Master   Thesis

Process Enhancement by Incorporating Negative Instances in Model Repair

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Outline

- **Research Scope**

- **Literature Review**

- **Problem Definition**

- **Algorithm**
  - Framework
  - Design

- ~~**Implementation**~~

- **Evaluation**

- **Conclusion**

- ~~**Appendix**~~
  - ~~References~~
  - ~~Support Plugin Development~~
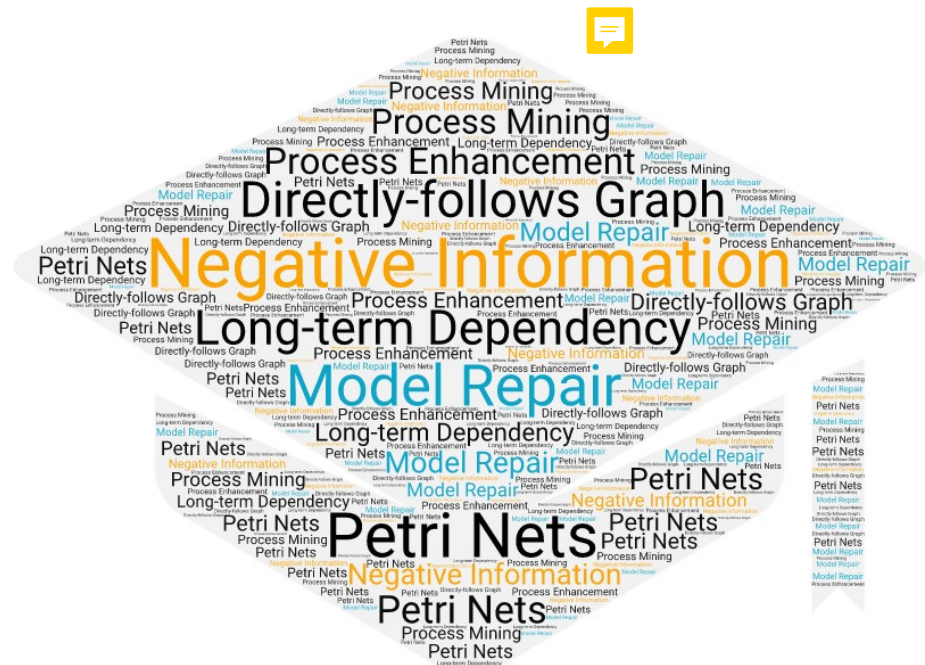
Scope

- ~~Process Mining~~

- ~~Process Enhancement~~

  - ~~Reference model~~

- ~~Model repair~~

  - ~~Fitness~~

  - ~~Similarity~~

- ~~Performance~~

  - ~~Negative instances~~

Process Mining

Process Enhancement

Model Repair

Positive instances

focus

Negative instances

Chair of Process and Data Science

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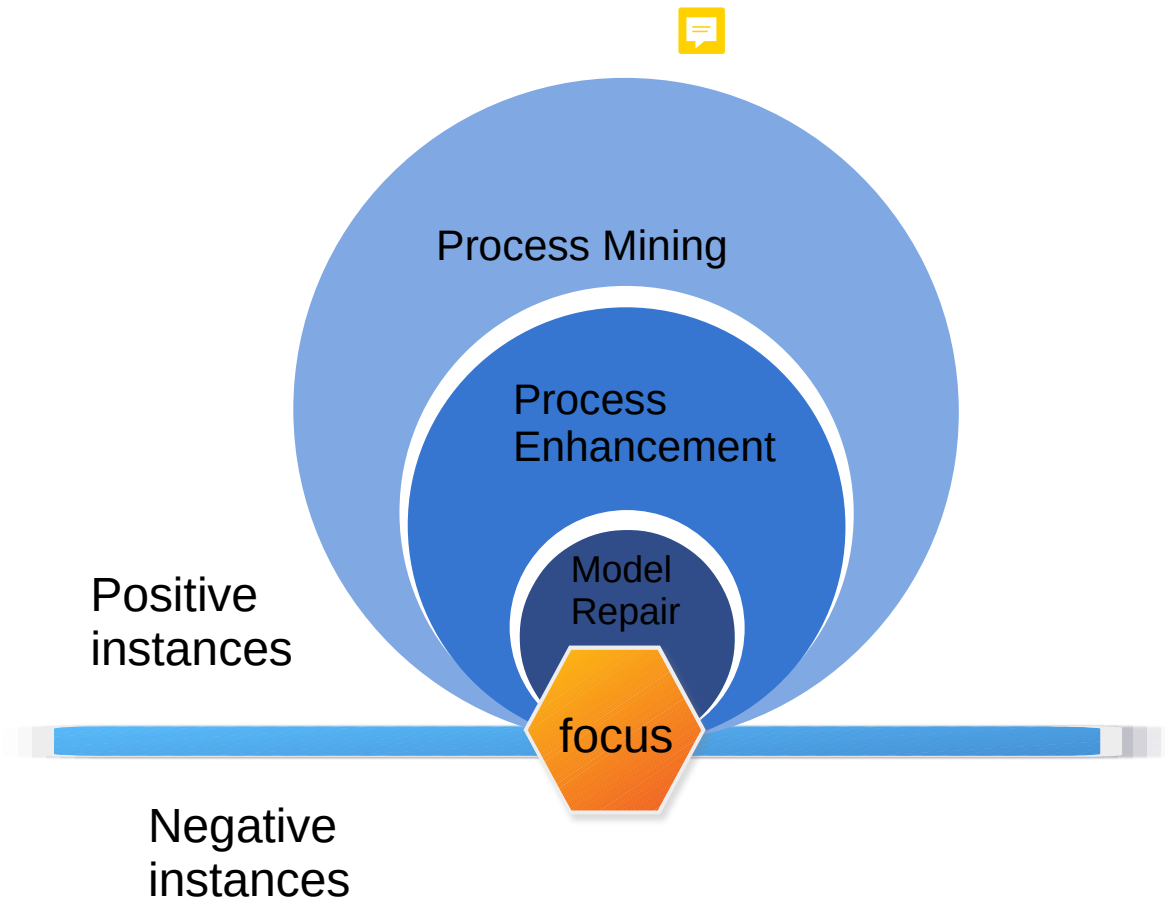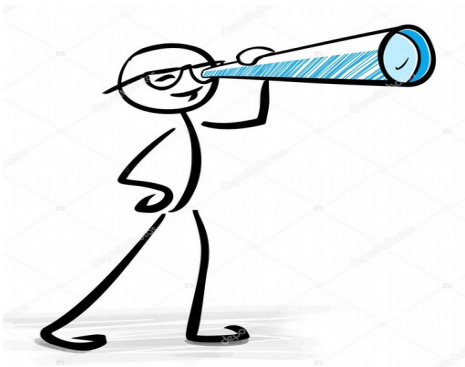
Literature Review

- **Rediscovery**
  - Inductive Miner

- **Model Repair by Fahland**
  - Deviations
  - Subprocesses

- **Model Repair by Dees**
  - Data with performance labels
  - Classify deviations
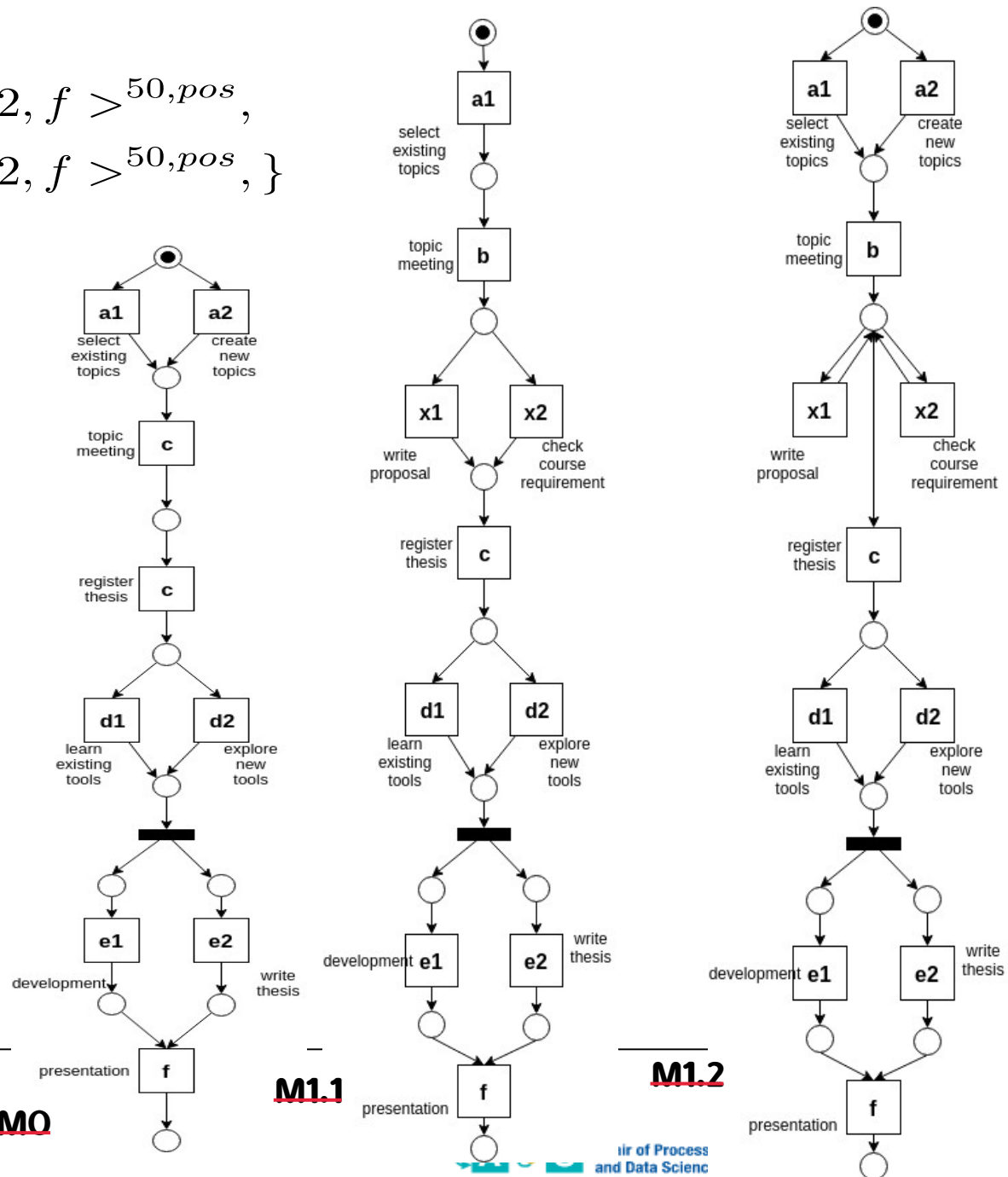 - Fahland's repair only on positive deviations

