Model Repair by Incorporating Negative Instances In Process Enhancement

Master Thesis

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Registration date : 2018-11-15

Submission date : 2019-04-08

This work is submitted to the institute

PADS RWTH University

Acknowledgments

The acknowledgments and the people to thank go here, don't forget to include your project advice.

Abstract

Based on business execution history recorded in event logs, Process Mining provides visual insight on the business process and supports process analysis and enhancements. It bridges the gap between traditional business process management and advanced data analysis techniques such as data mining and gains more interests and application in recent years.

Process enhancement, as one of the main focuses in process mining, improves the existing processes according to actual business execution in the form of event logs. The records in an event log can be classified as positive and negative according to predefined Key Performance Indicators, e.g. the logistic time, and production cost in a manufacture. Most of the current enhancement techniques only consider positive instances from an event log to improve the model, while the value hidden in negative instances is simply neglected.

This thesis provides a novel strategy that considers not only the positive instances and the existing model but also incorporate negative information to enhance a business process. Those factors are balanced on directly-follows relations of activities and generate a process model. Subsequently, long-term dependencies of activities are detected and added to the model, in order to block negative instances and obtain a higher precision.

We validate the ability of our methods to incorporate negative information with synthetic data at first. Then, we conduct experiments in a scientific workflow platform KNIME to show the statistical performance of our methods. The results showed that our method is able to overcome the shortcomings of the current repair techniques in some situations and repair models with a higher precision.

Chapter 1

Evaluation

This chapter presents an experimental evaluation of our repair techniques. At first, we define the evaluation criteria. Next, we briefly introduce the test platforms KNIME and relevant ProM plugins tools. Then, we conduct two kinds of tests. One is based one the demo example proposed in the introduction part, one is on the real life data.

1.1 Evaluation Measurements

We evaluate repair techniques based on the quality of repaired models with respect to the given event logs. In process mining, there are four quality dimensions generally used to compare the process models with event logs.

- *fitness.* It quantifies the extent of a model to reproduce the traces recorded in an event log which is used to build the model. Alignment-based fitness computation aligns as many events from trace with the model execution as possible.
- *precision.* It assesses the extent how the discovered model limits the completely unrelated behavior that doesn't show in the event log.
- *generalization.* It addresses the over-fitting problem when a model strictly matches to only seen behavior but is unable to generalize the example behavior seen in the event log.
- *simplicity.* This dimension captures the model complexity. According to Occam's razor principle, the model should be as simple as possible.

The four traditional quality criteria are proposed in semi-positive environment where only positive instances are available. Therefore, when it comes to the model performance, where negative instances are also possible, the measurement metrics should be adjusted. With labeled traces in the event log, the repaired model can be seen as a binary prediction model where the positive instances are supported while the negative ones are rejected. Consequently, the model evaluation becomes a classifier evaluation.

Confusion matrix has a long history to evaluate the performance of a classification model. A confusion matrix is a table with columns to describe the prediction model and rows for actual classification on data. The repaired model can be seen a binary classifier and

Table 1.1: Confusion Matrix

		repaired model	
		allowed behavior	not allowed behavior
actual data	positive instance	TP	FN
	negative instance	FP	TN

produces four outcomes- true positive, true negative, false positive and false negative shown in the Table 1.1.

- True Positive(TP): The execution allowed by the process model has an positive performance outcome.
- True Negative(TN): The negative instance is also blocked by the process model.
- False Positive(FP): The execution allowed by the process model has an negative performance outcome.
- False Negative(FN):The negative instance is enabled by the process model.

Various measurements can be derived from confusion matrix. According to our model, we choose the following ones as the potential measurements.

- recall. It represents the true positive rate and is calculated as the number of correct positive predictions divided by the total number of positives.

$$Recall = \frac{TP}{TP + FN}$$

- precision. It describes the ability of the repaired model to produce positive instances.

$$Precision = \frac{TP}{TP + FP}$$

- accuracy. It is the proportion of true result among the total number. It measures in our case how well a model correctly allows the positive instances or disallows the negative instances.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- F-score is is the harmonic mean of precision and recall.

$$F_1 = \frac{2 * Recall * Precision}{Precision + Recall}$$

Generally, there is a trade-off between the quality criteria. So the measurements are only used to compare specific aspects of our techniques.

