Model Repair by Incorporating Negative Instances In Process Enhancement

Master Thesis

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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

In this chapter, we evaluate the proposed repair techniques based on the quality of repaired model. 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, and the other is on the real life data.

1.1 Evaluation Criteria

We evaluate the 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 how well the model reproduces traces in the event log which is used to build the model.
- *Precision.* It quantifies 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 the environment where only positive instances are available. Therefore, when it comes to the model performance, where negative instances are also possible, the measurement metrics need to 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 and confusion matrix is applied in our experiments.

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

Table 1.1: Confusion Matrix

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

actual classification on data. As seen as a binary classifier, the repaired model produces four outcomes according to confusion matrix – true positive, true negative, false positive and false negative, which is shown in the Table 1.1.

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

Various measurements can be derived from confusion matrix. According to our application, the following criteria are chosen. Generally, there is a trade-off between the quality criteria. So the measurements below are only used to evaluate specific aspects of repair techniques.

- 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.

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

1.2 Experiment Platforms

KNIME, as a scientific workflow analytic platform, supports automation of test workflow, which helps us repeat experiments efficiently. Yet, the integration of traditional process mining plugins into KNIME is out of our capability due to the time limit. Therefore, partial experiments with current repair techniques are still 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. Two nodes *Loop Start* and *Loop End* explicitly express the beginning and end of a loop structure, where the workflow between those two node is the loop body and 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 parameterize node settings dynamically. When it combines with loop control structure, tests with different settings is able to conduct automatically.

Furthermore, there are nodes provided by KNIME to optimize the value of some parameters with respect to a cost function. As long as the cost function is provided, KNIME is able to automatically optimize the corresponding parameters.

1.2.2 Experiments with ProM Plugins

Due to the frequent errors on the corresponding plugin, we exclude the tests on repair techniques in [4] and conduct experiments with 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 [5] 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 Dfg-Repair 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.

1.3 Experiment Results

We conduct our experiments into two main parts. One is to verify if our method overcomes the limits of current repair algorithms. This experiment is based on the synthetic data and models from Introduction chapter. The other experiment is based on real life data, in order to test the feasibility of our repair techniques.

1.3.1 Test on Demo Example

In this part, experiments are performed on the motivating examples which are listed in Introduction. Thereby, we are able to answer whether our repair method overcomes shortcomings of current techniques which are shown in the introduction chapter.

1.3.1.1 Answer to Situation 1

Situation 1 shows the drawbacks of current repair methods [4, 5] that unexpected behaviors are introduced into model by adding subprocess in the form of loops. Moreover, rediscover strategy with IM doesn't take the original model into account and generates a new model that deviates from the original model.

Given the process model M_0 and the event log L_1, additional activities **x1,x2** in L_1 lead to good performance and need to be added into the model M_0. Applying proposed repair techniques dfg-repair, we obtain the repaired model listed in Figure 1.1a. The parameters for our method are set in the following : weight for the existing model is 0.45, weight for positive examples is 1.0, the Inductive Miner for Infrequent is chosen and has a noise with 20, which is the same setting as the rediscovery method by Inductive Miner in Introduction.

As seen in Figure 1.1a, the subprocesses for **x1,x2** are added in a sequence with others. In this way, $M_{1.3}$ is able to reflect the deviations in positive instances while keeping similar to the reference model M_0. Compared to techniques in [5], it increases the precision without loops.

