An Approach for Workflow Improvement based on Outcome and Time Remaining Prediction

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Abstract: Some business processes are critical to organizations. The efficiency at which involved tasks are performed define the quality of the organization. Detecting where bottlenecks occur during the process and predicting when to dedicate more resources to a specific case can help to distribute the work load in a better way. In this paper we propose an approach to analyze a business process, predict the outcome of new cases and the time for its completion. The approach is based on a transition system. Two models are then developed for each state of the transition system, one to predict the outcome and another to predict the time remaining until completion. We experimented with a real life dataset from a financial department to demonstrate our approach.

1 INTRODUCTION

Some business processes are critical to organizations. The speed and the efficiency at which the involved tasks are performed define the quality of the organization. Detecting where bottlenecks occur during the process, as well as predicting when to dedicate more resources to a specific case, can help to distribute the work load in a better way.

High costs and long response times are mainly due to lack of information and/or due to a non-optimal distribution of resources. In order to reduce them, it is critical for such an organization to classify the process instances that take longer than expected. Even more important is to be able to determine the reasons why this happens. With these extra insights about the process flow, it is possible to redistribute in a better way the workload of the organization and/or allocate more resources to activities that cause the bottlenecks.

In addition, it would be equally important to predict (in real time) how long each process instance will take to be classified, as well as to know its outcome in advance. If the system can predict cases' outcomes before they are over, the involved parties can take action to accelerate the process and avoid the bottleneck, which for some cases could save a considerable amount of time.

Based on the aforementioned problems, this paper proposes an approach to represent the flow of activities of a business process in order to take into account the current state of the execution, i.e. the performed activities can influence the outcome and the time remaining until completion. In addition, we discuss which models can be considered appropriate to predict, in real time, the final outcome of a case and its time remaining until completion.

Extracting insights from the business process and implementing prediction methods should allow the organization to improve their coordination of tasks. For instance, it could allow the creation of alerts for cases with unexpected outcomes or when the estimated time until completion goes over a certain limit.

This paper is organized as follows. Section 2 discusses related research done in this domain. Section 3 describes the approach proposed in this paper. A case study from a financial department is then explained in Section 4 and the results achieved are presented in Section 5. Finally, our conclusions and some future perspectives are discussed in Section 6.

2 RELATED WORK

Process mining together with data mining is used in (Aalst, van der et al., 2011) to predict the remaining processing time of an insurance claim. To do so, they build an annotated transition system and then apply different mathematical formulas in order to estimate the remaining time. The system is implemented in ProM [1], a process mining tool developed at Eind-

[1] http://www.promtools.org/doku.php

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hoven University of Technology. In (van der Aalst et al., 2008), they also propose the use of transition systems to represent process data, since they offer a great balance between under-fitting and over-fitting the model. As transition systems showed to be a good approach for the same purpose of this project, the same idea will be used and we will create an annotated transition system. This transition system will then be used to apply machine learning to predict the status and the time until completion.

Regarding the prediction of the final status of a case, (Zeng et al., 2008) demonstrates how supervised learning can be used to build models for predicting the payment outcomes of new invoices. They predict how long a customer will take to pay (5 different classes). They tested different algorithms (PART, C4.5, Boosting, Logistic and Naive Bayes) and they compare the accuracy obtained against a baseline approach (predicting the mayor class). With some configurations they obtained better results than with the baseline approach. In this project, similar algorithms are used, but the approach is different since there are less attributes and they are mainly categorical. Furthermore, given that the data is imbalanced, to measure the performance of the model different metrics are used (e.g. AUROC, true positive rate, false negative rate).