1.2 Experiment Platforms

KNIME, as a scientific workflow analytic platform, supports automation of test workflow, which helps us repeat experiments efficiently. Yet, traditional evaluation plugins in ProM are not integrated into KNIME, so partial experiments are conducted in ProM.

1.2.1 KNIME

KNIME supports automation of test workflow mainly through the following mechanisms.

- Loop Control Structure. KNIME provides a bunch of control nodes which support re-executing workflow parts. Nodes representing *Loop Start* appear in pairs with nodes for *Loop Nodes*, the workflow between pairs is executed recursively in a fixed number, or until certain conditions are met. In our test, we repeat our repair techniques for different parameter settings by applying loop structure into KNIME workflow.
- Flow Variables. Flow Variables are used inside a KNIME workflow to parameter node settings dynamically. When it combines with loop control structure, tests with different settings is able to conduct automatically.

What's more, there are nodes provided by KNIME to optimize the value of some parameters with respect to a cost function. As long as a cost function is provides, KNIME is able to automatically optimize any kind of parameters.

1.2.2 ProM Evaluation Plugins

Although KNIME offers a powerful approach to conduct experiments, the integration of traditional process mining evaluation plugins into KNIME is out of our capability due to the time limits. To evaluate repaired models with traditional metrics, we use an existing ProM plugin called ***Multi-perspective Process Explorer*** [1]. This plugin accepts Petri net and an event log as inputs, and gives out fitness, and precision measurements which are based on the traditional alignment conformance checking.

1.3 Experiment Results

1.3.1 Test on Demo Example

In this experiment, we aim to answer the question: Will our repair method overcome shortcomings of current techniques which are shown in the introduction chapter?

1.3.2 Comparison To Other Techniques

This section represents some situations where current repair techniques can't handle properly, while our algorithm gives out an improved repaired model.

Situation 1, unfit part!! added subprocess are too much!! Where the addition of subprocesses and loops are allowed, while the structure changes are impossible, Fahrland's method applies the extension strategy to repair model by adding subprocesses and loops in the procedure. It introduces unseen behavior into the model. However, if the behaviors which are already in the model is unlikely to be removed from the model. One simple example is shown in the following part.

Dee's method is based on Fahrland's method. Deviations are calculated at first and used to build subprocesses for model repair. However, before building subprocesses, it classifies the deviations into positive and negative ones with consideration of trace performance. Only positive deviations are applied to repair model. Different to Fahrland's method, it improves the repaired model performance by limiting the introduced subprocesses. Still, it can't get rid of the defect mentioned before.

Situation 2, For fitted data in the model, can not recognize them!! where overlapped data noise can not be recognized, trace variant with more negative effect is treated as positive and kept in the model, which we should delete them.

Situation 3, with long-term dependency!! fitted part or new added part!! none of the current techniques can handle this problem yet. Simple examples listed, but will this repeat the last section??

For one exclusive choices, but with long-term dependency detected and added in the model, precision and accuracy increase, since model with long-term dependency blocks the negative information by adding transitions and places to limit activity selection.

1.3.3 Test On Real life Data

We choose a publicly available event log from BPI challenge 2015 as our user cases and compare current repair techniques on it.

1.3.3.1 Data Description

The data set for BPI Challenge 2015 contain 5 event logs which are provided by five Dutch municipalities respectively. Those event logs describe the building permit application around four years. We choose it as our user cases due to the following reasons.

- The event logs hold attributes as potential KPIs to classify traces. Attribute **SUMleges** which records the cost of the application is a candidate to label traces as positive or negative if its value is over one threshold. What's more, we can take the throughput time of the application as another potential KPI.
  In a word, this data set provides us information to reasonably label traces.
- The five event logs describe an identical process, but includes deviations caused by the different procedures, regulations in those municipalities. Also, the underlying processes have changes over four years.
  So, this data set gives us a basic process but also allows deviations of the actual event logs and predefined process, which builds the environment for repair techniques.

Firstly, we conduct our experiments on event log called **BPIC15_1.xes.xml**. This event log includes 1199 cases and 52217 events. But the event classes for those events are with the sum of 398. So we preprocess the event log and get a proper subset of data as our user case.

