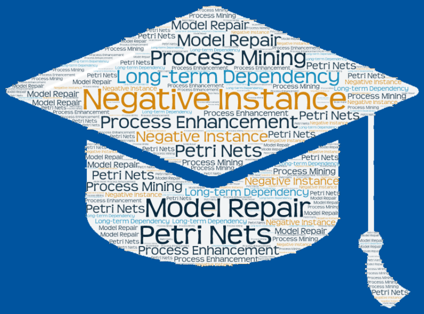
Master Thesis



Model Repair by Incorporating Negative Instances in Process Enhancement

Author: **Kefang Ding**

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

Chair of Process and Data Science

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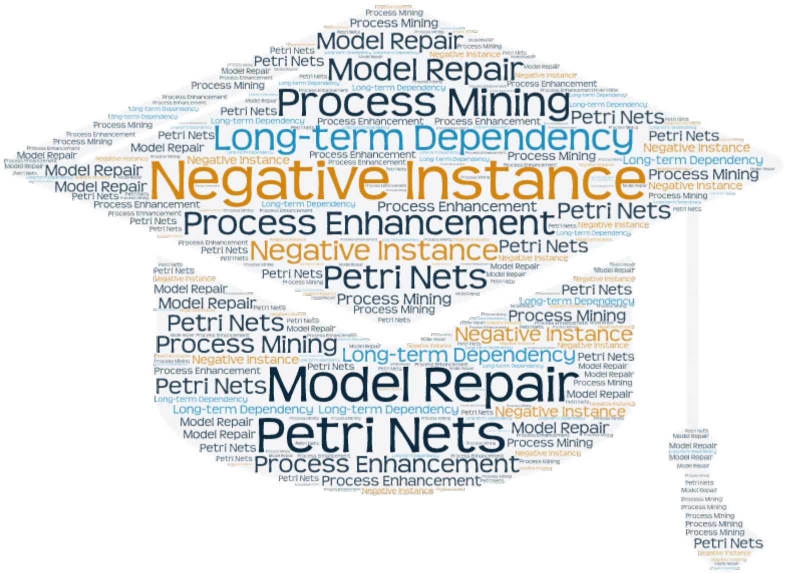

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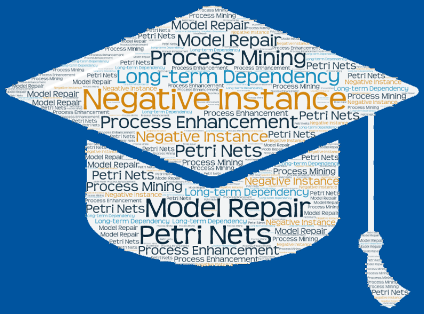

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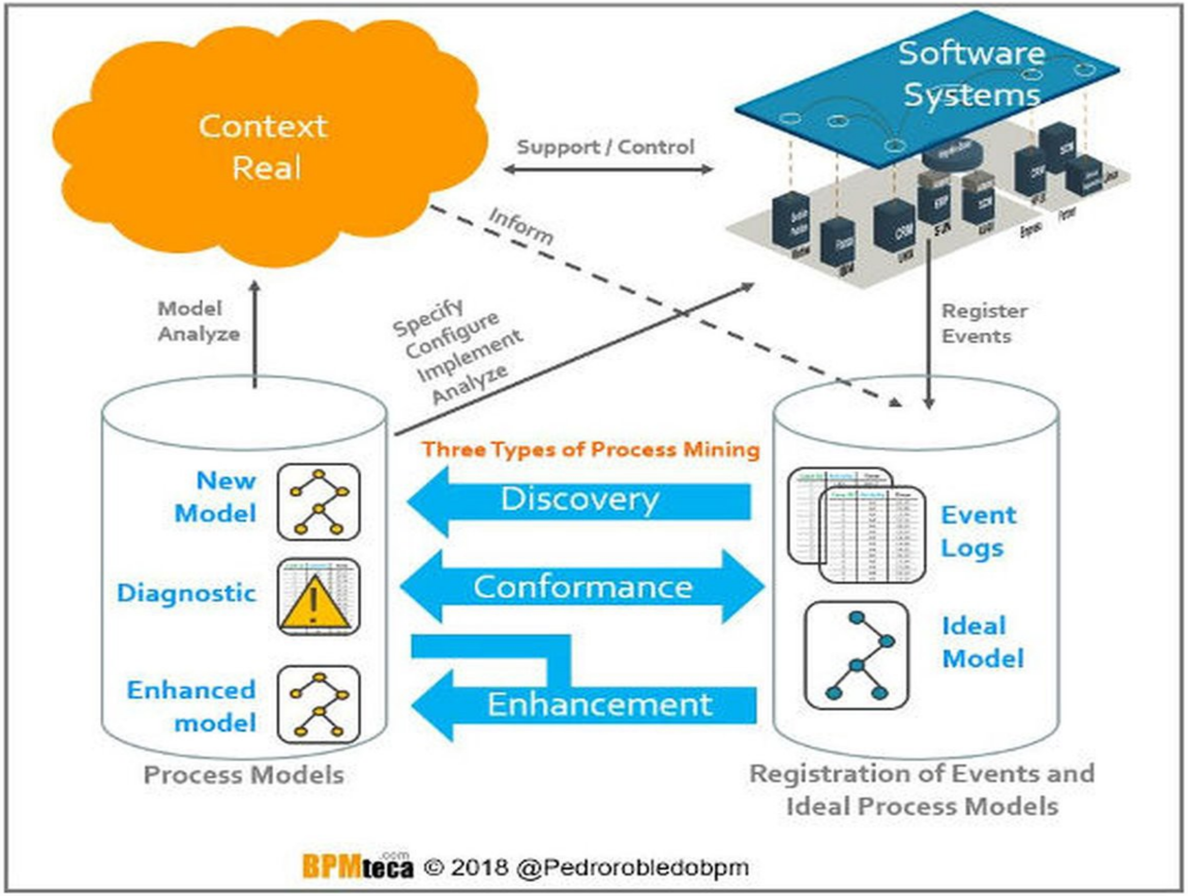
Outline

- **Motivation**
- **Problem Definition**
- **Approach**
- **Demo**
- **Evaluation**
- **Conclusion**

Outline

- **Motivation**
  - Scope
  - Related work
  - Motivating examples
- **Problem Definition**
- **Approach**
- **Demo**
- **Evaluation**
- **Conclusion**

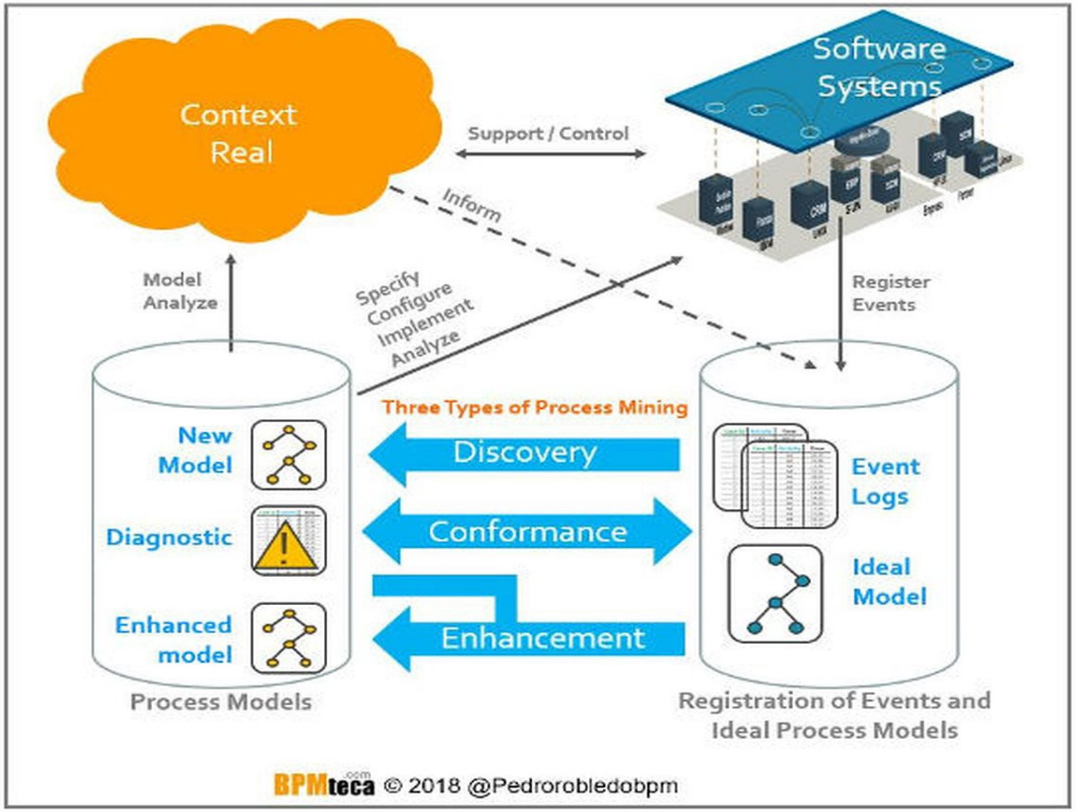
Scope

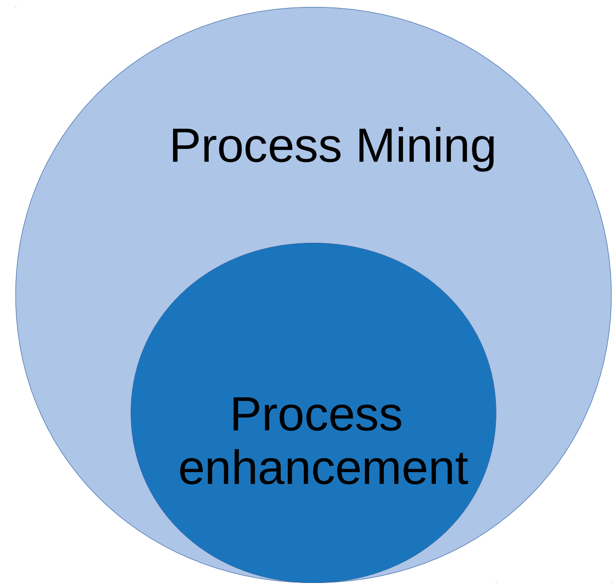


Process Mining

https://medium.com/@pedrorobledobpm/process-mining-plays-an-essential-role-in-digital-transformation-384839236bbe

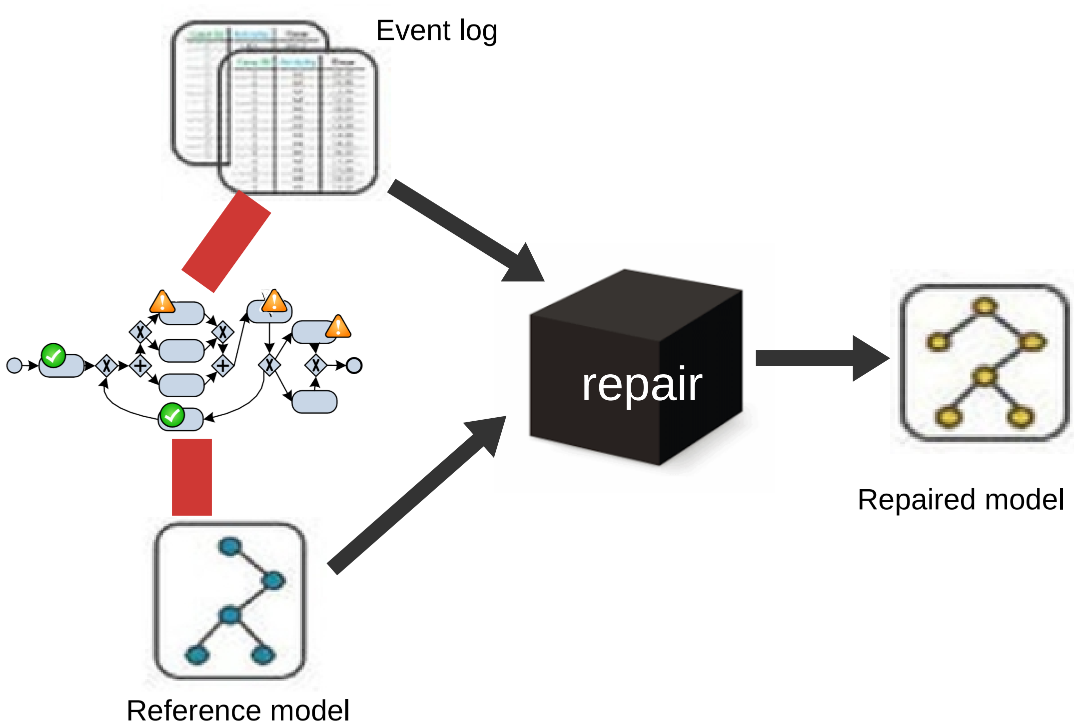
Scope

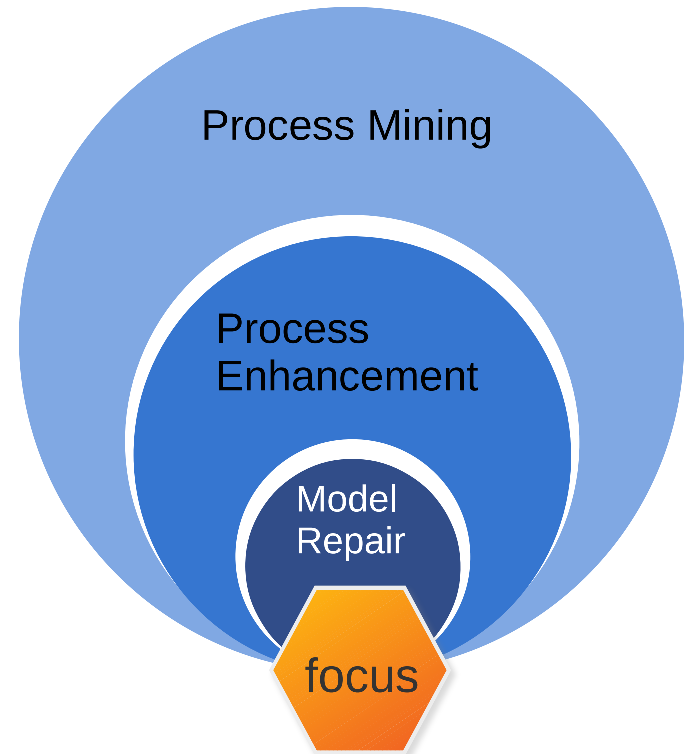




https://medium.com/@pedrorobledobpm/process-mining-plays-an-essential-role-in-digital-transformation-384839236bbe