As previously mentioned, (Aalst, van der et al., 2011) uses annotated transition systems to predict the time remaining until a claim is processed. In (van Dongen et al., 2008), they propose the use of non-parametric regression to predict the time until a case is finished. (Antonio et al., 2017) compares advanced regression techniques for predicting ship CO2 emissions. Even though the data is different, the methods used were found interesting, so some of them were implemented (Multi Linear Regression, Super Vector Regression, Random Forest, LASSO, Boosting). As their data was linearly related, their best results were obtained with LASSO and Multi Linear Regression. In this project, there is not a linear relation in the data, so other methods performed better.

3 APPROACH

In this section we explain how we represent and store information about activities and cases in order to be able to predict the outcome of each case and the expected time for the case to be finished. For that, we use transition systems to represent the current state of the case and to store the information about similar cases in the training phase. The transition system and the additional attributes present in the log are used in the prediction phases. In one hand we are able to predict the outcome of the case, and on the other hand we can estimate the time the case will take to finish. Figure 1 gives an overview of this approach.

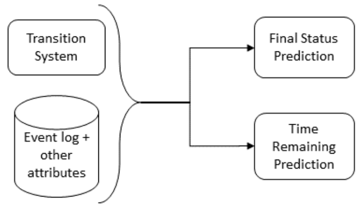


Figure 1: Overview: the information stored in the transition system and additional attributes in the log serve as input to final status and time remaining prediction phases.

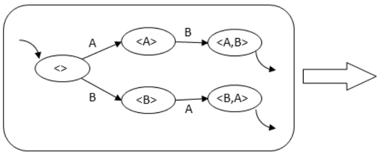
3.1 Transition Systems

Transition systems can be built following different configurations, and each one can provide a completely different outcome. Therefore, it is important to choose the right configuration to the system that will be modeled. van der Aalst (Aalst, van der et al., 2011) refers to the configuration as abstractions. This is because different abstractions are applied to the cases to obtain a system at the end without many states. He recommends using three abstractions:

1. *Maximal Horizon*: The basis of the state calculation can be the complete case or just a part of it. In the latter, only a subset of a trace is considered. This is called the horizon (also known as sliding window).
2. *Filter*: This abstraction consists on removing certain events from the event log because they are not considered important.
3. Sequence, bag or set: For a sequence, the order of activities is recorded in each state. For the bag, the number of times each activity happens is recorded, but not their order. And for the set, it does not keep neither the order nor the number of occurrences of each activity

Note that the order in which the abstractions are applied can change the final results.

When analyzing real life logs, the number of traces present are incredibly high. So, one of the main challenges of building a transition system is to build it fast and for it to occupy the least memory possible. For every case that is in a state, the elapsed time until the case got to that state is kept, as well as the remaining time since the case enters that state until the case is finished. This will be used later on in the prediction phase. In Figure 2, it is possible to see that keeping the elapsed and remaining times make the number



Case ID	State "<>"			State "<A>"			State "<A,B>"			
	V	ET	RT	V	ET	RT	V	ET	RT	...
01	1	0	15	1	10	5	1	12	3	...
02	1	3	7	0	-	-	0	-	-	...

V: visited; ET: elapsed time; RT: remaining time

Figure 2: An illustration of how the transition system is stored. On the left, a transition system with 5 states. On the right, the table that records whether a case have visited (V) the state, the elapsed time (ET), and the remaining time (RT).

of columns bigger (three times the number of states). We have one column that contains if the case went through that state or not (0 and 1 as values, respectively) and the other two to keep the times elapsed and remaining (in seconds).

3.2 Final Status Prediction

Status prediction is one of the most common techniques within Data Science. In most of the cases, there is data that leads to an outcome and the main objective is to classify each case in a group or predict its outcome/final status. Most of machine learning algorithms developed until now accept similar inputs to what there is available in the process used in this research and they can give as an outcome a status.

In this paper, the objective is to predict the outcome of each trace in real time. For that, one new prediction will be made every time an activity occurs (the case moves from one state to another in the transition system).