We filter the raw event log by ***Filter Log By Simple Heuristic*** in ProM with the following setting. 40 for the start, end activities and the events between them, at end. We get the event log $D1$. After this, we calculate the throughput time for each trace and add it as a trace attribute **throughput time**. Then we classify traces according to **SUMleges** and **throughput time** separately. When our performance goal is to reduce the cost of application, if **SUMleges** of one trace is over 0.7 of the whole traces, this trace is treated as negative, else as positive. The similar strategy is applied on the attribute **throughput time**. A trace with **throughput time** higher than 0.7 of all traces is considered as a negative instance. Following this preprocess, we have event logs in Table 1.2 available for our tests.

Table 1.2: Test event log from real life data BPI15-1

Data ID	Data Description	Traces Num	Events Num	Event Classes
D1	Heuristic filter with 40	495	9565	20
D2	Apply heuristic filter on D1 with 60	378	4566	12
D3.1	classify on SumLedges; values below 0.7 as positive	349	6744	20
D3.2	classify on SumLedges; values above 0.7 as negative	146	2811	20
D3.3	union of D3.1 and D3.2	495	9596	20
D4.1	classify on throughput time; values below 0.7 as positive	349	6744	20
D4.2	classify on throughput time; values above 0.7 as negative	146	2811	20
D4.3	union of D4.1 and D4.2	495	9596	20

Based on the filtered data, we derive corresponding Petri nets as reference process models. The Table 1.3 lists the models with different setting. **IM-infrequent** is one variant of Inductive Miner working on event logs with infrequent traces. **Noise** is set as the threshold to filter out infrequent traces. After mining a reference model, we compare them with corresponding event logs to get the basis lines for later evaluation. As seen in

Table 1.3: Generated reference models for test

Model ID	**Used Data**	**Setting**	**Event Class**	**CM Evaluation**								
				Data	TP	FP	TN	FN	recall	precision	accuracy	F1
M1	D1	IM-infrequent: Noise Setting: 20	20	D3.3	112	40	106	237	0.321	0.737	0.440	0.447
				D4.3	131	21	128	215	0.379	0.862	0.523	0.526
M2	D1	IM-infrequent: Noise Setting: 50	20	D3.3	106	39	107	243	0.304	0.731	0.430	0.429
				D4.3	125	20	129	221	0.361	0.862	0.513	0.509
M3	D2	IM-infrequent: Noise Setting: 20	12	D3.3	0	0	146	349	0	NaN	0.295	0
				D4.3	0	0	149	346	0	NaN	0.301	0
M4	D2	IM-infrequent: Noise Setting: 50	12	D3.3	0	0	146	349	0	NaN	0.295	0
				D4.3	0	0	149	346	0	NaN	0.301	0

table above, the reference models don't apply well to the corresponding event logs. So changes on the models are in demand, to reflect better the reality and also to enforce the positive instances and avoid negative instances.

1.3.3.2 Test Result

We conduct experiments in the following types.

- **Type 1** Inductive Miner only on the positive event log to discover a model. The default setting with infrequent variant and noise threshold as 20 is chosen. Later, the mined model is checked on the labeled event with positive and negative instances. This method is abbreviated as IM.

- **Type 2** Repair Model from [2] is applied on the positive event log to discover a model. The default setting is chosen. Later, the mined model is checked on the labeled event with positive and negative instances. This method is abbreviated as Fahland, named after the name of main author.
- **Type 3** The method proposed from our thesis, is applied on the labeled event log with positive and negative instances. Default setting for the control parameters is 1.0 while the parameters to generate Petri nets from directly-follows graph are set as the same as experiment Type 1. Later, the repaired model is evaluated on the labeled data. This method is abbreviated as Dfg.

Those types are applied on event log groups of D3.1,D3.2,D3.3 and D4.1,D4.2,D4.3 listed in Table 1.2 and models from Table 1.3. The experiment result is shown in the Table 1.4.