Scope – model repair

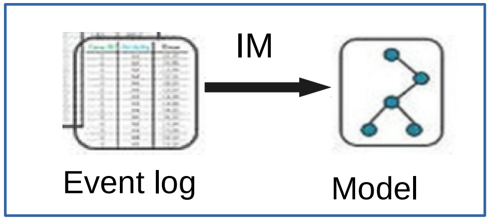




Enhancement related work

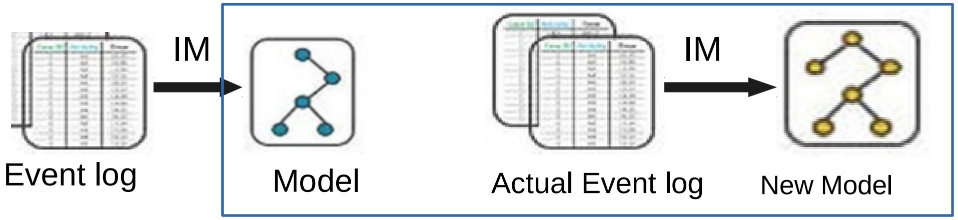
- **Rediscovery**

Process
discovery



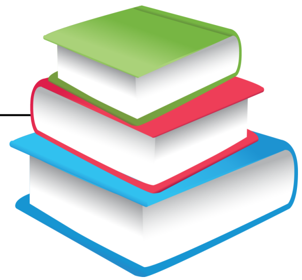
Enhancement related work

- **Rediscovery**

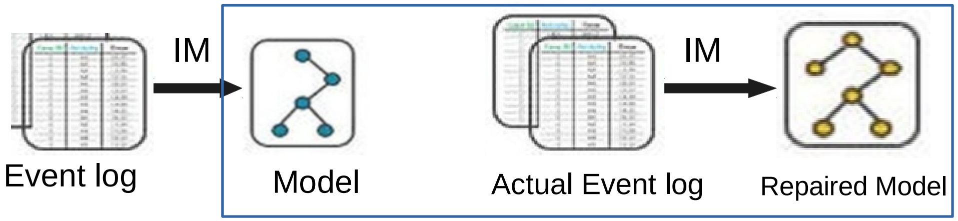


Process Rediscovery

Related Work

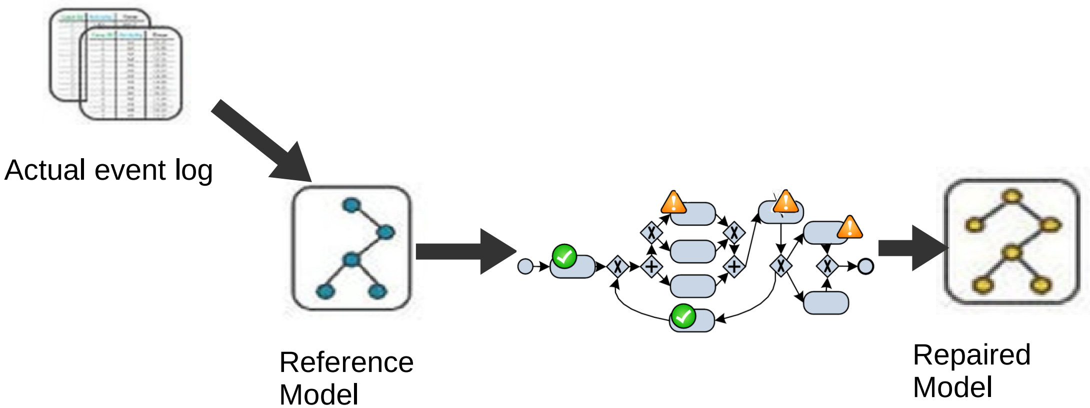


- **Rediscovery**



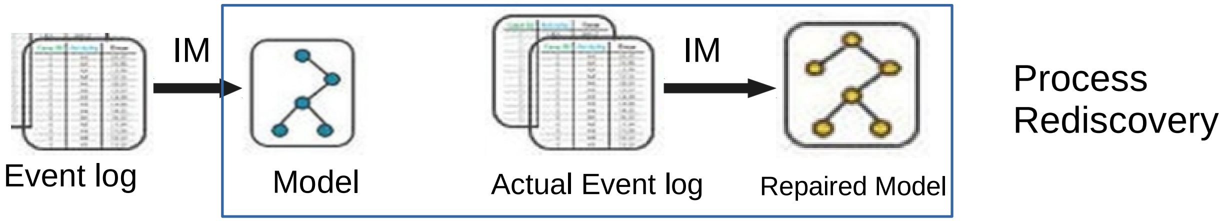
Process Rediscovery

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

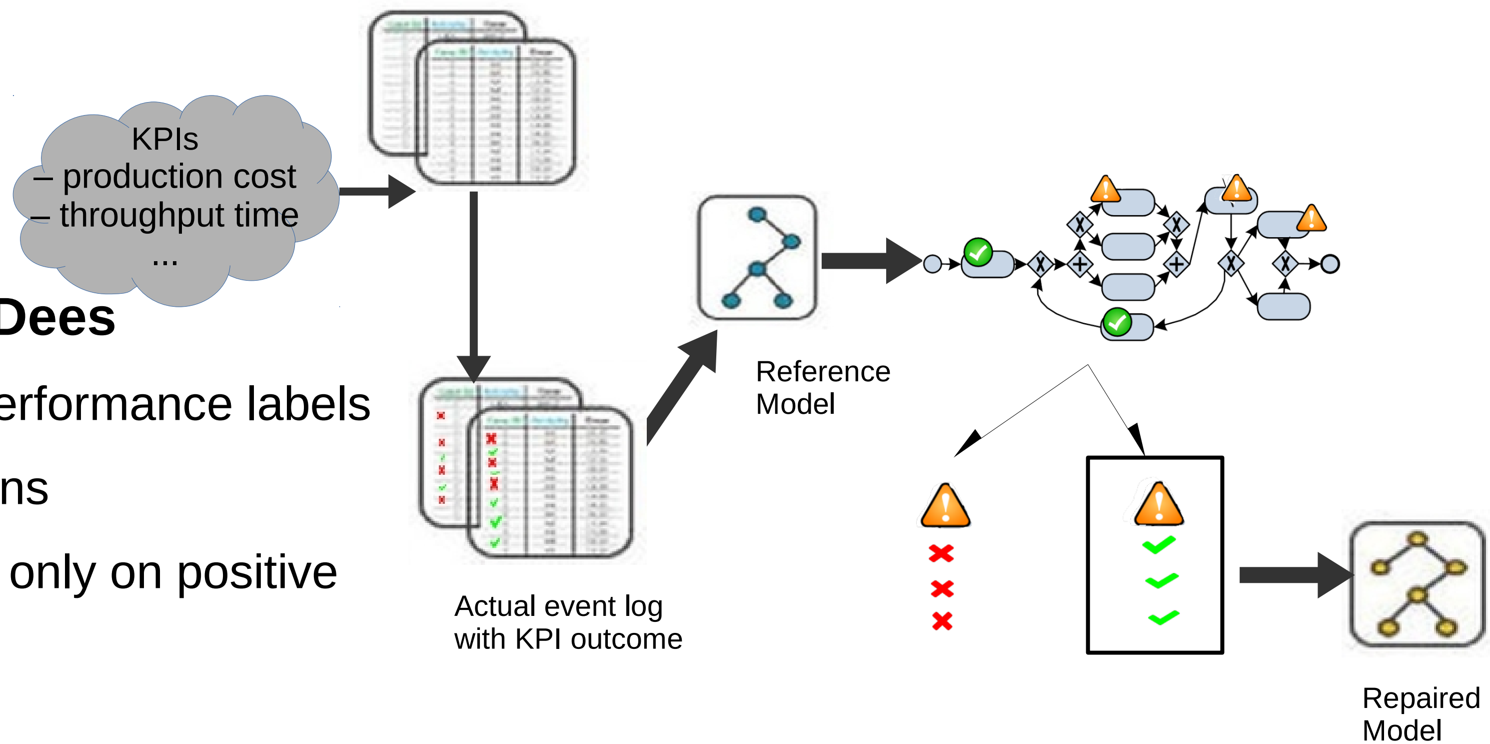


Related Work

- **Rediscovery**

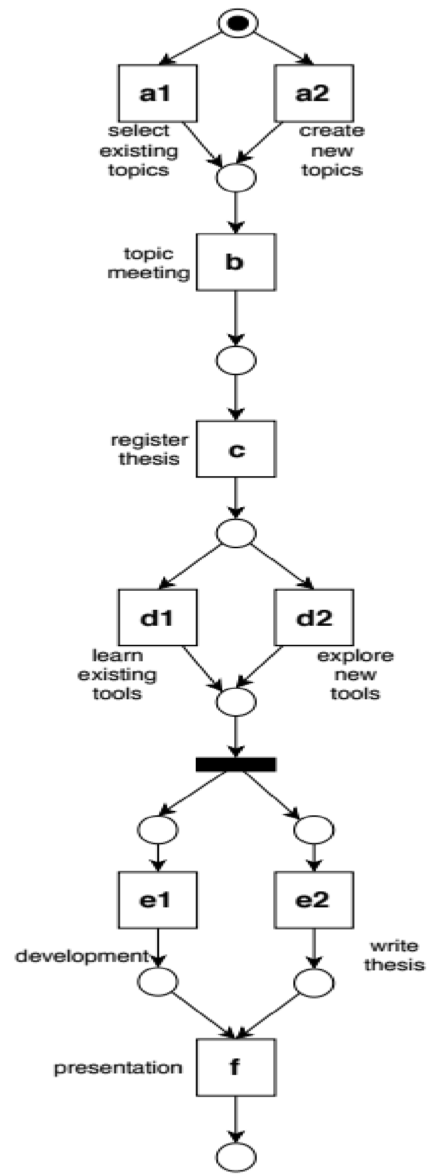


- **Model Repair by Fahland**
  - Deviations
  - Subprocesses



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

Motivation – reference model

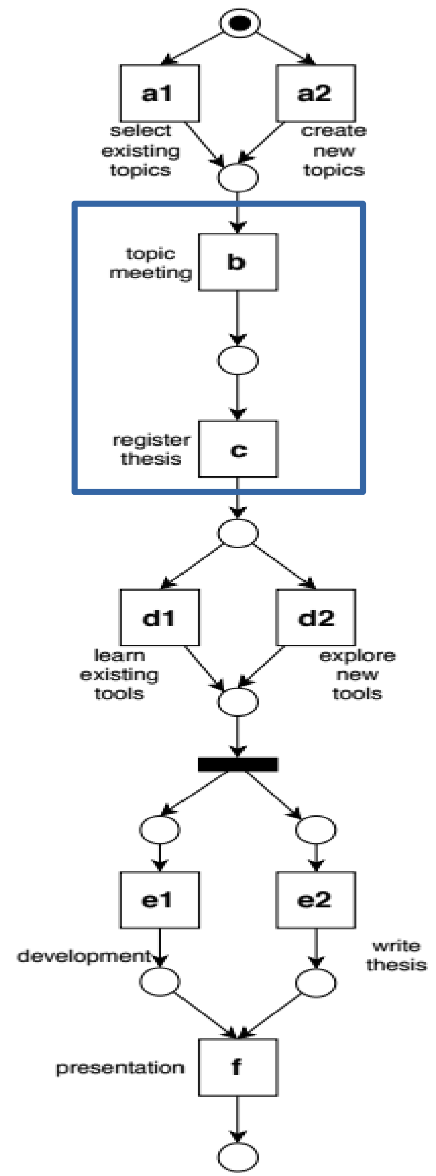


Reference model **M0**

Motivation – shortcomings

x1: write propose
x2: check course requirement

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



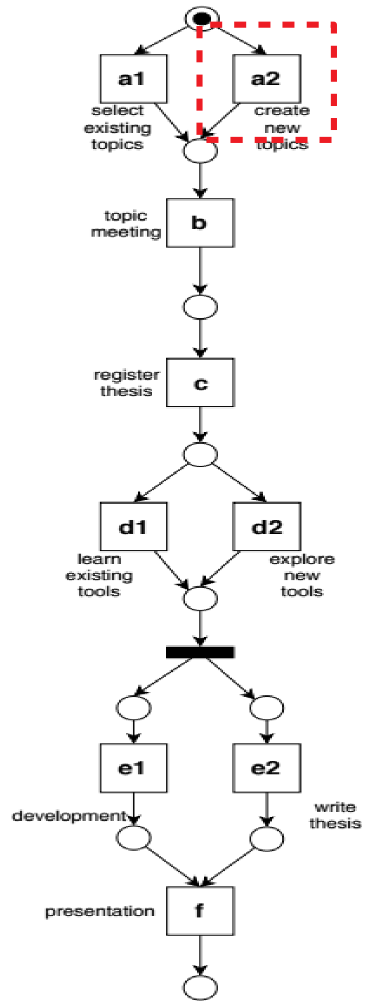
M0

Motivation – shortcomings

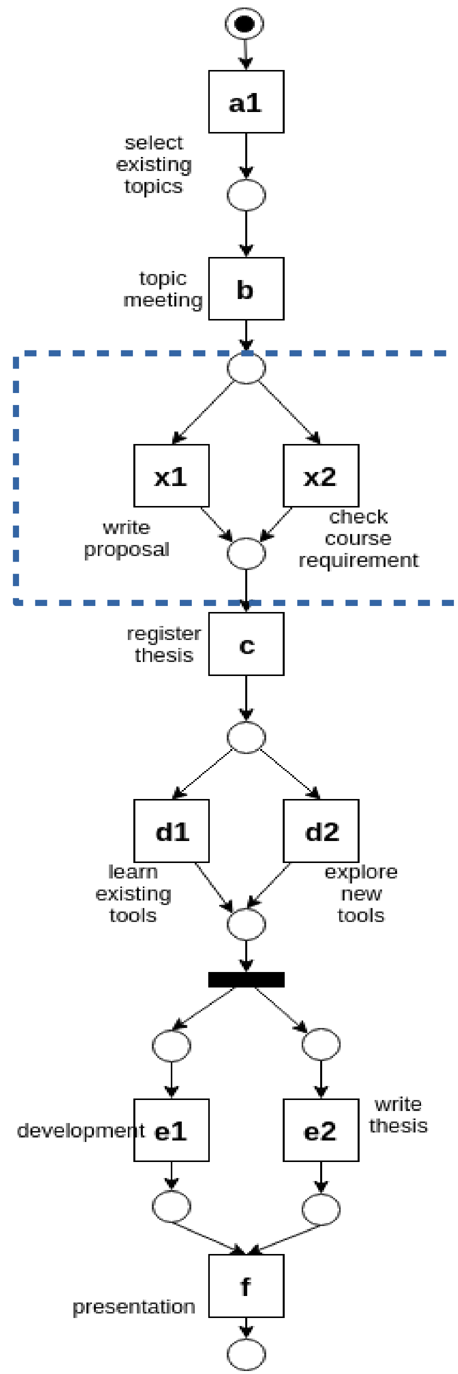
$$L_1 := \{< a1, b, \mathbf{x1}, c, d1, e1, e2, f >^{50,pos},$$
$$< a1, b, \mathbf{x2}, c, d2, e1, e2, f >^{50,pos}, \}$$

- **IM not consider reference model**

Similarity decreases!



M0



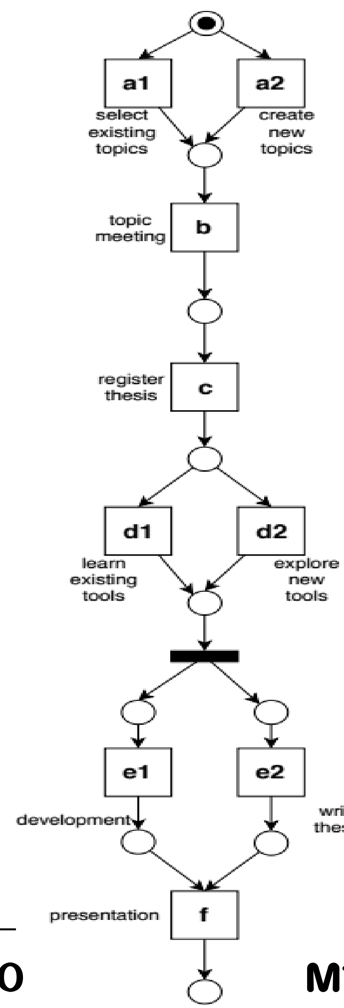
M1.1

Motivation – shortcomings

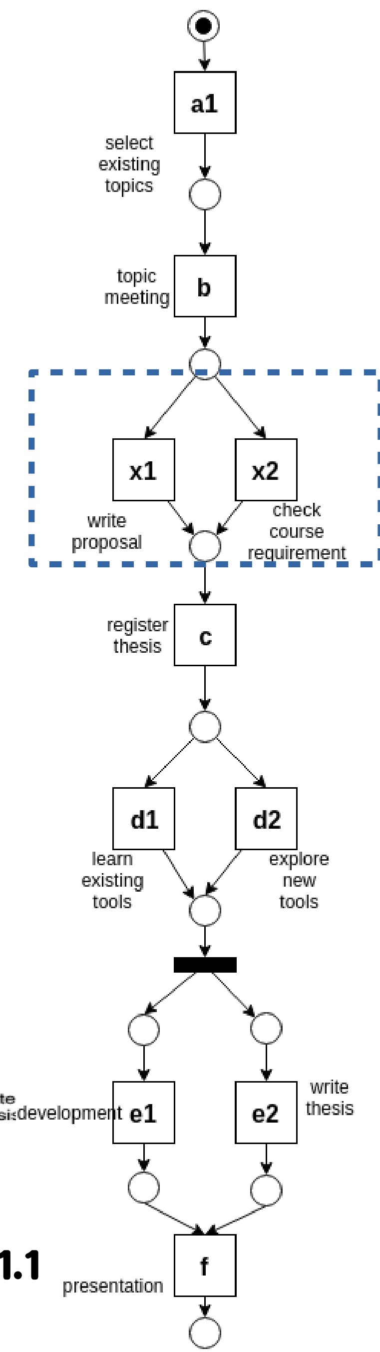
$$L_1 := \{< a1, b, \mathbf{x1}, c, d1, e1, e2, f >^{50,pos},$$
$$< a1, b, \mathbf{x2}, c, d2, e1, e2, f >^{50,pos}, \}$$

- **Fahland's: add subprocesses as loops**
- **Dee's: same as Fahland's method**

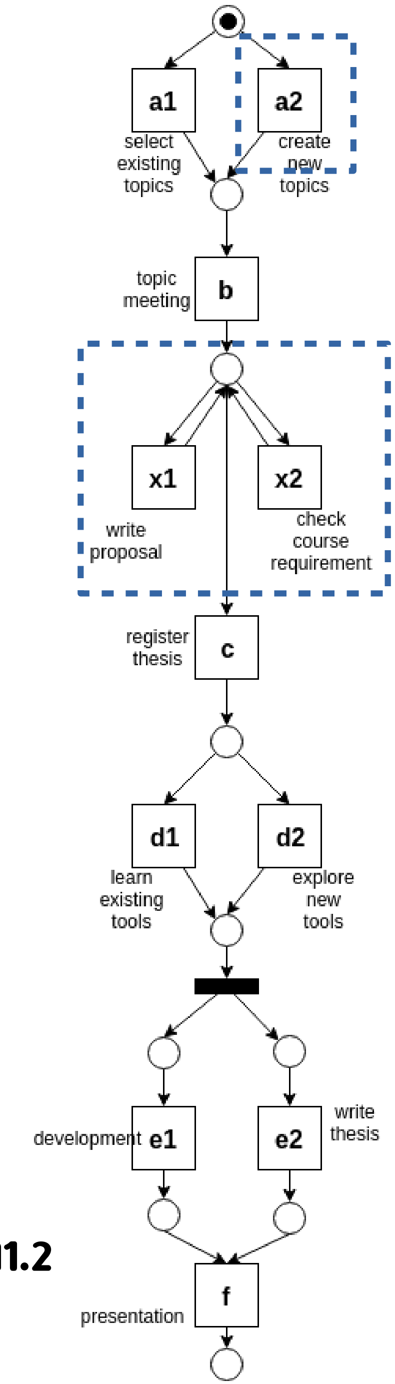
Precision decrease by adding subprocess in loops



