Master Thesis

Process Enhancement by Incorporating Negative Instances in Model Repair

Author: **Kefang**

Email: **kefang.ding@rwth-aachen.de**

Supervisor: Dr. Sebastiaan J. van Zelst

Examiners: Prof. Wil M.P. van der Aalst
Prof. Thomas Rose

Institute: Lehrstuhl für Process and Data Science

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Outline

- **Research Scope**
- **Literature Review**
- **Problem Definition**
- **Algorithm**
  - Framework
  - Design
- ~~**Implementation**~~
- **Evaluation**
- **Conclusion**
- ~~**Appendix**~~
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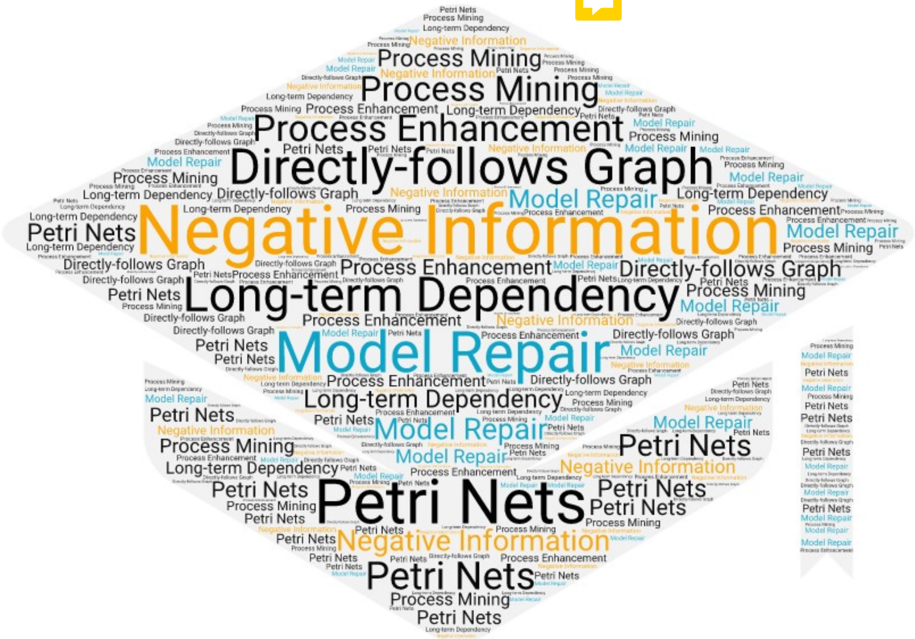
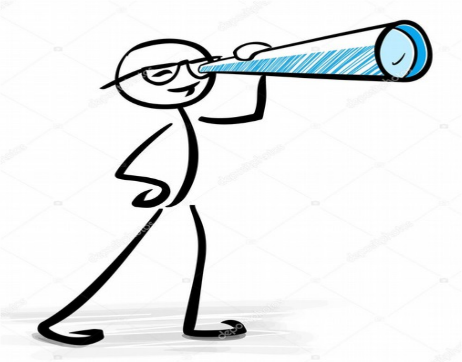
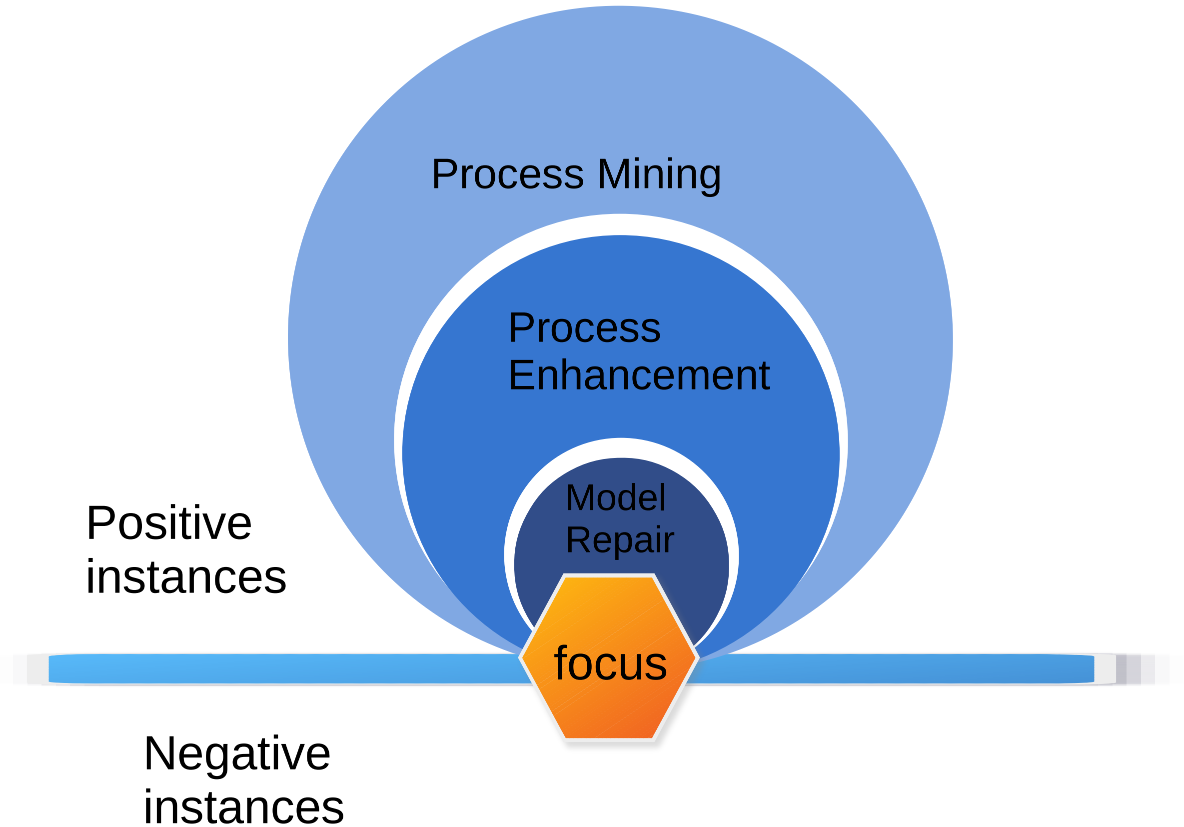
  - ~~Support Plugin Development~~



Scope

- ~~Process Mining~~
- ~~Process Enhancement~~
  - ~~Reference model~~
- ~~Model repair~~
  - ~~Fitness~~
  - ~~Similarity~~
- ~~Performance~~
  - ~~Negative instances~~





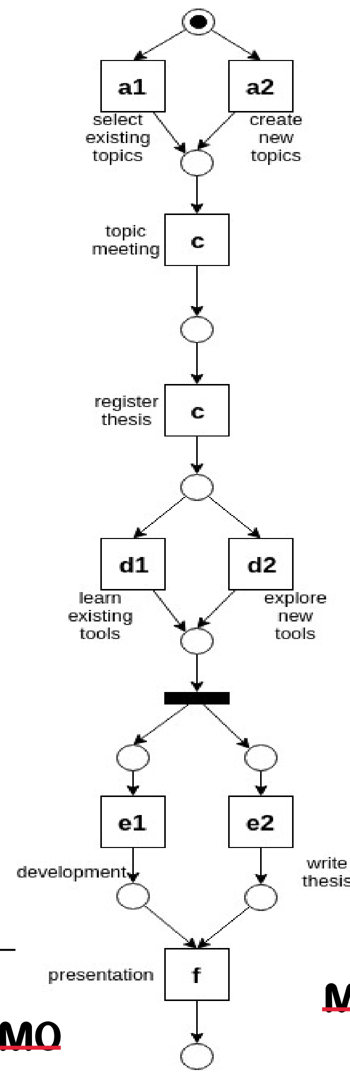
Literature Review

- **Rediscovery**
  - Inductive Miner
- **Model Repair by Fahland**
  - Deviations
  - Subprocesses
- **Model Repair by Dees**
  - Data with performance labels
  - Classify deviations
  - Fahland’s repair only on positive deviations

Research Problem – shortcominngs

$$L_1 := \{< a1, b, \mathbf{x1}, c, d1, e1, e2, f >^{50,pos}, \\ < a1, b, \mathbf{x2}, c, d2, e1, e2, f >^{50,pos}, \}$$

- **IM not consider reference model**
  - Inductive Miner- Infrequent
  - Noise threshold: 20%
- **Fahland's: add subprocesses as loops**
  - Default setting
  - Deviation found at same place
  - Subprocesses as loops
- **Dee's: same as Fahland's method**
- **Similarity, Precision decrease**



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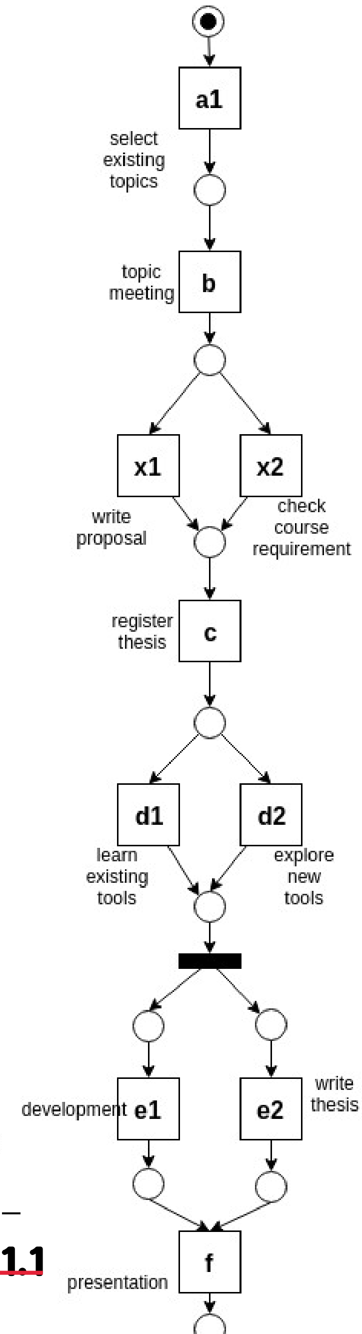
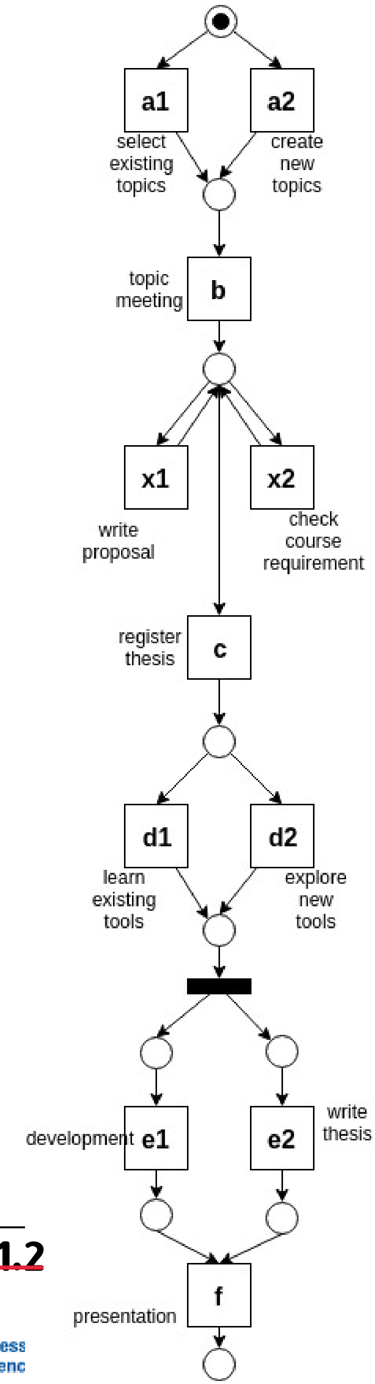


M1.1

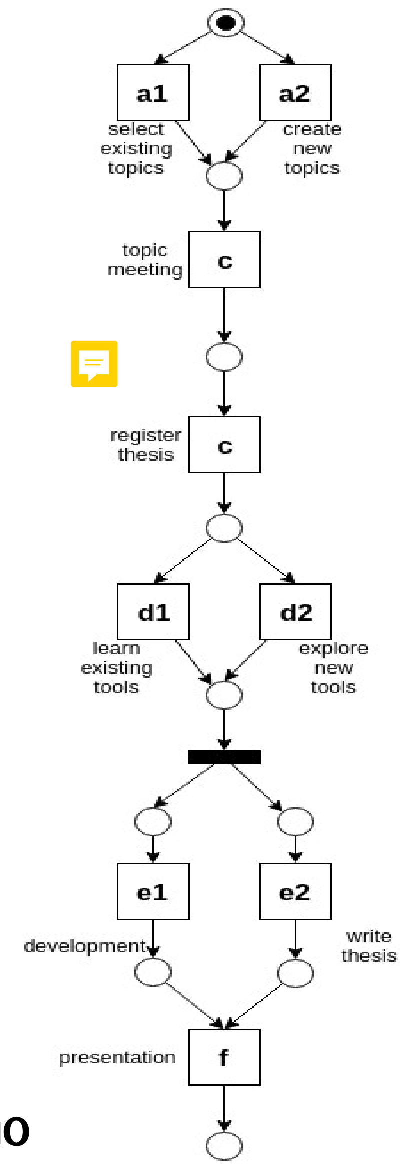


M1.2

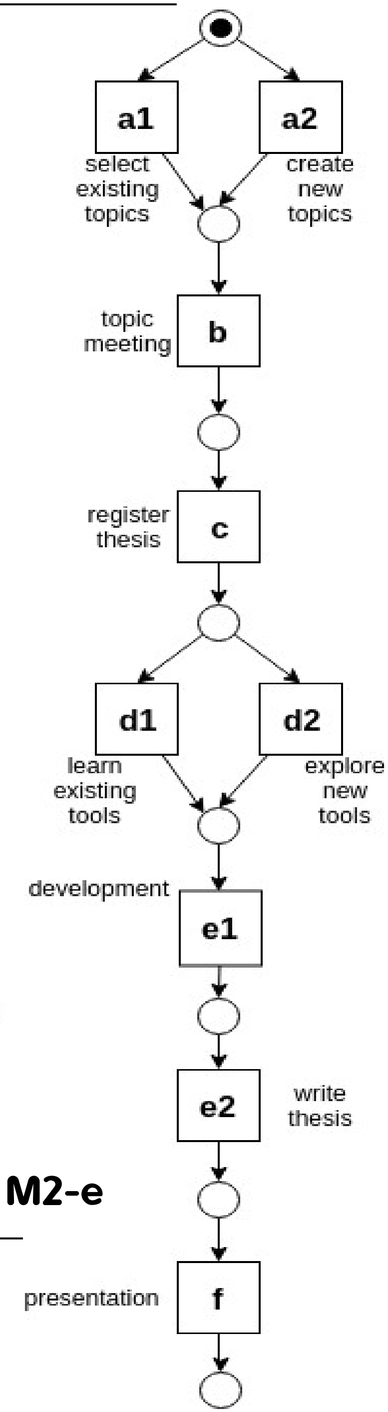
Research Problem – shortcomings

$$
\begin{aligned}
L_2 := \{ &< a1, b, c, d2, \mathbf{e1}, \ \mathbf{e2}, f >^{30,pos}, \\
&< a2, b, c, d1, \mathbf{e1}, \ \mathbf{e2}, f >^{20,pos}; \\
&< a2, b, c, d2, \mathbf{e2}, \ \mathbf{e1}, f >^{10,pos}; \\
&< a1, b, c, d2, \mathbf{e2}, \ \mathbf{e1}, f >^{20,neg}, \\
&< a1, b, c, d1, \mathbf{e2}, \ \mathbf{e1}, f >^{20,neg}; \\
&< a2, b, c, d1, \mathbf{e1}, \ \mathbf{e2}, f >^{5,neg} \}
\end{aligned}
$$