1.3.1.2 Answer to Situation 2

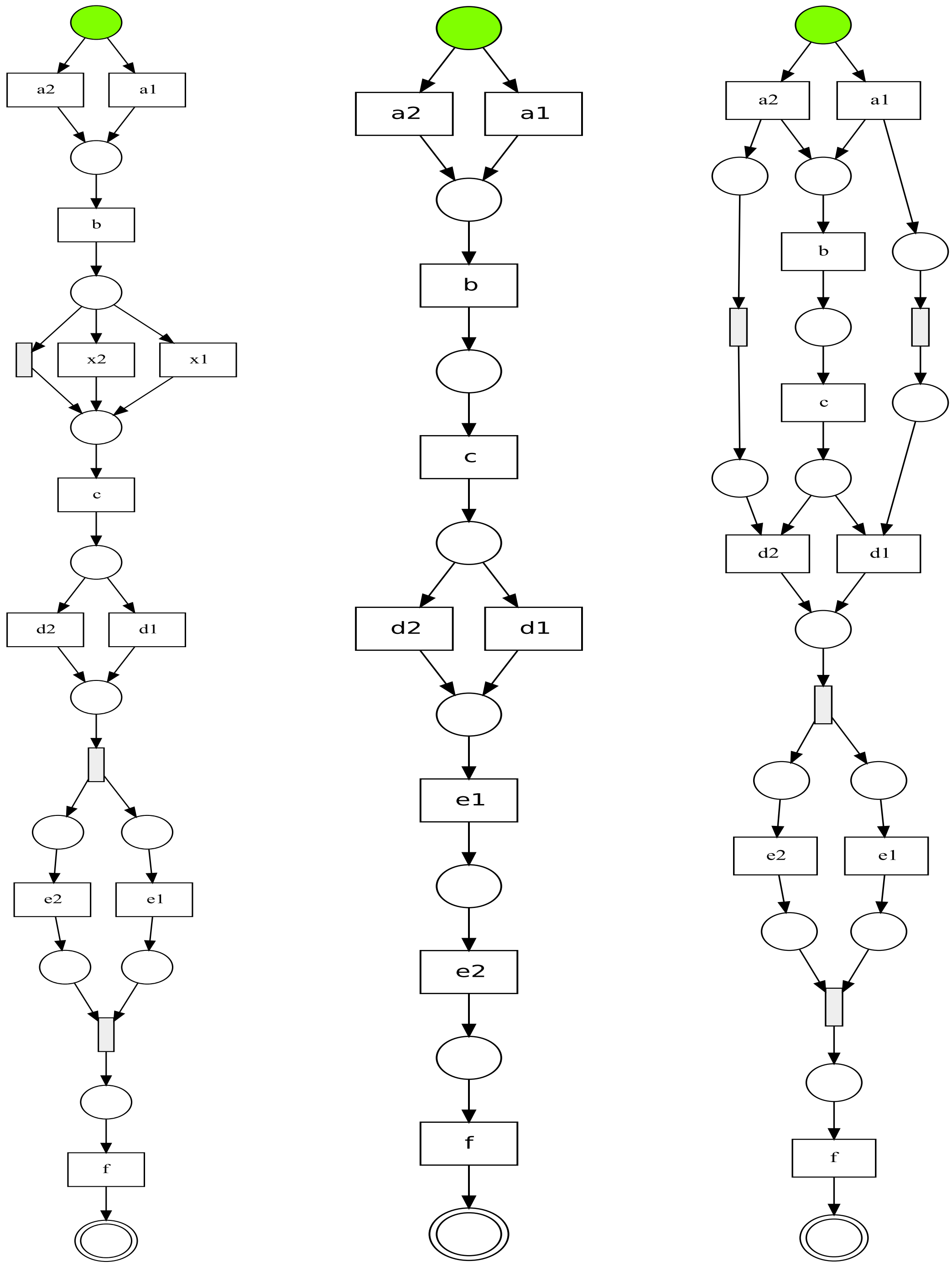
Situation 2 describes the inability of current repair methods that fitting traces with negative performance outcomes cannot be used to repair a model. The execution order of **e1, e2** affects the performance outcomes and **e1** is expected to position before **e2**. Without negative information, the repaired models have the same structure as the reference one~~s~~, because the execution of **e2** before **e1** brings also the positive outcomes.

If we apply our repair methods on the model M_0 and event log L_2, with 1.0 for all control weights, and the same Inductive Miner-Infrequent with noise 20, the repaired model $M_{2.3}$ is obtained. In $M_{2.3}$, **e1** is executed before **e2**. It shows that our method is able to incorporate the negative information and balance the forces from the existing model, positive and negative instances.

1.3.1.3 Answer to Situation 3

Situation 3 concerns the long-term dependency in Petri nets, which is not handled in current repair and rediscovery techniques. As observed in event log, there exists the long-term dependency set, $LT = \{a1 \rightsquigarrow d1, a2 \rightsquigarrow d2\}$. With adding long-term dependency as expected in Figure **??**, precision and accuracy increase, since the model limits activity selection and blocks the negative behavior due to free execution of xor branches. Yet none of the current repair and rediscovery techniques are able to detect and add long-term dependencies in the Petri net.

In our repair techniques, the long-term dependency is taken into account with negative information. With ~~inputs of the~~ Petri net M_0 and event log L_3, our methods produce~~s~~ the repaired model $M_{3.3}$ with long-term dependency. Two silent transitions that are used to explicitly represent the long-term dependencies can be deleted with post procedure to reduce the redundant silent transitions and places. After reduction, our repaired model is simplified as the model M_3.



(a) $M_{1.3}$ for situation 1 (b) $M_{2.3}$ for situation 2 (c) $M_{3.3}$ for situation 3

Figure 1.1: repaired models with our techniques for situation 1,2 and 3 in Introduction part. The green place is the initial marking of the Petri net and the doubled place is the final marking.

1.3.1.4 Comparison with Confusion Matrix

In this section, we list the evaluation results of the repaired models based on confusion matrix. In Table 1.2, for Situation 1 with only positive instances, the repair techniques give the same confusion matrix result. However, $M_{1.2}$ with loops implicates a lower precision. In Situation 2, with current techniques or rediscovery methods in IM, the model stays the same as the reference model M_0. Since no negative instance is rejected, the recall is 1 but precision is below 0.6. In comparison, dfg-repair uses the negative instances and adjusts the model correspondingly. Therefore, the repaired model $M_{2.3}$ has higher precision, accuracy and F1 score. In Situation 3 with long-term dependency, our method succeeds to detect and add the long-term dependency in the model. In this way, no false positive or false negative instances are in the confusion matrix, and the repaired model holds the highest values for all listed measurements.