MO



M1.1



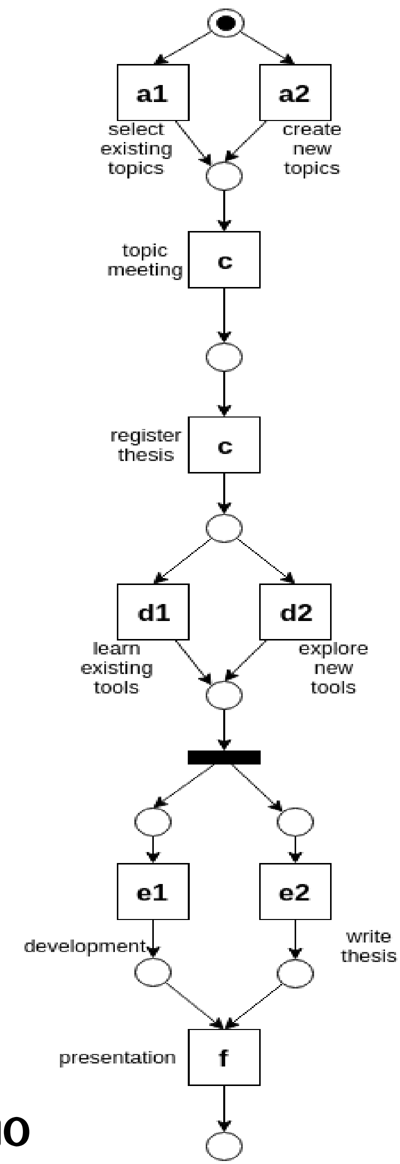
M1.2

Motivation – shortcomings

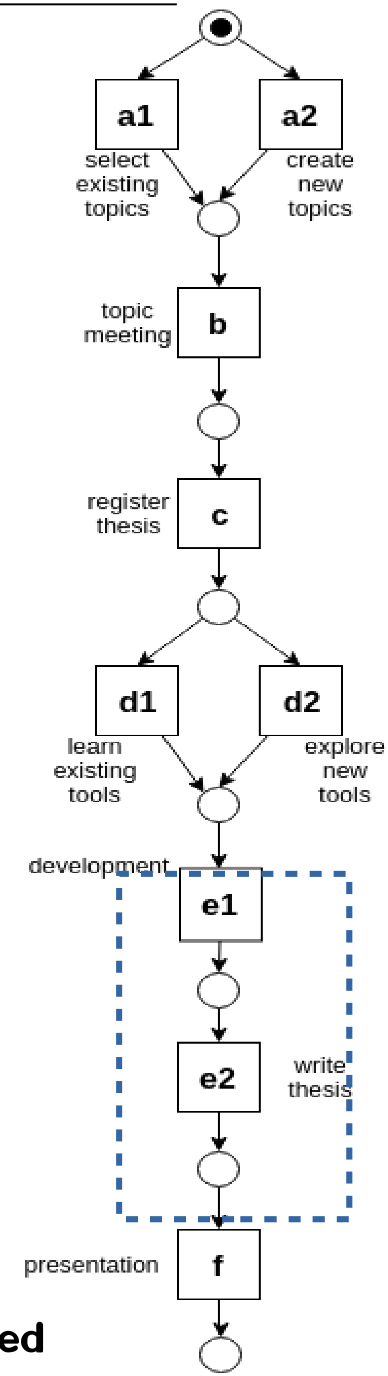
$$
\begin{aligned}
L_2 := \{ &< a1, b, c, d2, \mathbf{e1},\ \mathbf{e2}, f >^{30,pos}, \\
&< a2, b, c, d1, \mathbf{e1},\ \mathbf{e2}, f >^{20,pos}; \\
&< a2, b, c, d2, \mathbf{e2},\ \mathbf{e1}, f >^{10,pos}; \\
&< a1, b, c, d2, \mathbf{e2},\ \mathbf{e1}, f >^{20,neg}, \\
&< a1, b, c, d1, \mathbf{e2},\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

- **IM keeps the model same**
- **Fahland's/Dees keep model same**

Unable to adapt model with negative instances



M0



M2-expected

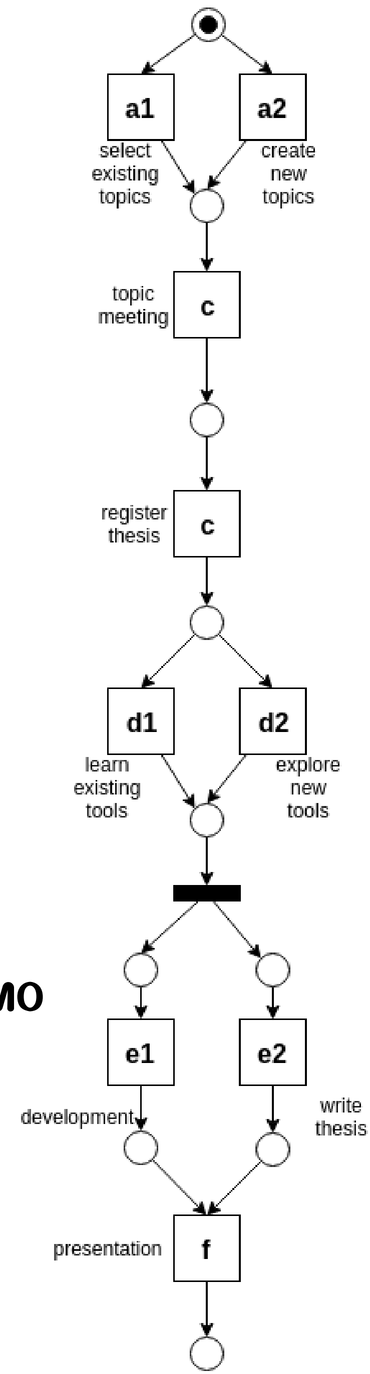
Motivation – shortcomings

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

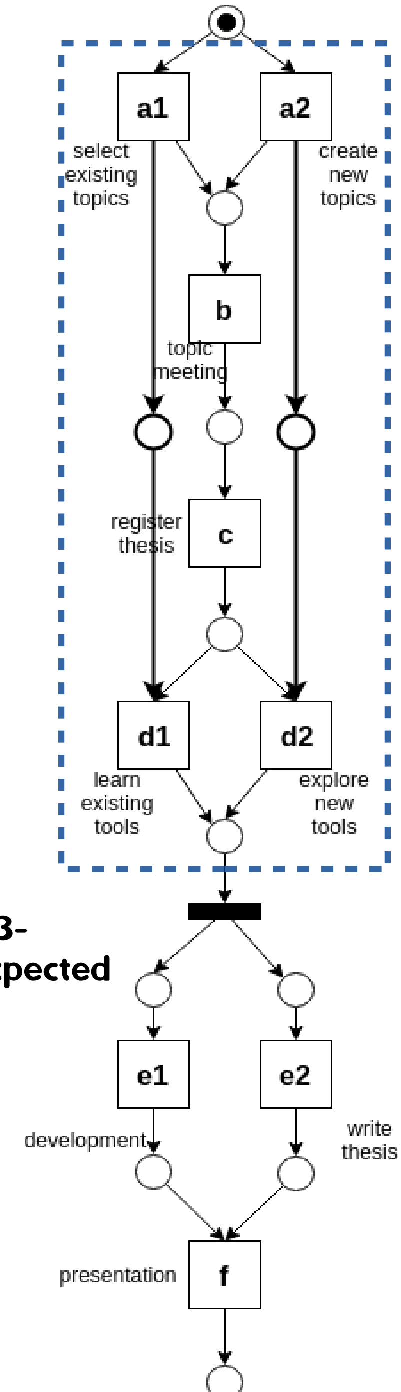
- **Long-term dependency**
  - Choices decide choices

Unable to detect long-term dependency

M0



M3-expected



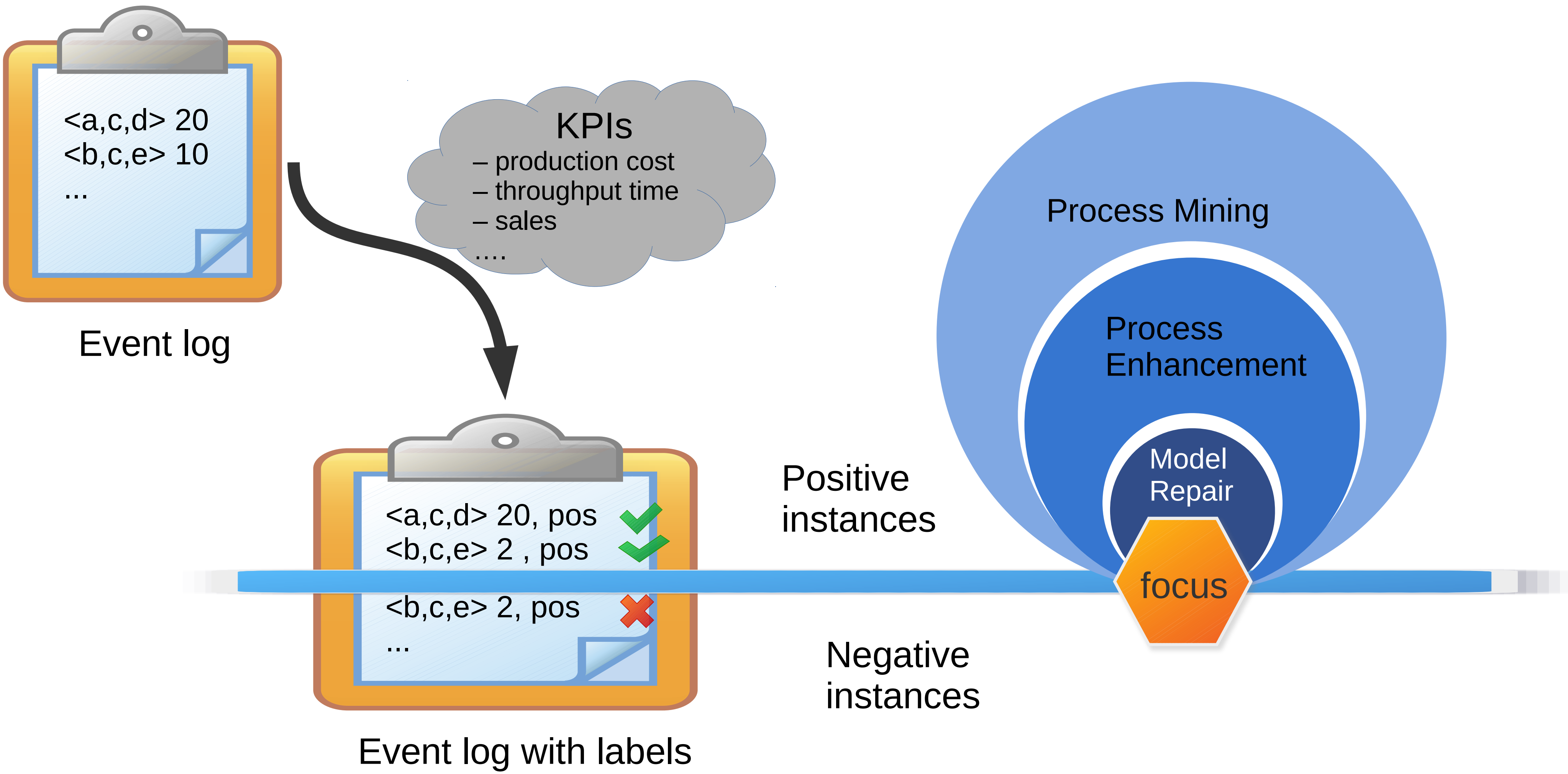
Motivation – Shortcomings

- Similarity decreases with rediscovery
- Precision decrease by adding subprocess in loops
- Unable to adapt model with negative instances
- Unable to detect long-term dependency

Outline

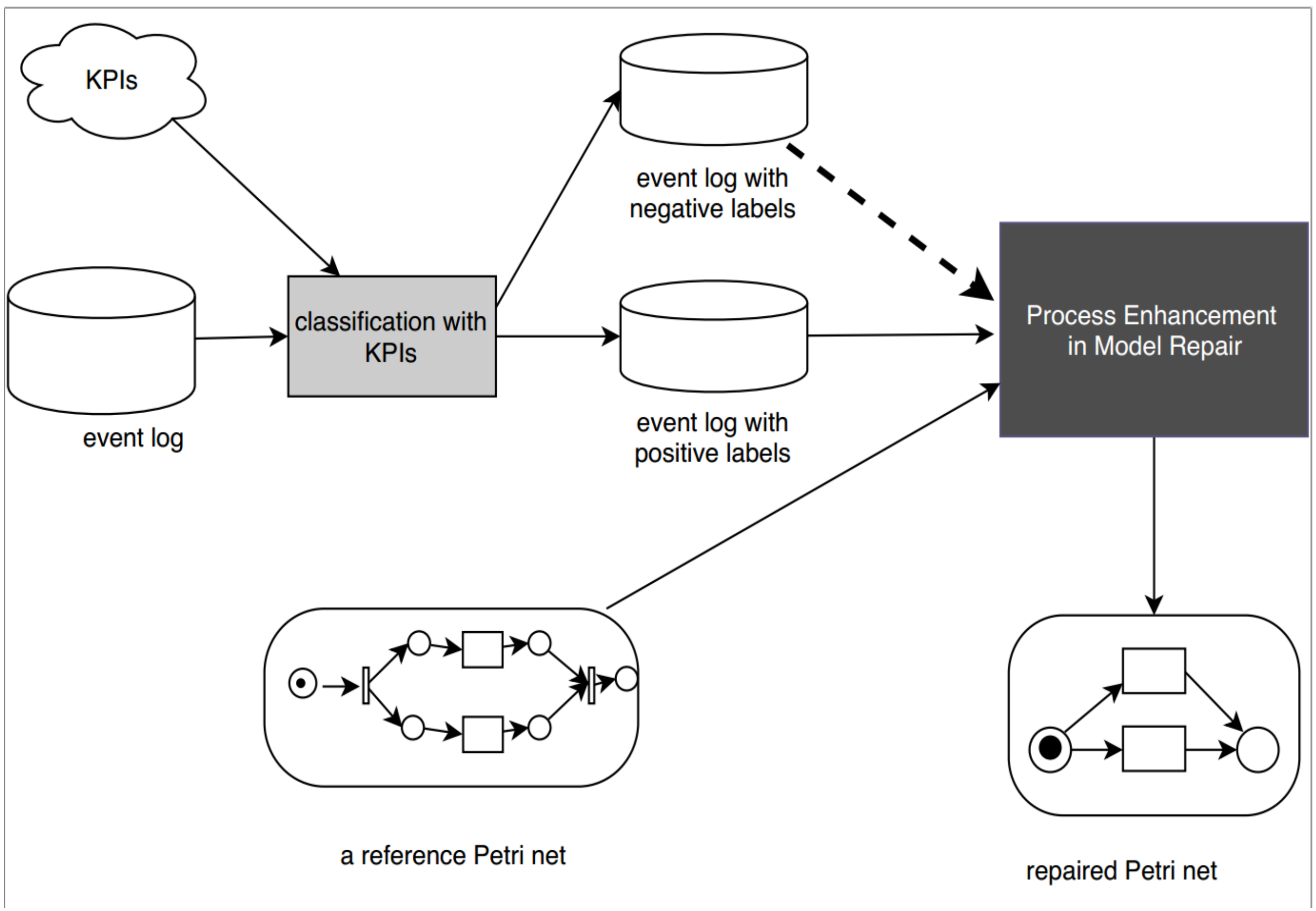
- **Motivation for Research**
- **Problem Definition**
- **Approach**
- **Demo**
- **Evaluation**
- **Conclusion**

Research Problem



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?