- **IM keeps the model same**
- **Fahland's keep model same**
- **Dee's keep model same**
- **Unable to adapt model with fit traces**



M0



M2-e

Chair of Process and Data Science

Research Problem – shortcomings

$$
\begin{aligned}
L_3 := \{ &< \mathbf{a1}, b, c, \mathbf{d1}, e1, e2, f >^{50,pos}, \\
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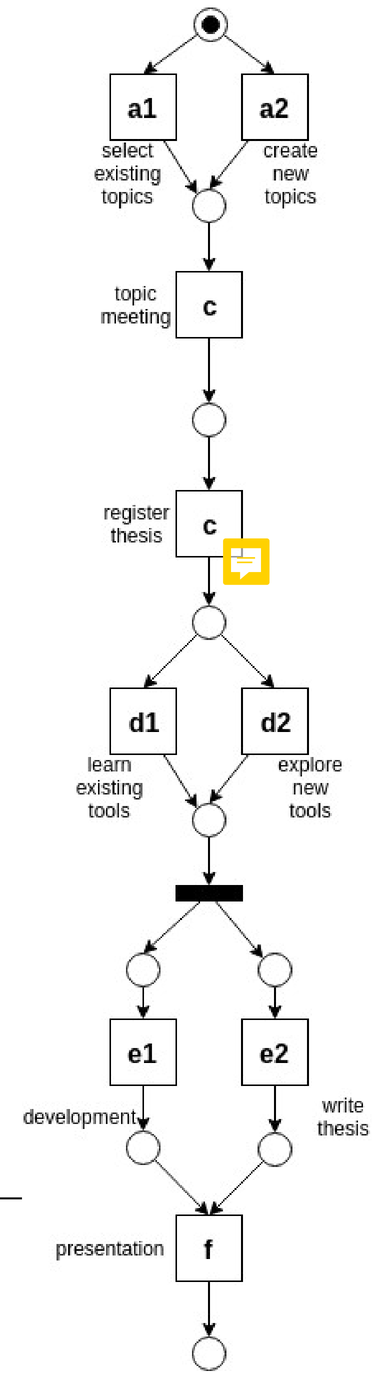
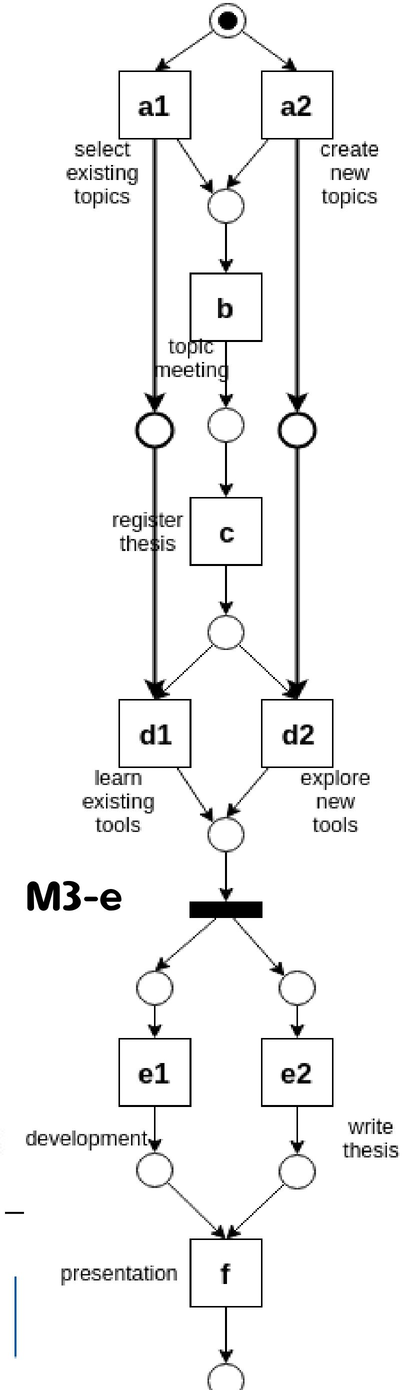
&< \mathbf{a2}, b, c, \mathbf{d1}, e1, e2, f >^{50,neg} \}
\end{aligned}
$$

- **Long-term dependency**
  - Choices decides choices
  - Additional places to limit behavior

→ **Unable to detect long-term dependency**

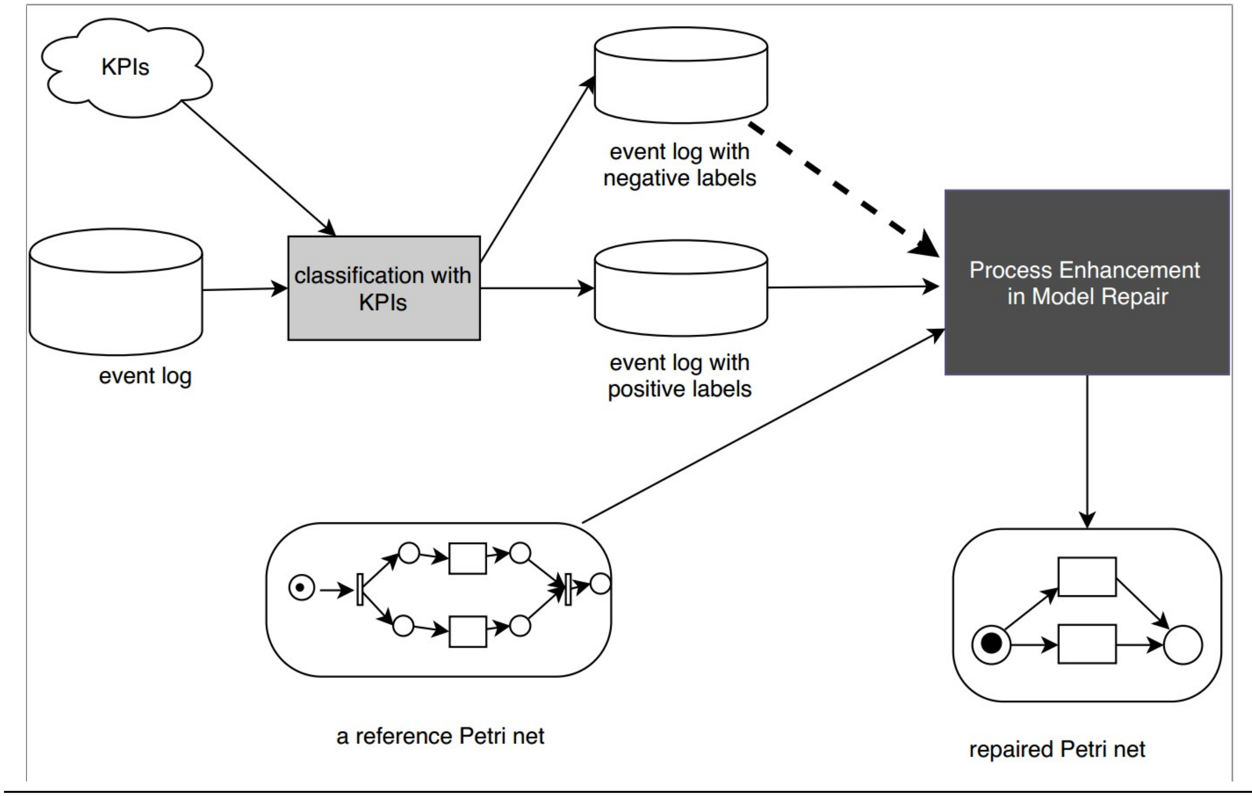
M0





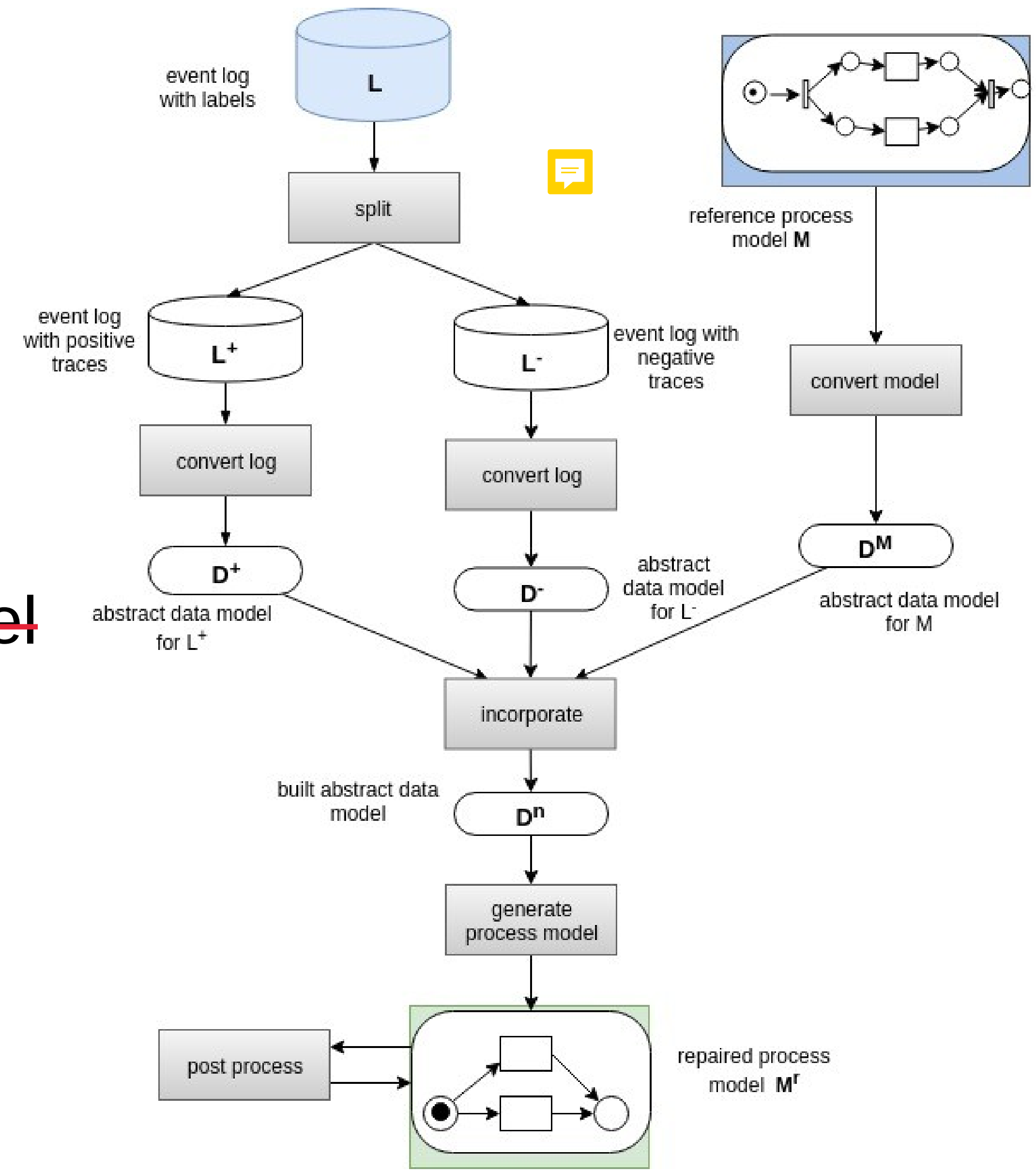
Research Problem

Given an **event log with labels**, a **reference Petri net**, how to incorporate **negative instances** to generate the **repaired Petri net** which supports better performance?