Table 1.4: Test Result on BPI15-M1 data

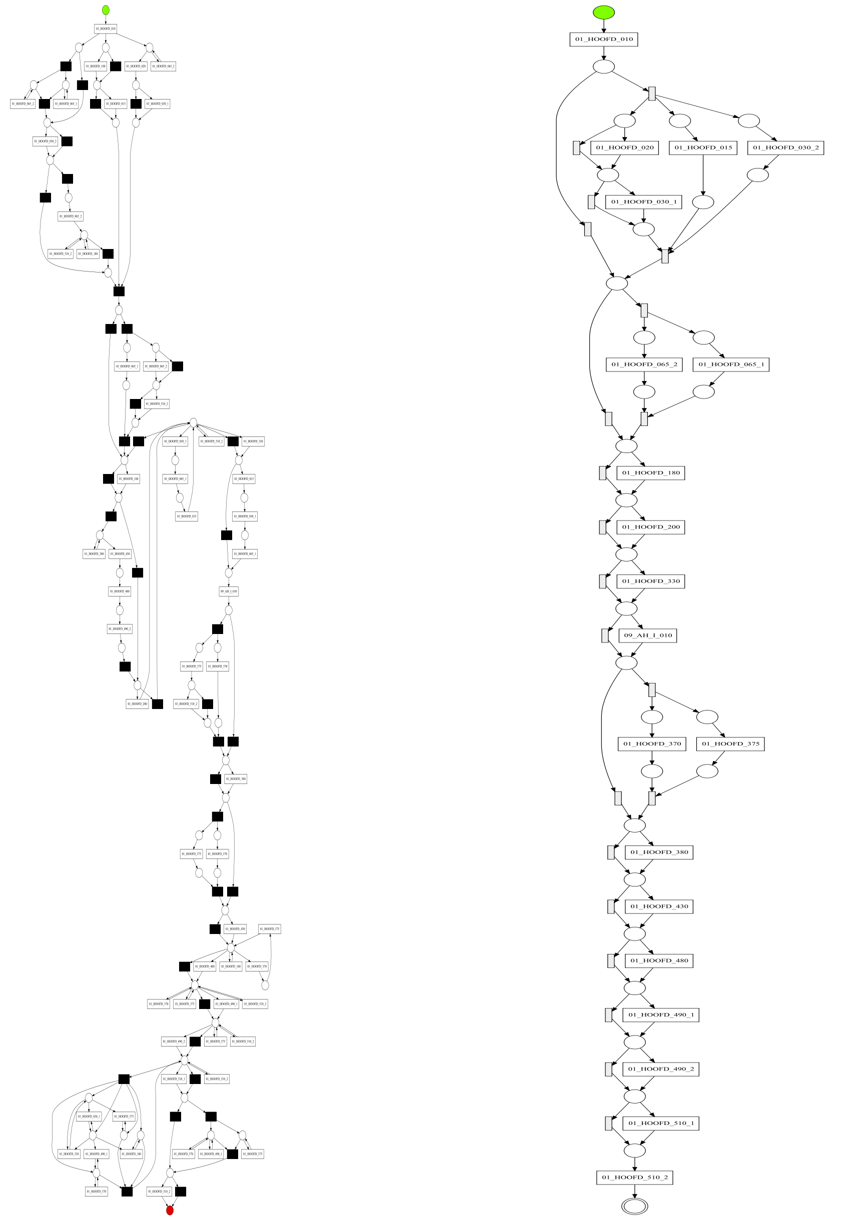
event log	reference model	method	confusion matrix metrics								traditional metrics	
			TP	**FP**	**TN**	**FN**	**recall**	**precision**	**accuracy**	**F1**	**fitness**	**precision**
D3.1	M1,M2,M3,M4	IM	137	48	118	289	0.32	0.74	0.43	0.45	?	?
D3.1	M1	Fahland	343	136	10	6	0.983	0.716	0.713	0.829	?	?
D3.3	M1	dfg	124	52	94	225	0.355	0.705	0.44	0.472	?	?
D3.1	M2	Fahland	317	133	13	32	0.908	0.704	0.667	0.793	?	?
D3.3	M2	dfg	124	52	94	225	0.355	0.705	0.44	0.472		
D3.1	M3	Fahland	349	145	1	0	1.0	0.706	0.707	0.828		
D3.3	M3	dfg	0	0	349	146	0	NaN	0.295	0		
D3.1	M4	Fahland	271	107	77	39	0.779	0.718	0.628	0.747	?	?
D3.3	M4	dfg	0	0	349	146	0	NaN	0.295	0	?	?
D4.1	M1	IM	131	21	128	215	0.379	0.862	0.523	0.526	?	?
D4.1	M1	Fahland	325	133	16	21	0.939	0.710	0.689	0.808		
D4.3	M1	dfg	139	36	113	207	0.402	0.794	0.509	0.534		
D4.1	M2	Fahland	325	130	19	21	0.939	0.714	0.695	0.811		
D4.3	M2	dfg	139	36	113	207	0.402	0.794	0.509	0.534		
D4.1	M3	Fahland	87	29	120	259	0.251	0.75	0.418	0.377		
D4.3	M3	dfg	0	0	346	149	0	NaN	0.303	0		
D4.1	M4	Fahland	63	20	129	283	0.182	0.759	0.388	0.294		
D4.3	M4	dfg	0	0	346	149	0	NaN	0.303	0		

With the similar measurements, it is observed that the repaired models from **Type 2** are more complex that Dfg method. One example is given for the tests of M1 on event log D4.1 for **Type 2** and M1 on event log D4.3.