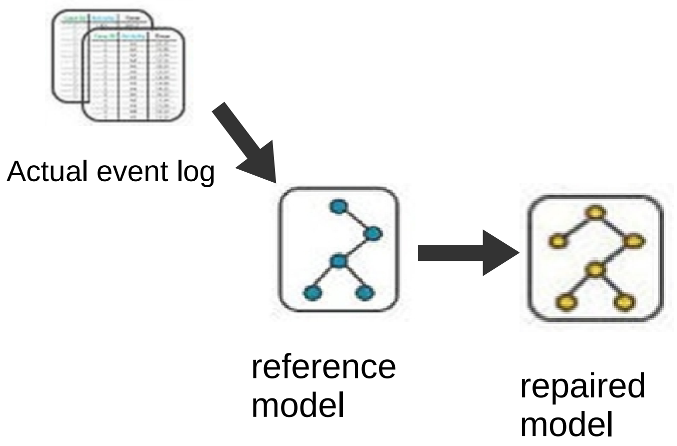


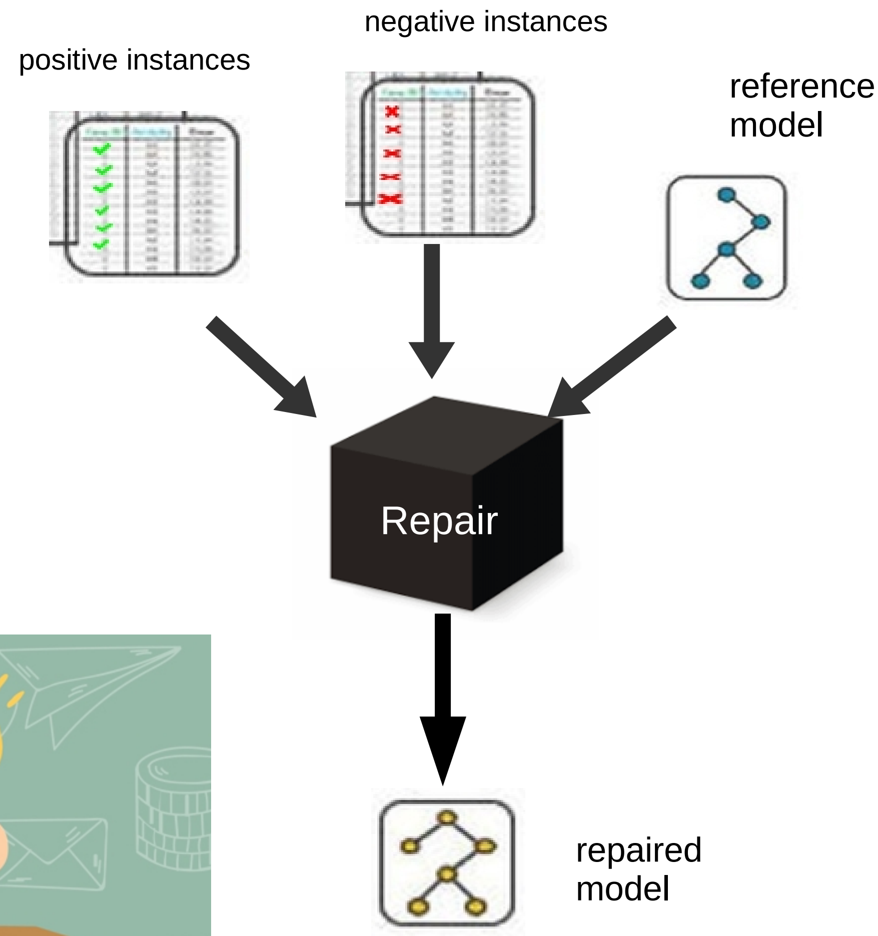
– enforce positive instances
– block negative instances
– similar
– simple
……

Outline

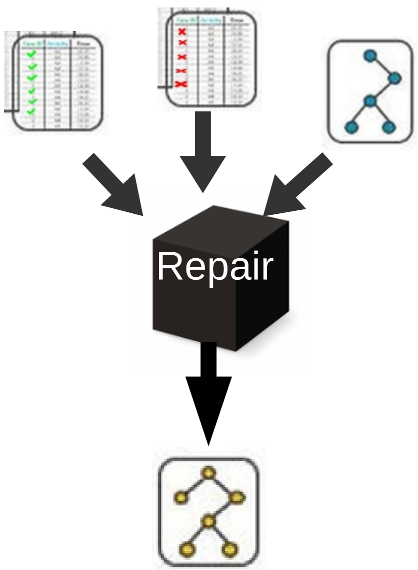
- **Motivation for Research**
- **Problem Definition**
- **Approach**
  - Framework
  - Data models
  - Modules
- **Demo**
- **Evaluation**
- **Conclusion**

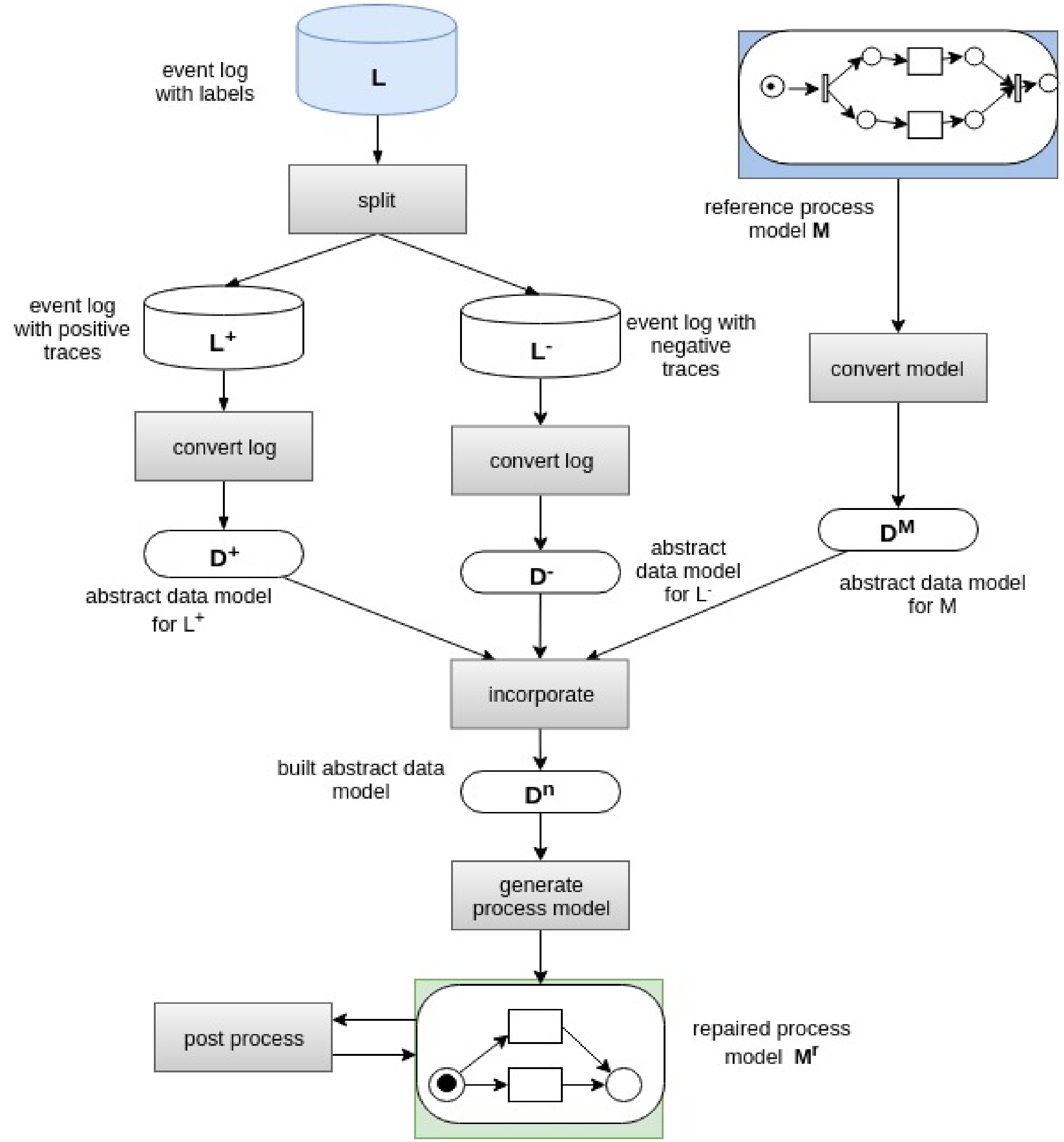
Algorithm – framework



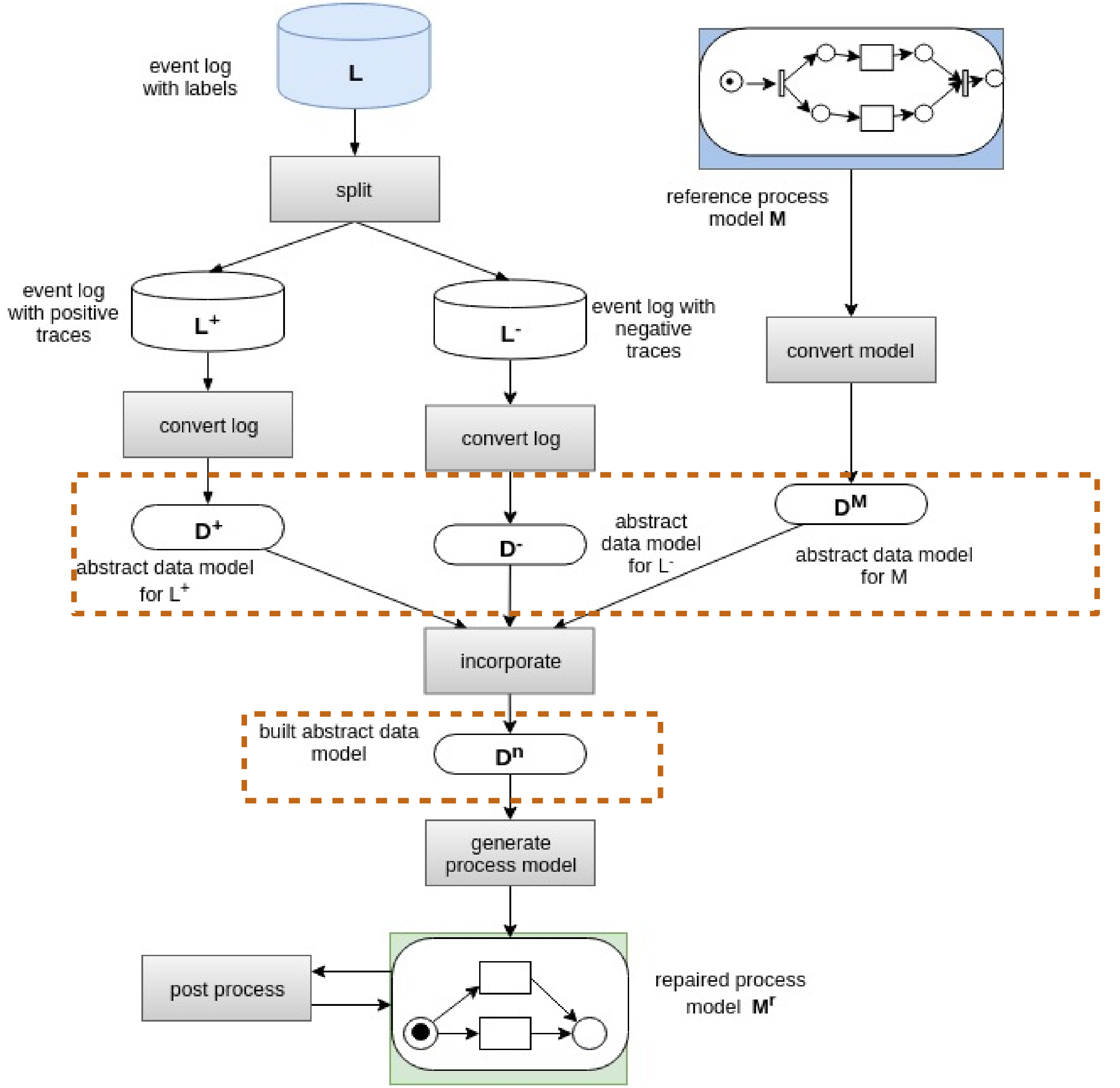


Algorithm – framework





Algorithm – data model

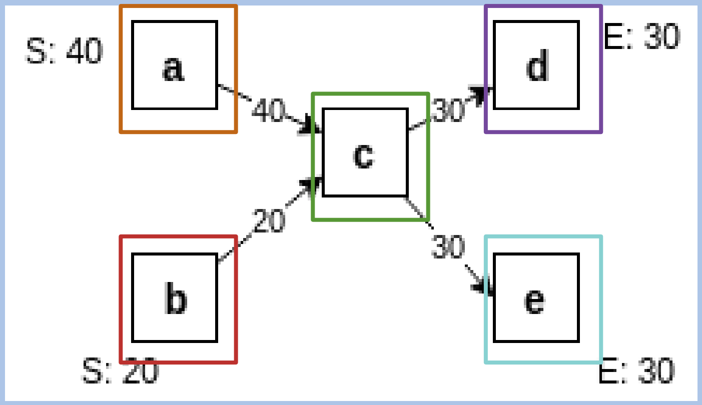


Data Model – directly-follows graph

$$G(L) = (A, F, A_{start}, A_{end})$$

- $A = A_L$

$L = \{\langle a, c, d\rangle^{20}, \langle b, c, e\rangle^{10}, \langle a, c, e\rangle^{20}, \langle b, c, d\rangle^{10}\}$

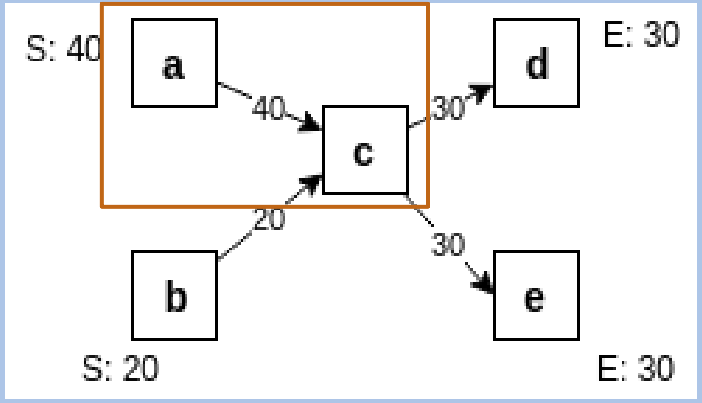


Data Model – directly-follows graph

$$G(L) = (A, F, A_{start}, A_{end})$$

- $A = A_L$
- $F = \{(a,b) \in A \times A \mid a >_L b\}$

$L = \{\langle a, c, d\rangle^{20}, \langle b, c, e\rangle^{10}, \langle a, c, e\rangle^{20}, \langle b, c, d\rangle^{10}\}$

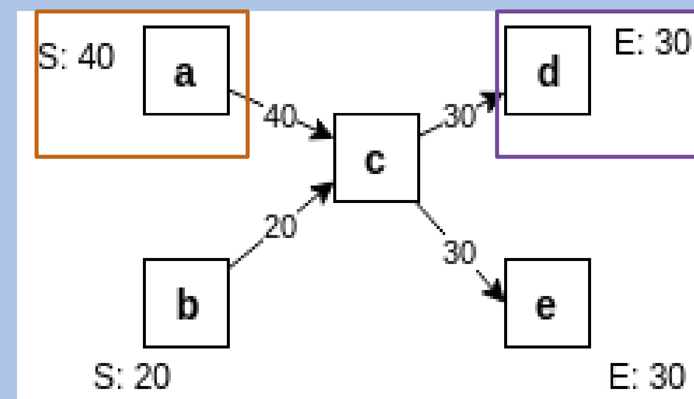


Data Model – directly-follows graph

$$G(L) = (A, F, A_{start}, A_{end})$$

- $A = A_L$
- $F = \{(a,b) \in A \times A \mid a >_L b\}$
- $A_{start} = \{a \mid \exists \sigma \in L, a = \sigma(1)\}$
- $A_{end} = \{a \mid \exists \sigma \in L, a = \sigma(|\sigma|)\}$

$L=\{\langle \boxed{a}, c, \boxed{d}\rangle^{20}, \langle b, c, e\rangle^{10}, \langle \boxed{a}, c, e\rangle^{20}, \langle b, c, d\rangle^{10}\}$



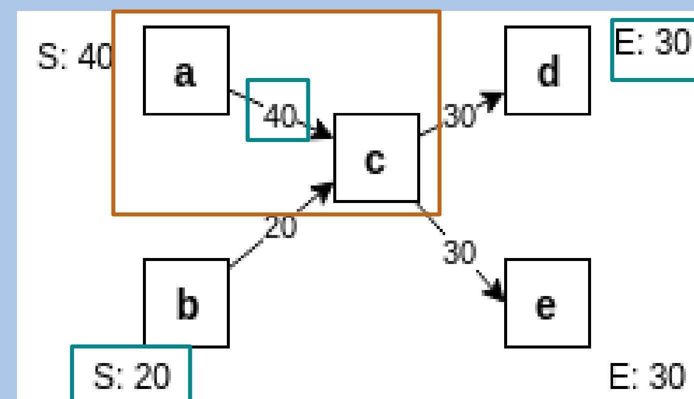
Data Model – directly-follows graph

$$G(L) = (A, F, A_{start}, A_{end})$$

- $A = A_L$
- $F = \{(a,b) \in A \times A | a >_L b\}$
- $A_{start} = \{a | \exists \sigma \in L, a = \sigma(1)\}$
- $A_{end} = \{a | \exists \sigma \in L, a = \sigma(|\sigma|)\}$
- Cardinality $c : F \rightarrow N$

  $A_{start} \cup A_{end} \rightarrow N$

$L = \{\langle a, c, d \rangle^{20}, \langle b, c, e \rangle^{10}, \langle a, c, e \rangle^{20}, \langle b, c, d \rangle^{10}\}$