Algorithm – framework

- ~~**Modules**~~
  - ~~Data model~~
  - ~~Convert event log~~
  - ~~Convert model~~
  - ~~Incorporate~~
  - ~~Generate process model~~
  - ~~Post process~~



Chair of Process and Data Science

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Data Model

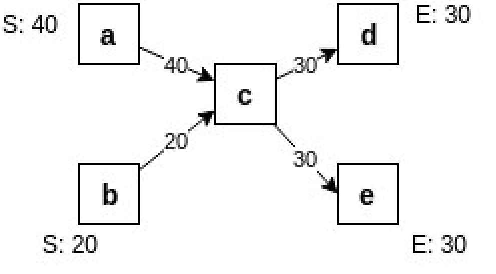
- **Directly-follows graph**
  - Directly-follows relation $a >_L b$

    $\exists \sigma \in L, 1 \leq i < |\sigma|, \sigma(i) = a \ and \ \sigma(i+1) = b.$

A directly follow graph of an event log L is $G(L) = (A, F, A_{start}, A_{end})$ where A is the set of activities in L, $F = \{(a,b) \in A \times A | a >_L b\}$ is the directly-follows relation set, A_{start}, A_{end} are the set of start and end activities respectively,

$$A_{start} = \{a | \exists \sigma \in L, a = \sigma(1)\}, A_{end} = \{a | \exists \sigma \in L, a = \sigma(|\sigma|)\}$$

$$L = \{<a,c,d>^{20}, <b,c,e>^{10}, <a,c,e>^{20}, <b,c,d>^{10}\}$$



Data Model

- **Cardinality of directly-follows graph**
  - For any directly-follows relation

$$\forall (a,b) \in F, c(a,b) = \sum_{\sigma \in L} |\{i \in \{1,2...|\sigma|\} | \sigma(i) = \sigma(i+1)\}|$$

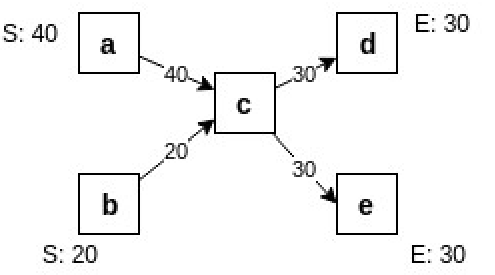
  - For start activity a

$$\forall a \in A_{start}, c(a) = \sum_{\sigma \in L} |\{\sigma | \sigma(1) = a\}|$$

  - For end activity b

$$\forall a \in A_{end}, c(a) = \sum_{\sigma \in L} |\{\sigma | \sigma(|\sigma|) = a\}|$$

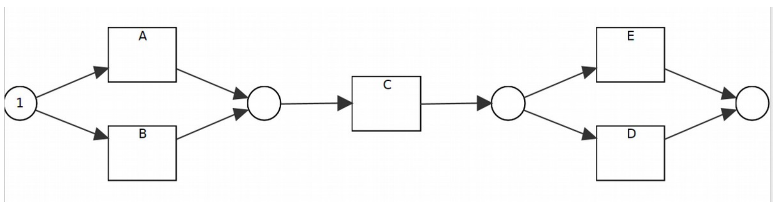
$$L = \{<a,c,d>^{20}, <b,c,e>^{10}, <a,c,e>^{20}, <b,c,d>^{10}\}$$

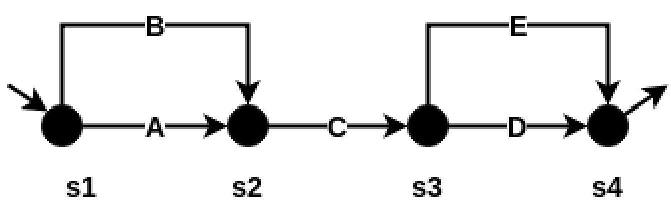


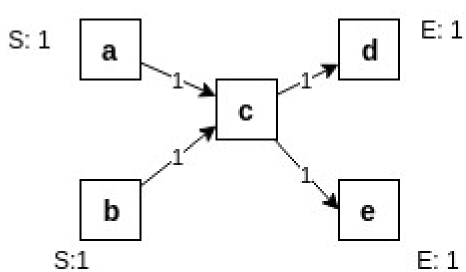
Convert to directly-follows graph

Petri net

- Transition System
- Transitions before and after states



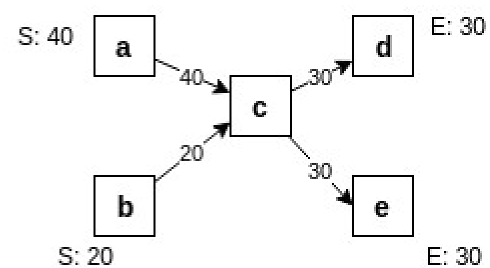




Event log

- Directly-follows relation
- plugin

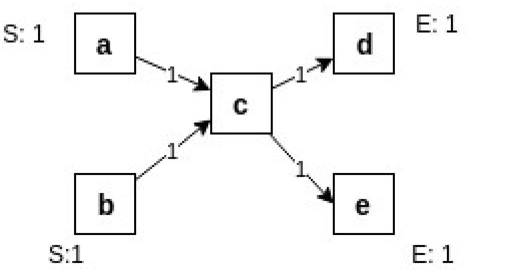
$$L = \{< a, c, d >^{20}, < b, c, e >^{10}, < a, c, e >^{20}, < b, c, d >^{10}\}$$

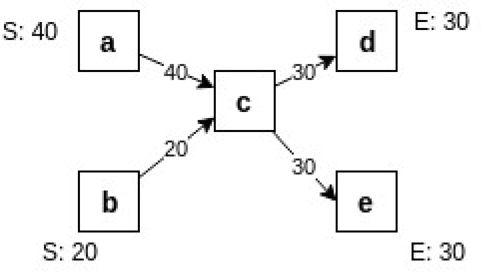


Data Model

- **Unification of cardinality**
  - Models from existing model, positive and negative event log
  - For any directly-follows relation
  - $$u(a,b) = \frac{c(a,b)}{\sum_{(a',b') \in F} c(a',b')}$$
  - For any start activity
  - $$u(a) = \frac{c(a)}{\sum_{a' \in A_{start}} c(a')}$$
  - For any end activity

$$u(a) = \frac{c(a)}{\sum_{a' \in A_{end}} c(a')}$$





Incorporate Data Models

Given directly-follows graphs D^+, D^-, D^M

- **Incorporate method**
  - For any directly-follows relation
$$\mathrm{u}^n(a,b) = u^M(a,b) + u^+(a,b) - u^-(a,b)$$
  - For any start activity,
$$a \in A^M_{start} \cup A^+_{start} \cup A^-_{start}, u^n(a) = u^M(a) + u^+(a) - u^-(a)$$
  - For any end activity,
$$a \in A^M_{end} \cup A^+_{end} \cup A^-_{end}, u^n(a) = u^M(a) + u^+(a) - u^-(a)$$
- **Weighted value**
  - Three control weights w^+, w^-, w^M
$$u^n_w(a,b) = w^M \cdot u^M(a,b) + w^+ \cdot u^+(a,b) - w^- \cdot u^-(a,b)$$

Generate Petri net

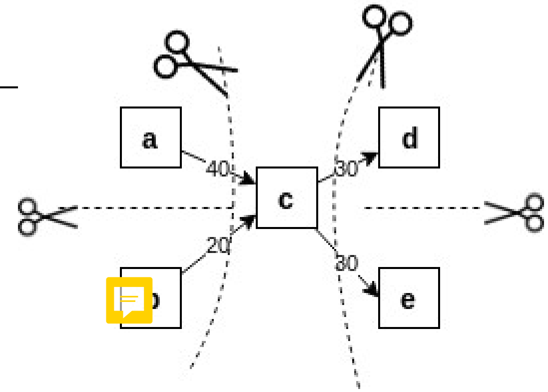
- ~~Choose directly-follows relation~~

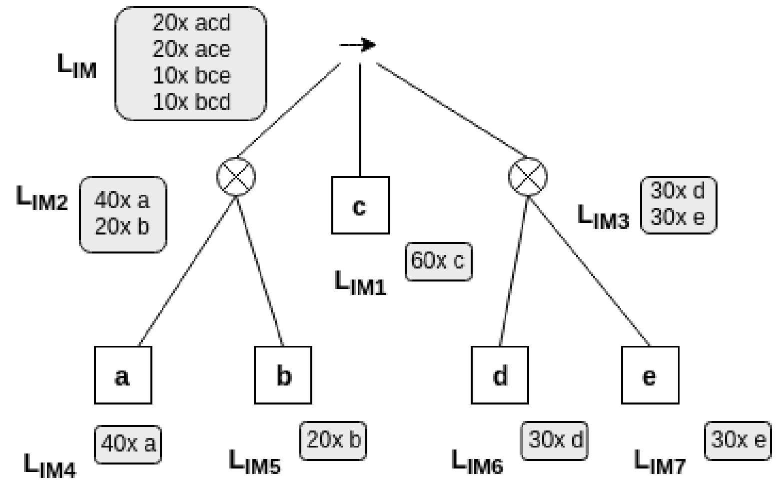
$$u_w^n(a,b) > t$$

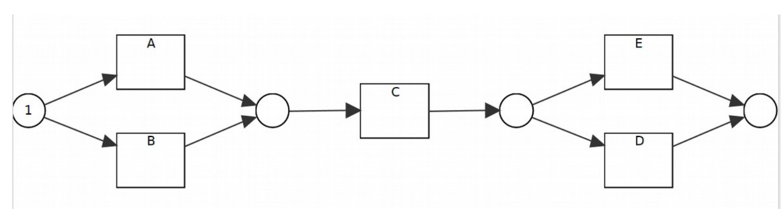
  - ~~t=0~~

- ~~Assign normal cardinality back~~
  - $c^n(a,b) = u_w^n(a,b) \cdot (|L^+| + |L^-|)$

- ~~IM discovery algorithm~~
  - ~~Directly-follows graph~~
  - ~~Process tree~~
  - ~~Petri net~~



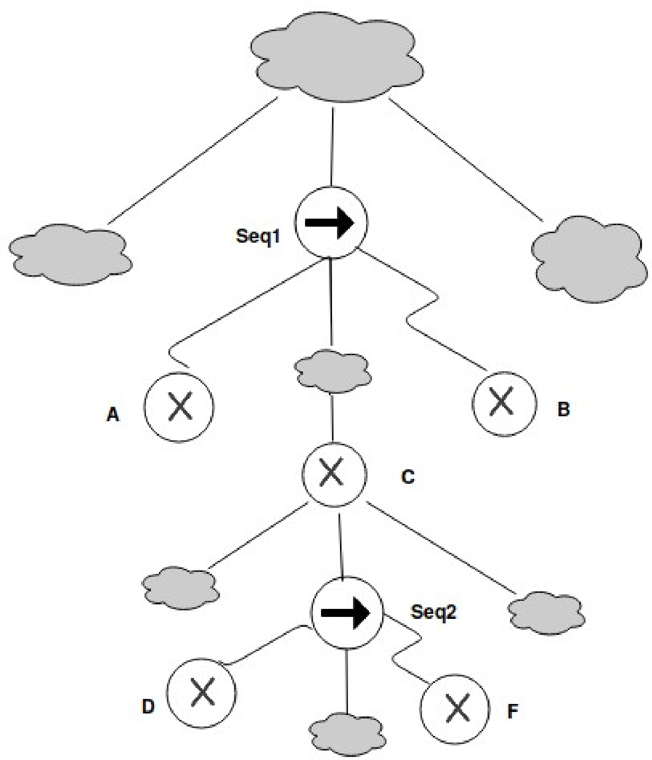


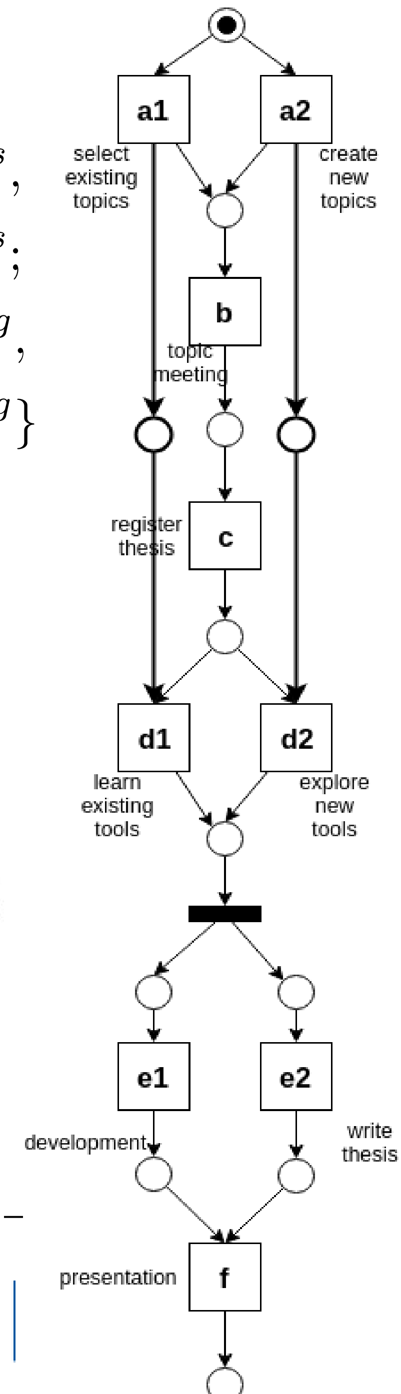


Post Process Petri net

- **Long-term dependency**
  - Choices dependency
  - Exclusive choices
    - ✓ Xor block/branches
  - In order
    - ✓ Least common ancestor is Seq
      - A < C < B, D<F
    - ✓ In same level
      - A,B,C pair
      - D,F pair
  - Strong correlation

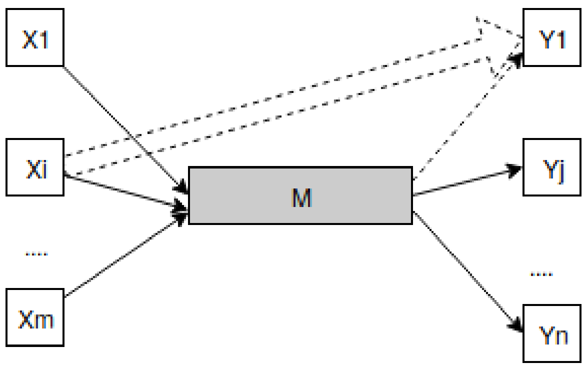
$$L_3 := \{< \mathbf{a1}, b, c, \mathbf{d1}, e1, e2, f >^{50,pos}, \\ < \mathbf{a2}, b, c, \mathbf{d2}, e1, e2, f >^{50,pos}; \\ < \mathbf{a1}, b, c, \mathbf{d2}, e1, e2, f >^{50,neg}, \\ < \mathbf{a2}, b, c, \mathbf{d1}, e1, e2, f >^{50,neg}\}$$