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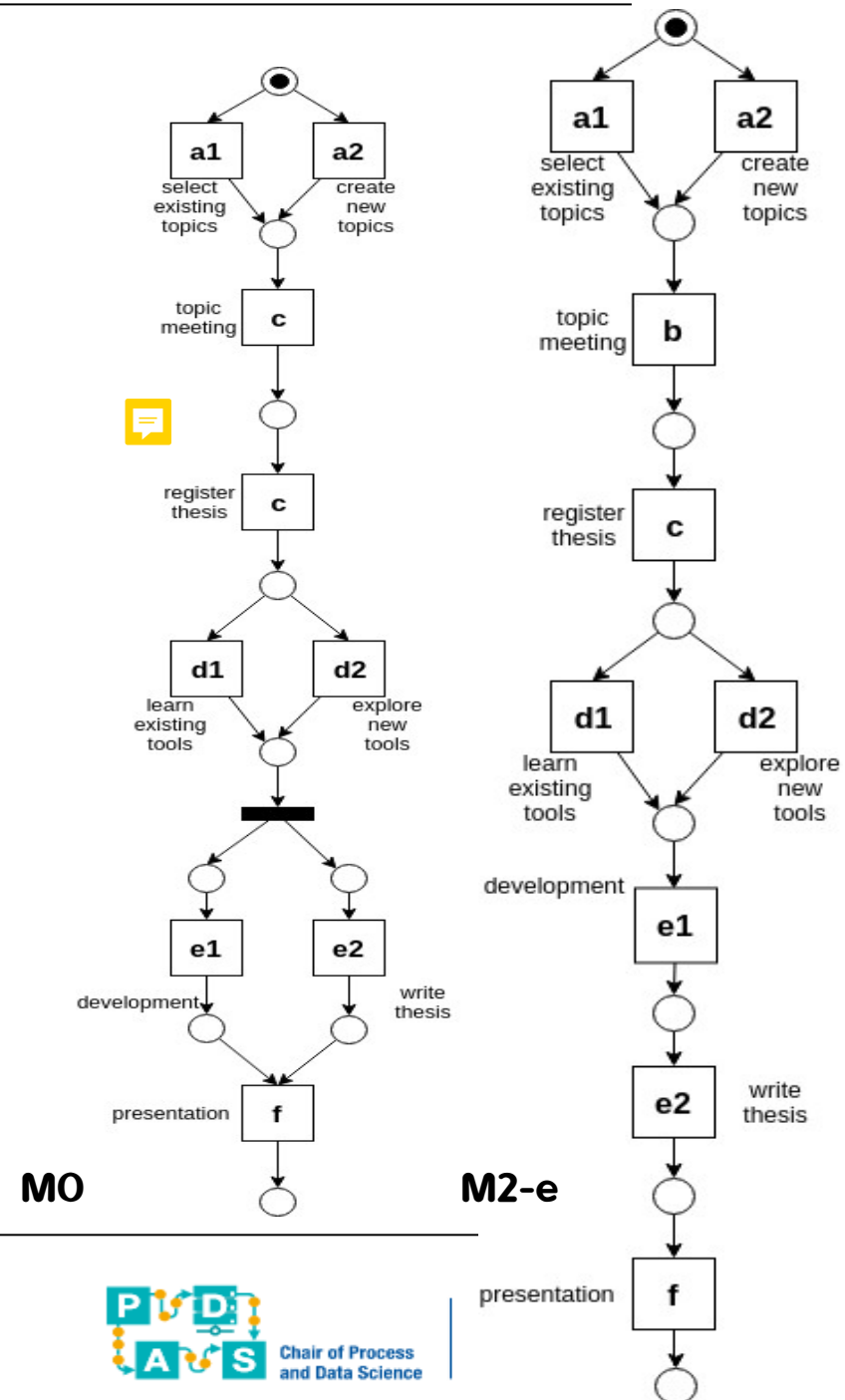$$< a1, b, \mathbf{x2}, c, d2, e1, e2, f >^{50,pos}, \}$$

- **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**

M0

M1.1

M1.2

5

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

- **IM keeps the model same**

- **Fahland's keep model same**

- **Dee's keep model same**

➔ **Unable to adapt model with fit traces**

MO

M2-e

Chair of Process and Data Science

Research Problem – shortcomings

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

- **Long-term dependency**
  - Choices decides choices
  - Additional places to limit behavior
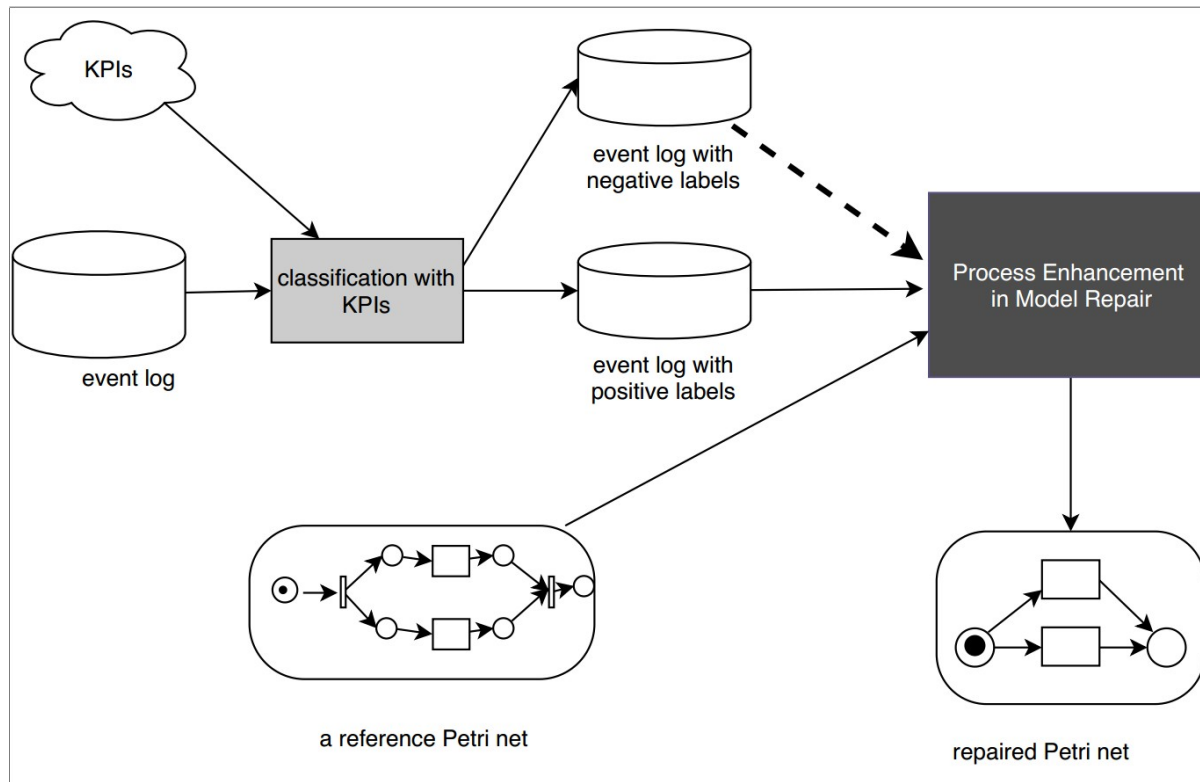
� **Unable to detect long-term dependency**
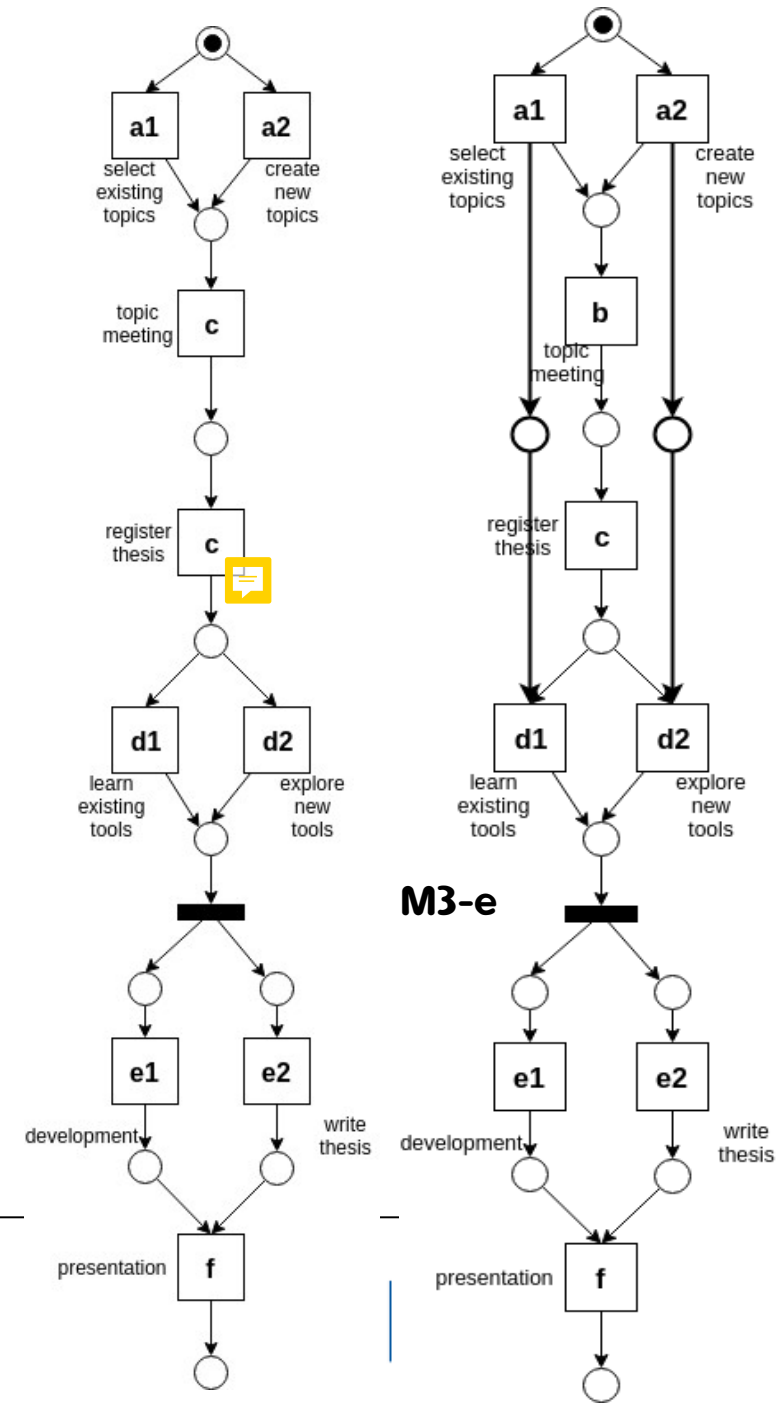
Research Problem