Table 1.2: Test Result on BPI15-M1 data

Situation	method	Generated model	confusion matrix metrics							
			TP	**FP**	**TN**	**FN**	**recall**	**precision**	**accuracy**	**F1**
S1	IM	$M_{1.1}$	50	50	0	0	1	0.5	0.5	0.667
S1	Fahland	$M_{1.2}$	50	50	0	0	1	0.5	0.5	0.667
S1	Dfg-repair	$M_{1.3}$	50	50	0	0	1	0.5	0.5	0.667
S2	IM/Fahland	M_0	60	45	0	0	1	0.571	0.571	0.727
S2	Dfg-repair	$M_{2.3}$	50	5	40	10	0.833	0.909	0.857	0.870
S3	IM/Fahland	M_0	100	100	0	0	1.0	0.5	0.5	0.667
S3	Dfg-repair	$M_{3.3}$	100	0	100	0	1	1	1	1

In conclusion, our proposed method is able to overcome shortcomings of current techniques mentioned in the Introduction. It avoids the loops in model by repairing the model with additional activities, incorporates the negative information in the data to adjust the model, also detect and add the long-term dependency into model. In this way, the repaired model has better recall~~,~~ and accuracy.

1.3.2 Test on Real Life Data

We choose publicly available event logs from BPI challenge 2015 and build a data set from them to test the feasibility of proposed repair techniques.

1.3.2.1 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 the 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 include~~s~~ 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.

We conduct our experiments on those event logs. However, due to the time limits, we only managed to get the result on experiments with the event log **BPIC15_1.xes.xml**. This event log includes 1199 cases and 52217 events in 398 classes. We preprocess the event log and get a proper subset of data as our user case.

Table 1.3: 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

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 1.3 available for our tests.

Based on the filtered data, we derive corresponding Petri nets as reference process models. The Table 1.4 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 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.

Table 1.4: 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

1.3.2.2 Test Result

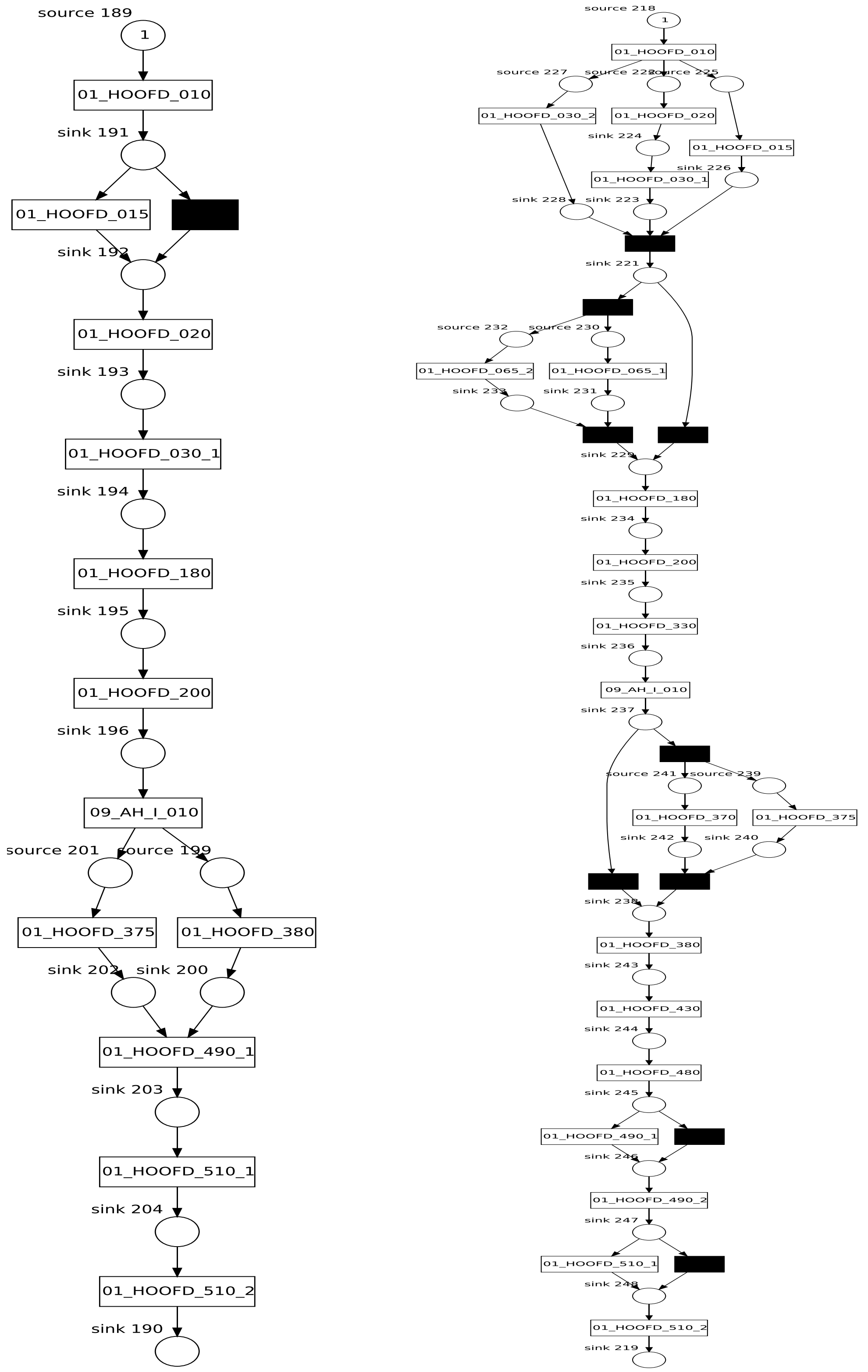
Three types of repair techniques which are **IM**, **Fahland** and **Dfg-repair**, are applied on preprocessed event log set in Table 1.3 and models from Table 1.4. The experiment result is listed in the Table 1.5. For better understanding, we give the details of one experiment set which is conducted with the reference model M3 and event log D3.1 and D3.3.