Post Process Petri net

- **Long-term dependency**
  - Strong correlation
    - Frequency



Frequency of an xor branch X_i in an event log L is the count of traces which replay this xor branch, $f : X \rightarrow N, f_L(X) = \sum_{\sigma \in L} |\{\sigma | \sigma \models X\}|$

Frequency of multiple xor branches is
$\mathrm{f}_L(X_1, X_2, ..., X_n) = \sum_{\sigma \in L} |\{\sigma | \forall X_i, \sigma \models X_i\}|$

- Correlation over t

$$d(X_i, Y_j) = w^+ \cdot d^+(X_i, Y_j) - w^- \cdot d^-(X_i, Y_j) > t$$

$$d^+(X_i, Y_j) = \frac{f_{L^+}(X_i, Y_j)}{\sum_{Y^k \in T, k \neq j} f_{L^+}(X_i, Y^k)} \quad d^-(X_i, Y_j) = \frac{f_{L^-}(X_i, Y_j)}{\sum_{Y^k \in T, Y^k \neq X_i} f_{L^-}(X_i, Y^j)}$$

Algorithm – add long-term dependency

- **Long-term dependency Situations**

$$LT_S := \{X_i | \exists Y_j, X_i \rightsquigarrow Y_j \in LT\}$$

$$LT_T := \{Y_j | \exists X_i, X_i \rightsquigarrow Y_j \in LT\}$$

1. $LT = \{A \rightsquigarrow D, A \rightsquigarrow E, B \rightsquigarrow D, B \rightsquigarrow E\}$.
   $LT_S = \{A, B\}, LT_T = \{D, E\}, |LT| = |S| \cdot |T|$.
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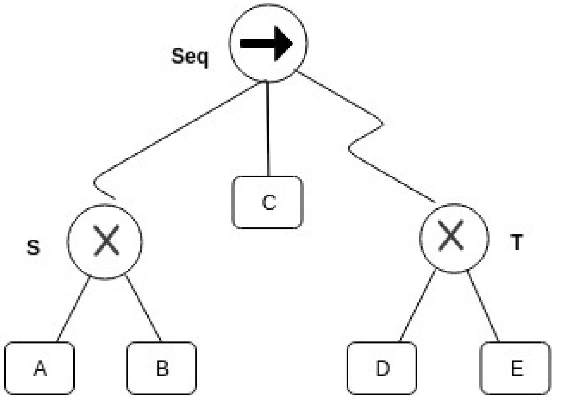
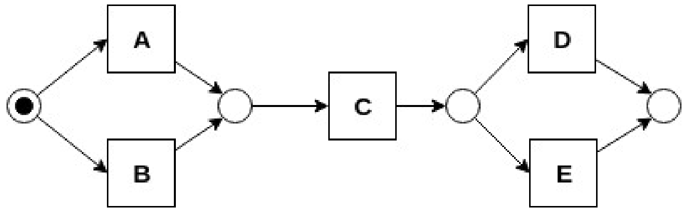
7. $LT = \emptyset$

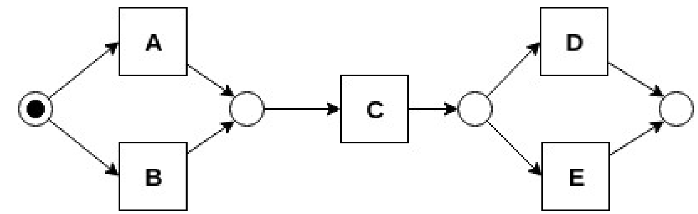




   - Situation 1 is full dependency ==> no consideration
   - Situation 7 is empty. ==> no consideration

Algorithm – add long-term dependency

- How to express on Petri net
  - ✓ Add silent transition
    - Add control place as post-place post after S



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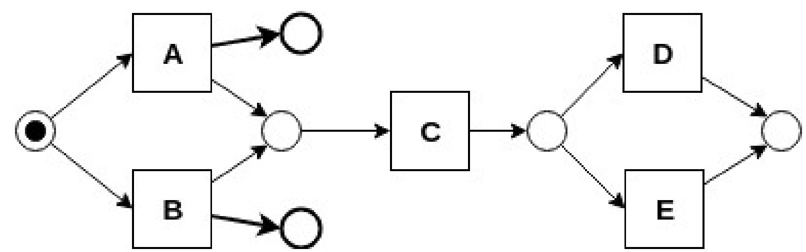

Algorithm – add long-term dependency

- How to express on Petri net
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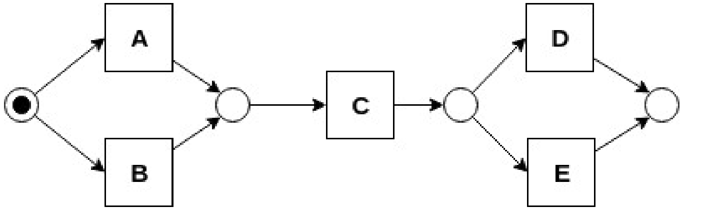
    - Add control place as post-place post after S
    - Add control place as pre-place before T



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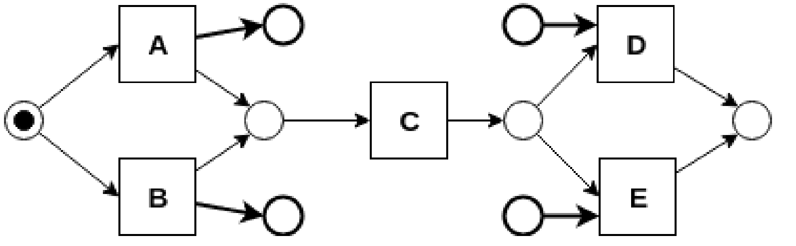

Algorithm – add long-term dependency

- How to express on Petri net
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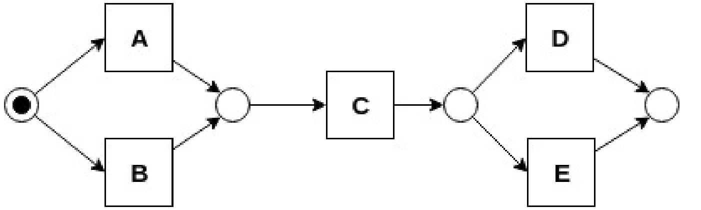
    - Add control place as pre-place before T
    - Add silent transitions for each long-term dependency



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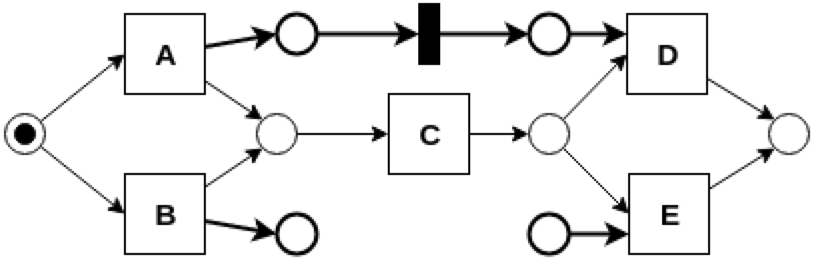

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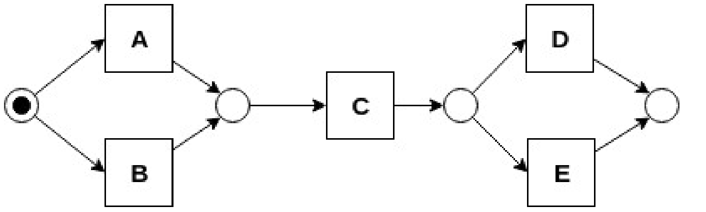

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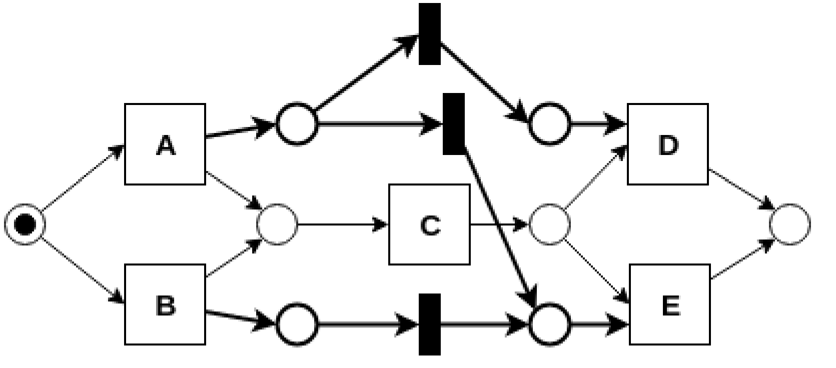

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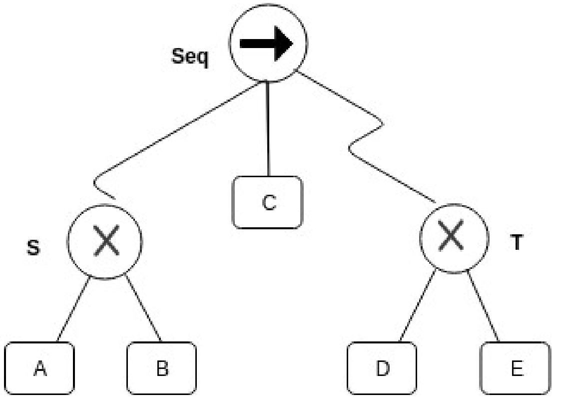
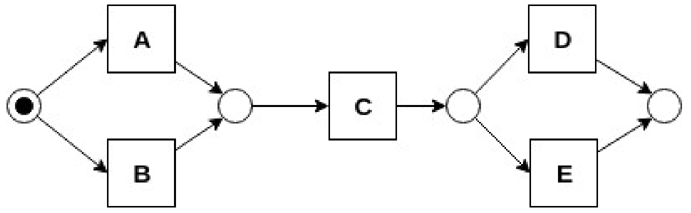




  - Situation 1 is full dependency ==> no consideration
  - Situation 7 is empty. ==> no consideration

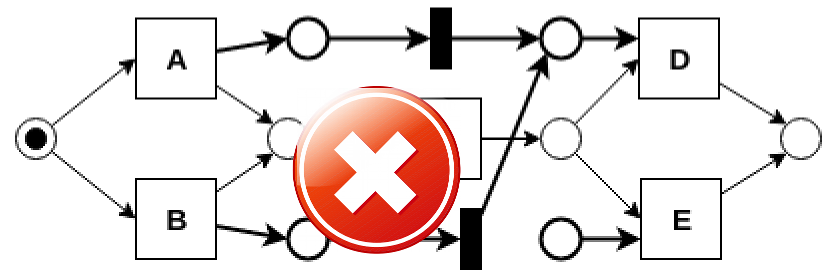
Algorithm – add long-term dependency

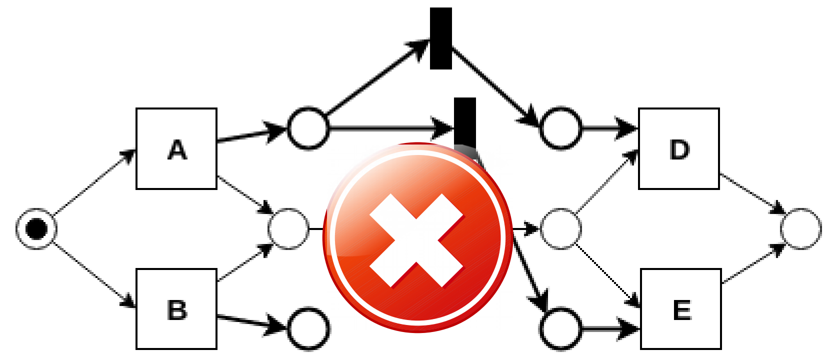
- **Express on Petri net**

4. $LT = \{A \rightsquigarrow D, B \rightsquigarrow D\}$.
   $LT_S = S, LT_T \subsetneq T$.

5. $LT = \{A \rightsquigarrow D, A \rightsquigarrow E\}$.
   $LT_S \subsetneq S, LT_T = T$.

6. $LT = \{A \rightsquigarrow E\}$.
   $LT_S \subsetneq S, LT_T \subsetneq T$.





Sound:
- ✓ Safeness.
- ✓ Proper completion.
- ✓ Option to complete.
- ✓ No dead parts.

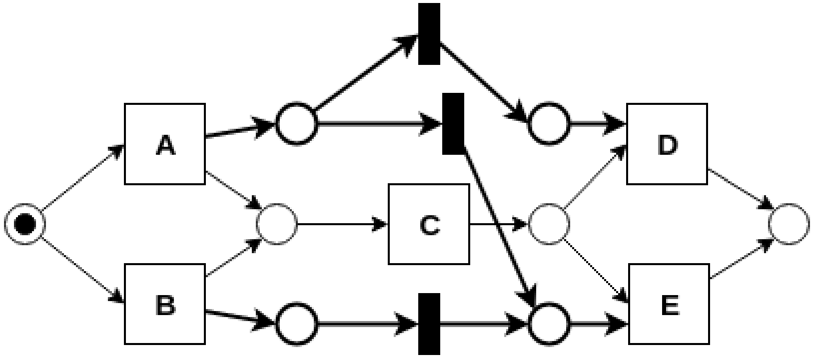
Petri net – soundnes

Sound:

- Safeness.
  Places cannot hold multiple tokens at the same time.
- Proper completion.
  If the sink place is marked, all other places are empty.
- Option to complete.
  It is always possible to reach the final marking from any reachable marking.
- No dead parts.
  For any transition, there exists a path from source to sink place through it.

Soundness proof

Given $S = \{X_1, X_2, ...X_m\}$ and $T = \{Y_1, Y_2, ...Y_n\}$ with $LT = \{X_i \rightsquigarrow Y_j | 1 \le i \le m, 1 \le j \le n\}$. W.l.o.g., X_i is fired.