Due to the different settings in our method, forces from the reference model, positive, and negative event logs are balanced differently during repair, which results in different process models. To investigate the effect of those setting on the repaired model, we repeat our experiments on the following setting.

Each of three control parameters for the existing model, positive and negative instances changes value from 0.0 to 1.0 with step 0.1. With this setting, directly-follows relation is generated. Afterward, the default setting of Inductive Miner Infrequent with noise threshold 20 is used to mine Petri nets from the generated directly-follows graph.

So in total, we conduct over thousand experiments to investigate our methods. Based on those results, we draw plots to show the tendency of evaluation results on the parameters



(a) repaired model $M_{1.1}$ with techniques in [2]

(b) expected model $M_{1.2}$

Figure 1.1: example for situation 1 where $M_{1.1}$ is repaired by adding subprocess in the form of loops, which results in lower precision compared with the expected model $M_{1.2}$.

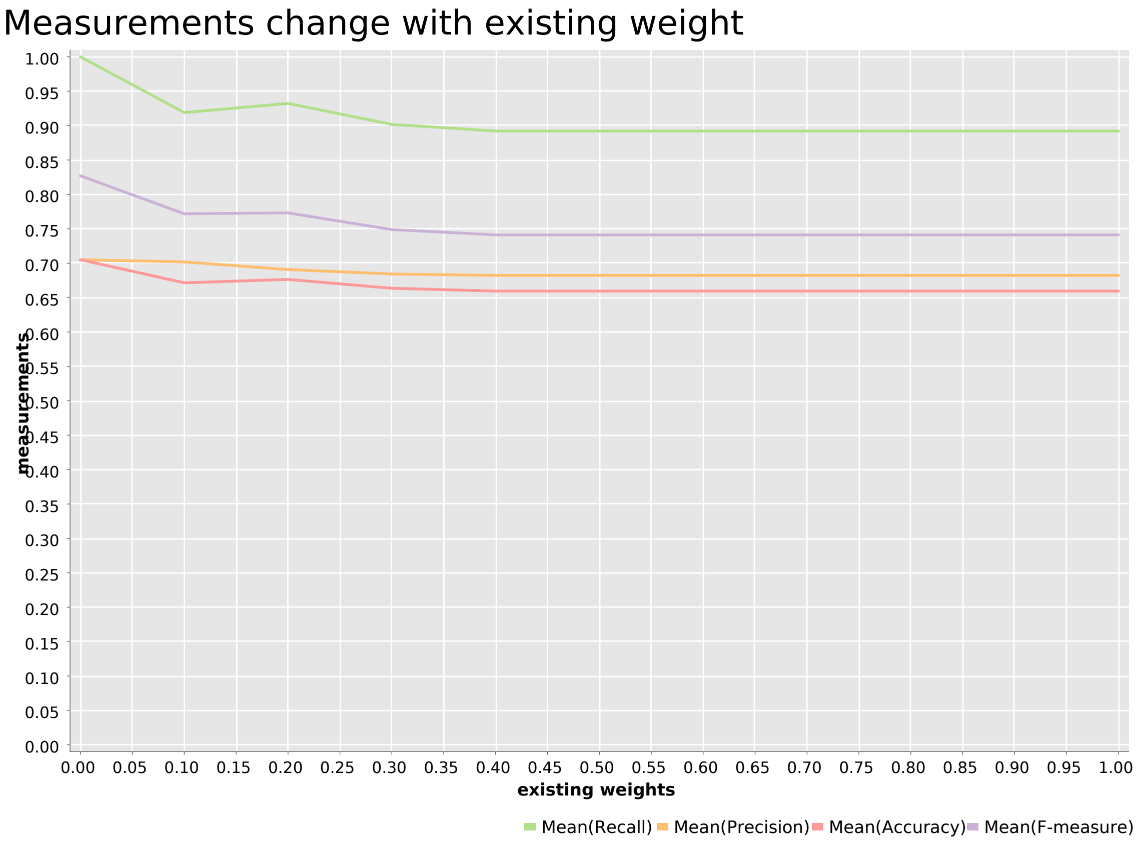


Figure 1.2: result with control parameter for existing model on event log D3.3 and model M3

for the existing model, positive and negative event logs.