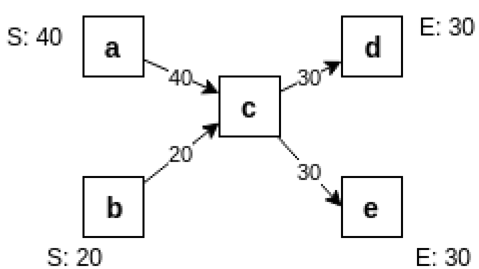


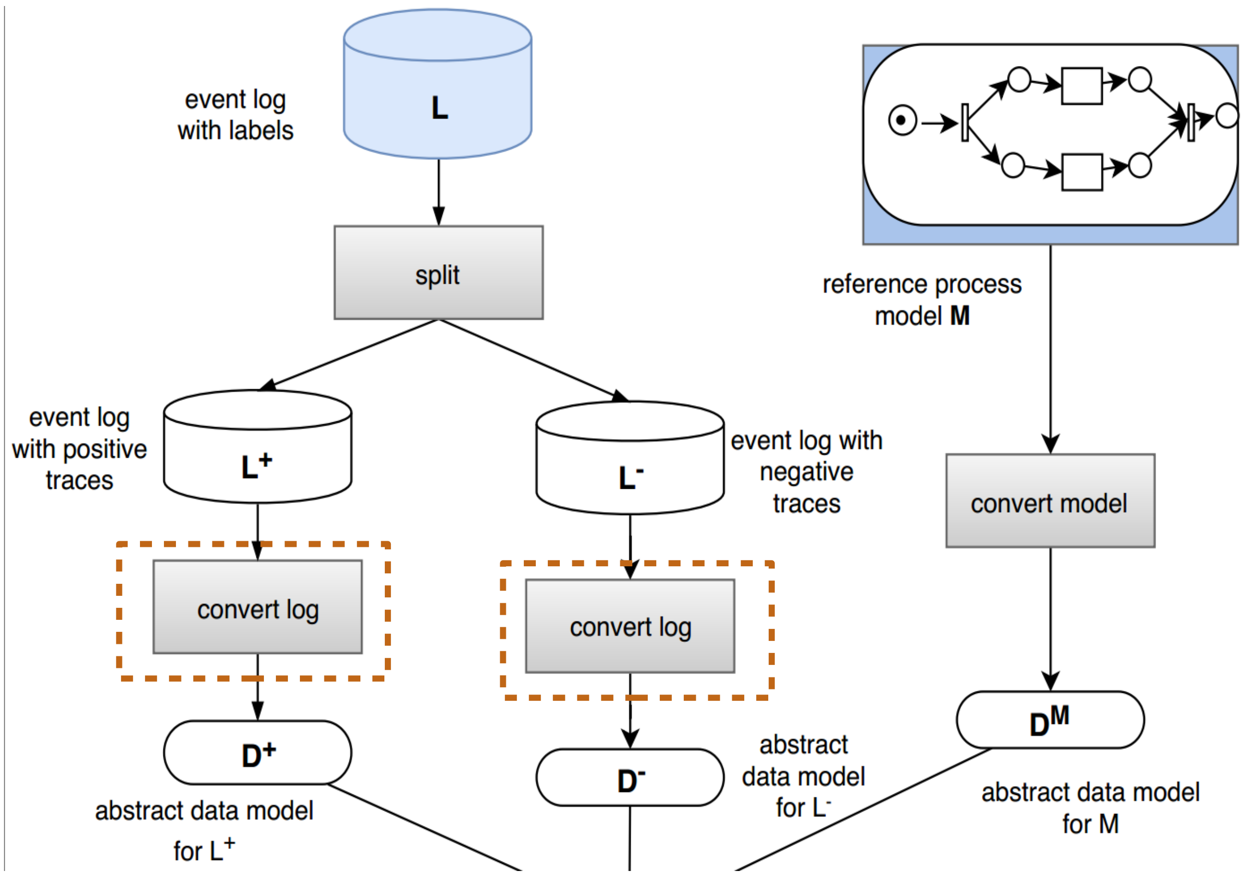
Convert to directly-follows graph

From Event log

- Directly-follows relation
- Existing plugin

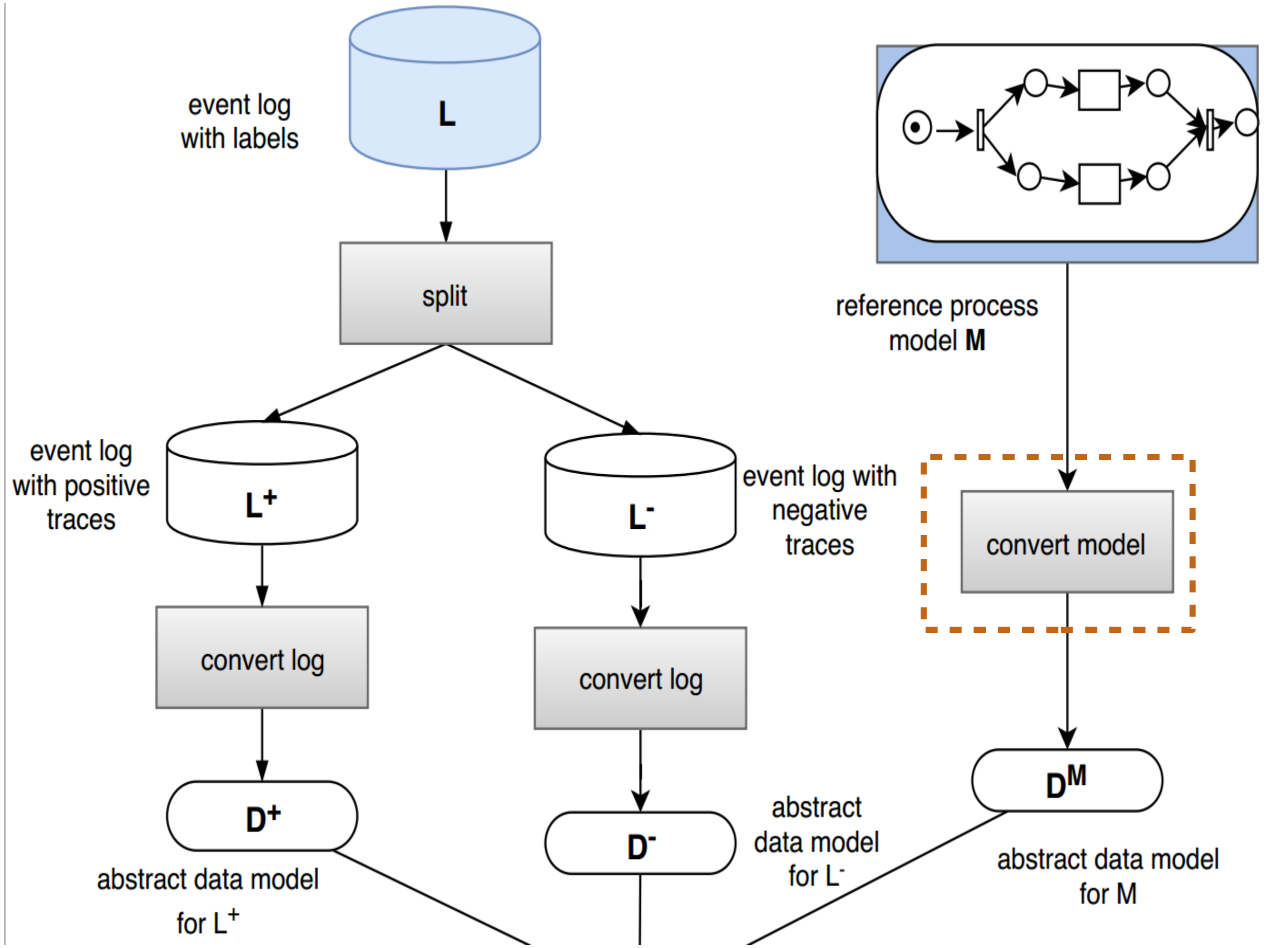
$$L=\{\langle a,c,d\rangle^{20}, \langle b,c,e\rangle^{10}, \langle a,c,e\rangle^{20}, \langle b,c,d\rangle^{10}\}$$





Convert to directly-follows graph

From Petri net

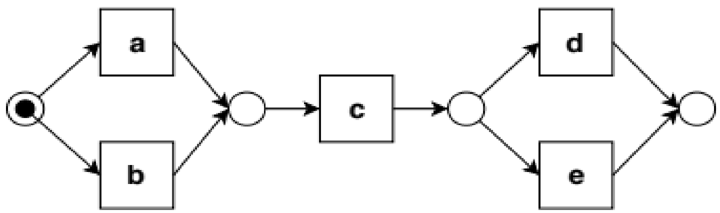


Convert to directly-follows graph

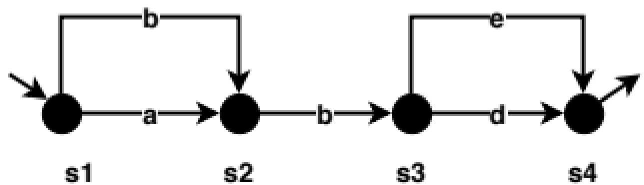
From Petri net

- Transition System
- Directly-follows relation from transitions before and after states

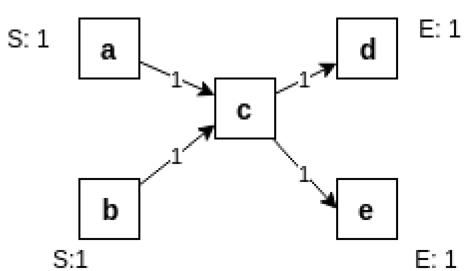
(1)

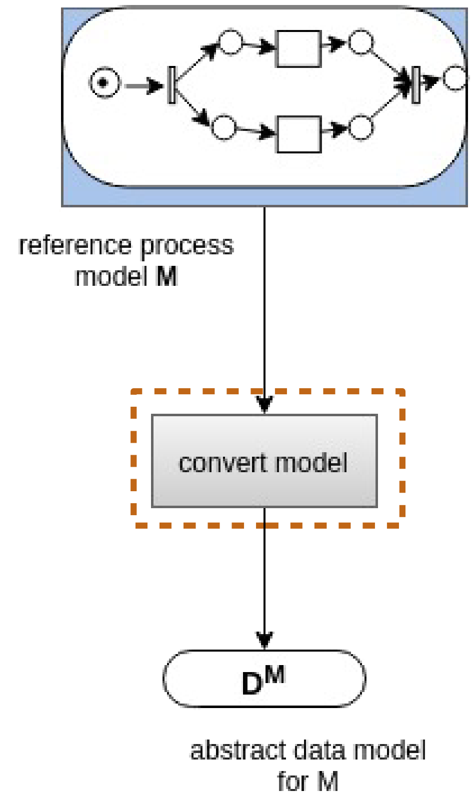


(2)



(3)





Data Model

- **Unification of cardinality**
  - Models from existing model, positive and negative event log
  - For any directly-follows relation

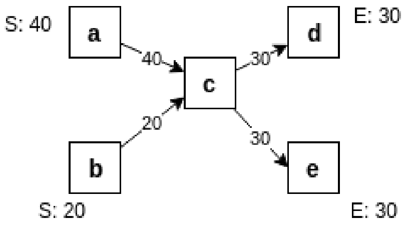
$$u(a,b) = \frac{c(a,b)}{\sum_{(a,b')\in F} c(a,b')}$$

  - For any start activity

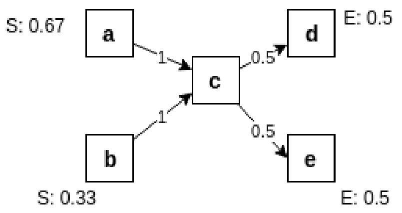
$$u(a) = \frac{c(a)}{\sum_{a'\in A_{start}} c(a')}$$

  - For any end activity

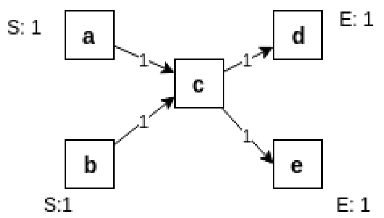
$$u(a) = \frac{c(a)}{\sum_{a'\in A_{end}} c(a')}$$