The marking distribution is

$$M(p_{X_i}) = 1; \quad \forall p_{X_{i'}} \in P_S, i' \neq i, M(p_{X_{i'}}) = 0$$

Type 1 $\quad LT_S = S, LT_T = T$

soundness

- Safeness.

$$\sum M(p_{X_i}) \le 1, \sum M(p_{Y_j}) \le 1$$

- Proper completion.

  After firing Y_j, $\sum M(p_{X_i}) = 0, \sum M(p_{Y_j}) = 0$

- Option to complete & No dead parts.

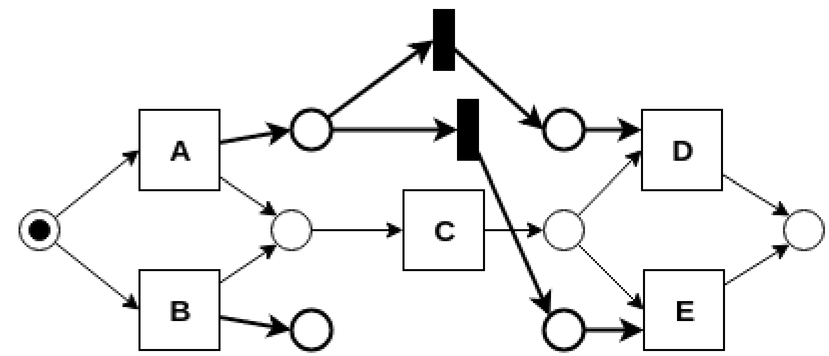
$$\forall X_i \in S \text{ is enabled at beginning}$$
$$\forall X_i \in S, \text{since } LT_S = S, \Rightarrow \exists Y_j \in T, X_i \rightsquigarrow Y_j,$$
$$\epsilon \text{ is enabled with } p_{X_i} \rightarrow \epsilon \rightarrow p_{Y_j}$$
$$\forall Y_j \in T, \text{since } LT_T = T, \Rightarrow \exists X_i \in S, X_i \rightsquigarrow Y_j$$

Soundness proof

Given $S = \{X_1, X_2, ...X_m\}$ and $T = \{Y_1, Y_2, ...Y_n\}$ with $LT = \{X_i \rightsquigarrow Y_j | 1 \le i \le m, 1 \le j \le n\}$. W.l.o.g., X_i is fired.

The marking distribution is

$$M(p_{X_i}) = 1; \quad \forall p_{X_{i'}} \in P_S, i' \neq i, M(p_{X_{i'}}) = 0$$



Type 2 $\quad LT_S \subsetneq S, LT_T \subsetneq T$

soundness

- Safeness.

$$\sum M(p_{X_i}) \le 1, \sum M(p_{Y_j}) \le 1$$

- Proper completion.

After firing Y_j, $\sum M(p_{X_i}) = 0, \sum M(p_{Y_j}) = 0$

- Option to complete & No dead parts.

$\forall X_i \in S$ is enabled at beginning

if $LT_S \subsetneq S, \Rightarrow \exists X_i \in S, X_i \notin LT_S$, token remains

if $LT_T \subsetneq T, \Rightarrow \exists Y_j \in T, Y_j \notin LT_T$, token misses

Algorithm – add long-term dependency

- **Long-term dependency Situations**

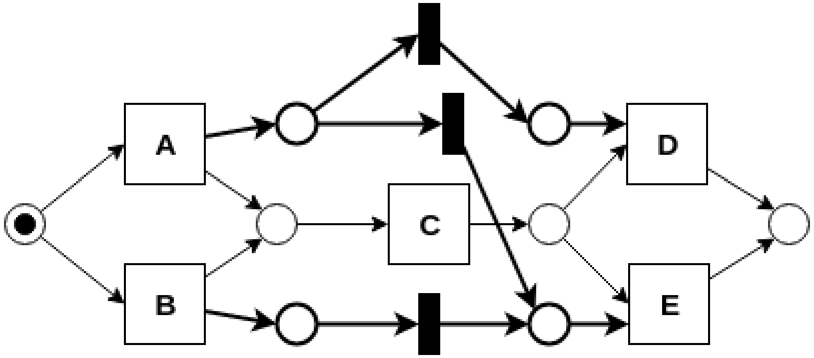
1. $LT = \{A \rightsquigarrow D, A \rightsquigarrow E, B \rightsquigarrow D, B \rightsquigarrow E\}$.
   $LT_S = \{A, B\}, LT_T = \{D, E\}, |LT| = |S| \cdot |T|$.
2. $LT = \{A \rightsquigarrow D, A \rightsquigarrow E, B \rightsquigarrow E\}$.
   $LT_S = \{A, B\}, LT_T = \{D, E\}$ $LT_S = S$ and $LT_T = T, |LT| < |S| \cdot |T|$.
3. $LT = \{A \rightsquigarrow D, B \rightsquigarrow E\}$.
   $LT_S = \{A, B\}, LT_T = \{D, E\}$ $LT_S = S$ and $LT_T = T, |LT| < |S| \cdot |T|$.
4. $LT = \{A \rightsquigarrow D, B \rightsquigarrow D\}$.
   $LT_S = S, LT_T \subsetneq T$.
5. $LT = \{A \rightsquigarrow D, A \rightsquigarrow E\}$.
   $LT_S \subsetneq S, LT_T = T$.
6. $LT = \{A \rightsquigarrow E\}$.
   $LT_S \subsetneq S, LT_T \subsetneq T$.
7. $LT = \emptyset$

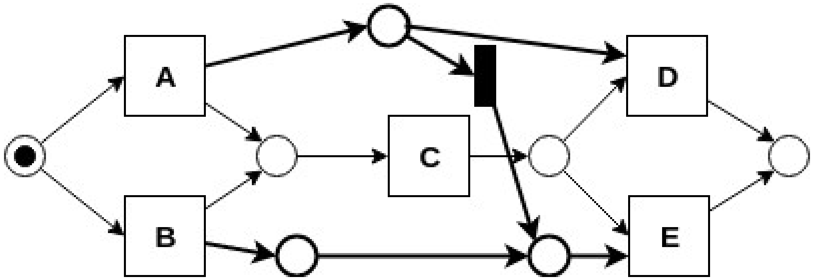
Sound:
- ✓ Safeness.
- ✓ Proper completion.
- ✓ Option to complete.
- ✓ No dead parts.

- Consider only $LT_S = S, LT_T = T, |LT| < |S| \cdot |T$

Post process

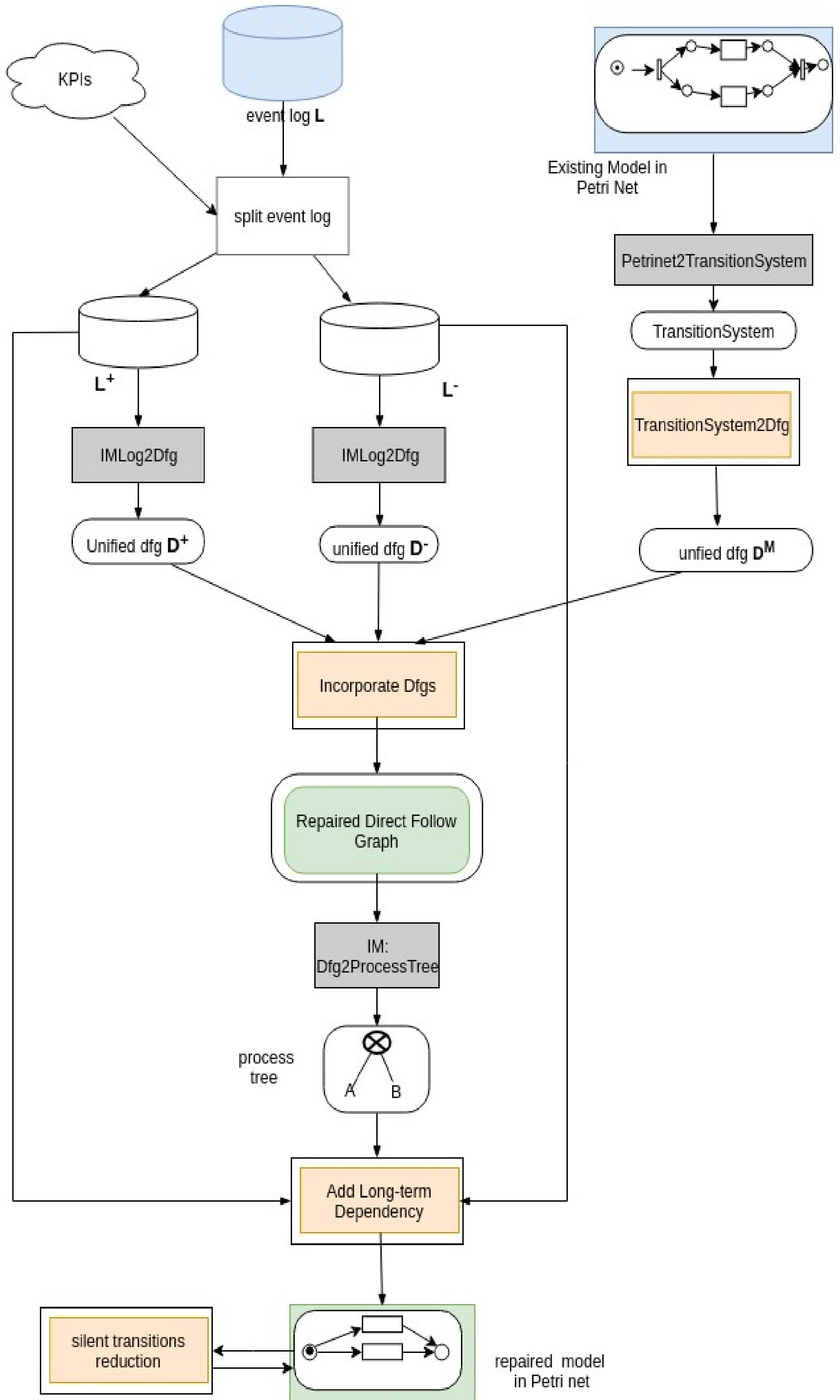
- **Delete redundant silent transitions**



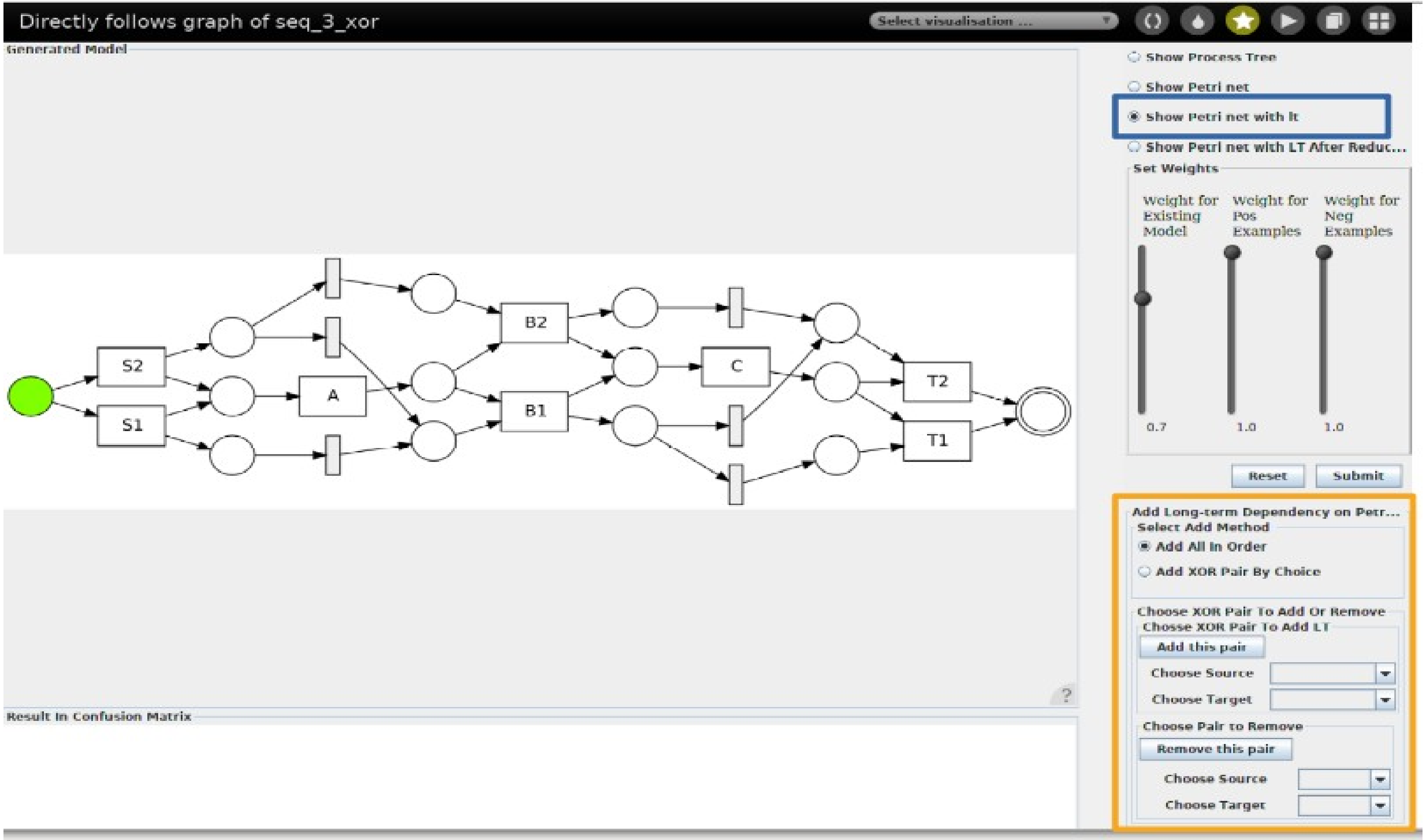


Algorithm – architecture

- Data ~~model~~
  -
- ~~Convert models~~
  -
- ~~Incorporate dfgs~~
  -
- ~~Add long-term dependency~~
  -
- ~~Delete redundant silent transitions~~
  -