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?
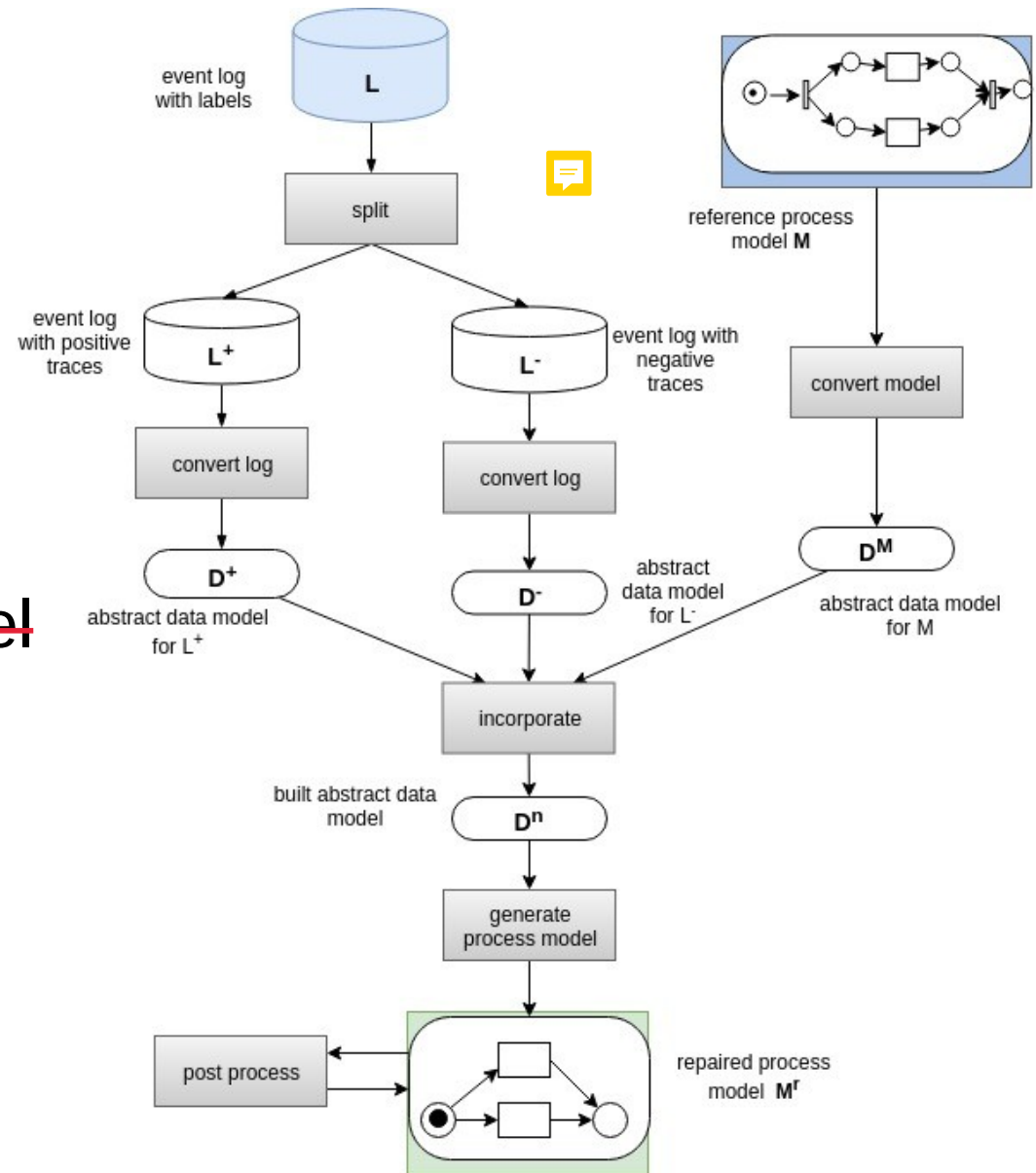
Algorithm – framework

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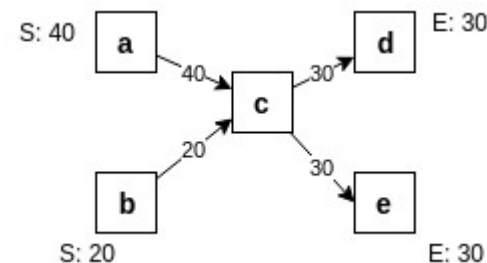 - ~~Post process~~

Data Model

- **Directly-follows graph**

  – Directly-follows relation $a >_L b$

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

  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

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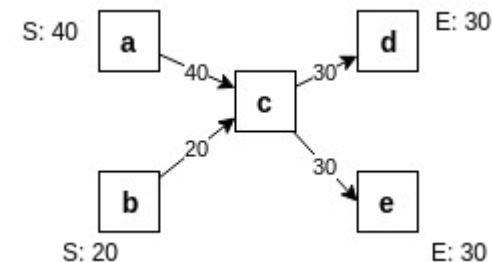
  - For start activity a

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

  - For end activity b

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

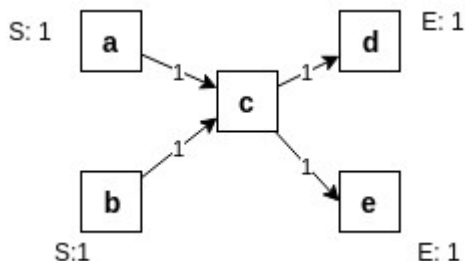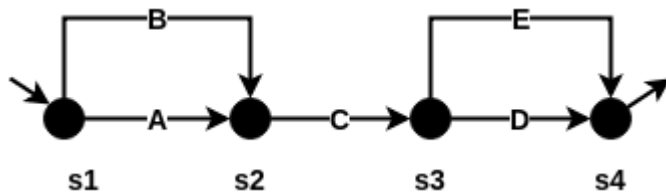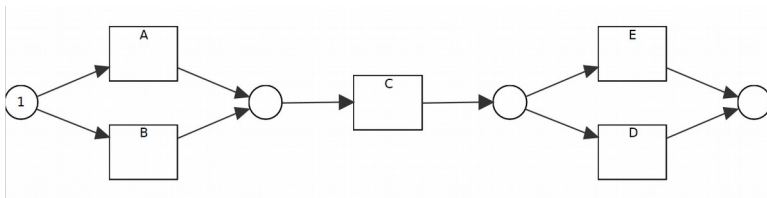$$L = \{< a, c, d >^{20}, < b, c, e >^{10}, < a, c, e >^{20}, < b, c, d >^{10}\}$$
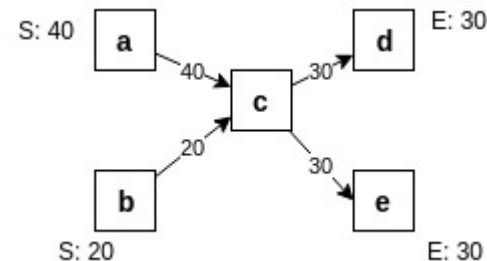
Convert to directly-follows graph

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
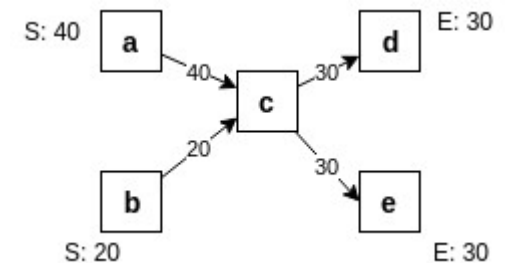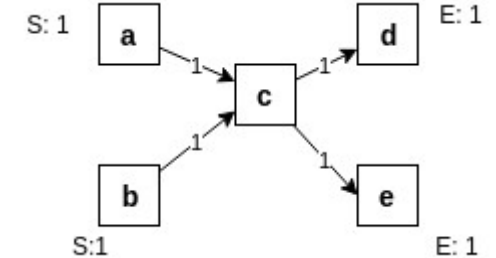
  - For any directly-follows relation

$$u(a, b) = \frac{c(a, b)}{\sum_{(a', b') \in F} c(a', b')}$$

  –

  - 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,
  $$a \in A_{start}^M \cup A_{start}^+ \cup A_{start}^-, u^n(a) = u^M(a) + u^+(a) - u^-(a)$$
  - For any end activity,
  $$a \in A_{end}^M \cup A_{end}^+ \cup A_{end}^-, u^n(a) = u^M(a) + u^+(a) - u^-(a)$$

- **Weighted value**
  - Three control weights w^+, w^-, w^M
  $$u_w^n(a,b) = w^M \cdot u^M(a,b) + w^+ \cdot u^+(a,b) - w^- \cdot u^-(a,b)$$

Generate Petri net

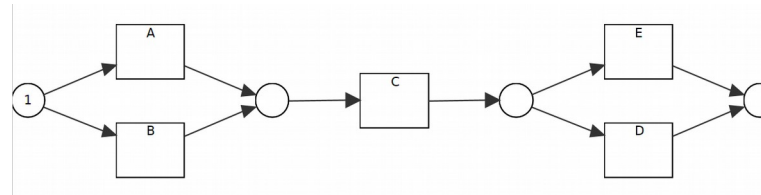- **Choose directly-follows relation**

$$u_w^n(a, b) > t$$
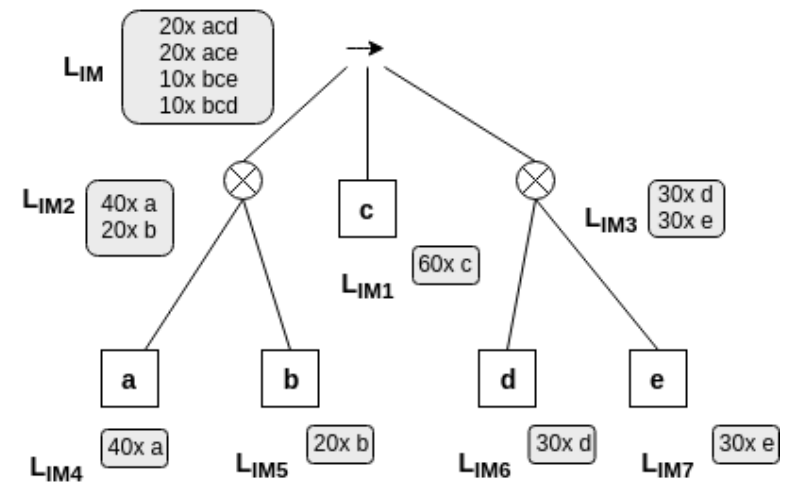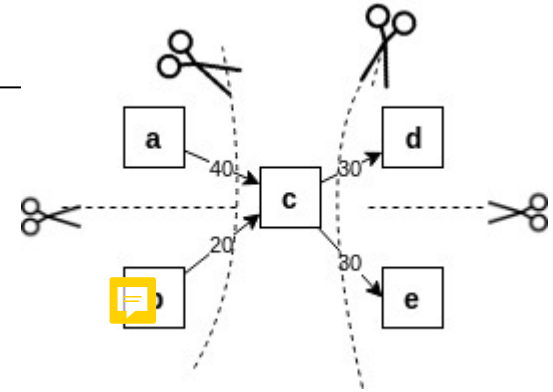
  - t=0

- **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
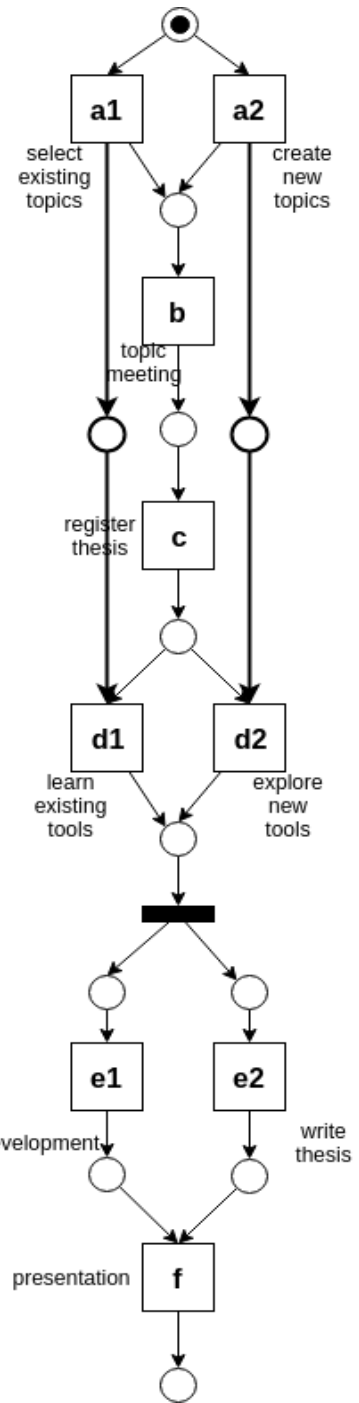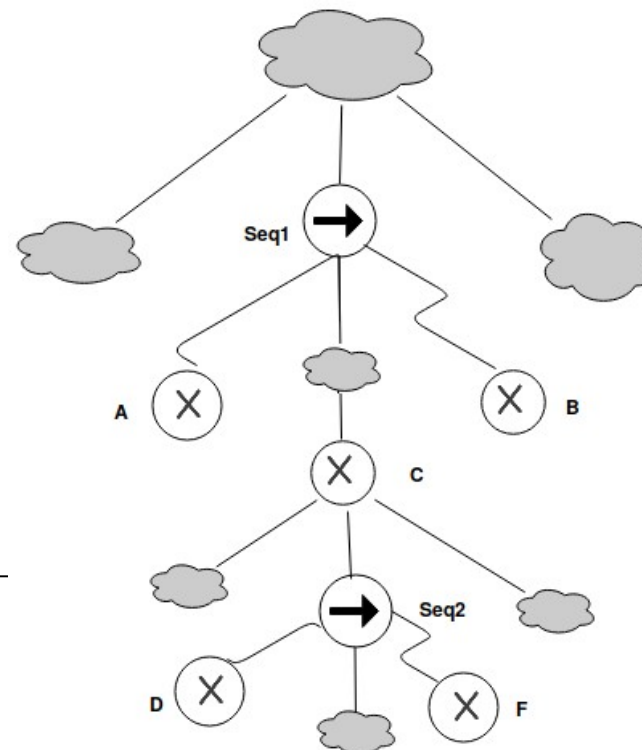   - ✔ Least common ancestor is Seq
            - A < C < B, D<F
        - ✔ In same level
            - A,B,C pair
            - D,F pair
    - Strong correlation