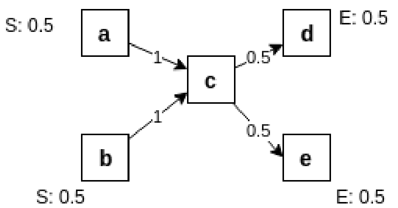
dfg from event log



Unified dfg from event log

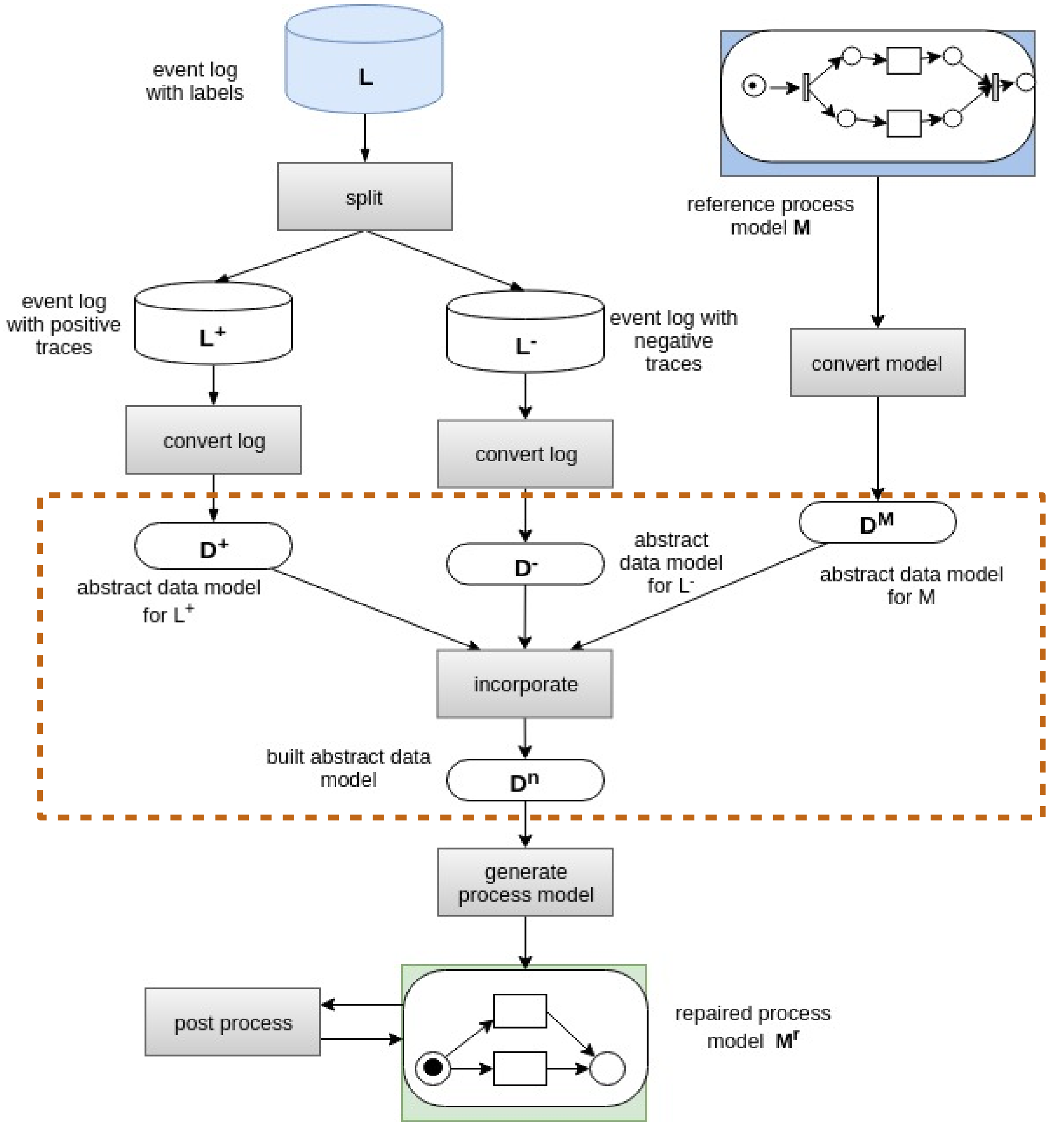


dfg from model



Unified dfg from model

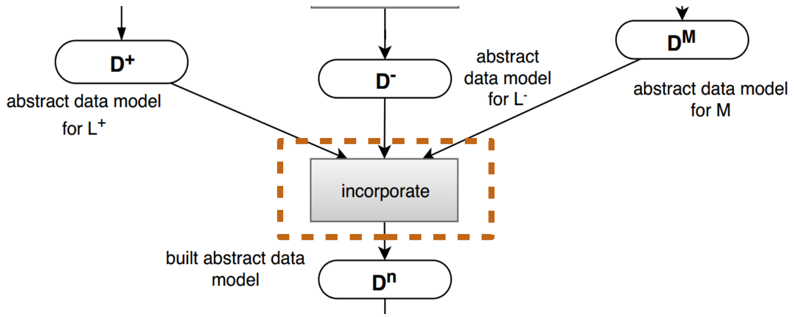
Algorithm – data model

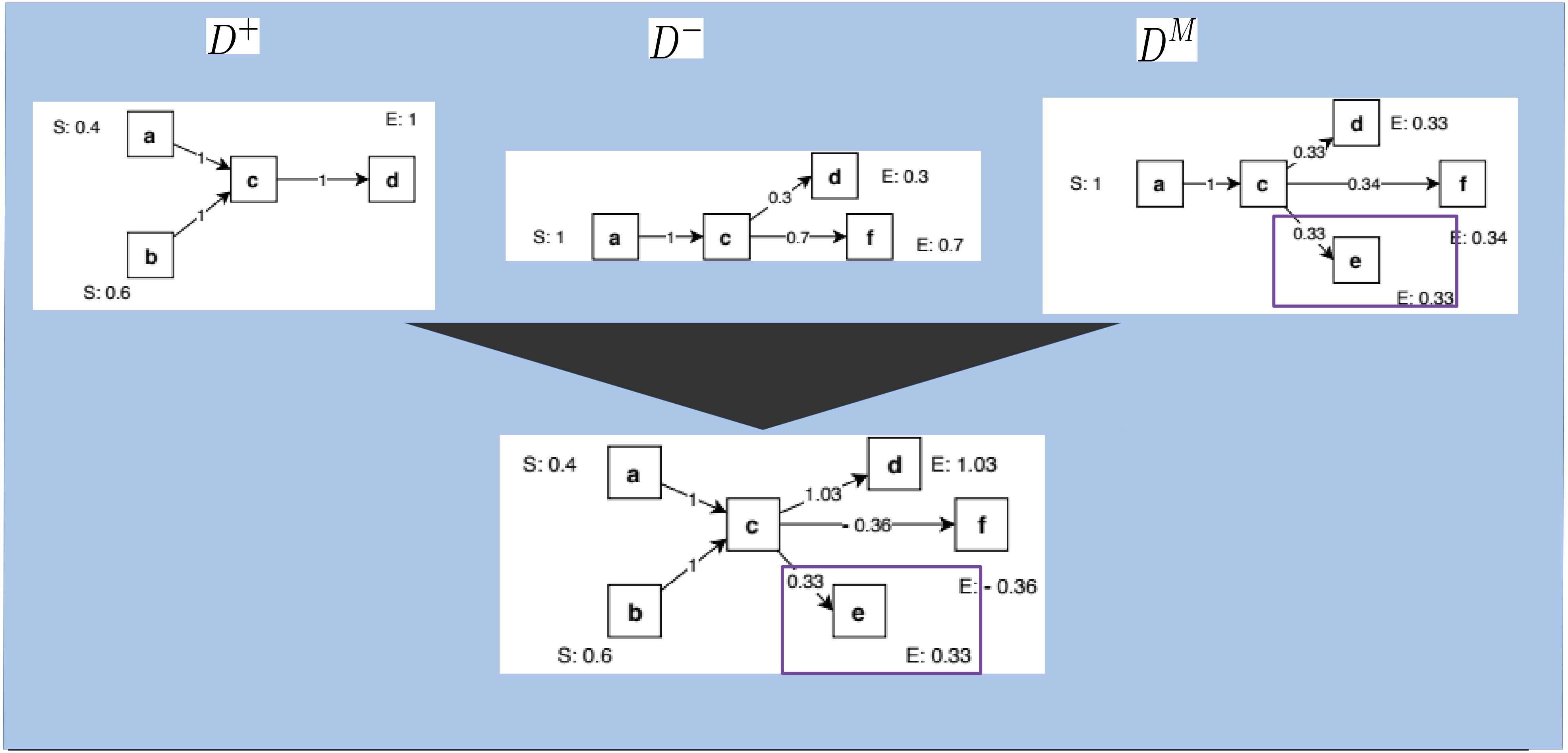


Incorporate Data Models

- **Incorporate method**
  - For any directly-follows relation

$$u^n(a,b) = u^M(a,b) + u^+(a,b) - u^-(a,b)$$

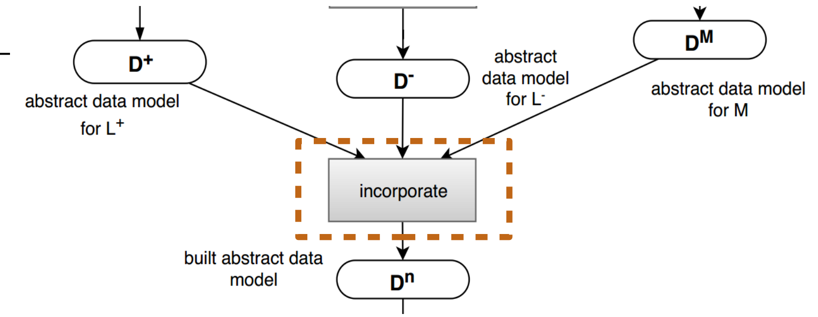


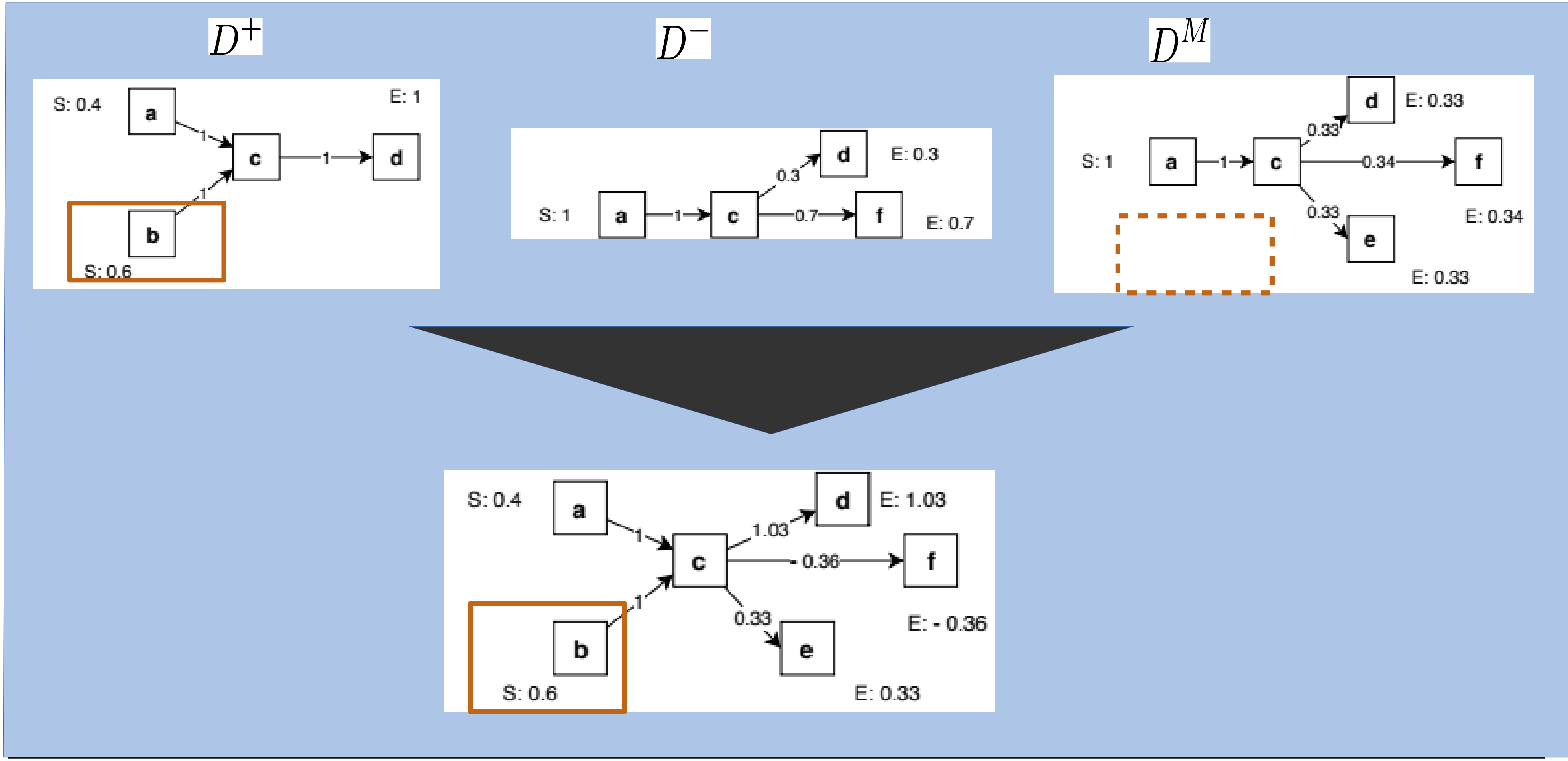


Incorporate Data Models

- **Incorporate method**
  - For any directly-follows relation

$$u^n(a,b) = u^M(a,b) + u^+(a,b) - u^-(a,b)$$

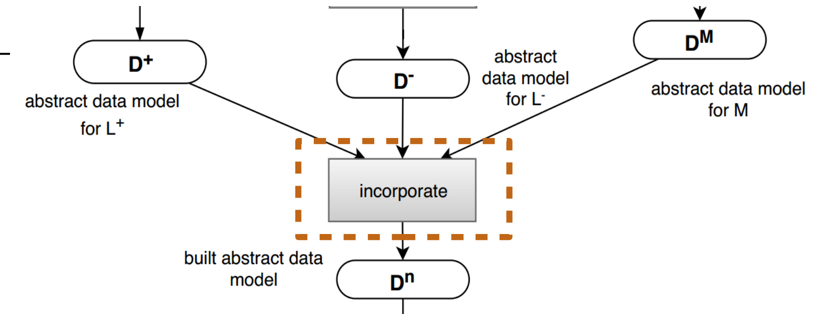


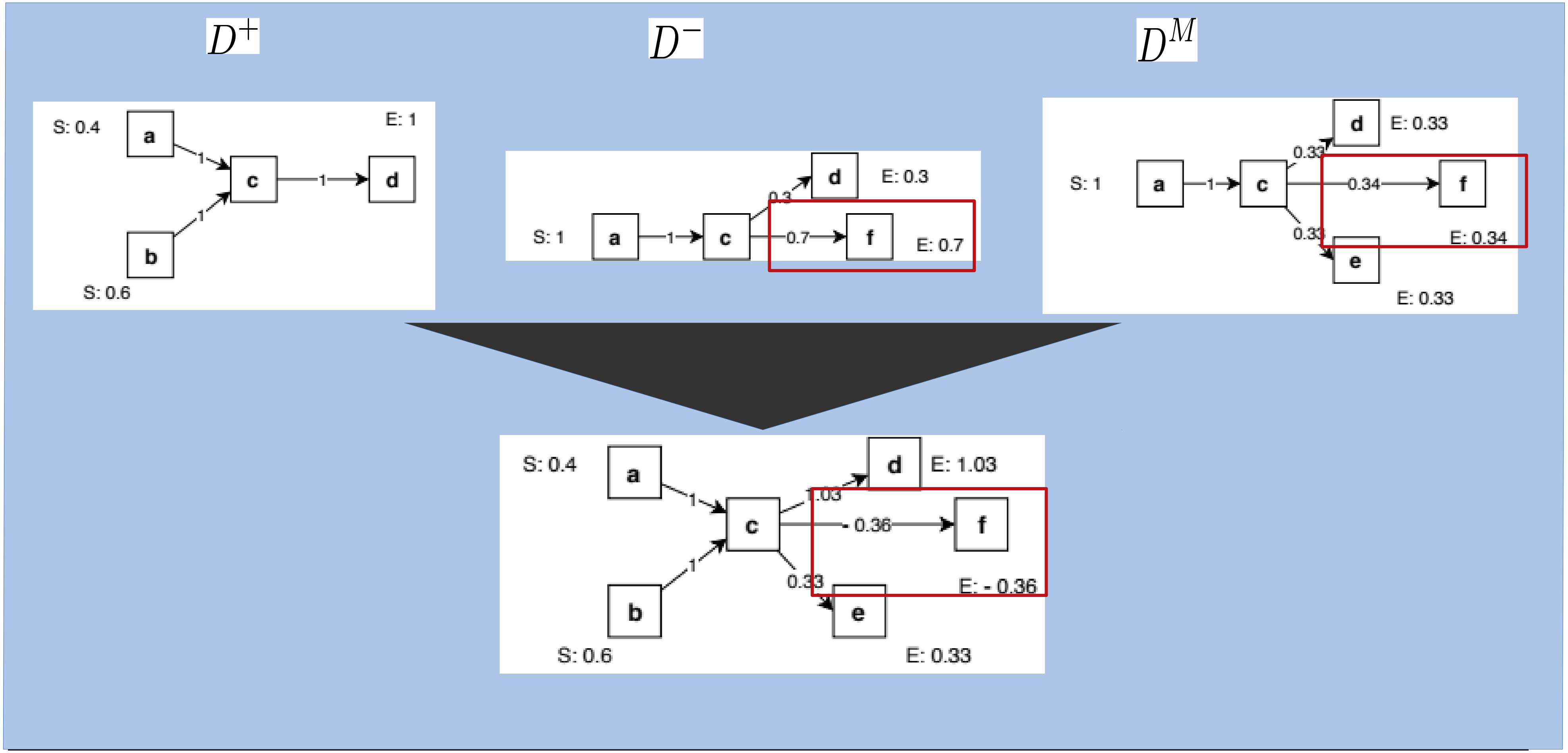


Incorporate Data Models

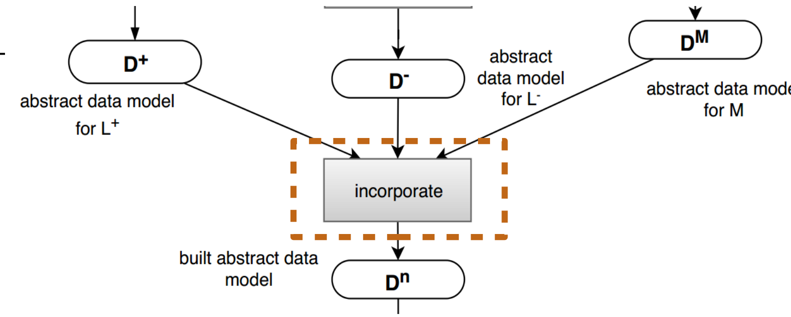
- **Incorporate method**
  - For any directly-follows relation

$$u^n(a,b) = u^M(a,b) + u^+(a,b) - u^-(a,b)$$



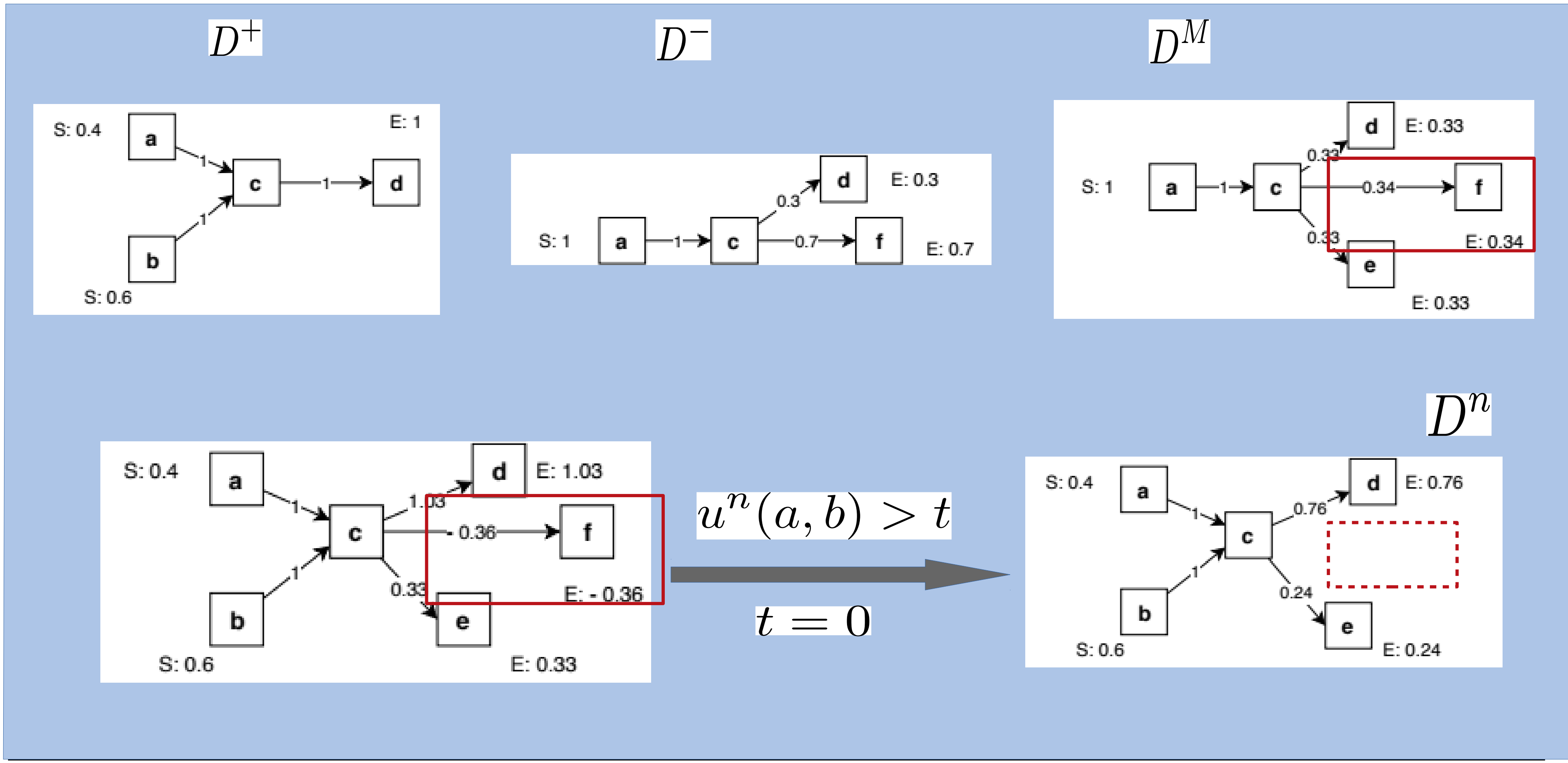


Incorporate Data Models

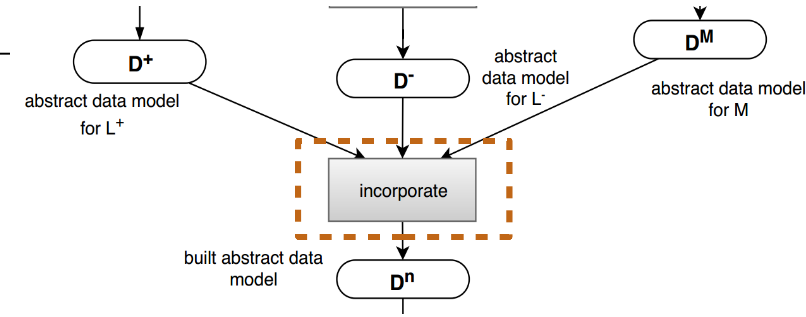


- **Incorporate method**
  - For any directly-follows relation

$$u^n(a,b) = u^M(a,b) + u^+(a,b) - u^-(a,b)$$

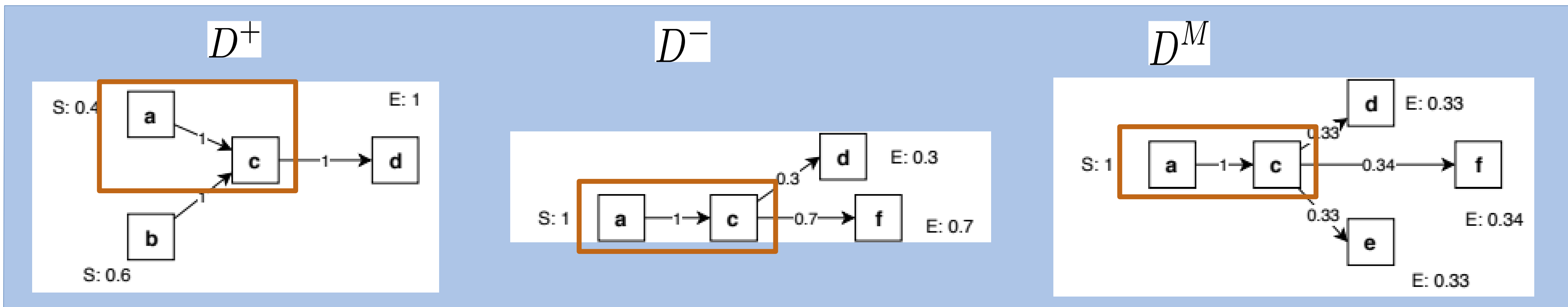


Incorporate Data Models

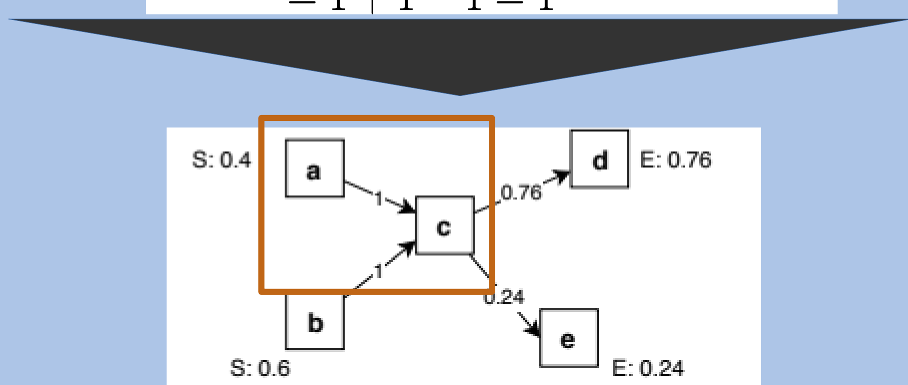


- **Incorporate method**
  - For any directly-follows relation

$$u^n(a,b) = u^M(a,b) + u^+(a,b) - u^-(a,b)$$



$$u^n(a,c) = u^M(a,c) + u^+(a,c) - u^-(a,c)$$
$$= 1 + 1 - 1 = 1$$



Incorporate Data Models

- **Incorporate method** **with weights** w^+, w^-, w^M
  - For any directly-follows relation