Figure 1.2a displays the reference model M3, which has 0 TP and 0 FP compared to D3.3. It implies that M3 leads to no positive performance outcome~~s~~. Firstly, the rediscovery technique~~s~~ – Inductive Miner for infrequent traces with noise threshold 0.2 is used on the positive event log D3.1 to rediscover a model. The generated model is shown in Figure 1.2b, which has changed a lot compared to the original model M3 as shown in the Figure 1.2a. After getting the generated model, we compare it with labeled event log D3.3 and compute the confusion matrix ~~criteria~~ as a baseline for our comparison.

After applying the Fahland's repair techniques from [5], the reference model M3 is repaired as ~~in~~ Figure 1.3a. With duplicated transitions, loops and silent transitions for ~~adding~~ subprocesses, it is more complicated than the reference model M3. When evaluating the repaired model with confusion matrix, we get 349 TP, 145 FP, 1 TN, and 0 FN, which leads to high recall. However, ~~it needs to notice that~~ the principle of Fahland repair techniques is to add subprocesses for deviations in the model. Without consideration of eliminating negative behavior, the repaired model is likely to damage the model precision and accuracy.

Dfg-repair techniques are firstly applied with the default setting, 1 for all control parameters. It results in a model with 0 TP, 0 FP, 146 TN, and 349 FN, which contrasts the result by Fahland repair techniques. This is probable because the forces from the existing model and negative instances exceed the positive force, and block~~s~~ behavior with positive outcomes.