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

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, $f : X \to N, f_L(X) = \sum_{\sigma \in L} |\{\sigma | \sigma \models X\}|$

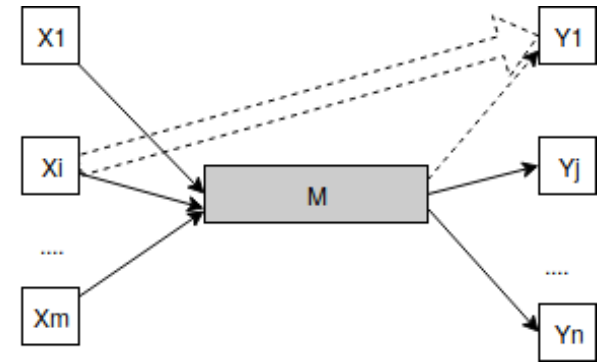Frequency of multiple xor branches is $f_L(X_1, X_2, ..., X_n) = \sum_{\sigma \in L} |\{\sigma | \forall X_i, \sigma \models X_i\}|$

- ✔ Correlation over t

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

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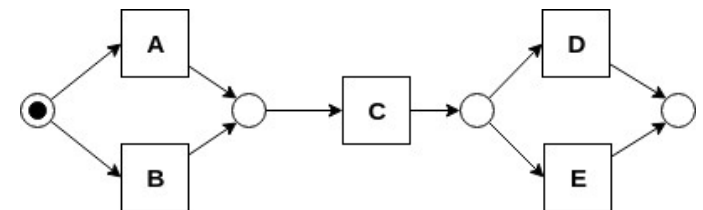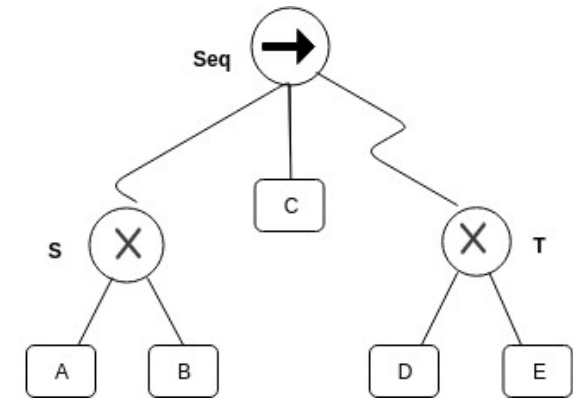
Algorithm – add long-term dependency

- **Long-term dependency Situations**

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

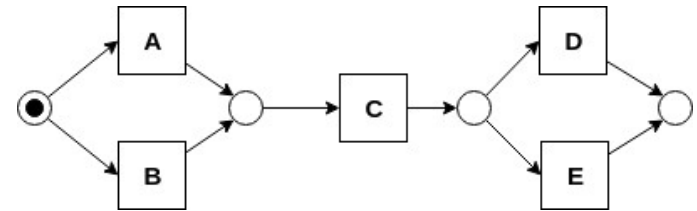$$LT_T := \{Y_j | \exists X_i, X_i \rightsquigarrow Y_j \in LT\}$$

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

2. $LT = \{A \rightsquigarrow D, A \rightsquigarrow E, B \rightsquigarrow D\}$.
   $LT_S = \{A, B\}, LT_T = \{D, E\}$ $LT_S = S$ and $LT_T = T, |LT| < |S| \cdot |T|$.

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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. $LT = \emptyset$

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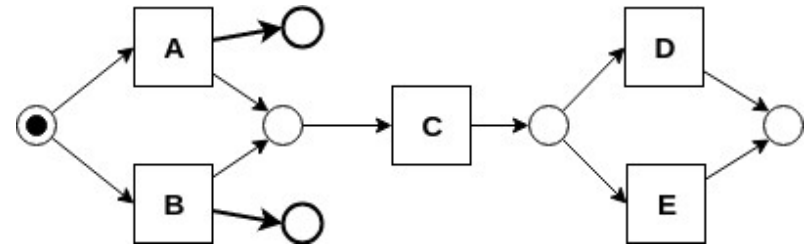
   - Situation 7 is empty. ==> no consideration

Algorithm – add long-term dependency

– How to express on Petri net

  ✔ Add silent transition

  – Add control place as post-place post after S

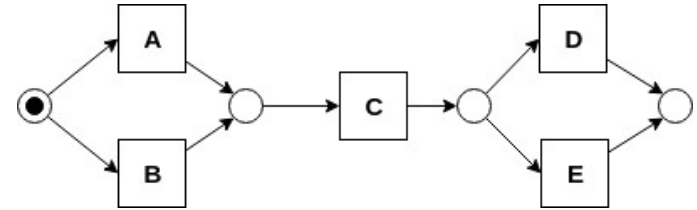$$LT = \{A \rightsquigarrow D, A \rightsquigarrow E, B \rightsquigarrow E\}.$$
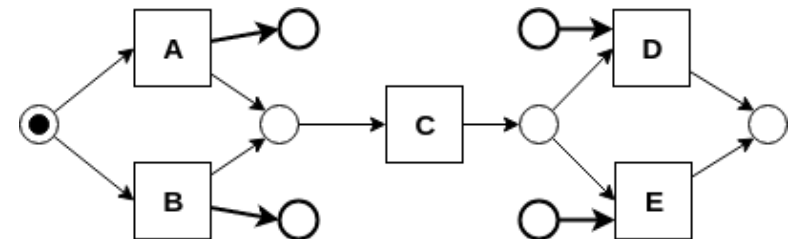
Algorithm – add long-term dependency

– How to express on Petri net

$$LT = \{A \rightsquigarrow D, A \rightsquigarrow E, B \rightsquigarrow E\}.$$

  ✔ Add silent transition

  – Add control place as post-place post after S

  – Add control place as pre-place before T
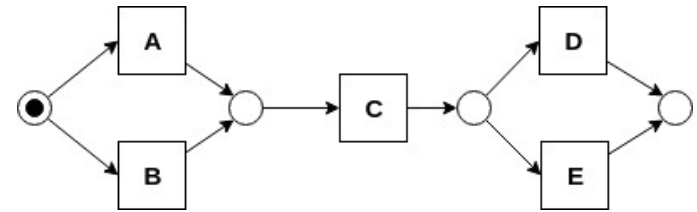
Algorithm – add long-term dependency

– How to express on Petri net
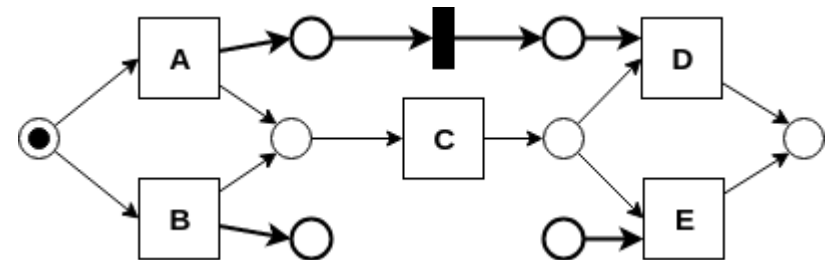
  ✔ Add silent transition

    – Add control place as post-place post after S

    – Add control place as pre-place before T

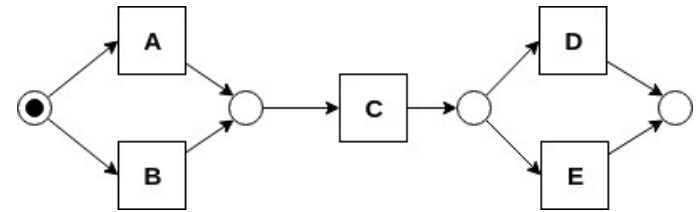   – Add silent transitions for each long-term dependency

$$LT = \{A \rightsquigarrow D, A \rightsquigarrow E, B \rightsquigarrow E\}.$$
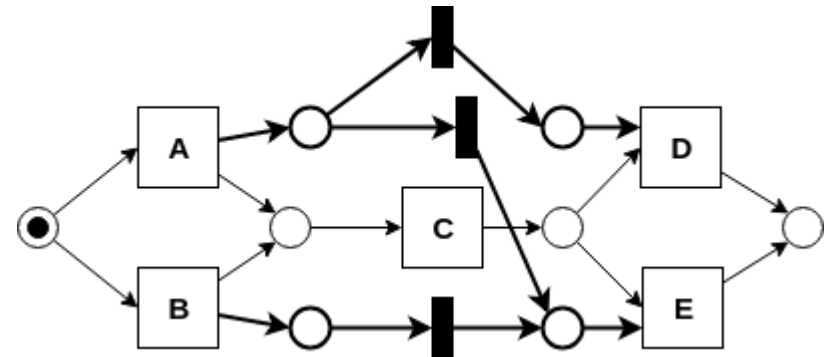
Algorithm – add long-term dependency

– How to express on Petri net

  ✔ Add silent transition

   – Add control place as post-place post after S

$$LT = \{A \rightsquigarrow D, A \rightsquigarrow E, B \rightsquigarrow E\}.$$

   – Add control place as pre-place before T

   – Add silent transitions for each long-term dependency

Algorithm – add long-term dependency

- **Long-term dependency Situations**

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

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

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

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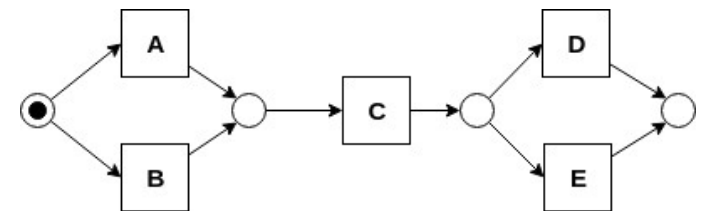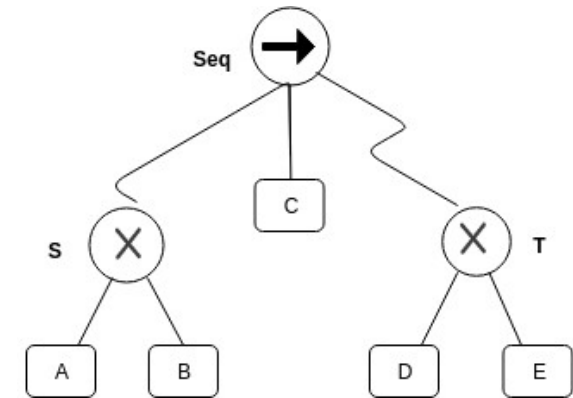 $LT_S \subsetneq S, LT_T = T$.