The objective is to predict the outcome in each activity with the intention of improving it as the case progresses since the state in which it is will be considered. To take into account the state of the transition system for the prediction, one model will be built in each state, taking as training data only the cases that have been through that state. This model, apart from the additional attributes, will also take into account the elapsed time of the cases. In Section 5 we compare different existent machine learning techniques that can be used for the prediction of final outcome.

3.3 Time Remaining Prediction

As specified before, (Aalst, van der et al., 2011) recommends building a transition system, storing information on it, and later on using that information to predict the time remaining. Their first proposition consists on, given a case that is in a state, the time remaining for that case to finish is the average time of the time remaining for the cases that were previously in that state. Also, they give other options such as taking the minimum or maximum value of the past cases that were in that state. In some situations they propose to calculate the standard deviation and instead of returning a value, returning a range.

This might not the best approach, because one could face with more information available apart from the time remaining. For instance, in Section 4, the invoice data from a financial department also contains information about billing amount of the line item, vendor etc. and these attributes probably have an influence in the total duration of a case.

Based on the literature analysis, in Section 5, different methods are tested and the results are compared using Mean Squared Error (MSE) (as recommended in (van Dongen et al., 2008) and (Antonio et al., 2017)) and Mean Absolute Error (MAE).

The methods tested can be divided into the following groups: ensembling models (Random- Forest, boosting and bagging), linear models (LASSO and MLR) and K-NN.

4 CASE STUDY

The proposed approach was applied in a log from a financial department, an Invoice Approval flow. Usually, each item of an invoice follows an independent approval process, but in some cases the whole invoice (even if it has several items) follows an approval process. Depending on the case, the case ID might refer to an item or an invoice (this fact will be represented in a variable in the system).

Each case ID is composed by several fields. If it is an invoice, the case ID will adopt the following pattern: ”PM02-17-6362100959”, composed by a plant identifier (”PM02”), a year (17) and a document number (6362100959). If it is a line item, the case ID will adopt the following pattern: ”8185652-2310187277-1”, composed by a purchase order number (8185652), a document number (2310187277), and a purchase order item (1).

Each case goes through one or more activities, each with a starting and finishing timestamp. Furthermore, the user that did every activity is present on the dataset. Apart from the data required for process mining, there are other attributes available: billing amount, vendor ID, currency of the invoice, company code, and status. In order to get these attributes some preprocessing was done.

Table 1: Most common activities in the process.

Activity Name	Occurrences
Invoice Approval Task Confirmation of receipt	114811
Invoice Approval Task Invoice Approval	89579
Error Error	19651
Invoice Rejection Handling Invoice Rejection AP WFT	7748
Error Technical Error	7205

Table 2: Distribution of activities per case.

Number of activities	Number of cases
1 activity	143858
2 activities	23400
3 activities	9132
4 activities	2473
5 or more activities	4121

There are 23 different activities that can happen during the invoice approval process. Some examples are: InvoiceApprovalTask - Confirmation of receipt; InvoiceApprovalTask - Invoice approval; InvoiceApprovalTask - Budget variance; InvoiceRejectionHandling - Invoice Rejection AP WFT; ManageBuyerRejection - Missing Goods Receipt; Error - Error; Error - Technical Error; and RequestforAdditionalInformation - Request for Information. If a case is only composed by activities starting with ”InvoiceApproval...” it is considered that the case follows the ”happy” path.

In total, there are 182.984 cases and 270.921 activities (23 unique ones), which means that, on average, a case is composed by 1,48 activities. Table 1 summarizes the most common activities and their number of occurrences. The average time of a case is 7,7 days, while the median time is 2,9 days. This means that there are some outliers that have a high influence on the average time.

It is also important to analyze the distribution of activities in cases, in order to know what kind of process is being analyzed. Table 2 shows this distribution. Most of the main variants in the process are composed of one single activity, which proves that cases are likely to be short. This information is useful to explain the insights found in section 4.1 and the configuration chosen to build a transition system in 5.1.