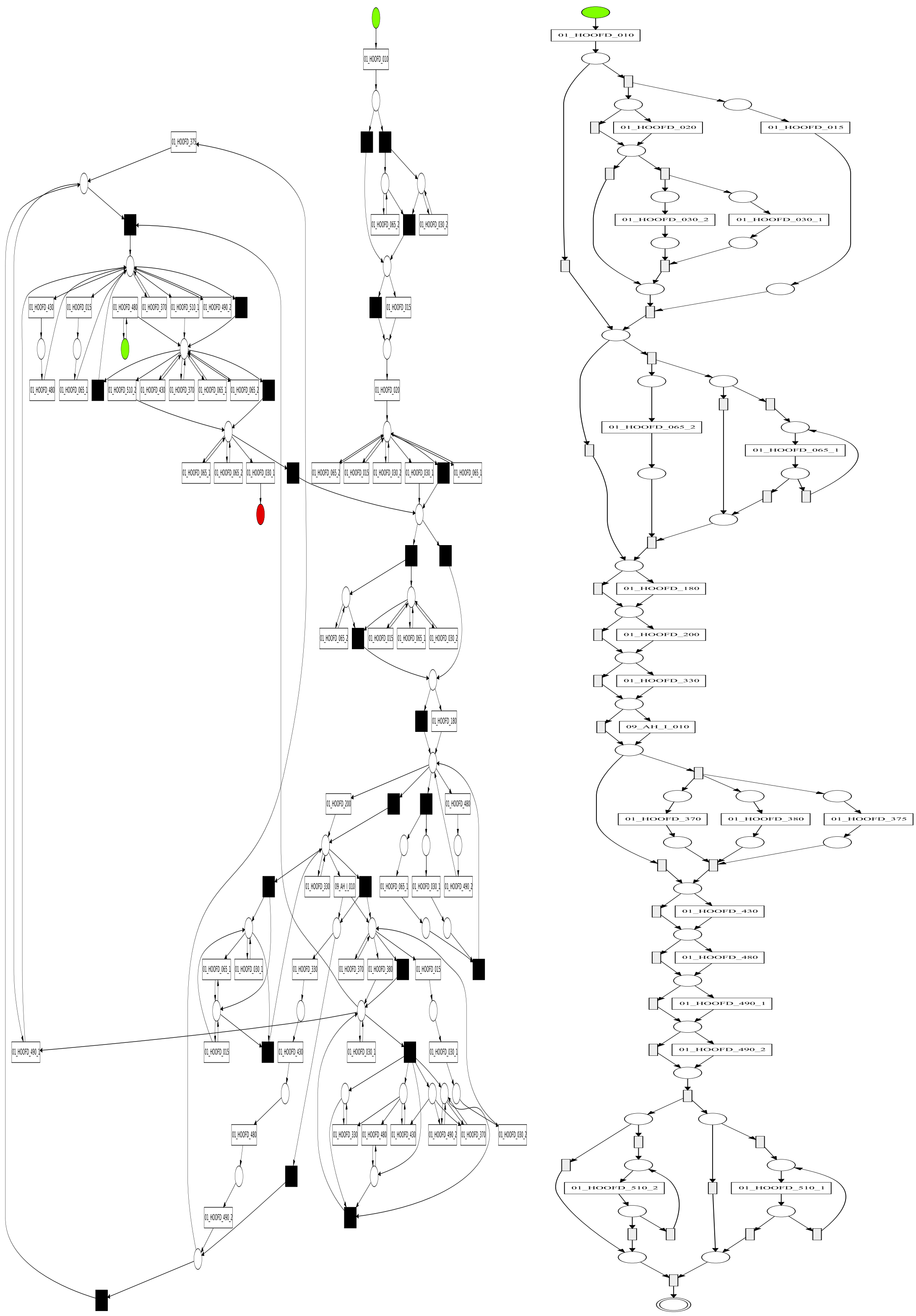
As a comparison, we change the control parameter setting to 0.5 for the existing model, 1 for the positive instances, 0.5 for the negative instances. After repeating the experiment, the confusion matrix changes to 131 TP, 63 FP, 83 TN, and 217 FN, while recall increases from 0 to 0.378, accuracy from 0.294 to 0.428, and F1 from 0 to 0.485. Apparently, the quality is improved due the the new setting. The possible reason is that three forces are balanced more properly for the repaired model.



(a) reference model M3

(b) repaired model with IM

Figure 1.2: The left model is the reference model M3. The rediscovery algorithm IM generates a new model based on the positive instances which is shown in the right side.



(a) repaired model with Fahland　　(b) repaired model with Dfg-repair

Figure 1.3: Repaired model for M_3 based on event log D3.1 with positive instances for Fahland's repair techniques while event log D3.3 with both positive and negative instances for Dfg-repair. The weight setting for Dfg-repair is 0.5 for the existing model, 1 for positive and 0.5 for negative instances. Default setting is chosen for Fahland's method.

Table 1.5: Test Result on BPI15-M1 data

event log	**reference model**	**method**	**confusion matrix metrics**							
			TP	**FP**	**TN**	**FN**	**recall**	**precision**	**accuracy**	**F1**
D3.1	-	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-repair:1-1-1	124	52	94	225	0.355	0.705	0.44	0.472
D3.3	M1	Dfg-repair:0.5-1-0.5	155	66	80	194	0.444	0.701	0.474	0.544
D3.1	M2	Fahland	317	133	13	32	0.908	0.704	0.667	0.793
D3.3	M2	Dfg-repair:1-1-1	124	52	94	225	0.355	0.705	0.44	0.472
D3.3	M2	Dfg-repair:0.5-1-0.5	155	66	80	194	0.444	0.701	0.475	0.544
D3.1	M3	Fahland	349	145	1	0	1.0	0.706	0.707	0.828
D3.3	M3	Dfg-repair:1-1-1	0	0	146	349	0	NaN	0.295	0
D3.3	M3	Dfg-repair:0.5-1-0.5	132	63	83	217	0.378	0.677	0.434	0.485
D3.1	M4	Fahland	349	144	2	0	1.0	0.708	0.709	0.829
D3.3	M4	Dfg-repair:1-1-1	0	0	146	349	0	NaN	0.294	0
D3.3	M4	Dfg-repair:0.5-1-0.5	125	59	87	224	0.358	0.679	0.428	0.469
D4.1	-	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-repair:1-1-1	139	36	113	207	0.402	0.794	0.509	0.534
D4.3	M1	Dfg-repair:0.5-1-0.5	172	48	101	174	0.497	0.782	0.552	0.608
D4.1	M2	Fahland	325	130	19	21	0.939	0.714	0.695	0.811
D4.3	M2	Dfg-repair:1-1-1	139	36	113	207	0.402	0.794	0.509	0.534
D4.3	M2	Dfg-repair:0.5-1-0.5	172	48	101	174	0.497	0.782	0.552	0.608
D4.1	M3	Fahland	87	29	120	259	0.251	0.75	0.418	0.377
D4.3	M3	Dfg-repair:1-1-1	0	0	346	149	0	NaN	0.303	0
D4.3	M3	Dfg-repair:0.5-1-0.5	182	49	164	100	0.526	0.788	0.70	0.631
D4.1	M4	Fahland	63	20	129	283	0.182	0.759	0.388	0.294
D4.3	M4	Dfg-repair:1-1-1	0	0	346	149	0	NaN	0.303	0
D4.3	M4	Dfg-repair:0.5-1-0.5	172	48	101	174	0.497	0.782	0.552	0.608