From the Figure 1.2, with the parameter for the existing model going up, recall goes up while accuracy and precision goes down. The reason behind it is possibly ????.

Figure 1.3 shows that if the parameter for negative event log increases, precision and accuracy go up. By addressing negative force, our techniques tend to block behavior which leads to low performance output. However, if the negative force is over the force from positive event log and the existing model, certain behavior which contributes to positive performance will also be deleted from the models. In contrast, this creates a model with less recall.

Figure 1.4 displays the tendency with the parameter for positive event log. When the positive parameter rises, the recall increases. Precision and accuracy also increases but with ???.

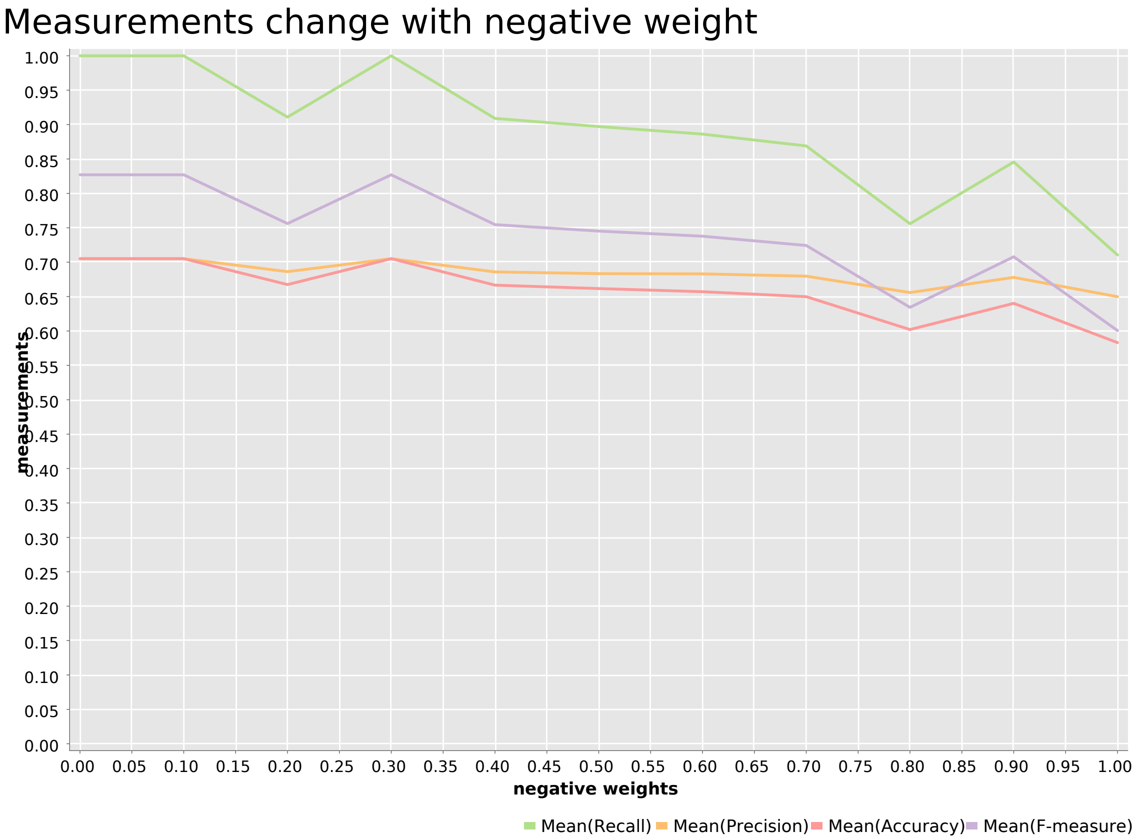


Figure 1.3: result with control parameter for negative instance on event log D3.3 and model M3