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

7. $LT = \emptyset$

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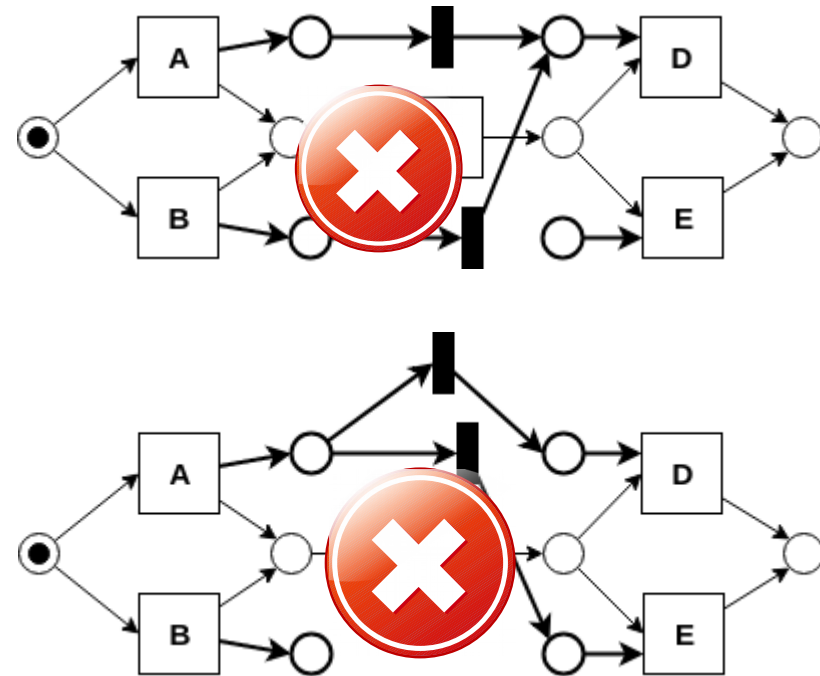- Situation 7 is empty. ==> no consideration

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.
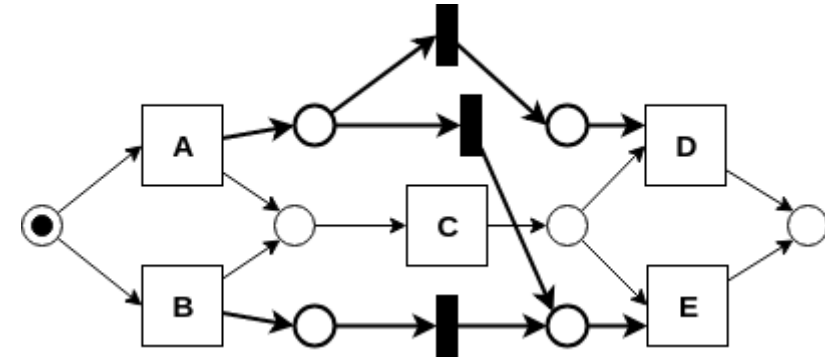- ✓ No dead parts.
  For any transition, there exists a path from source to sink place through it.

Soundness proof

Given $S = \{X_1, X_2, ...X_m\}$ and $T = \{Y_1, Y_2, ...Y_n\}$ with
$LT = \{X_i \rightsquigarrow Y_j | 1 \leq i \leq m, 1 \leq j \leq n\}$. 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.
$$\sum M(p_{X_i}) \leq 1, \sum M(p_{Y_j}) \leq 1$$

- Proper completion.
  After firing Y_j , $\sum M(p_{X_i}) = 0, \sum M(p_{Y_j}) = 0$
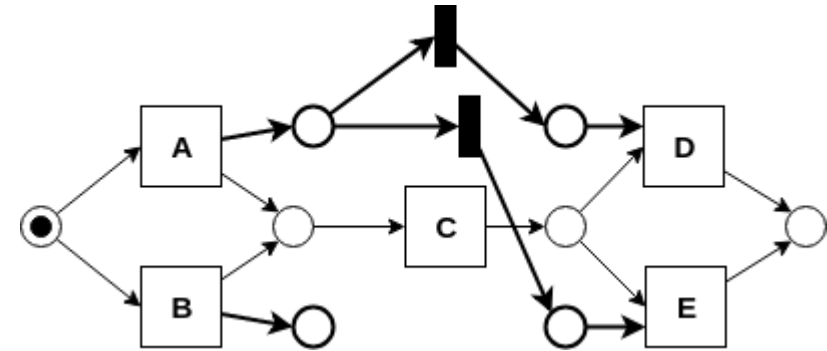
- Option to complete & No dead parts.
$$\forall X_i \in S \text{ is enabled at beginning}$$
$$\forall X_i \in S, \text{since } LT_S = S, \Rightarrow \exists Y_j \in T, X_i \rightsquigarrow Y_j,$$
$$\epsilon \text{ is enabled with } p_{X_i} \rightarrow \epsilon \rightarrow p_{Y_j}$$
$$\forall Y_j \in T, \text{since } LT_T = T, \Rightarrow \exists X_i \in S, X_i \rightsquigarrow Y_j$$

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.

$$\forall X_i \in S \text{ is enabled at beginning}$$
$$\text{if } LT_S \subsetneq S, \Rightarrow \exists X_i \in S, X_i \notin LT_S, \text{token remains}$$
$$\text{if } LT_T \subsetneq T, \Rightarrow \exists Y_j \in T, Y_j \notin LT_T, \text{token misses}$$

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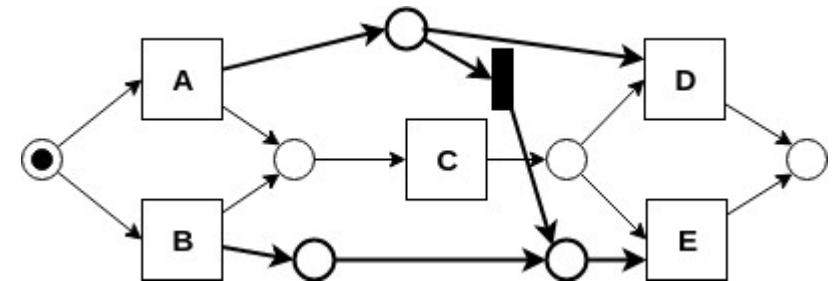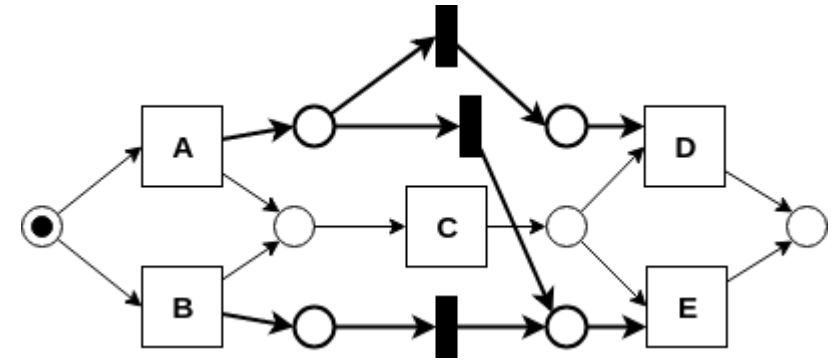
7. $LT = \emptyset$