Overview all the results in Table 1.5, Fahland's repair techniques from [5] tend to have high recall but low values for true and false negative. The possible reasons are that (1) it repairs the reference model with the positive instances, which addresse~~s~~ the fitness of positive traces. (2) it repairs the model by adding subprocesses and introduces more behavior into the model, which also allows ~~for~~ the negative instances. Inductive Miner rediscovers a new model from the given positive instances, while the reference models are simply ignored. As a result, the generated model in Figure 1.2b has changed a lot compared to the original model M3 ~~as~~ shown in ~~the~~ Figure 1.2a.

Dfg-repair techniques uses control parameters to balance the forces from the existing model, positive and negative instances. Therefore, with different setting, Dfg-repair techniques repair the model in different ways. To address this phenomenon, besides the default setting with value 1 for all parameters, another setting with 0.5 for the existing model, 1 for the positive instances, 0.5 for the negative instances is used to conduct experiments. Compared to the default setting, the setting with values 0.5, 1 and 0.5 results in models with higher recall, accuracy, and F1 score. The reasons behind might be that the force from negative instances affects model a lot, with the weight 1.0. It possibly blocks the behavior which contributes to positive performances. With lower value on it, the forces from the existing model, positive and negative are balanced better and the quality of the repaired model is improved. As an example, the experiments on D3.3 and M3, or D.3. and M4, ~~which~~ show~~s~~ the quality changes due to different setting.

Except for the weight for negative instances, the weights for the existing model and positive instances also affect the quality of repaired model. To investigate the effect of those weights on the repaired model, we conduct~~s~~ our experiments with the following settings.

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. In total, 1000 experiments are conducted with proposed Dfg-repair method. After filtering out the data with missing value NaN, we average the confusion matrix results fixed with the analyzed weight, and draw plots to show the tendency of evaluation results on the weight for the existing model, positive and negative event logs, respectively.