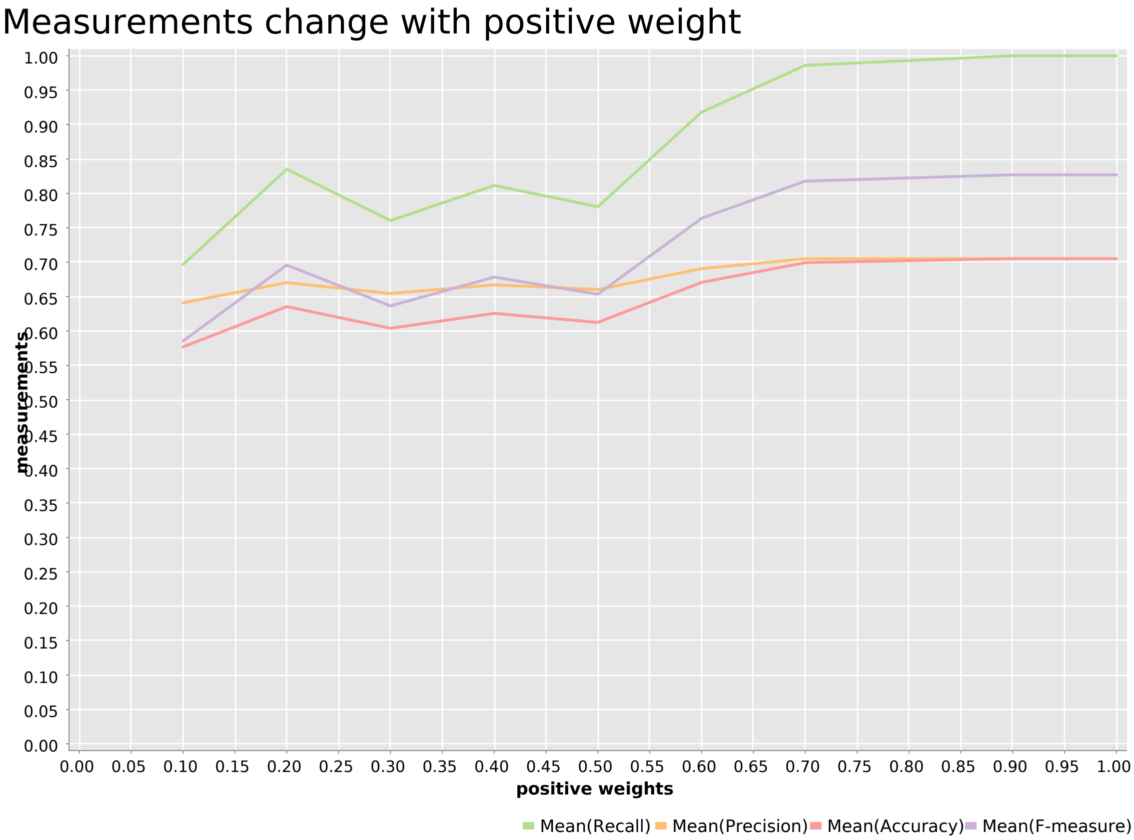


Figure 1.4: result with control parameter for positive instance on event log D3.3 and model M3

Chapter 2

Conclusion

In this thesis, we explore ways to use negative information in model repair and propose our innovative method. Firstly, we analyzed the current techniques on model repairs based on performance and detect their shortcomings. Then we proposed a general framework to incorporate the forces from the existing model, positive and negative event logs. Three abstraction data models in the same type are built to represent those forces. Later, forces are balanced based on data models and expressed in a new data model. From this new data model, process models are discovered and converted into repaired models with the required type. Optional post processes include long-term dependency detection and silent transition reduction, which further improves the repaired model.

Moreover, we demonstrate the usage of our method by conducting experiments with real life data. Our method is able to provide better repaired models than other repair methods in some situations. Also, with respect to other methods, it runs faster and generates simpler models.

Future work might be to improve the rules of balancing different forces, which choose the directly-follows relation on the simple subtraction and sum of those forces. Advanced data mining techniques such as association rules discovery, and Inductive Logistic Programming can be used on those forces to derive rules for building a process model. The same improvement can be applied on the long-term dependency discovery. Moreover, in this implementation, the long-term dependency discovery is restricted on the activities with exclusive choices relation. Later, we should extend the long-term discovery on other possible relations, like parallel relation. Also, we can drop the process tree as our intermediate result and adopt it directly on the Petri net.

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