4.1 Data Analysis

In this section a deeper analysis about the data is performed. Firstly, in section 4.1.1, the preprocessing

Table 3: Columns of the final table and their meanings after preprocessing.

Column	Explanation
case_id	Identifier of a case
activity	Activity of the process
start_time	Starting time of the activity
finish_time	Finish time of the activity
user_id	User that did the activity
company_code	Place to where the item was shipped
vendor_id	Identifier of a vendor
vendor_summarized	Attribute to reduce the number of vendors
currency	Currency of the invoice
price	Price of the line item
status	Final status of the invoice
approved	1 if approved, 0 if cancelled or reversed
purchase_order	1 if related to a purchase order, 0 otherwise

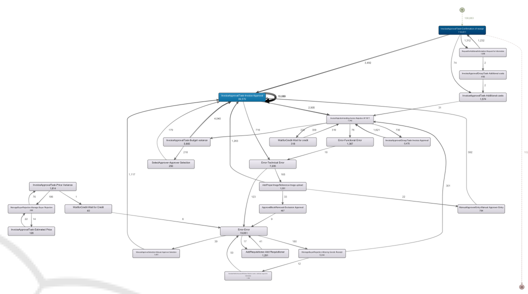


Figure 3: Initial image shown by Disco.

needed to train the models and to understand the process is explained. Then, in section 4.1.2, the insights obtained using process mining are presented. Disco was used to do so.

4.1.1 Preprocessing

Data were provided in four CSV files: general info, invoice, invoice item and status. These files were loaded in a MySQL database. A new table with all the connections between the initial files was created using MySQL scripts. Table 3 shows the columns (with their meaning) of this new table, it also includes some (not real for confidentiality reasons) examples. The first 5 columns are related to the process, while the rest are attributes related to the case. All columns except activity, start_time and finish_time are repeated so that the data can be correctly interpreted by the application when they are loaded in the program.

4.1.2 Process Mining Analysis

The tool used for this task was Disco. The table created in the previous section was exported into a CSV file and used as input for these tools.

When the data is loaded, an image of the process like the one of figure 3. This is just showing some of the connections that exist, and it can be observed that it is a complex process.

The initial approach consisted on analysing which activities where the slowest ones. In order to not be influenced by outliers, the median was taken, instead of the average. The slowest activities are: Price Variance, Invoice Approval Group task and Estimated price. The last one does not occur too often, but the other two do.

After this initial analysis, the cases were split in two groups: those that followed the ”happy” path and those that did not. In the case of the first ones, they wanted to analyse where the bottlenecks were. It was found that the main bottlenecks are in the same activities mentioned above, but also in the connection between some activities: Invoice Approval and Budget Variance; and Invoice Approval and Confirmation of Receipt. In theory, the cases should move between activities without time delay, so this was a non expected finding.

Then, the analysis of the cases that did not follow the ”happy” path was done. These cases were those that contained, at least, one of the following activities (defined by experts): Approve Block Removal, Decide to Wait for Answer or Withdraw, Invoice Rejection Handling, Manage Buyer Rejection, Manual Approver Entry, Manual Approver Selection, Request for Additional Information, Select Approver and Wait for Credit. These cases were 6% of the total (11.655).

5 Results

5.1 Transition System

As explained in 3.1, to build a transition system some choices need to be made. There are three different abstractions and the chosen values were the following.

- *Maximal Horizon:* To choose this value it is important to know that there are in total more than 180.000 cases, and a lot of them follow different paths. The key point is to find a good balance between enough information kept and an efficient system. The following values were analysed: 1 (current activity), 2, 3 and 4. In the case of 1, there were 23 states, as many as different activities. In the case of 2, there were 218 different states, in the case of 3, 785 and in the case of 4, 1.617. The best results were achieved with horizon 1, so it was the chosen one.
- *Filter:* Activities were not filtered, since there are not many in total (23) and all of them are considered important.
- *Sequence, Bag or Set:* After analysing the cases and talking to experts from the finance department the decision was to take into account the order of the activities in every case, since the final outcome is influenced by this fact. This abstraction does not influence the transition system because the we use horizon 1.