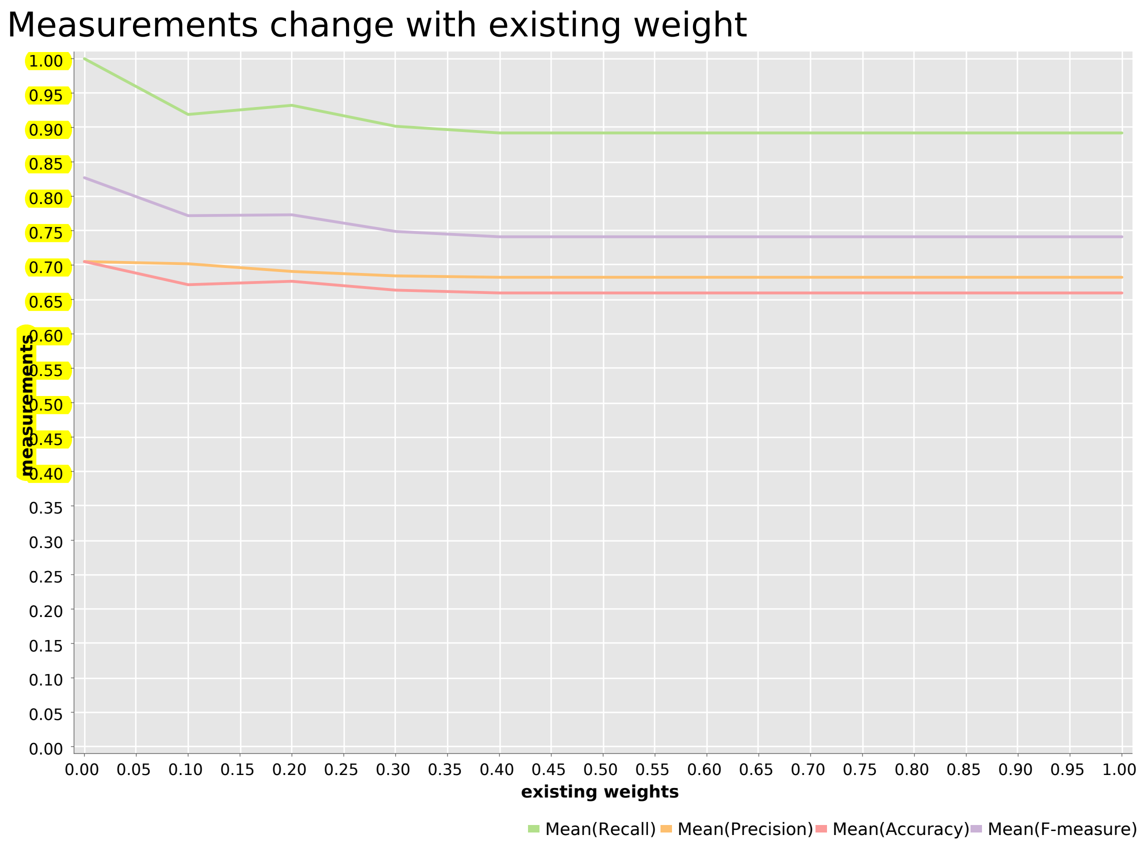


Figure 1.4: result with control parameter for existing model on event log D3.3 and model M3

For the experiments on From ~~the~~ Figure 1.4, ~~with~~ the parameter for the existing model go~~ing~~ up, recall, accuracy and F1 go down firstly and then become stable. Because the reference model M3 leads to block positive behavior from model, with the weight for the existing model going up, the force to keep the model as M3 increases. Thereby, the repaired model fits less positive instances and the recall goes lower.

Figure 1.5 displays the tendency with the weight for positive event log. When the weight rises, recall, precision and accuracy increase. The reason might be the forces from the existing model and negative event logs tend to block the positive behavior. With higher values,

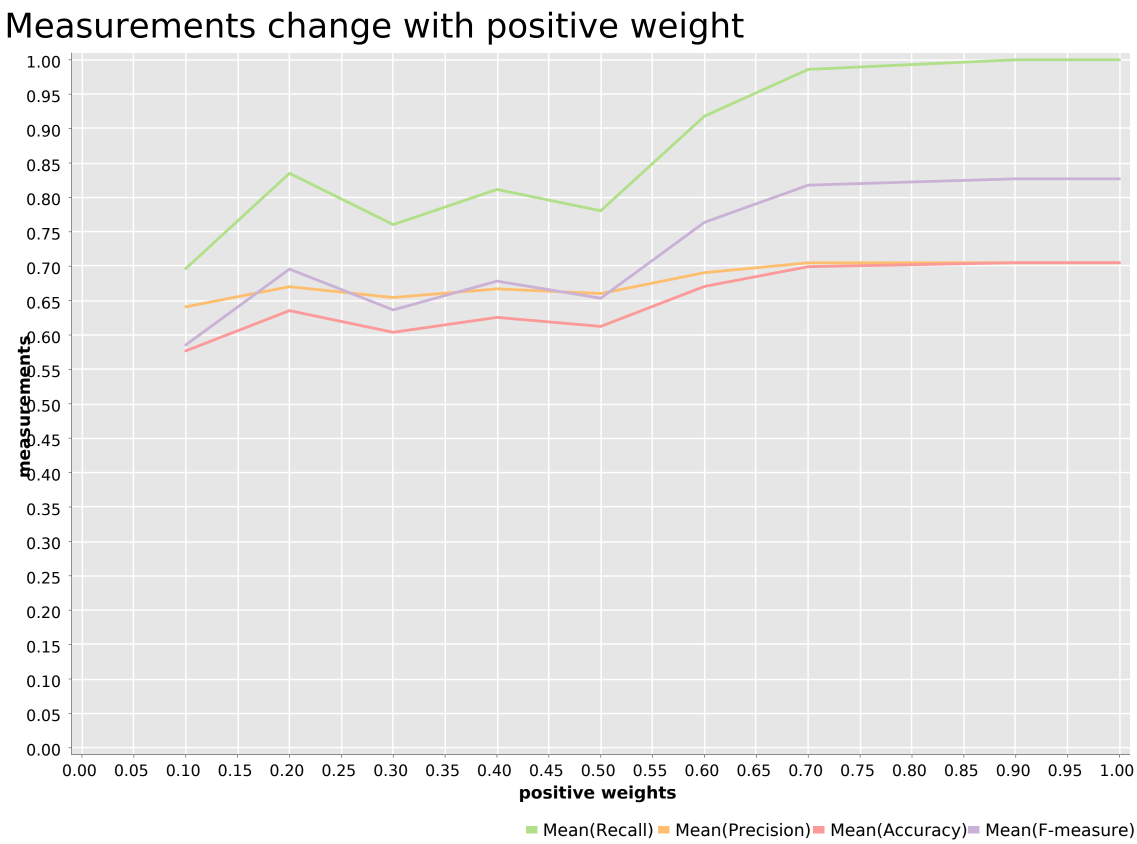


Figure 1.5: result with control parameter for positive instance on event log D3.3 and model M3

the force for the positive instances adjusts the model with better balance. Therefore, as the weight for positive event log increases, the repaired model allows ~~for~~ more positive behavior and leads to the increase of all criteria related to confusion matrix.