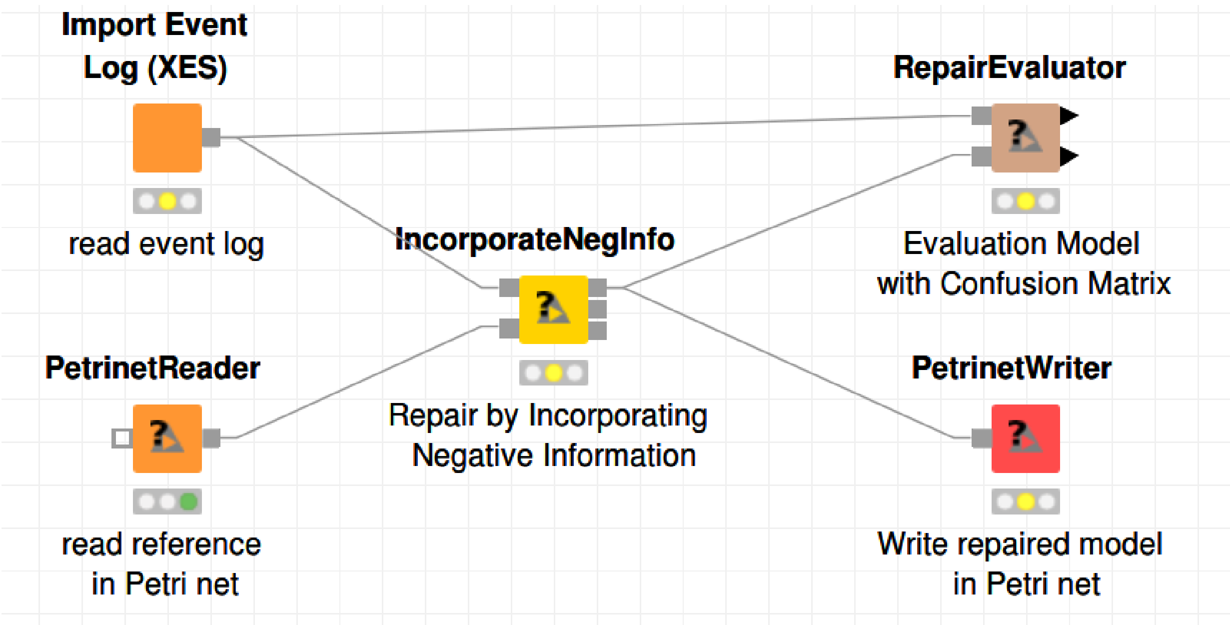
Demo



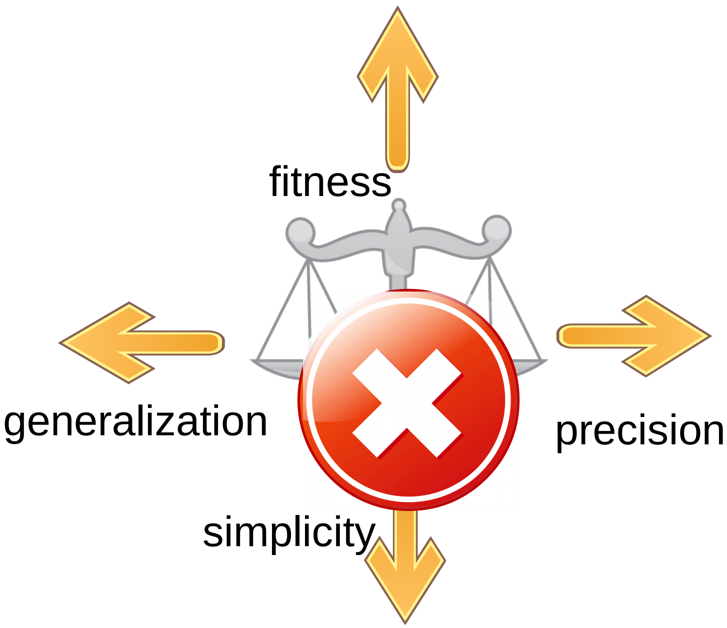
Directly follows graph of seq_3_xor
Select visualisation ...
Generated Model
S2
S1
A
B2
B1
C
T2
T1
Result In Confusion Matrix
Show Process Tree
Show Petri net
Show Petri net with lt
Show Petri net with LT After Reduc...
Set Weights
Weight for Existing Model
Weight for Pos Examples
Weight for Neg Examples
0.7
1.0
1.0
Reset
Submit
Add Long-term Dependency on Petr...
Select Add Method
Add All In Order
Add XOR Pair By Choice
Choose XOR Pair To Add Or Remove
Choose XOR Pair To Add LT
Add this pair
Choose Source
Choose Target
Choose Pair to Remove
Remove this pair
Choose Source
Choose Target

Demo

One more slide to show the workflow in KNIME?? But not here, right??



Evaluation



- **Confusion matrix**
  - Recall

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

  - Precision

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

  - Accuracy

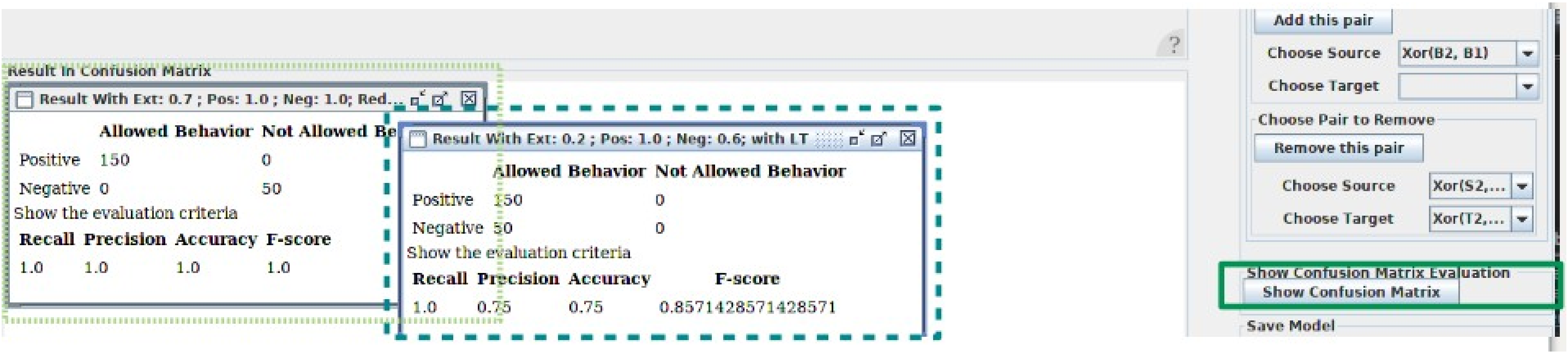
$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

  - F1

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

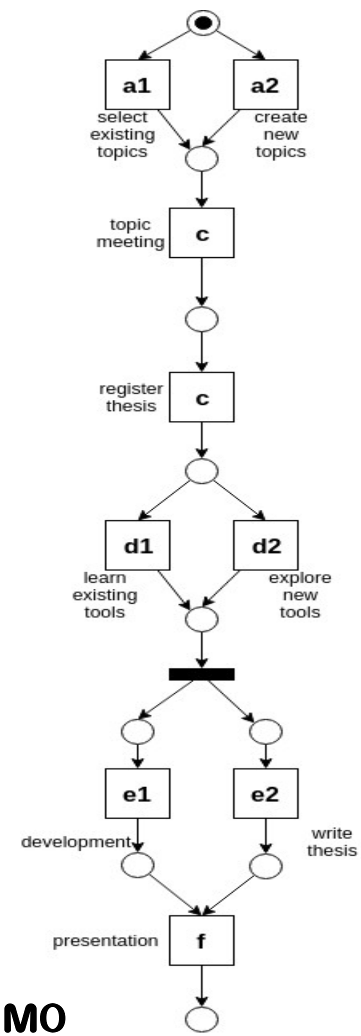
✓	Allowed behavior	Not allowed behavior
positive	TP	FN
negative	FP	TN

Demo --result



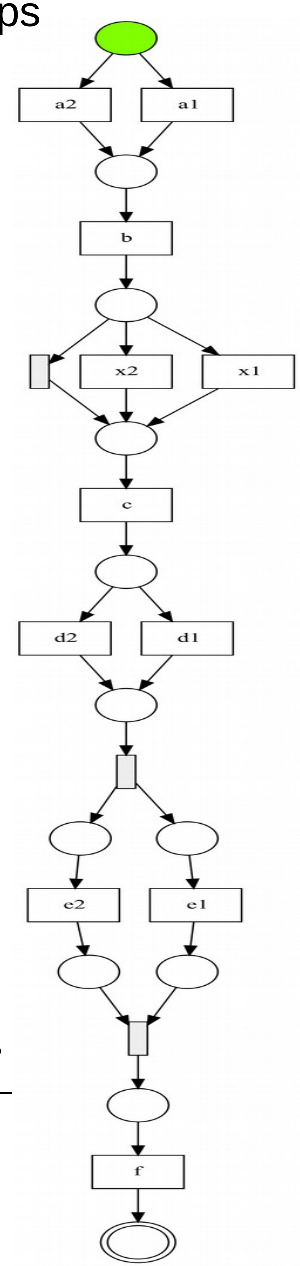
Result In Confusion Matrix
Result With Ext: 0.7 ; Pos: 1.0 ; Neg: 1.0; Red...
Allowed Behavior Not Allowed Be
Positive 150 0
Negative 0 50
Show the evaluation criteria
Recall Precision Accuracy F-score
1.0 1.0 1.0 1.0
Result With Ext: 0.2 ; Pos: 1.0 ; Neg: 0.6; with LT
Allowed Behavior Not Allowed Behavior
Positive 150 0
Negative 50 0
Show the evaluation criteria
Recall Precision Accuracy F-score
1.0 0.75 0.75 0.8571428571428571
Add this pair
Choose Source Xor(B2, B1)
Choose Target
Choose Pair to Remove
Remove this pair
Choose Source Xor(S2,...
Choose Target Xor(T2,...
Show Confusion Matrix Evaluation
Show Confusion Matrix
Save Model

Demo --result



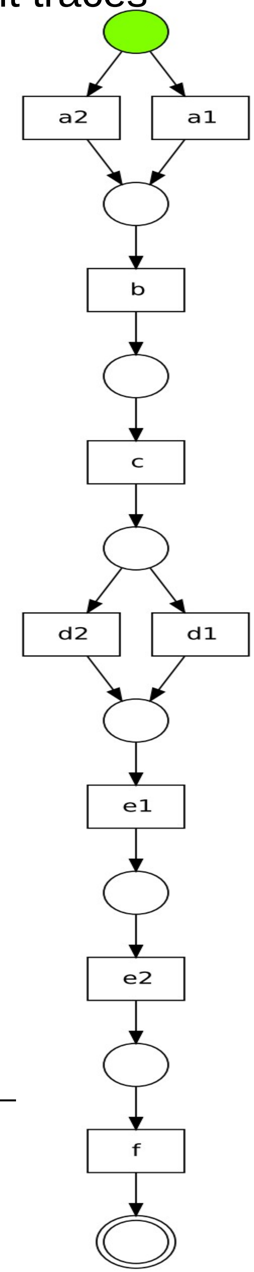
M0

Overcome s1:
add subprocesses
as loops



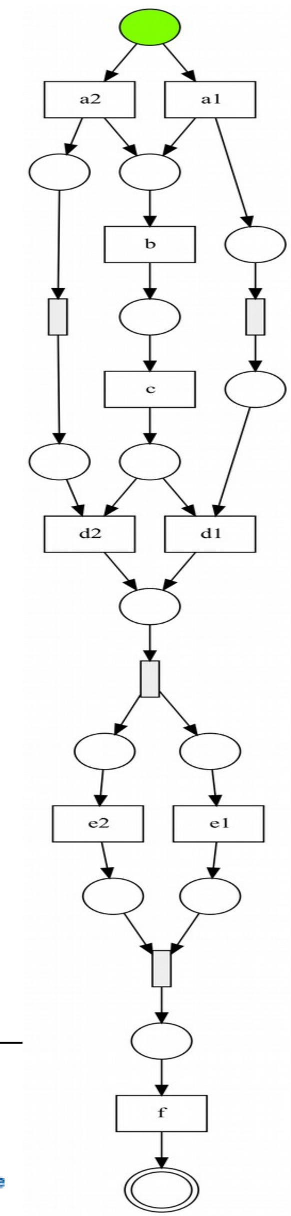
M1.3

Overcome s2:
Unable to adapt model
with fit traces



M2.3

Overcome s3:
Unable to detect
long-term dependency



M3.3

Demo --result

Situation	Method	Generated Model	Confusion matrix measurements							
			TP	FP	TN	FN	recall	precision	accuracy	F1
S1	IM-Infrequent Noise threshold: 20%	M1.1	50	50	0	0	1	0.5	0.5	0.667
	Fahland's Repair Model	M1.2	50	50	0	0	1	0.5	0.5	0.667
	Dfg-repair	M1.3	50	50	0	0	1	0.5	0.5	0.667
S2	IM/Fahland's	M0	60	45	0	0	1	0.571	0.571	0.727
	Dfg-repair	M2.3	50	5	40	10	0.833	0.909	0.857	0.870
S3	IM/Fahland repair	M0	100	100	0	0	1	0.5	0.5	0.667
	Dfg-repair	M3.3	100	0	100	0	1	1	1	1

Conclusion:

- ✓ Conquer shortcomings of current techniques in listed situations,
- ✓ Better precision, accuracy, F1 score