Table 4: Recarray containing the transition system.

ID	**Case_ID**	**State 1**	**State 1 ET**	**State 1 RT**	**...**	**State 23 RT**
0	1384571...	1	0	150	...	240
1	3189485...	1	120313	1450	...	120
⋮	⋮	⋮	⋮	⋮	⋱	⋮
182573	EI01-17...	1	0	150000	...	1000

This transition system only focuses on past activities since the intention is to use it for prediction in real time, when future activities are not available.

One of the main challenges of building a transition system having more than 180.000 cases and 23 different states is to build it fast and for it to occupy the least memory possible. For every case that is in a state, the elapsed time until the case got to that state is kept, as well as the remaining time since the case enters that state until the case is finished. This data, together with the attributes related to the line items, are used later on in the prediction phase. There is a column that contains if the case went through that state or not (0 and 1 as values) and the other two to keep the times elapsed and remaining (in seconds).

To avoid having a bigger transition system, only cases with 15 activities or less were taken into account. There are only 310 cases that have more than 15 activities, and most of them were classified as not relevant cases by experts from the finance department.

The transition system was stored in a numpy recarray[2], due to its high speed when iterating through it. This kind of array is known because its columns can have names. In this case, apart from the columns related to the states we have a column that contains the case IDs.

As explained above, the outcome is an array with two dimensions, so it can be seen as a matrix whose rows represent the cases, and the columns are: the case ID (string), the states and the elapsed and remaining times for the states. When a case has been through a state, there is a 1 in the corresponding cell, and the cells related to the elapsed and remaining times contain the time in seconds. Table 4 shows an extract of how the recarray looks.

[2]https://docs.scipy.org/doc/numpy/reference/generated/numpy.recarray.html

5.2 Final Status Prediction

The objective is to predict the outcome of each invoice (Approved, Reversed, Cancelled) in real time. One new prediction will be made every time an activity occurs (the case moves from one state to another in the transition system). Vendor, company code, price, if the invoice is related to a purchase order or not, currency and time elapsed were taken into account in order to do the prediction.

As the data is so imbalanced (91% of the cases are approved, 6% cancelled, and 3% reversed) and, from the business and flow point of view, cancelled and reversed cases are really similar, both of them are unified under the class NotApproved. This way, the problem is less imbalanced and the classification has to be done only between two classes, which should help improving the performance.

The objective is to predict the outcome in each activity with the intention of improving it as the case progresses since the state in which it is will be considered. To take into account the state of the transition system for the prediction, one model will be built in each state, taking as training data only the cases that have been through that state. This model, apart from the initial attributes, will also take into account the elapsed time of the cases. This is the way Data Mining and Process Mining are combined in this project.

In order to train the models, 80% of the data is used in cross validation (to find the best configuration of each model) and the 20% remaining is used to test which model is the best. Cross validation is set up with 5 splits and it is stratified, this means each split has the same distribution of Approved and NotApproved as the initial dataset.

The following techniques are compared: SVM, random forest, K-NN and Naive Bayes. Different configurations of the models are compared using the ROC curve, since data is imbalanced and using accuracy would not be a correct approach (classifying everything as approved would return a 91% of accuracy). The final comparison between the best configurations of the models is done using the ROC Curve, F1 score, recall and precision, taking as the main class the NotApproved cases (Cancelled and Rejected).

As more than 90% of the cases are 'Approved', an up-sampling and down-sampling technique was applied with the intention of improving the balance of the dataset. The function used was SMOTETTomek (Batista et al., 2003), which consists in a mix of down-sampling the major classes and up-sampling the minor classes.