Figure 1.6 shows the tendency with the weight for negative event log. With lower value, the weight leads to higher recall, precision and accuracy. The negative force is possibly over the force from positive event log. When the weight increases, behavior which contribute~~s~~ to positive performance ~~is~~ likely to ~~deleted~~ from the models. In this way, the measurements go down with the weight going up.

By applying our proposed method in the real life data, it is feasible to repair model in reality. Compared to IM with the same rediscovery setting, it is able to output models with higher recall, accuracy and F1 score. At the same time, it keeps the models as similar to the reference models, while IM simply ignores the reference models. Compared to Fahland repair techniques, which bring more behavior into the model and cause high values with TP and FP, Dfg-repairs takes negative information into account and can produce models with higher values in TN. Moreover, the repaired models from Dfg-repair are simpler than the ones from Fahland repair techniques. With observation, Dfg-repair also runs faster. Yet, we need to notice that the optimal control parameter setting differs in various situations. Trials is in demand to find the optimal setting.

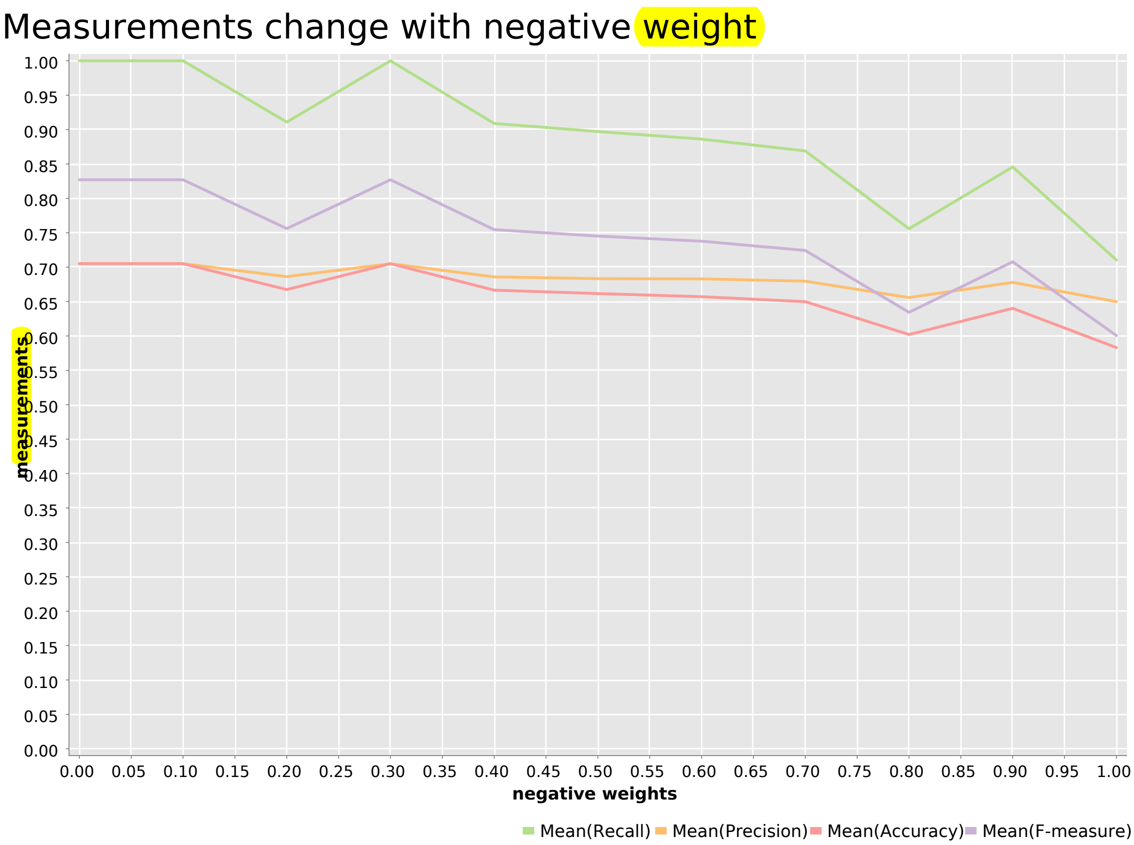


Figure 1.6: result with control parameter for negative instance on event log D3.3 and model M3

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 synthetic data and real life data. In the situations shown with synthetic data, our method is able to overcome the shortcomings of the current repair techniques and provide repaired models with higher accuracy and precision. In experiments with the real life data, Additionally, with respect to other methods, it runs faster and generates simpler models.

As future work, we consider improving 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. Also, we can drop the process tree as our intermediate result and adopt it directly on the Petri net.

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