). The first three are mathematically equivalent and inter-changeable. On the other hand, DFG shows a different view of BPMN graph constructed by aggregating all possible link between any pair of events that follows each other.

There are pros and cons in choosing Petri net vs DFG. DFGs can be constructed directly from the event logs, and are simple to understand. Petri nets (as well as the equivalents) can only be generated heuristically, for example, through inductive or heuristics miners (which PM4PY supports). The difference mainly lies on how concurrency is handled. For example, say there are two activities X and Y that are sandwiched between A and B. In other words, the following are both legitimate sequence of executions:

$$A \rightarrow X \rightarrow Y \rightarrow B$$
$$A \rightarrow Y \rightarrow X \rightarrow B$$

While both Alpha Miner and Inductive Miner would correctly deduct (probabilistically) that X and Y have no inter-dependency but are instead concurrent events, DFG would not be able to discern that, because all it saw was Y directly follows X in the first example, and X directly follows Y in the second. As a result, concurrency would show up in DFGs as tight loops between two activities, yet there is no way to prove that tight loops imply concurrency. As a result, if DFGs become too complicated, they will confuse rather than aide reasoning.

For our purpose, however, we still believe is the preferred approach as the statistics on the edges of a DFG can be made readily available, and more easily reasoned with. We just need to make sure we have a model that is not too complicated.

How many top variants do we use to build the model? We did experiment with different values of k, where k is

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[2]BPMN stands for Business Process Model Notation

the number of top variants (of the cleaned dataframe) to be used to build the DFG. We evaluated many factors, though somewhat informally, and came to the conclusion that we got the best balance between coverage and robustness if we keep approximately 15 to 25% of the top variants, depending on data (higher for domestic, and lower for international). Figures 3 and 4 shows the DFG models we picked for domestic and international reimbursement respectively. In each figure, the DFG to the left is annotated with the number of directly following edges, and the DFG to the right is annotated with the mean duration between the two events.

B. Results

Now that we have a robust process model built on reasonably clean data, we can now answer the question: Where are the bottlenecks in the process of a travel declaration?

The biggest bottleneck is the supervisor activities for both International and Domestic declarations. For the supervisor to do the final approval and request payment, it takes an average of 4 to 5 days. If we simply have to identify one activity, PAYMENT HANDLED is the biggest bottleneck. That said, it might be outside of the organization's control and may be more of a financial institution issue.

Note that PM4PY does not allow us to customize the performance graph output, instead, it rounds up the time to days instead of leaving it in an hour format. Also, PM4PY does not have a method of superimposing the frequency and performance.

VI. FUTURE WORK

A. Conformance Analysis

Once we have developed a process model either extracted through process discovery, or built on some reference guidelines. It would be interesting to investigate further into conformance checking to see how well the data fits the model, while in turn would help us evaluate and improve on the model.

This can be done with a method called token-based replay (TBR) on the Petri-net converted from the process model. For each trace, we would try to see if it can be executed on the petri-net in a mathematically sound way, keeping track of additional tokens added to avoid deadlock, and check for unused tokens at completion. We define the total fitness simply as the percentage of traces that fit the model. Another technique is alignment analysis, which is similar to TBR, except that events of a trace are aligned to a legal and model-fitting trace trajectory subject to certain cost functions. TBR and alignment analysis would both identify non-conformance, but the latter is more informative, although it comes at the expense of runtime complexity. Behavior analysis entails the analysis of concepts that are present in the event log but either impossible or expensive to capture in the event formalism (e.g. the person who submits the request cannot be the same person who approves). These techniques can be used to better identify the hows and whys of non-conformance, and to build better models.

Getting to 100% total fitness is not necessarily a desired goal. Instead, what we seek is a tradeoff. On the one hand, you want the model to be robust enough to elegantly explain the process. On the other hand, we do not want to over-build the model to make it so complex that it is hard to reason about. Let's use our specific problem as an example. We ran an experiment to examine such relationships. We ran the inductive miner on different values of k, where k is the number of top variants we used to build the model. And we ran the conformance check to get the total fitness, and wrote code to examine the model. In this figure, the red line is the total fitness, and the blue line is the size of the model. We see that, as we include more traces, the model gets more complex, but the fitness also improves. If we would include only the top 3 variants, we can explain 90% of the traces. But if we blindly up the ante to 18 variants, we can now account for 99% of the traces, but the model is 5 times bigger, and much harder to understand.

The sweat spots happen at k = 5, which can explain 96% of the traces. Moreover, it can properly capture the submission, approval, rejection, resubmission, and the final payment.

We have only scratched the surface of conformance analysis, as much more can be done.

B. Machine Learning and Timely Analysis

Another area of interest is to apply machine learning techniques to perform (1) flow analysis to predict likelihood of resubmission, rejection, payment delay, or over-budget based on other variables (time since submission, request amount, prior owner approval), and (2) timing analysis to determine mean-time-to-trace-completion. This provides important clues to administrators and employees alike about the time frame of payment in the best-case scenario. We are also interested in detecting non-compliance "as it happens" and sending alerts to administrators.