A summary of the different attributes available for each case and activity is shown:

- Vendor id: There are 4.766 different vendors, each of them with an ID. More than 2.000 appear only 3 times or less.
- Vendor id summarised: To reduce the number of vendors some IDs were modified. Vendors whose invoices have always been approved were assigned ID 1, those whose invoices have always been reversed were assigned ID 2; and those whose invoices have always been been cancelled were assigned ID 3. All the other vendors were assigned their own IDs. The number of vendors was reduced from 4.700s to 1.600s.
- Company code: It identifies to which part of the company the ordered item belongs to.
- Price of the line item.
- Currency: There are more than 10 different currencies, and it is considered an important variable at the moment of approving or not approving a line item (together with the price).
- Purchase order related: Identifies items related to a Purchase Order Number (1) or unrelated (0).
- Time elapsed until the case reached the current state.

Vendor id, vendor summarised, company code, currency are categorical attributes, and it is necessary to apply one hot encoding (Vasudev, 2017). It consists on converting categorical attributes into binary variables. It is important to remark that due to this, the number of attributes increases exponentially, from 7-8 to almost 5000, which slows down the training of the models. This is why vendor summarised was created, with the intention of reducing the final number of attributes (by more than 3000). Vendor summarised was used instead of vendor id because it improved the results and the execution time.

5.2.1 Comparison

This section compares different configurations of the algorithm, sampling and not sampling training data. The ones with the best Area under the ROC curve (AUROC) are kept. A model is trained individually in every state of the transition system, and sampling is applied individually to the data from each state.

The performance between these two approaches (without and with sampling) is compared using the area under the ROC curve. The thresholds used are set up manually, from 0 to 1 every 0,01, there being in total 101 thresholds. As mentioned before, each state has its own model, but to compare two approaches it is easier if the results of all the states are summarised into one single result. Knowing that to

Table 5: Comparison for final status prediction using the best configurations from several models.

Algorithm	Configuration	AUROC
Random Forest	**Not sampling** **100 estimators** **Class weight "None"**	**0,5935**
LinearSVC	Not sampling Loss function "Hinge" Class weigth "None	0,5032
K-NN	**Sampling** **50 neighbours** **Manhattan Distance**	**0,5690**
Gaussian Naive Bayes	Not sampling Default Configuration	0,5032

Table 6: Comparison between Random Forest and K-NN.

Method	Best Threshold	F1 Score	Precision	Recall	AUROC
Random Forest	0,09	30,92	22,45	50,94	0,6869
K-NN	0,47	23,06	15,64	56,40	0,6461

generate a ROC curve the True Positive Rate (TPR) and False Positive Rate (FPR) with different thresholds are needed, their values obtained in each state are averaged taking into account the number of cases that are part of each state (weighted average).

Initially, in every state of the transition system, the TPR and FPR are calculated for each different threshold taking into account the number of cases that are in the state. Then, for each threshold, the TPR and FPR are obtained by adding the values specified in the previous step. These values can be used to draw a ROC curve and obtain the area under it. The models with their best configurations are shown in table 5.

The best configurations of the best algorithms presented (the bold ones) are compared using the testing data (20% not used before). The Naive Bayes and LinearSVC approaches are discarded because of their low AUROC value. This leaves two different algorithms to compare: Random Forest and K-NN.

Random Forest has a better AUROC, but in this section other metrics such as the F1 score, the precision and the recall are also compared. To compare the F1 score, the precision and the recall it is necessary to choose a threshold. The threshold is chosen using the Youden's index (Ruopp et al., 2008). This comparison is made in table 6. The conclusion is that Random Forest performs better since it has a better F1 score (even though the recall is lower than in K-NN).

5.3 Time Remaining Prediction

This section presents the different approaches that were followed to predict the time left of a case until completion. The methods tested were regression methods: bagging, boosting, random forest, MLR, LASSO and K-NN, as specified in 3.3. To test the different configurations, cross validation was used, as recommended in (Sharma et al., 2013).

Table 7: Comparison for time remaining prediction using the best configurations from several models.