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

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

Chair of Process and Data Science

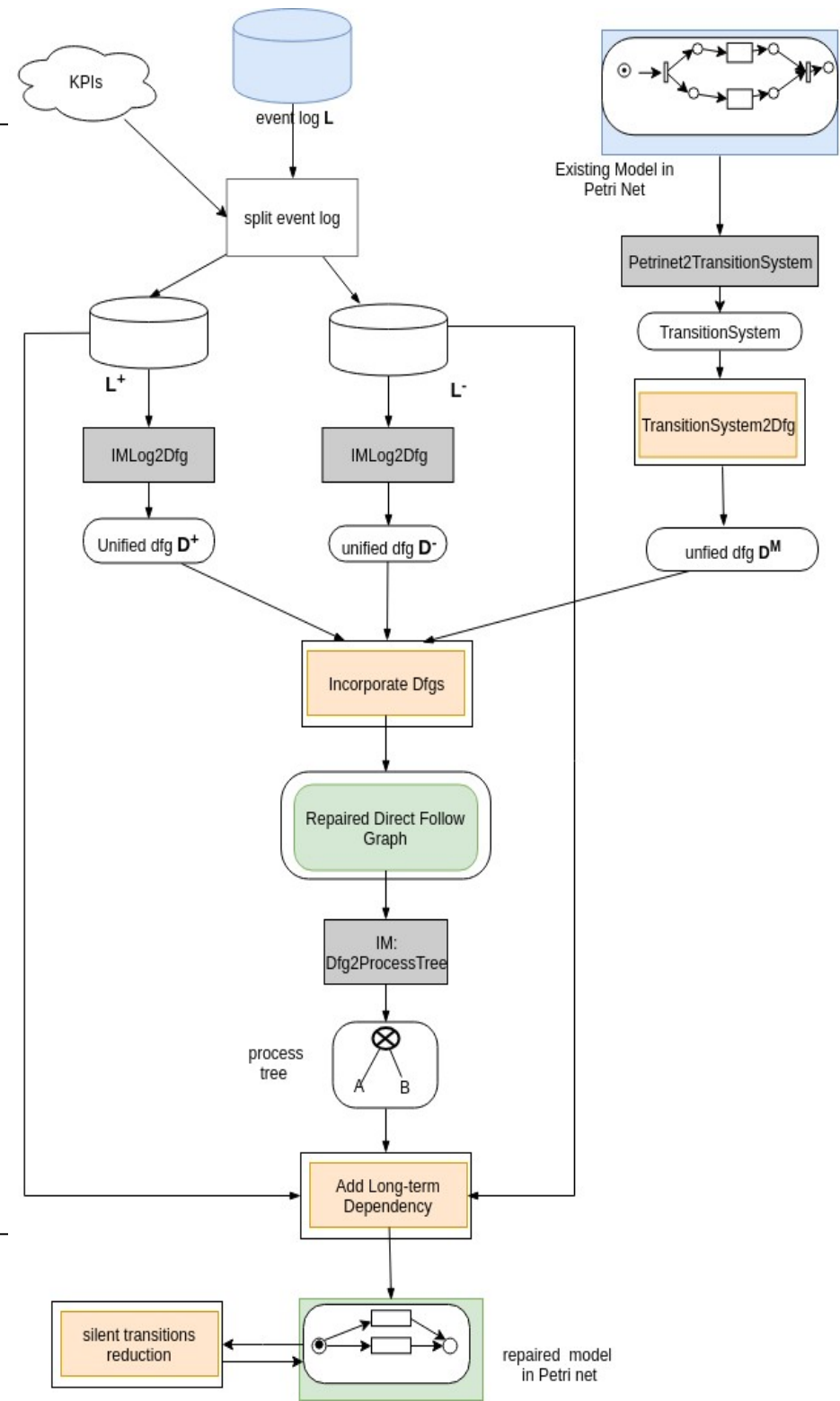RWTH AACHEN UNIVERSITY

Post process

- **Delete redundant silent transitions**
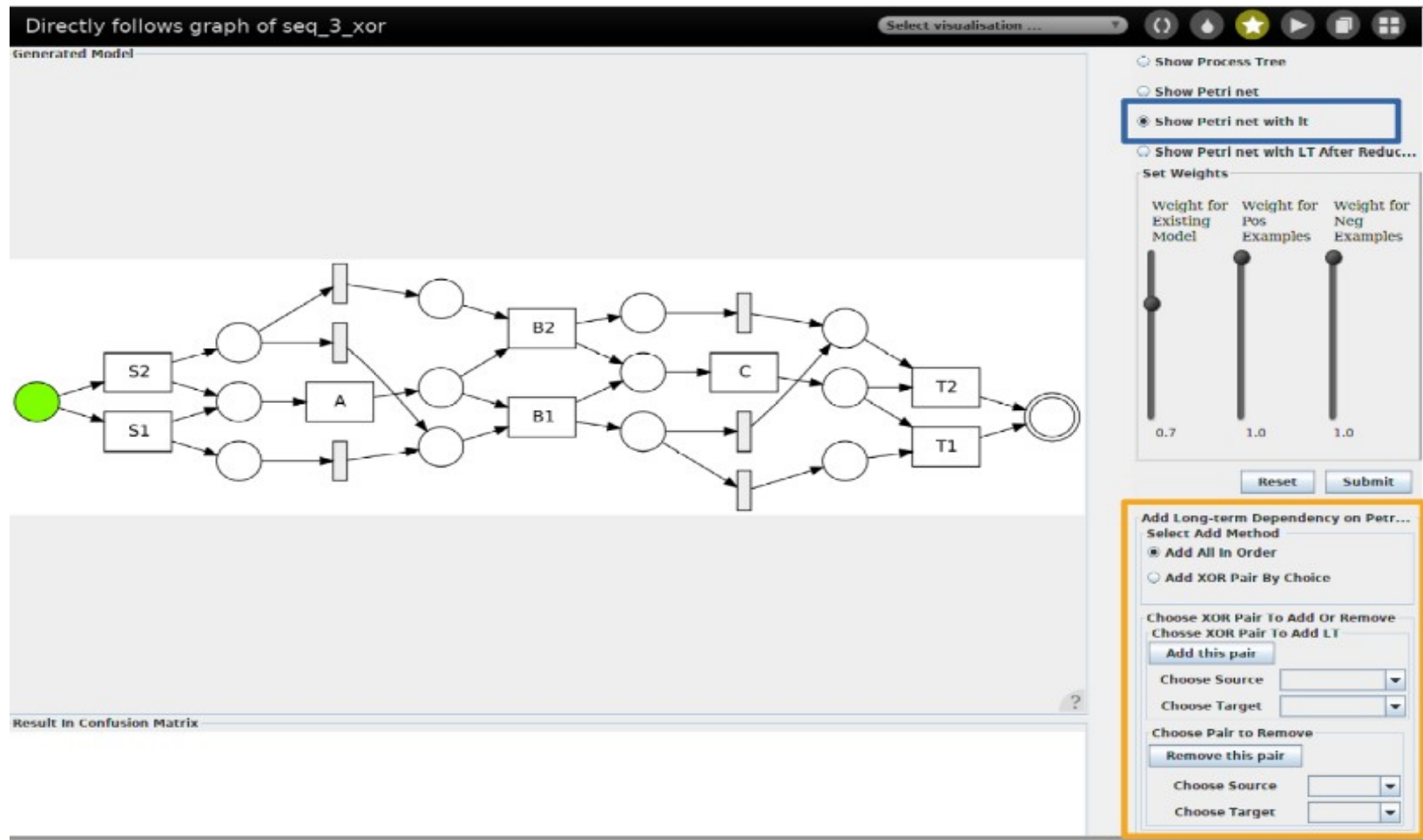
Algorithm – architecture

- Data ~~model~~
    -

- ~~Convert models~~
    -

- ~~Incorporate dfgs~~
    -

- ~~Add long-term dependency~~
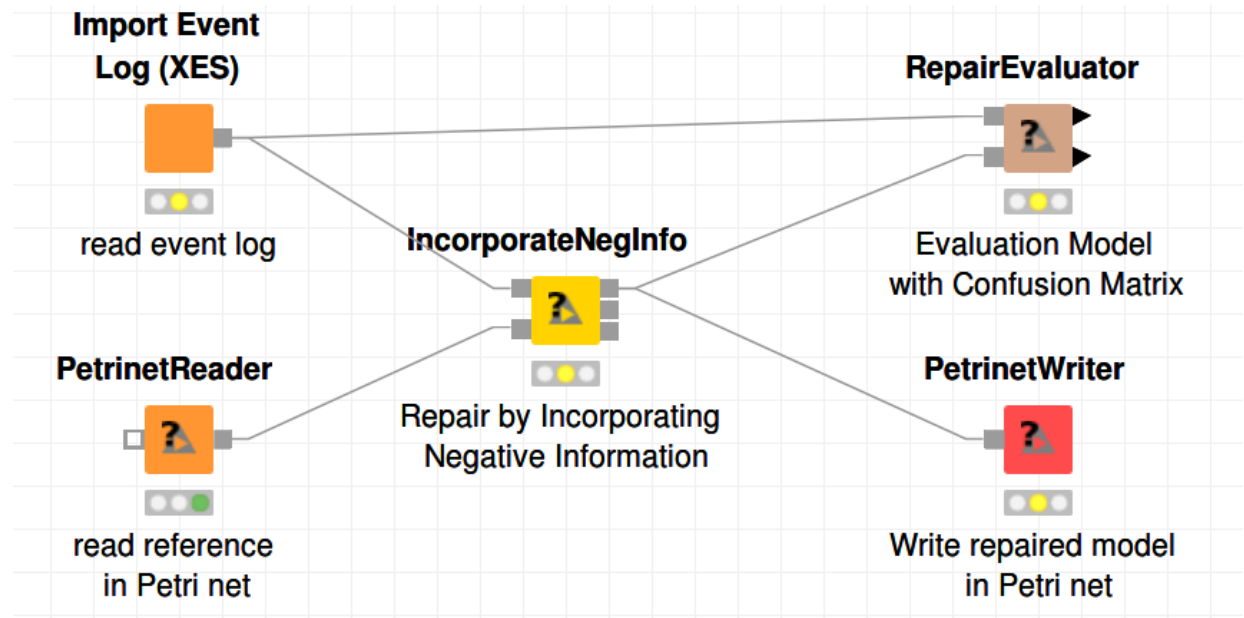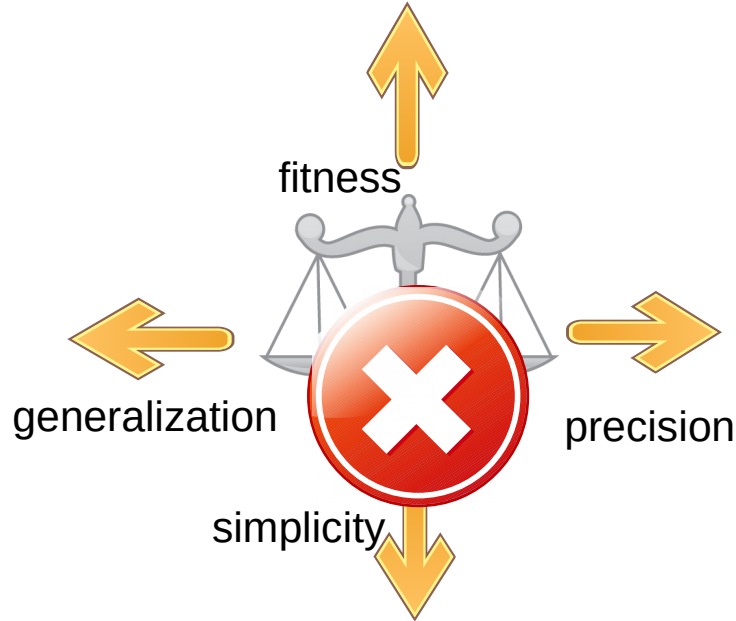   -

- ~~Delete redundant silent transitions~~
    -

Demo

Demo

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

Evaluation

fitness

generalization

precision

simplicity

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

- **Confusion matrix**
  - Recall
  $$Recall = \frac{TP}{TP + FN}$$
  - Precision
  $$Precision = \frac{TP}{TP + FP}$$
  - Accuracy
  $$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$
  - F1
  $$F_1 = \frac{2 * Recall * Precision}{Precision + Recall}$$

Demo --result

Demo --result

Overcome s1:
  add subprocesses
  as loops
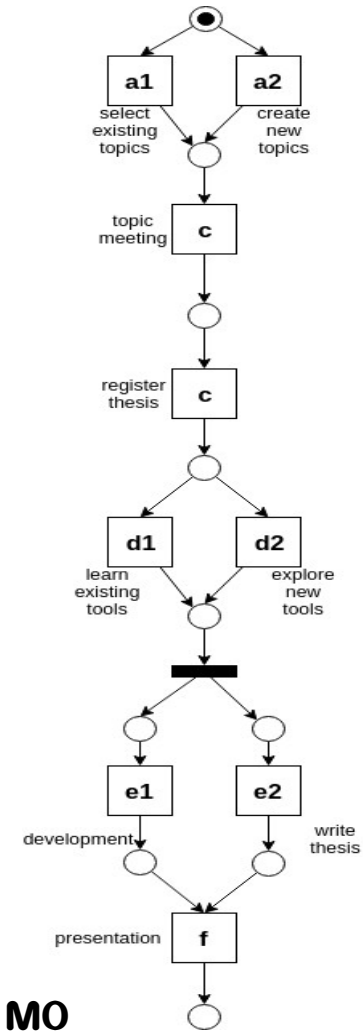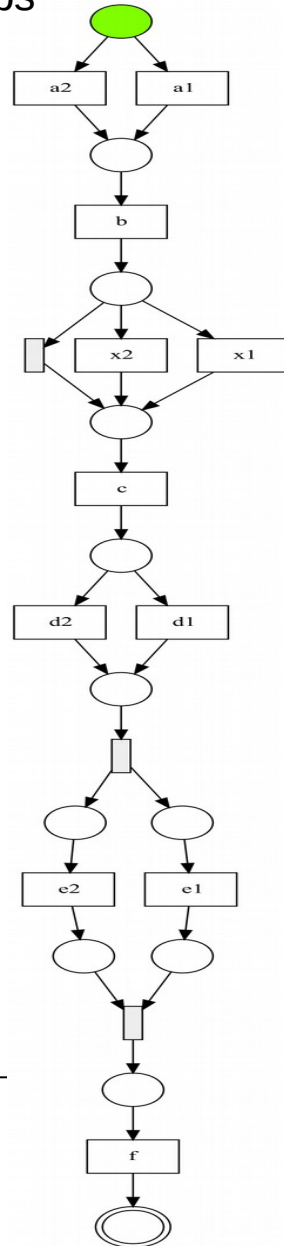
Overcome s2:
  Unable to adapt model
  with fit traces