VII. CONCLUSION

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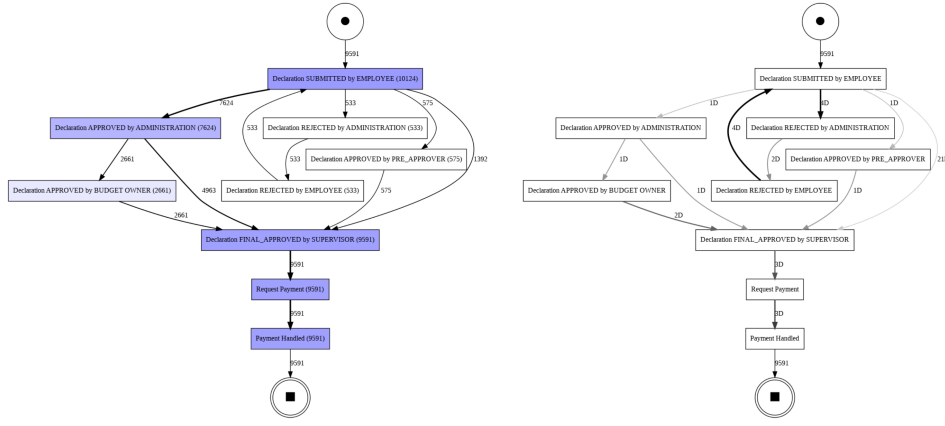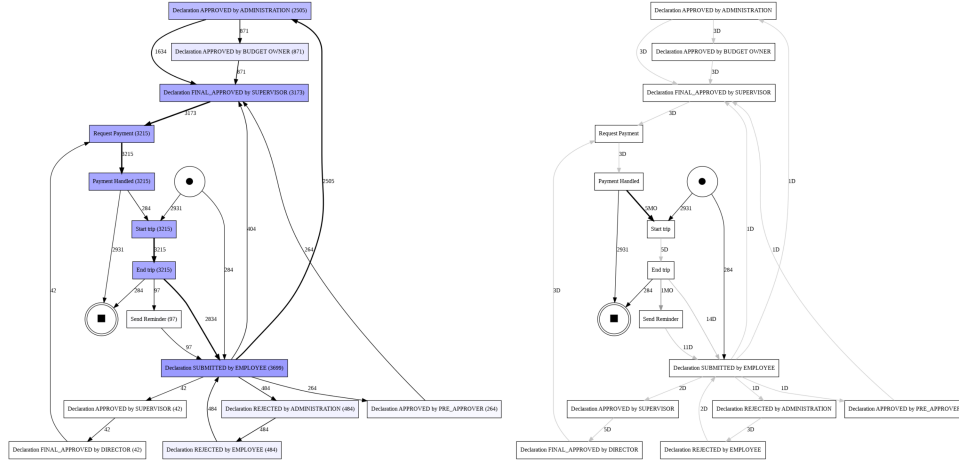
Fig. 3. DFG Model for Domestic Reimbursement.

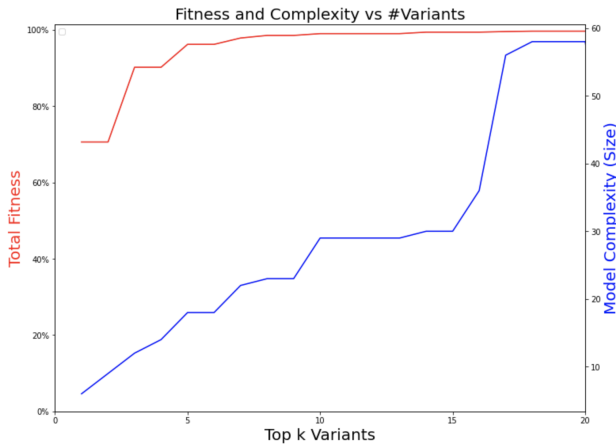Fig. 4. DFG Model for International Reimbursement.

Fig. 5. Fitness and Complexity vs Top k Variants.

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VIII. Contributions

The following is a breakdown of our individual contributions:

- **Martin Alvarez-Lopez** – advocated for the original proposal, and set the overall direction of the project. He contributed to data preparation, the main body of work on process mining, and gave the main part of the presentation.
- **Carlos Hernandez** – wrote the first draft of the term paper, completed with extensive literature survey, project outline, report template, as well as a significant portion of the writeup.
- **Hardy Leung** – did an early investigation on PM4PY, and worked on conformance analysis. He also migrated the paper to the IEEE template, and wrote the second half of the term paper.
- **Divyam Sobti** – worked closely with Martin A. on data preparation as well as the main investigation on process mining. He set up the CoLab environment, and contributed to report writing as well.