Method	Configuration	MSE Hours ^2	MAE Hours ^2	Exec. Time (sec.)
Average	**-**	**103.324**	**171,2**	**27**
Random Forest	50 estimators	118.929	172,6	10.257
K-NN	**50 neighbours** **Manhattan Distance**	**106.267**	**174,0**	**290**
Boosting	**Gradient Method** **Learning Rate 0,08** **50 estimators**	**98.227**	**166,0**	**1.348**
Bagging	Default Configuration	122.226	174,7	1.079

The time elapsed and the time remaining are kept in every state of the transition system. This makes possible predicting remaining time of a case in every state. The time is kept in seconds. The attributes used for this section are the same as the ones in section 5.2.

In order to train the models, 80% of the data is used in cross validation (to find the best configuration of each model) and the 20% remaining is used to test which model is the best. Cross validation is set up with 5 splits.

5.3.1 Comparison

To compare the different configurations of each model the Mean Squared Error (MSE) and Mean Absolute Error (MAE) are the used metrics. To better understand the results obtained, the Mean Squared Error and the Mean Absolute Error are converted into hours.

The procedure followed to obtain the MSE and the MAE of a method is the following. For each state, cross validation is applied (5 splits). In each iteration, 4 splits are used for training and one for validation. The MSE and MAE are stored for each case that is validated, then, the average of both metrics is obtained, and it is used to compare the different configurations. The best configurations for the tested models are presented in table 7. MLR and LASSO are not shown since the results obtained were extremely bad.

The best configurations of the best algorithms presented (in bold) are compared using the testing data (20% not used before). These algorithms are: average, K-NN and Gradient Boosting. In table 8, it can be observed that the best results are obtained with Gradient Boosting, regarding MSE and MAE.

The time of training might be important since the model needs to be updated when new cases are over. In this case, the fastest methods are average and K-NN, but Gradient is also fast.

It can be observed that, on average, the models are around 160 hours off in each prediction. Cases

Table 8: Performance analysis for time remaining prediction.

Method	MSE Hours^2	MAE Hours	Execution Time (in seconds)
Average	98.498,91	171,34	7
K-NN	96.481,01	166,89	79
Gradient Boosting	85.460,92	159,48	381

last, on average, 184,8 hours. The median duration of a case is 70,2 hours. This means that the predictions are bad given the median and average duration, but it is important to take into consideration how much the duration of a case can vary and the number of activities of a case. Usually, a short case is composed of one activity, while longer cases can be composed of 3 or more activities. The short ones, easy to predict, go just through one state; while the others go through more states and are harder to predict. This means that the long cases, which go through more states, are predicted more times, and they are more likely to be miss predicted (since they are so far from normal values). This leads to the "high" errors shown above. There are over 10.000 cases that last 30 days or more, and they appear, on average, in 3 states. These cases will have more weight than short cases on the MSE and MAE shown above.

6 CONCLUSIONS AND FUTURE WORK

In this paper we presented an approach to have insights about a business process. The approach is mainly divided into three parts: 1) a transition system; 2) a final status prediction; and 3) a time remaining prediction. For that, Process Mining and Data Mining techniques were used. Several data mining algorithms were built over the different states of a transition system. This way, the path that a case followed was taken into account.

To validate our approach, we used a case study from a financial department with real life data. The transition system allowed to take into account the path that a case followed by just using the cases that are in the same state to train the data mining model (for status and time remaining prediction).

The case study used to test classification algorithms had two main problems: 1) imbalanced dataset, with more than 90% of the cases being approved, and 2) some cases have similar attributes and similar paths, but they have different final status. For this scenario, as explained in Section 5, to predict the final status of a case Random Forest was the algorithm with the best performance.

Regarding the time remaining prediction, interesting results were achieved with different algorithms. The poor performance of the linear models proved that there is no linear relation between the attributes and the time until completion. The best results were achieved with Gradient Boosting.

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