Overcome s3:
  Unable to detect
  long-term dependency

M0

M1.3

M2.3

M3.3
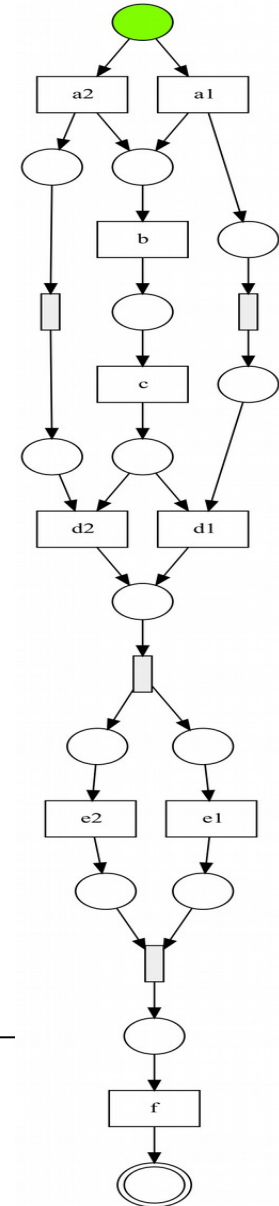
Demo --result

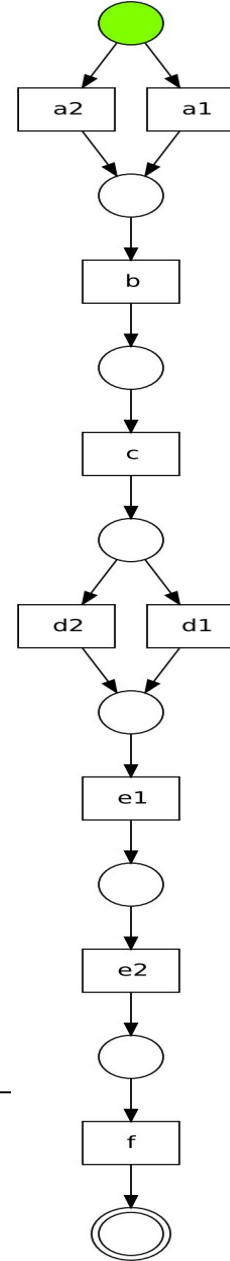| Situation	Method	Generated Model	Confusion matrix measurements							
			TP	FP	TN	FN	recall	precision	accuracy	F1
S1	IM-Infrequent Noise threshold: 20%	M1.1	50	50	0	0	1	0.5	0.5	0.667
	Fahland's Repair Model	M1.2	50	50	0	0	1	0.5	0.5	0.667
	Dfg-repair	M1.3	50	50	0	0	1	0.5	0.5	0.667
S2	IM/Fahland's	M0	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
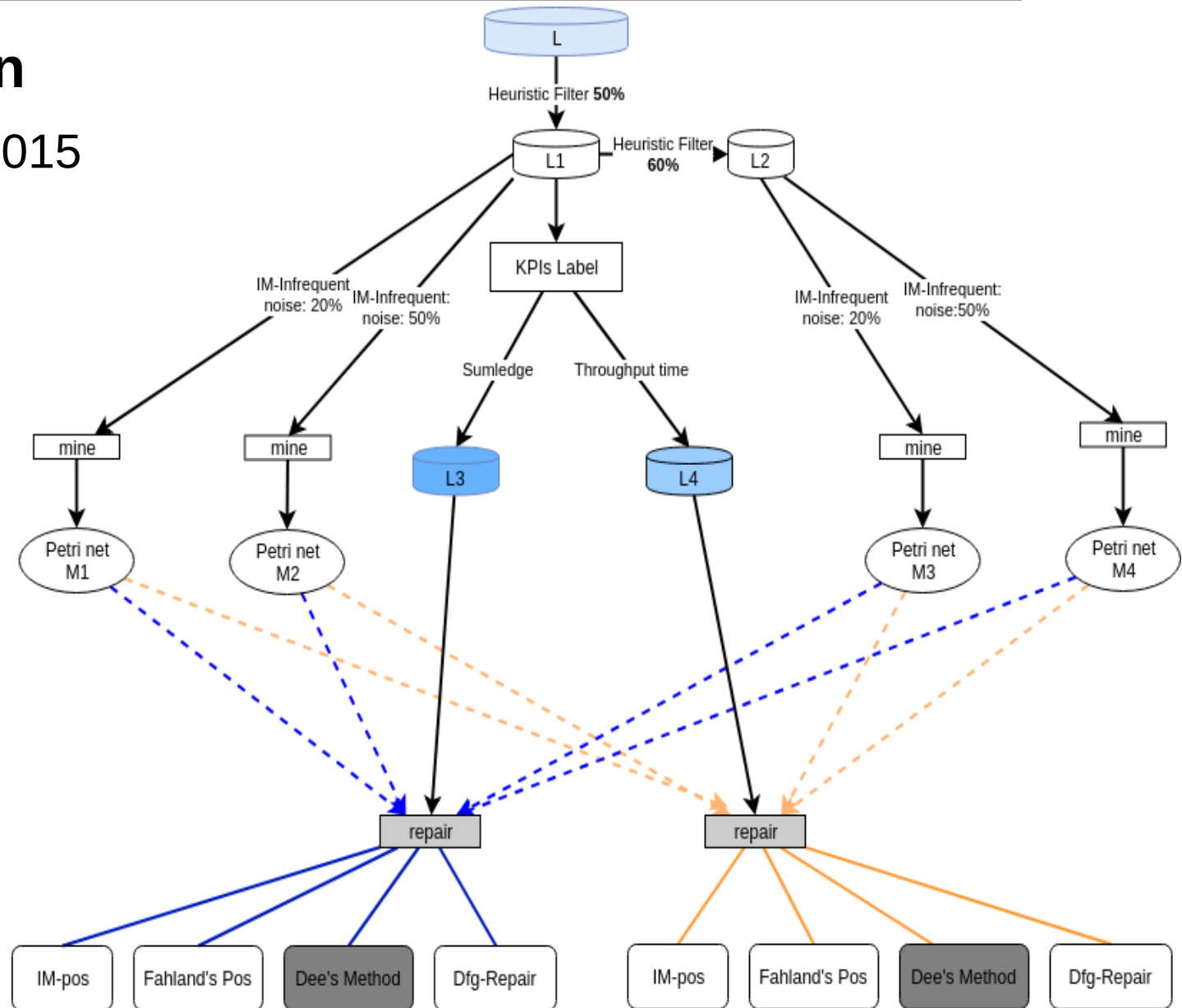
Experiments -- Real life data

- **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**
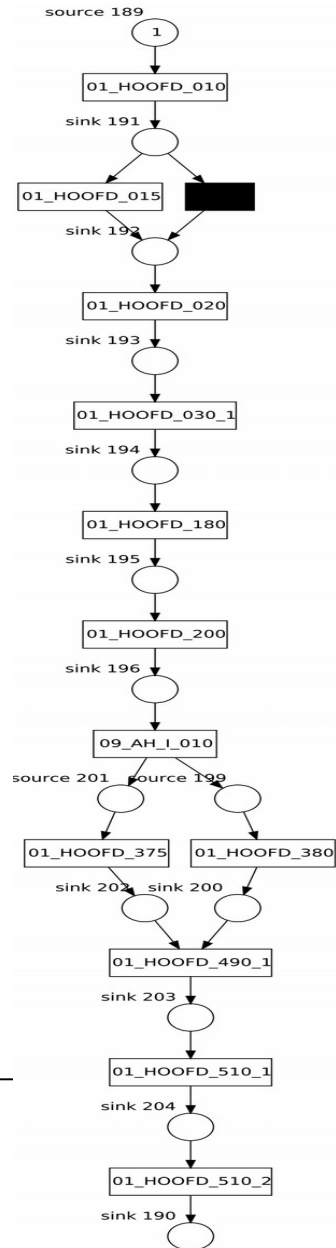
M3

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

Fanhland's method to repair M3 with default setting

Experiments results

Dfg-repair with default setting

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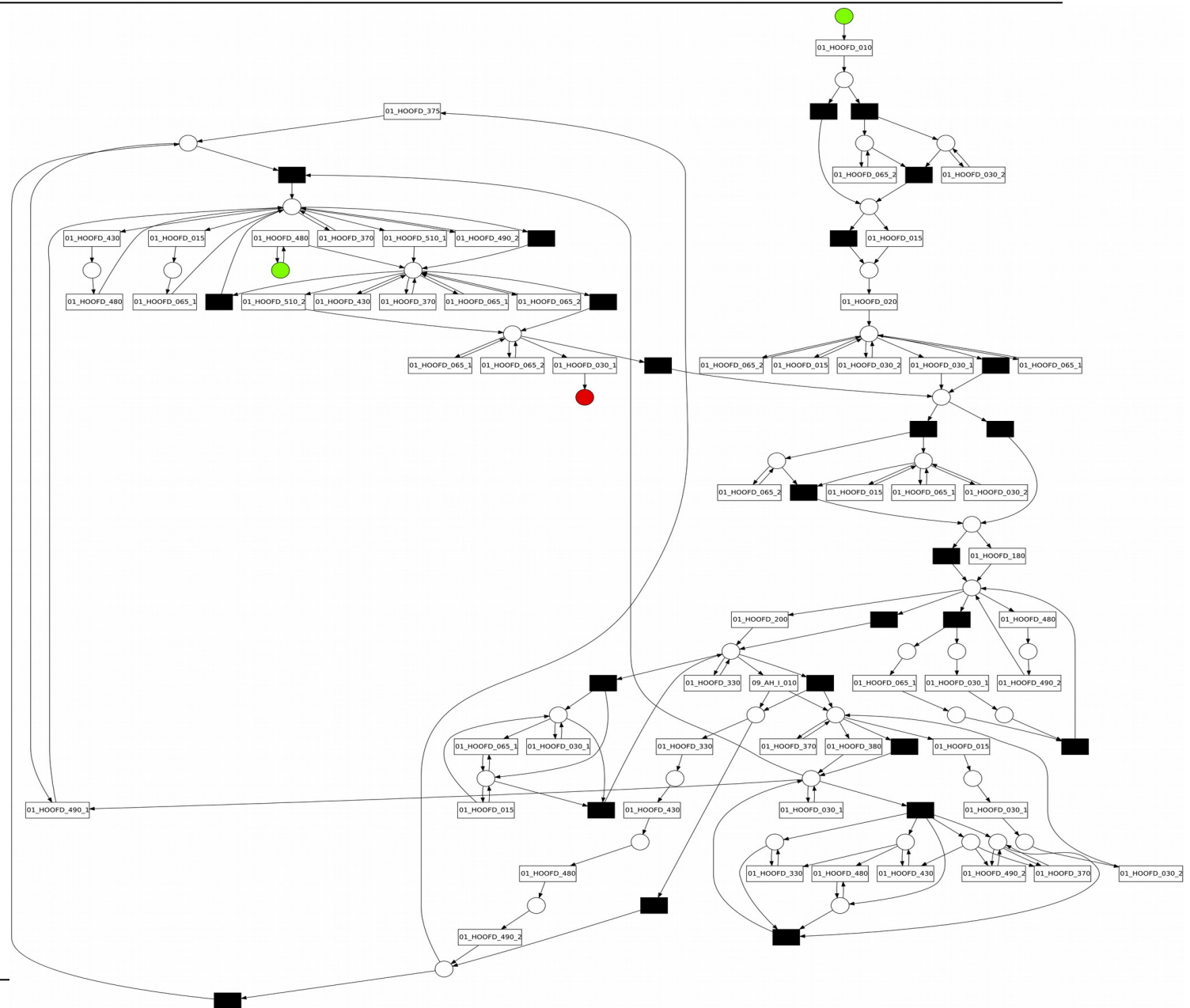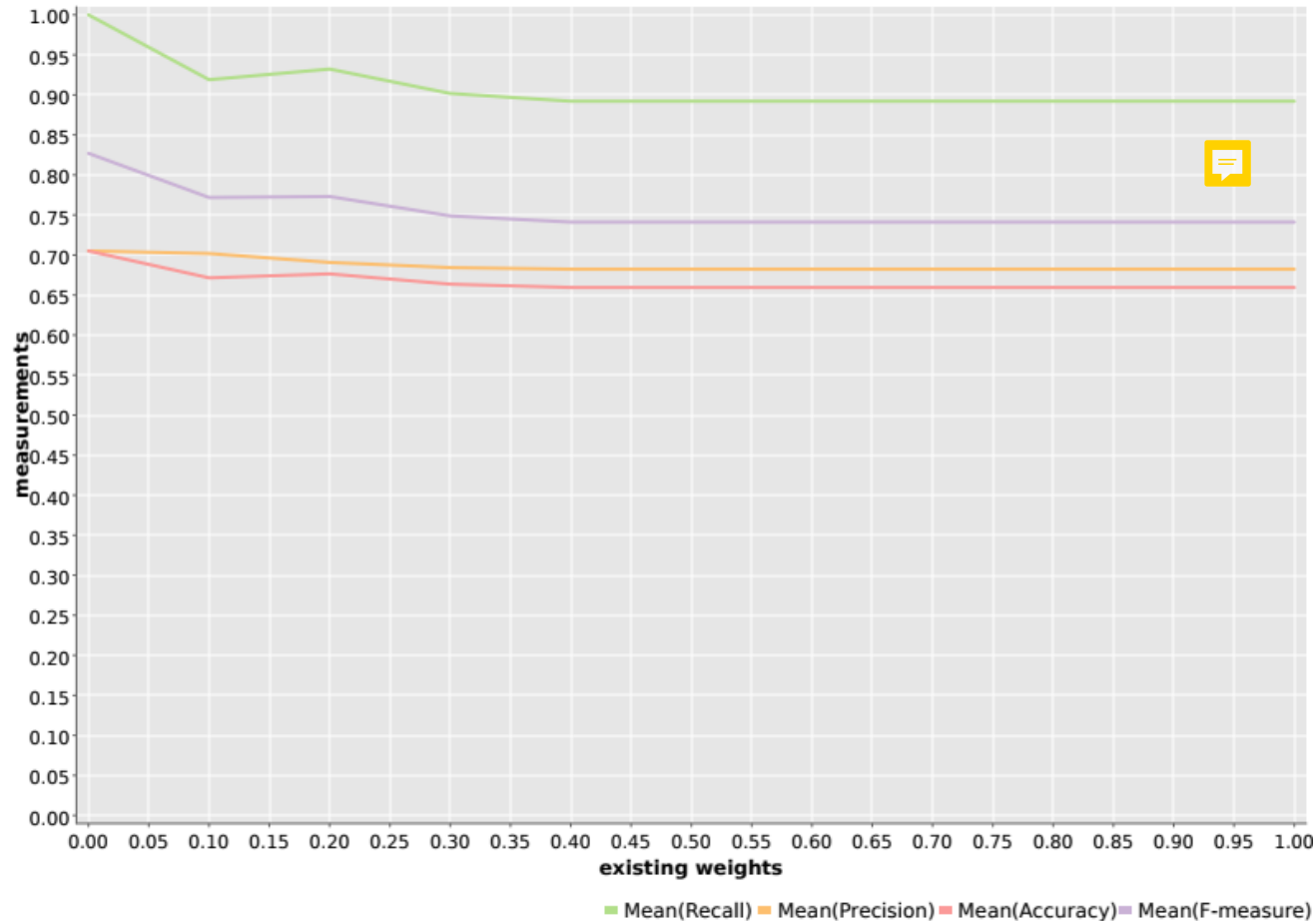
Experiment result