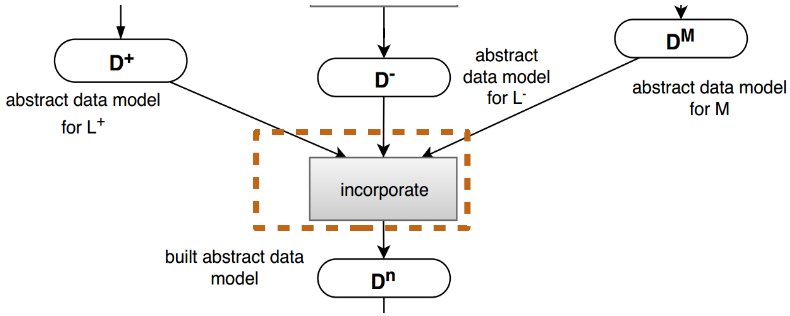
$$u_w^n(a,b) = w^M \cdot u^M(a,b) + w^+ \cdot u^+(a,b) - w^- \cdot u^-(a,b)$$

  - For any start activity,

$$a \in A_{start}^M \cup A_{start}^+ \cup A_{start}^-, u^n(a) = w^M \cdot u^M(a) + w^+ \cdot u^+(a) - w^- \cdot u^-(a)$$

  - For any end activity,

$$a \in A_{end}^M \cup A_{end}^+ \cup A_{end}^-, u^n(a) = w^M \cdot u^M(a) + w^+ \cdot u^+(a) - w^- \cdot u^-(a)$$

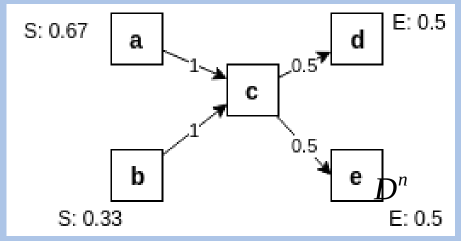


$$w^M = 1, w^+ = w^- = 0$$

➡ Keep the reference model

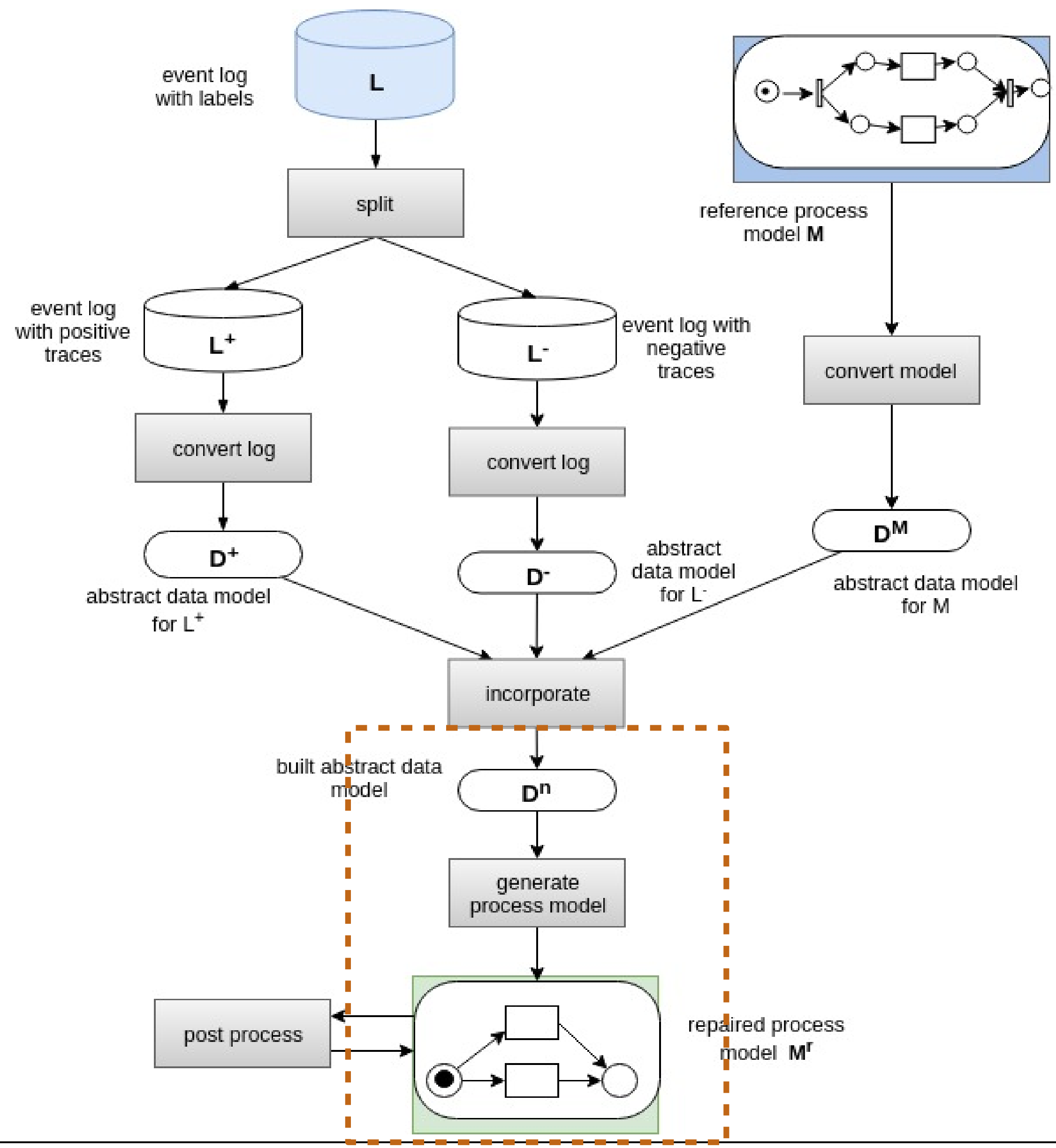
$$w^+ = 1, w^M = w^- = 0$$

➡ Mine a new model from positive instances



new unified dfg D^n

Algorithm – data model



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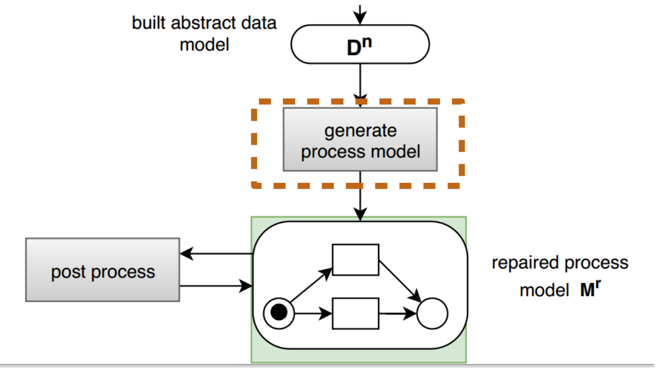
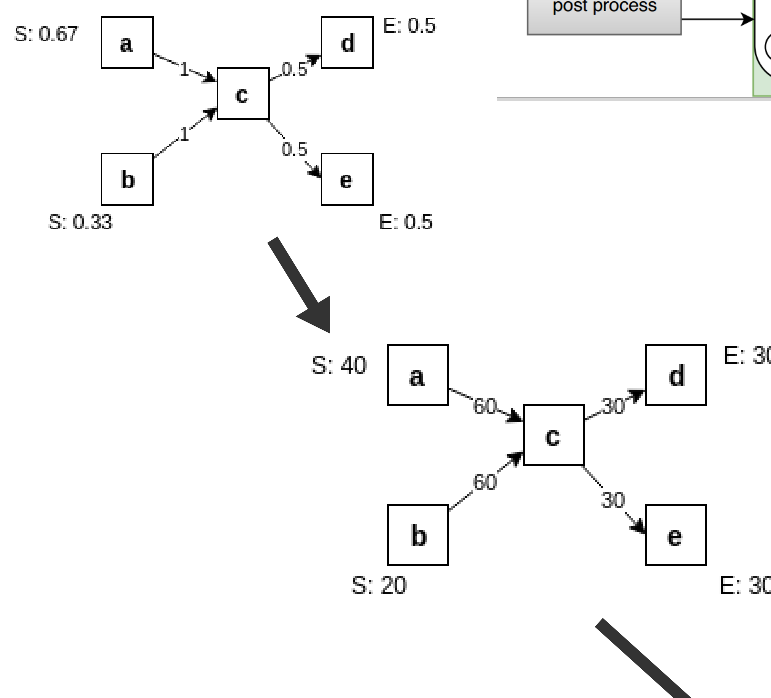
Generate Petri net

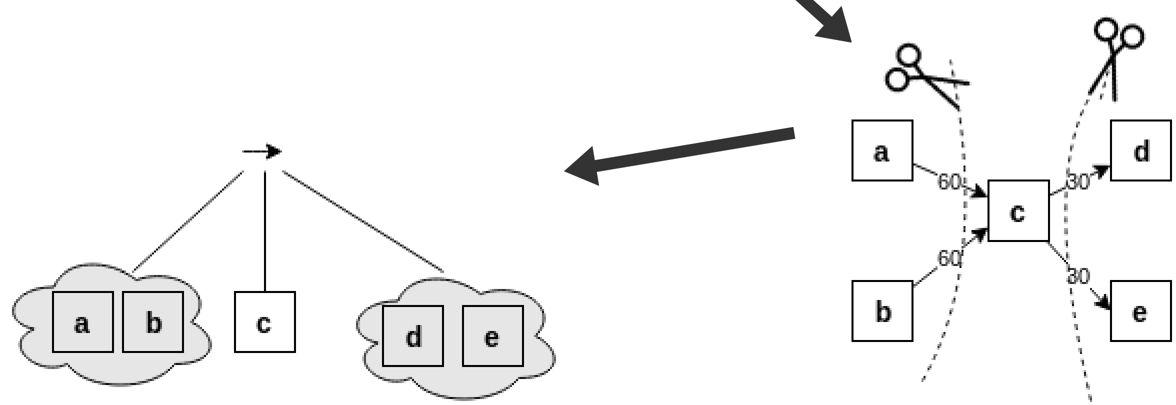


- **Transform into normal dfg**

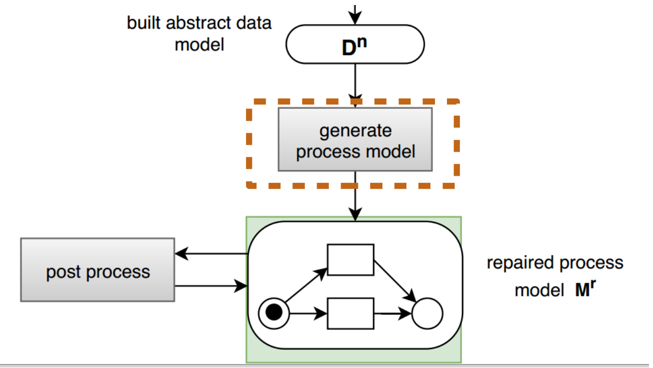
$$c^n(a,b) = u^n_w(a,b) \cdot (|L^+| + |L^-|)$$