Experiments -- Real life data

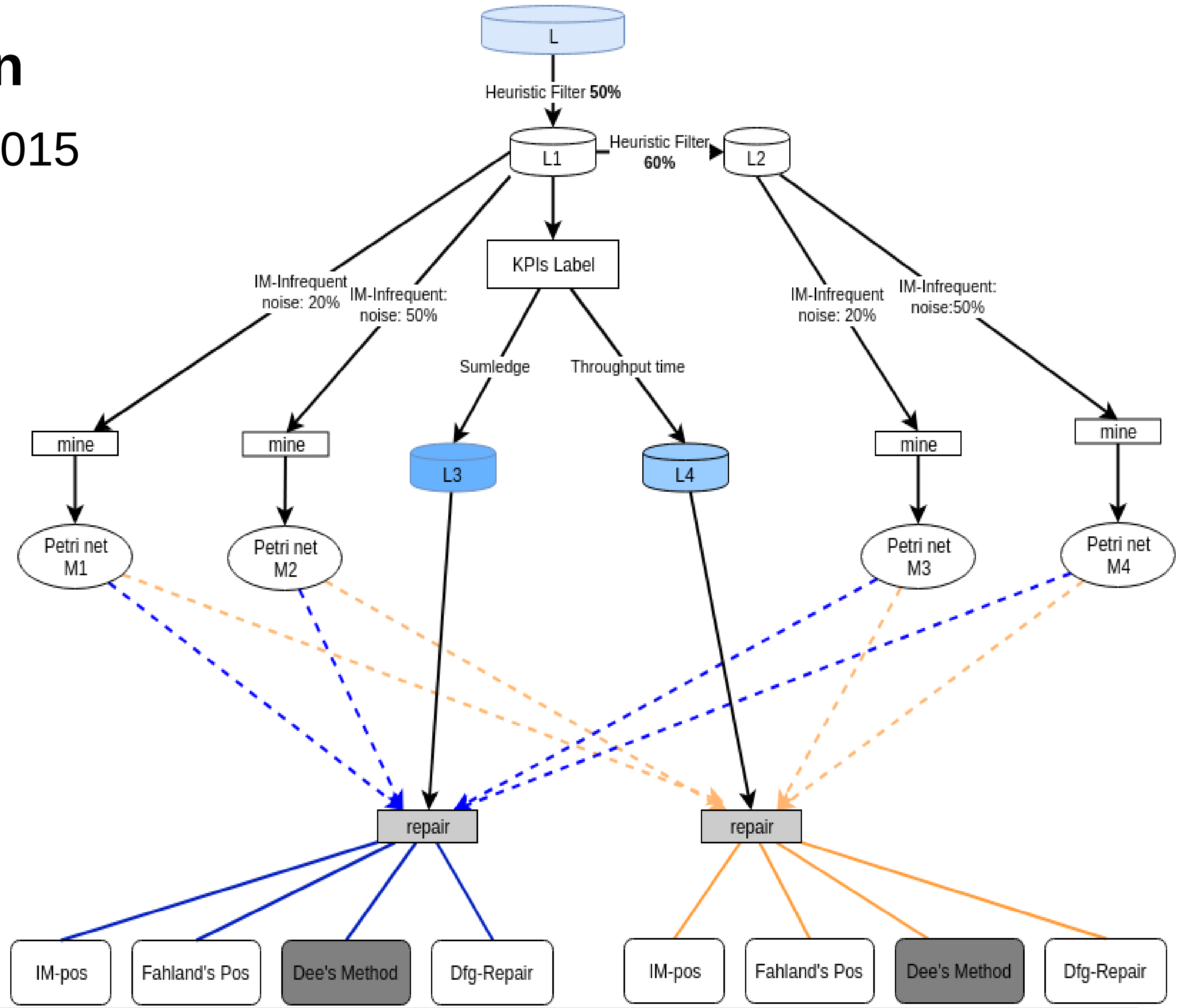
- **Data description**
  - BPI Challenge 2015

    BPIC15_1.xes.xml:

      1199 cases,

      52217 events

      398 event classes



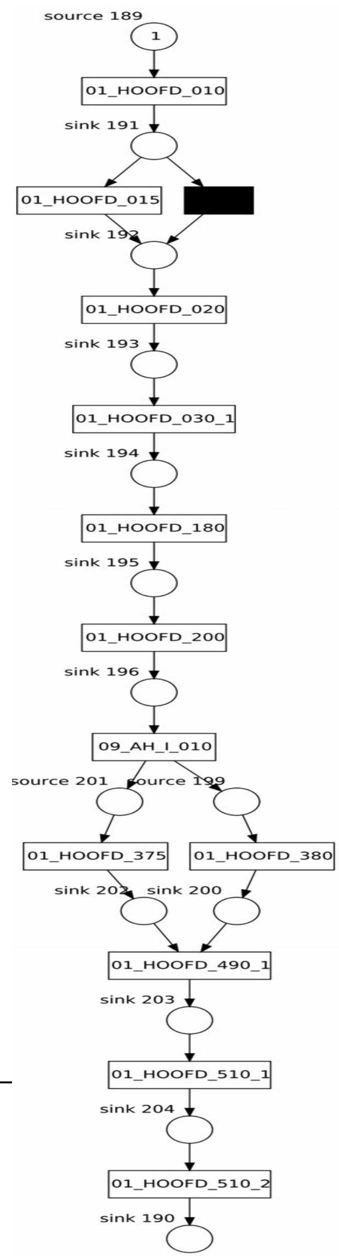
Experiments

- **Event logs**

ID	Description	Traces Num	Events Num	Event Class
D1	Heuristic filter 40%	495	9565	20
D2	Heuristic filter 60% on D1	378	4566	12
D3.1	Classify on Sumledge; Below 70% as positive	349	6744	20
D3.2	Classify on Sumledge; over 70% as negative	146	2811	20
D3.3	Union of D3.1 and D3.2	495	9565	20
D4.1	Classify on throughput time; Below 70% as positive	346	6719	20
D4.2	Classify on Sumledge; over 70% as negative	146	2846	20
D4.3	Union of D4.1 and D4.2	495	9565	20

Experiments

- **Petri net Models**

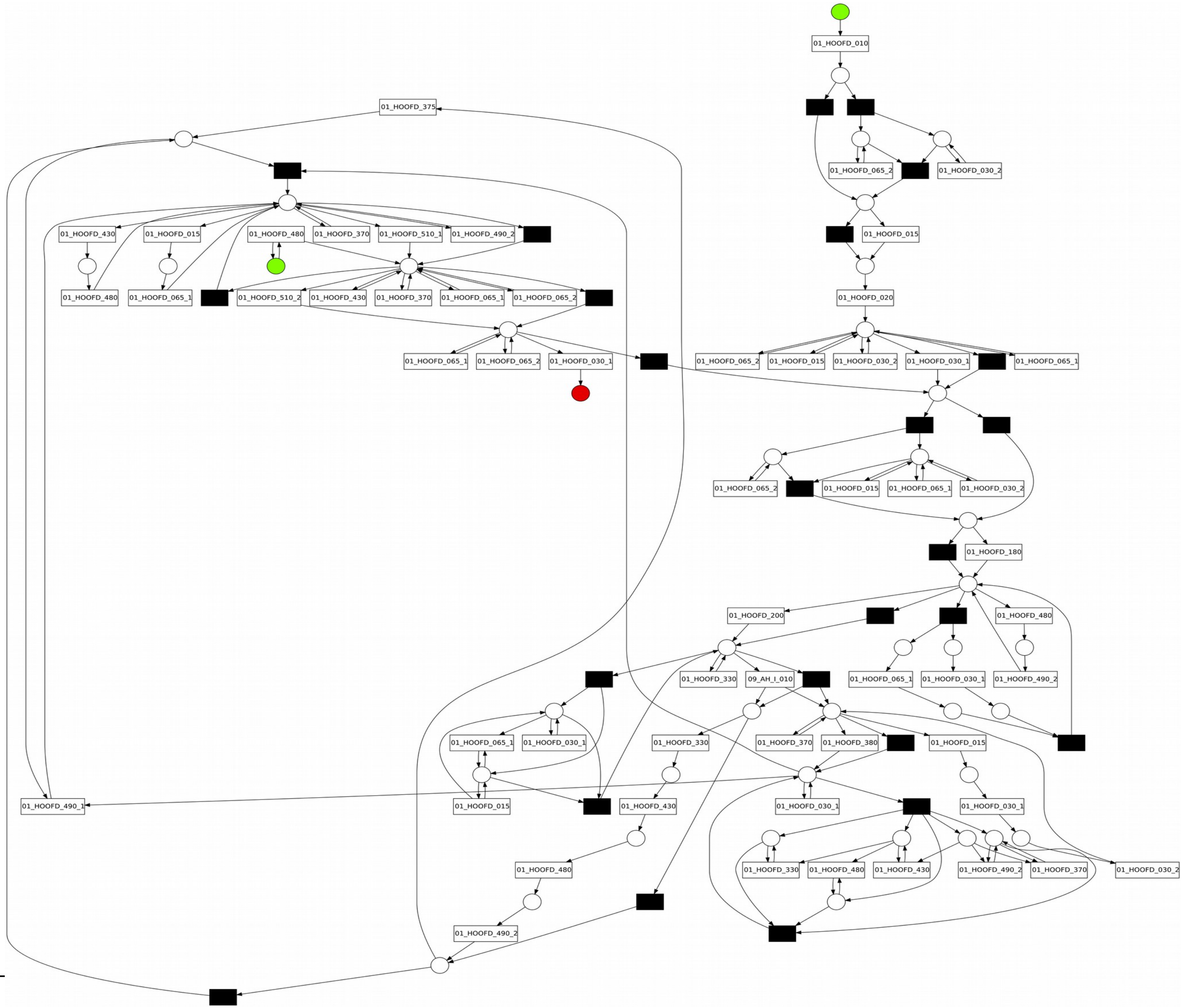


M3

Model ID	Data ID	Confusion matrix							
		TP	FP	TN	FN	recall	Precision	Accuracy	F1
M1	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	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	D3.3	0	0	146	349	0	NaN	0.295	0
	D4.3	0	0	149	346	0	NaN	0.301	0
M4	D3.3	0	0	146	349	0	NaN	0.295	0
	D4.3	0	0	149	346	0	NaN	0.301	0

Experiments- result

Fanhland's method to repair M3 with default setting



Chair of Process and Data Science

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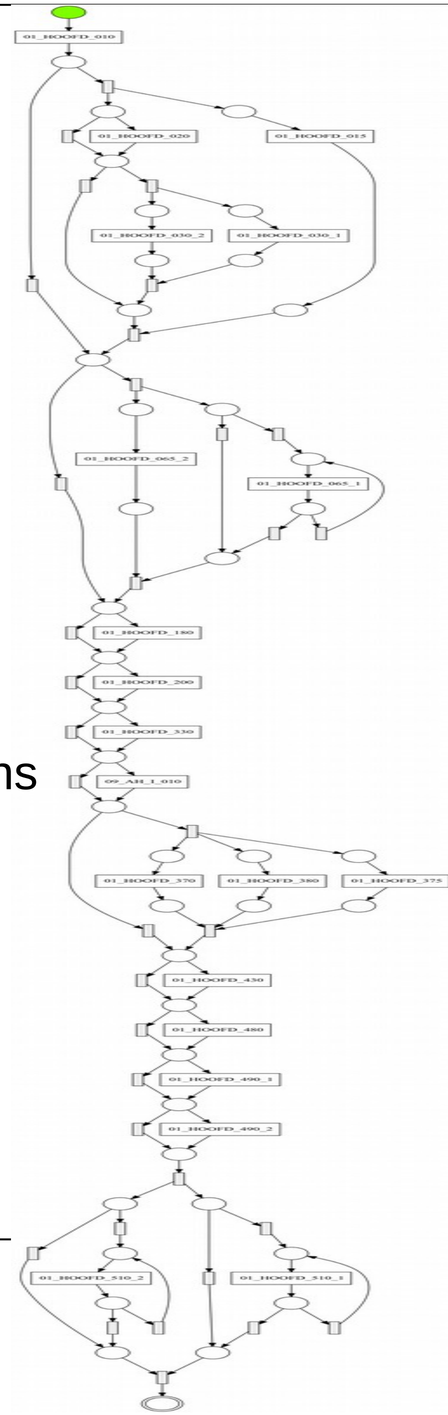
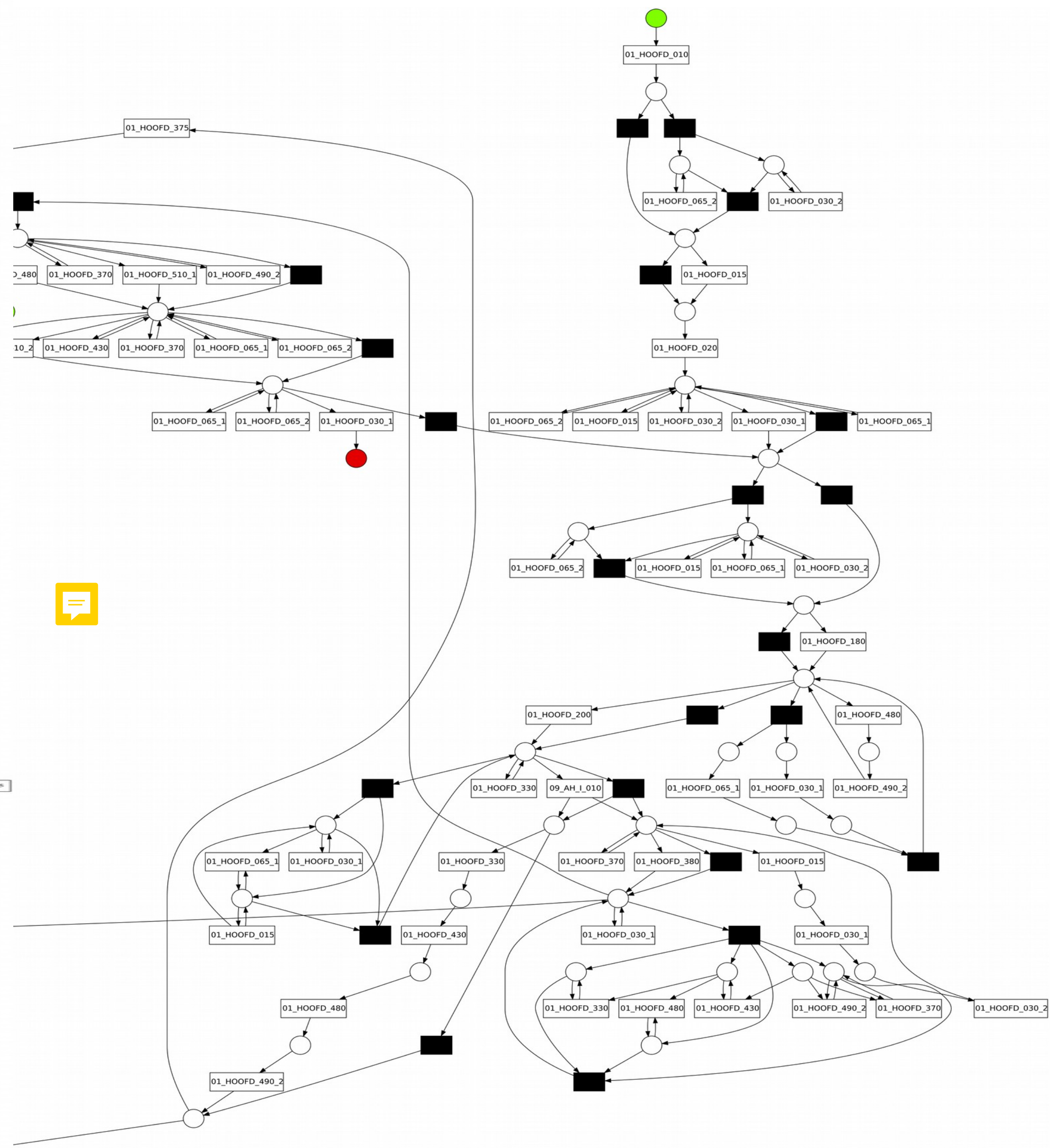
Experiments results