Experiment result

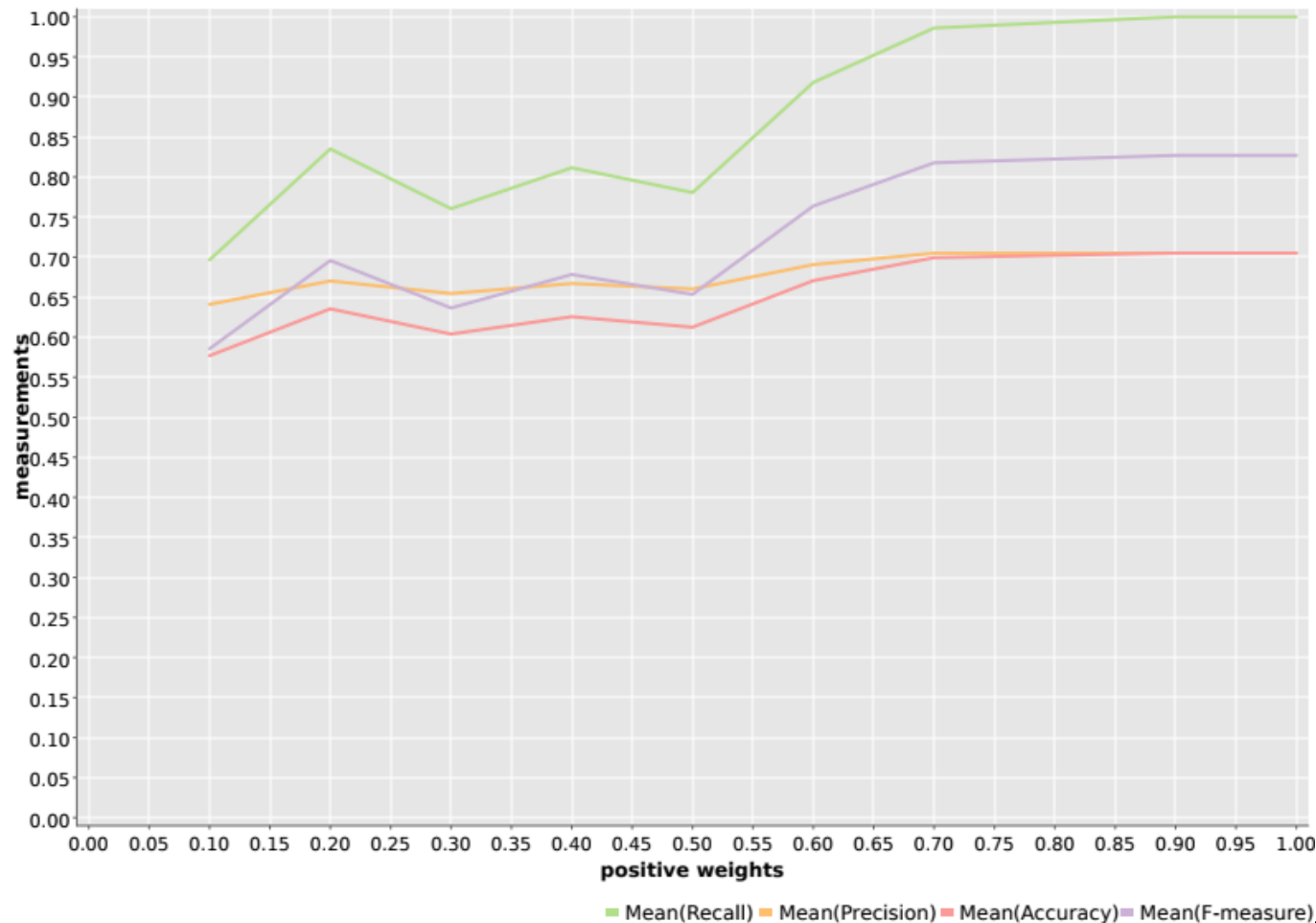- ## **Weight for the reference model**

Measurements change with existing weight

Experiment result

- ## **Weight for positive instance**
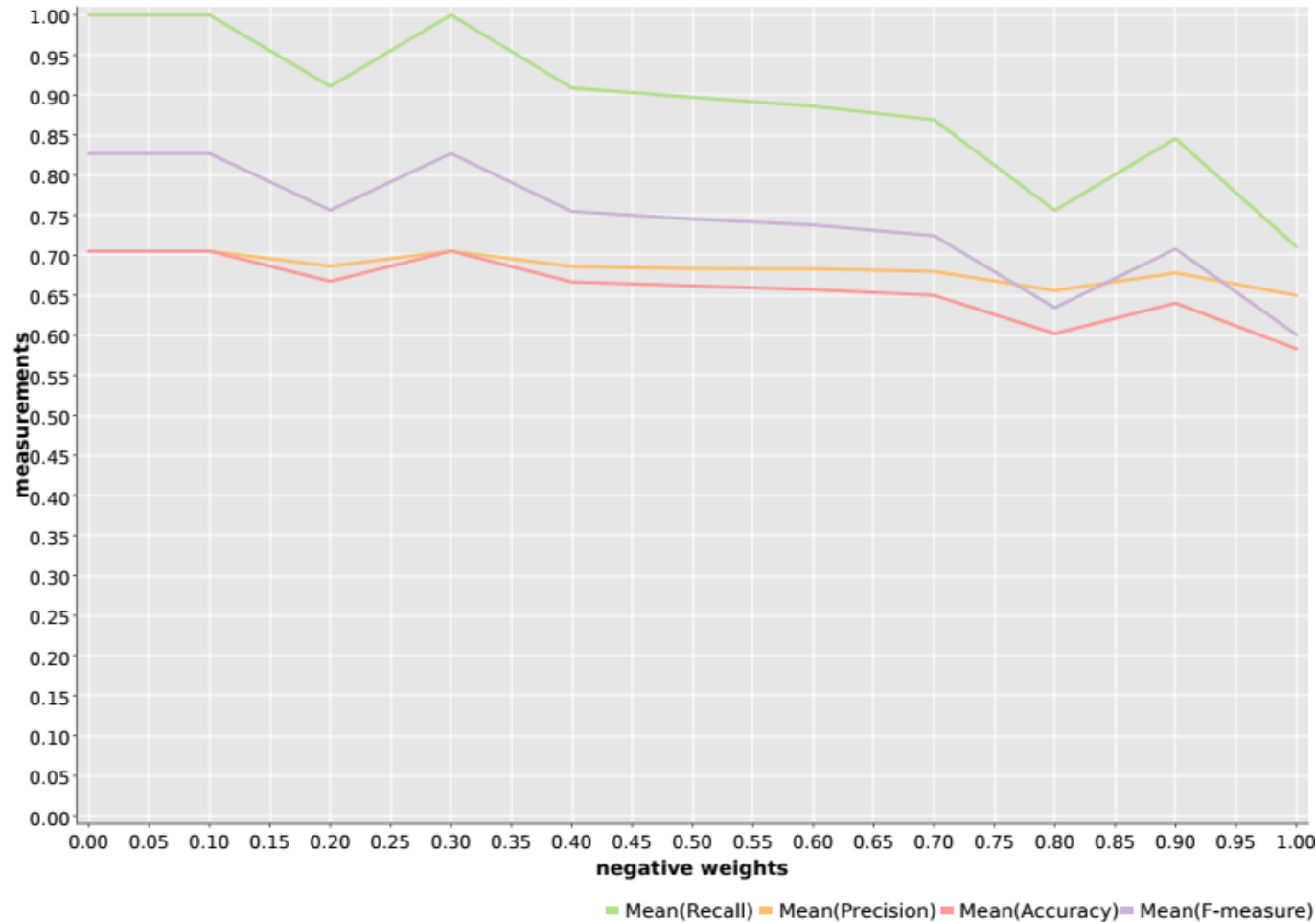
Measurements change with positive weight

Experiment result

- ## **Weight for negative instance**

Measurements change with negative weight

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