Dfg-repair with default setting



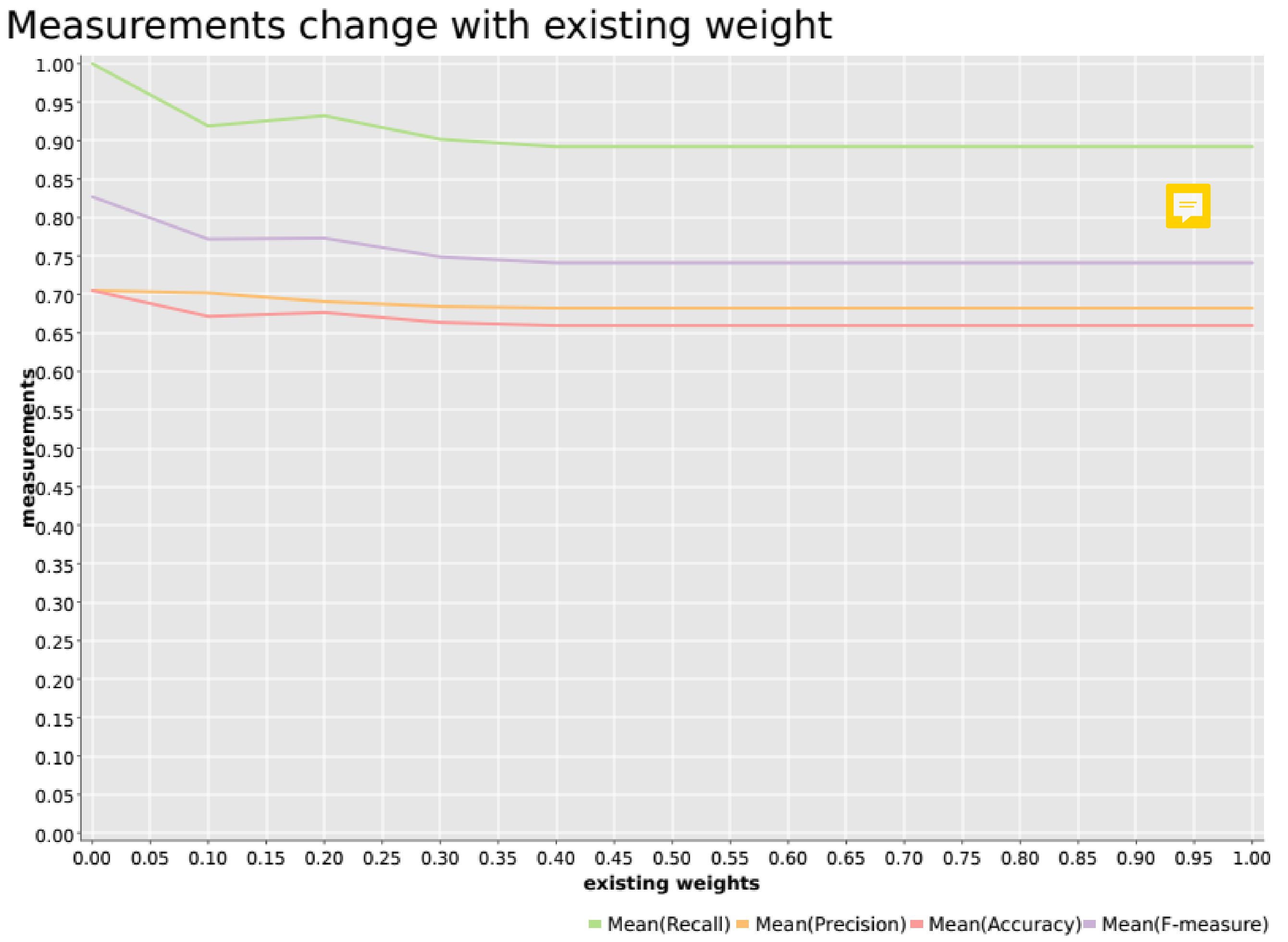
Much simpler with **less** silent transitions and **no** duplicate transitions



Experiment result

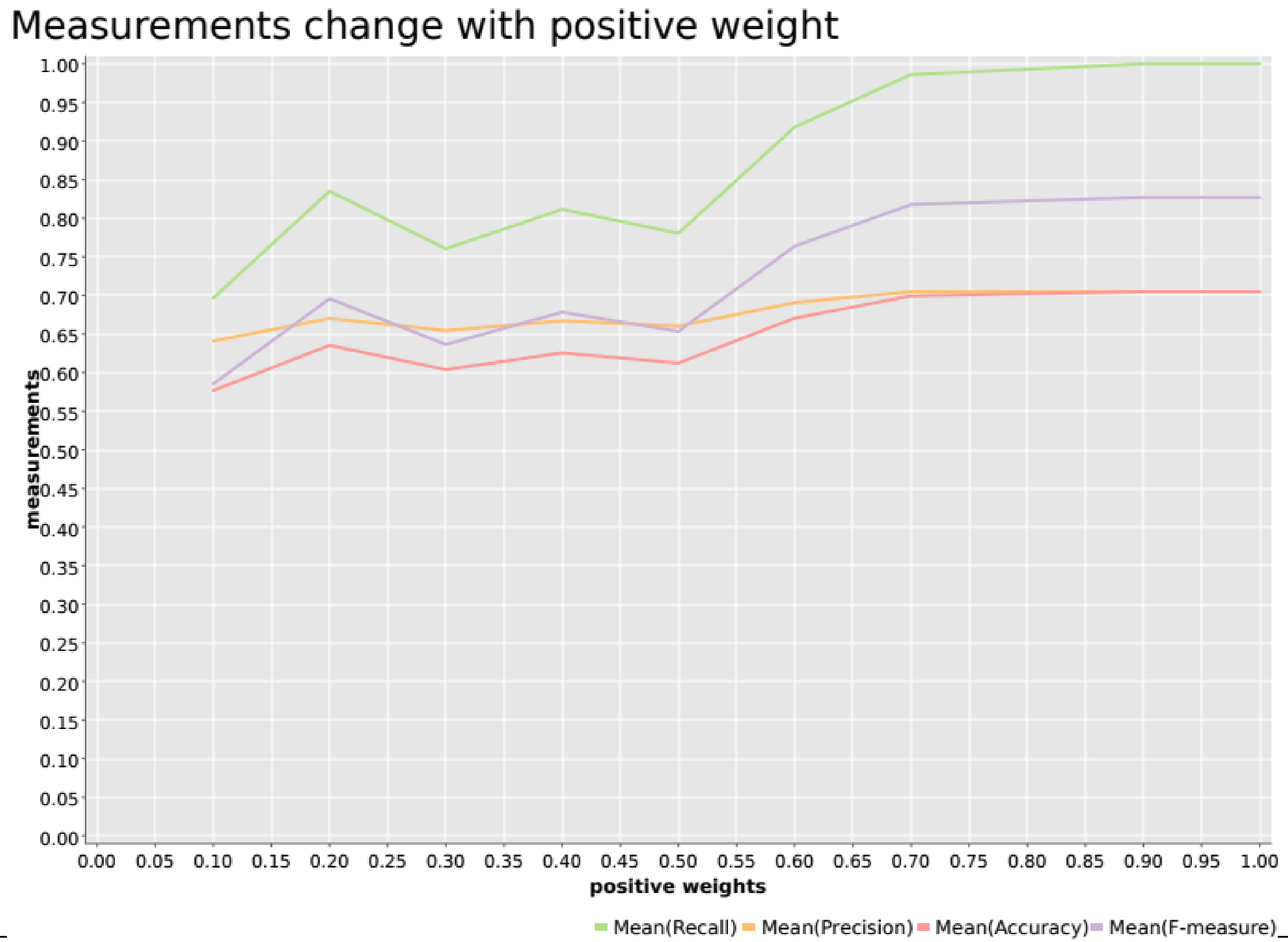
Experiment result

- **Weight for the reference model**



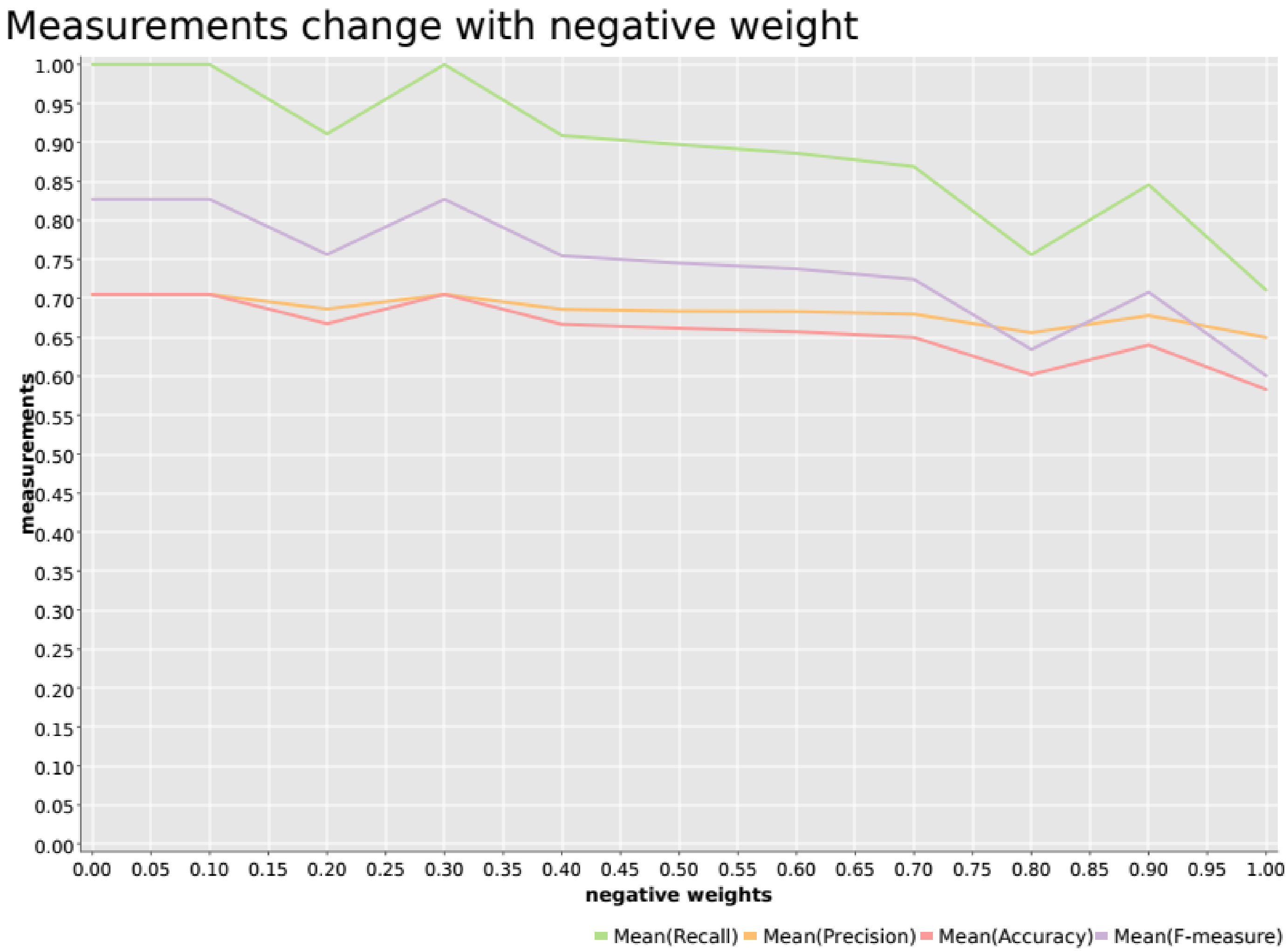
Experiment result

- **Weight for positive instance**



Experiment result

- **Weight for negative instance**



Conclusion

- **Conquer the shortcomings**
- **Repair model with better precision, accuracy, F1**
- **Repaired model simpler,**
- **Run faster**

- **Feasible to use in practice**

Further Work

- **Improve the balance rules**
- **Improve the rules for long-term dependency**
- **Drop process tree as intermediate model**
- **Extend to another choice relation**

Questions & Answers



References

Support Plugins