- **IM algorithm**
  - Directly-follows graph
  - Process tree
  - Petri net



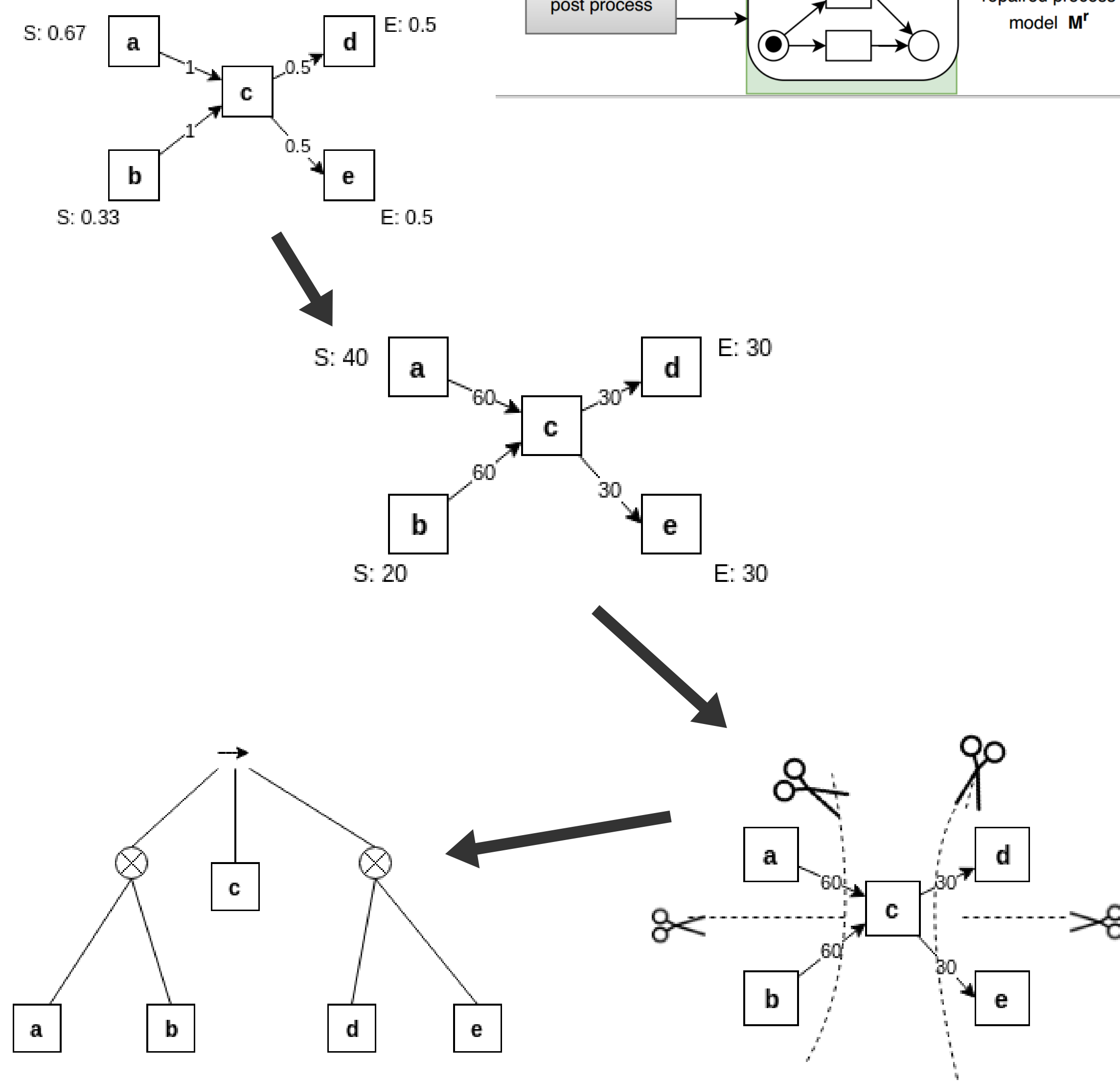
Generate Petri net



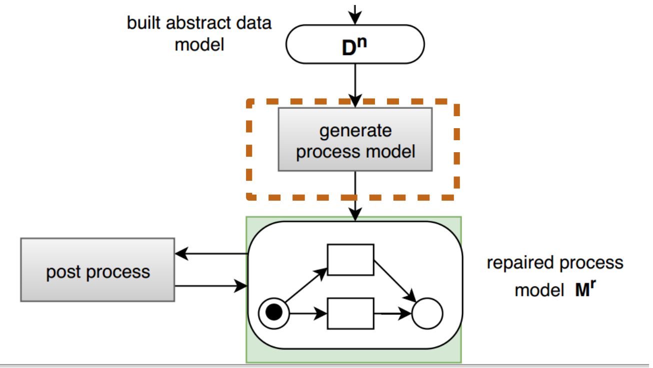
- **Transform into normal dfg**

$$c^n(a,b) = u^n_w(a,b) \cdot (|L^+| + |L^-|)$$

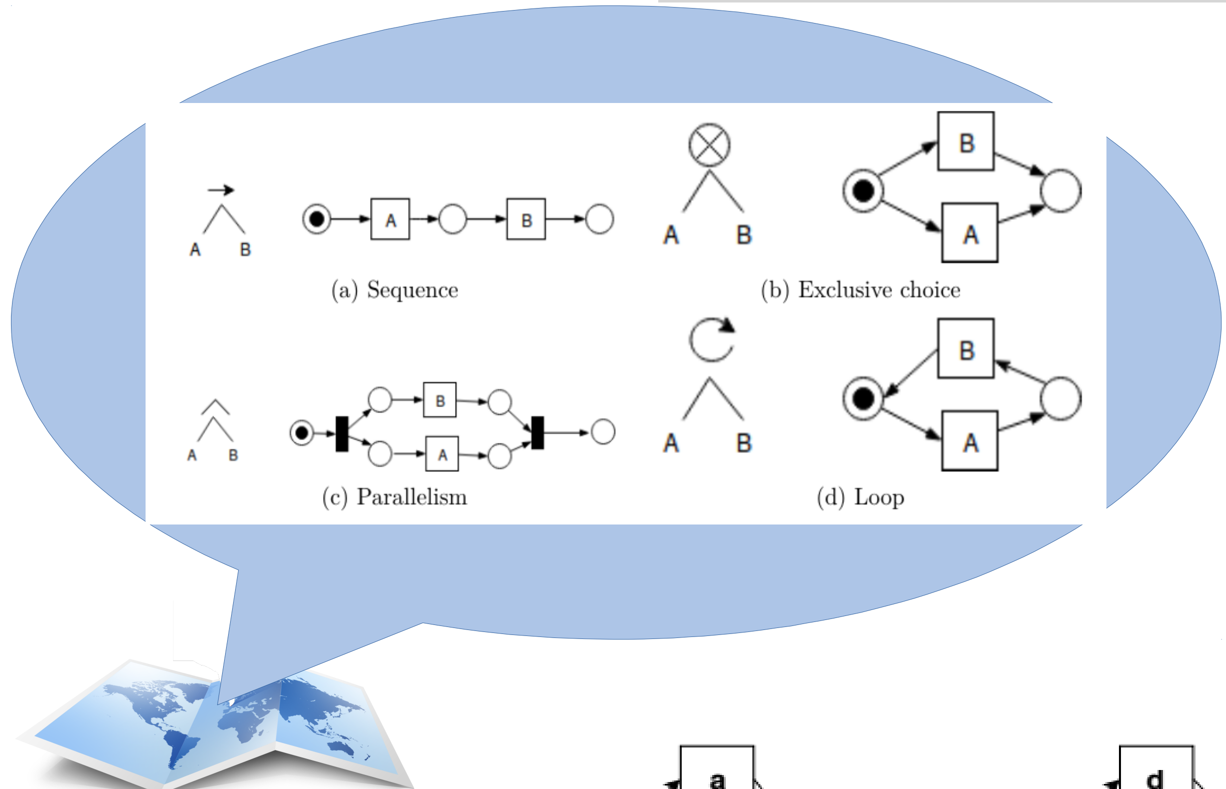
- **IM algorithm**
  - Directly-follows graph
  - Process tree
  - Petri net

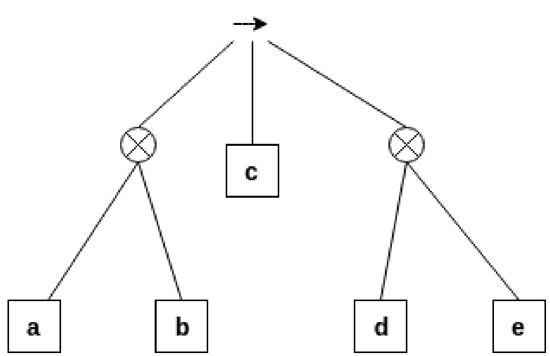


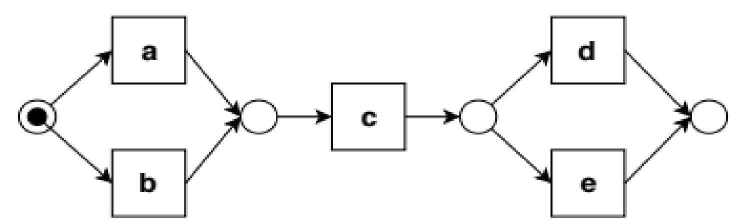
Generate Petri net



- **Transform into normal dfg**
- **IM algorithm**
  - Directly-follows graph
  - Process tree
  - Petri net



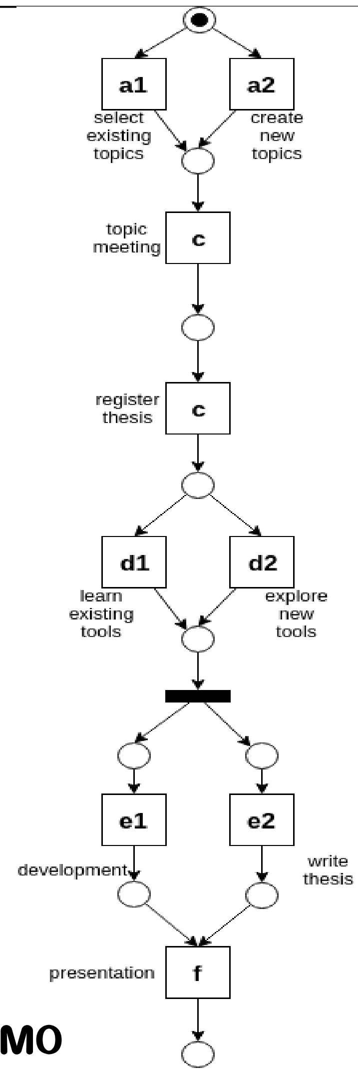




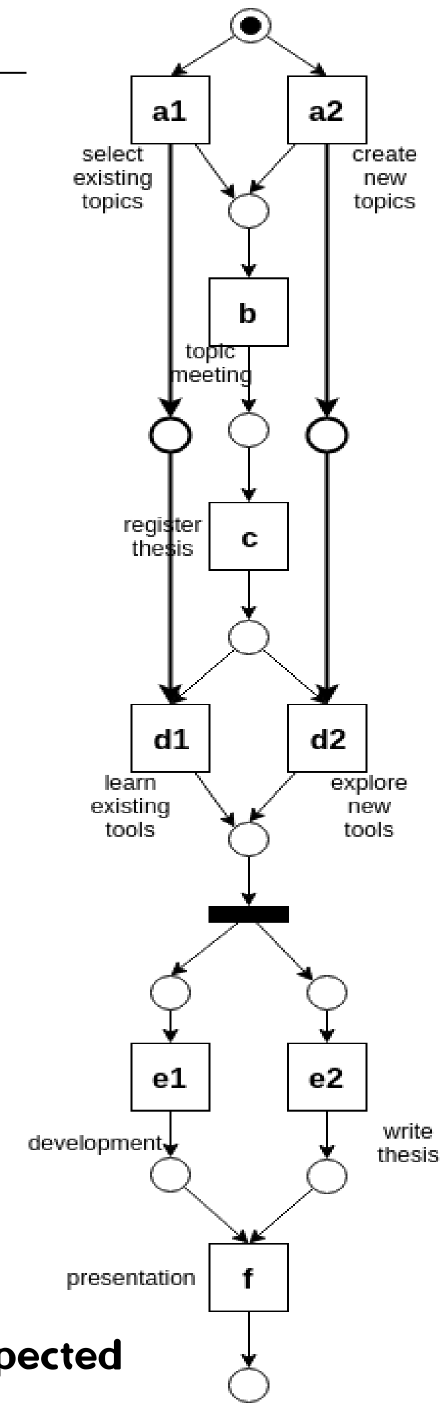
Post Process Petri net

- **Long-term dependency**

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



M0

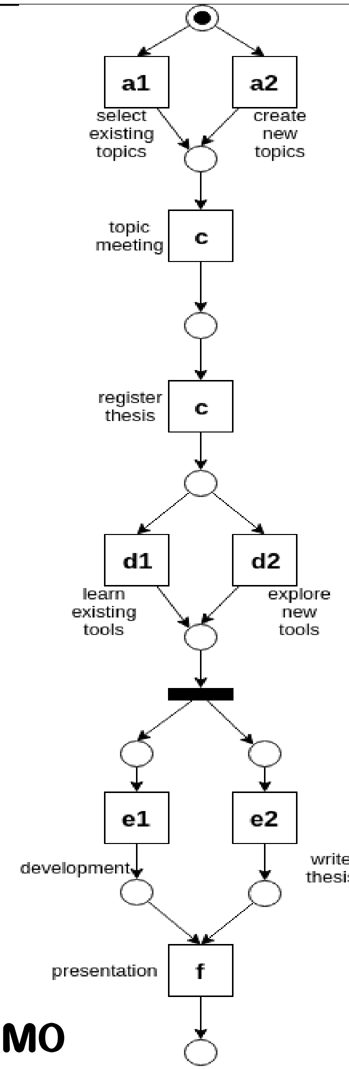


M3-expected

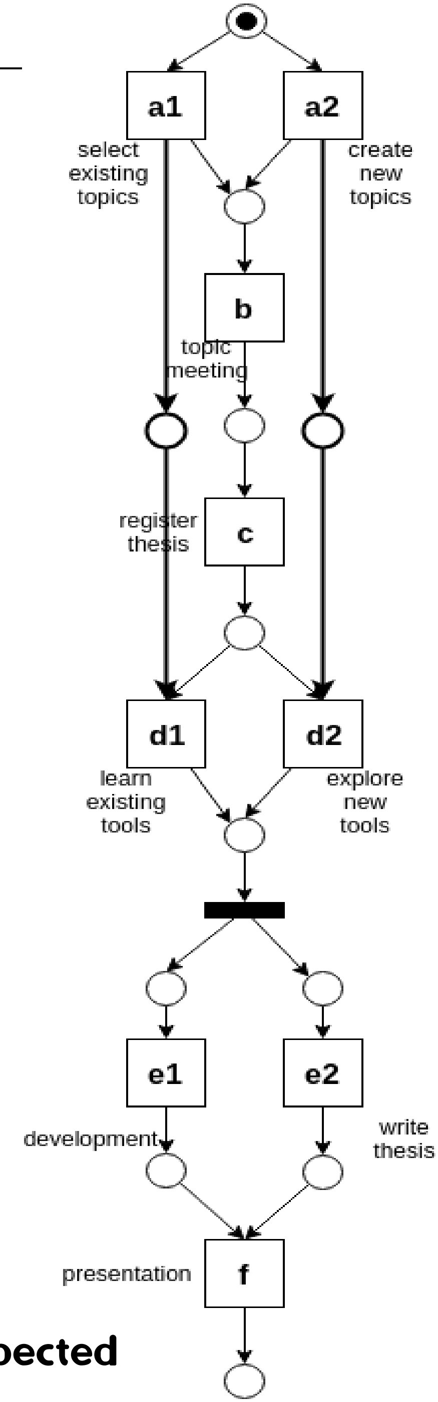
Post Process Petri net

- **Long-term dependency**
  - Choices dependency
  - Exclusive choices
  - Strong correlation

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



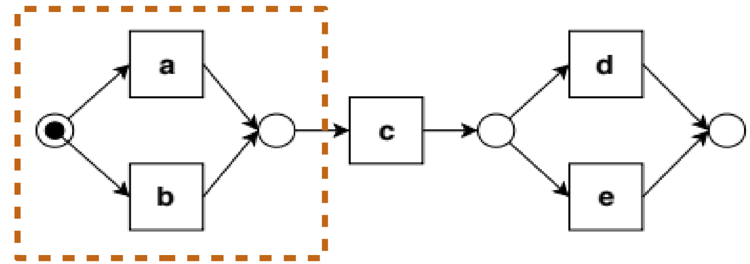
M0

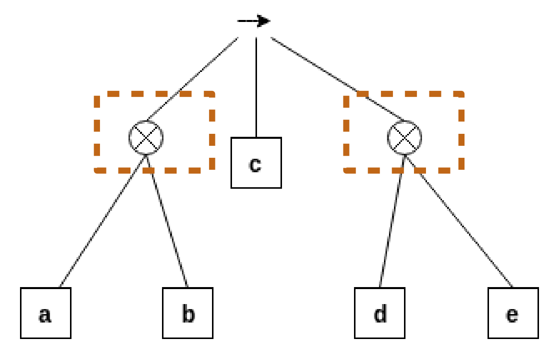


M3-expected

Post Process Petri net

- **Long-term dependency**
  - Exclusive choices
    - xor blocks/branches

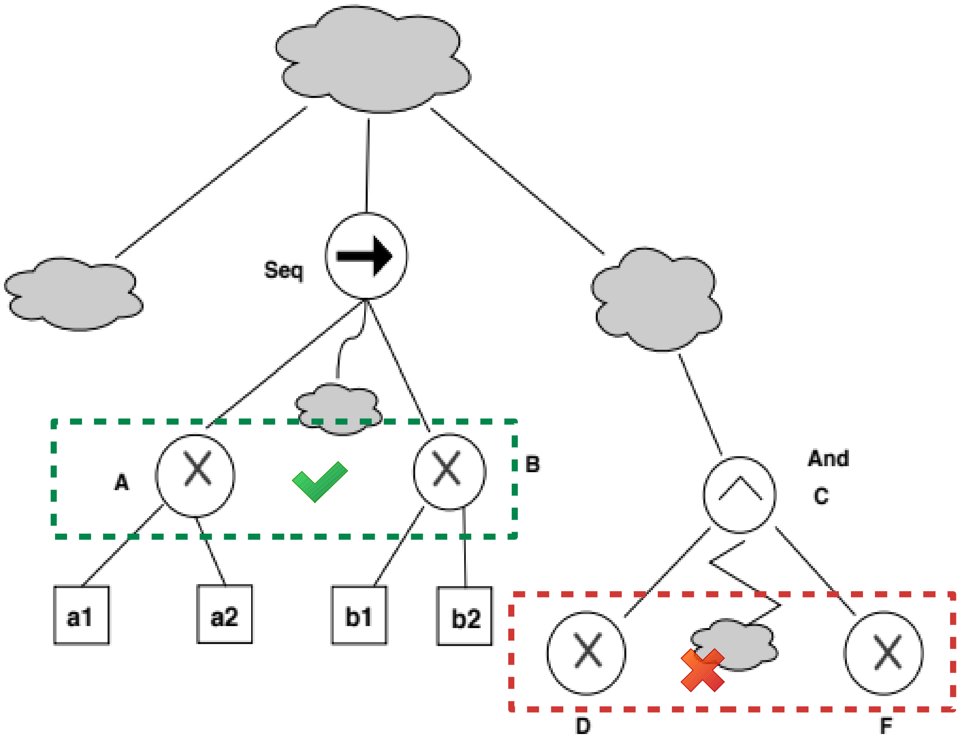




Post Process Petri net

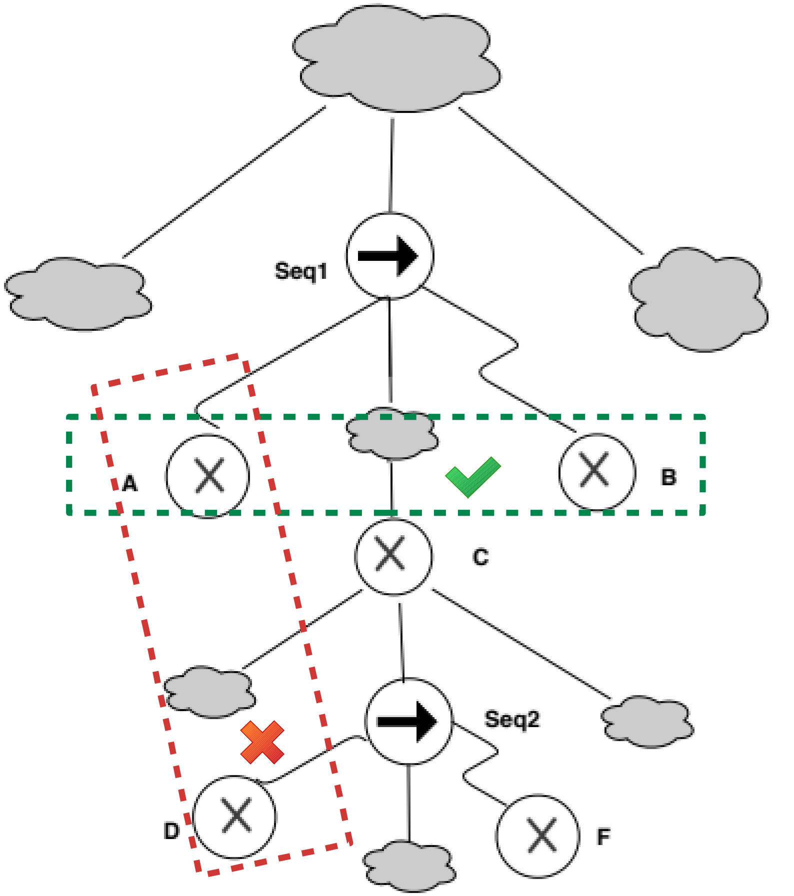
- **Long-term dependency**
  - Exclusive choices
    - xor blocks/branches
    - In order: Least common ancestor is Seq

      A < B, ! D< F



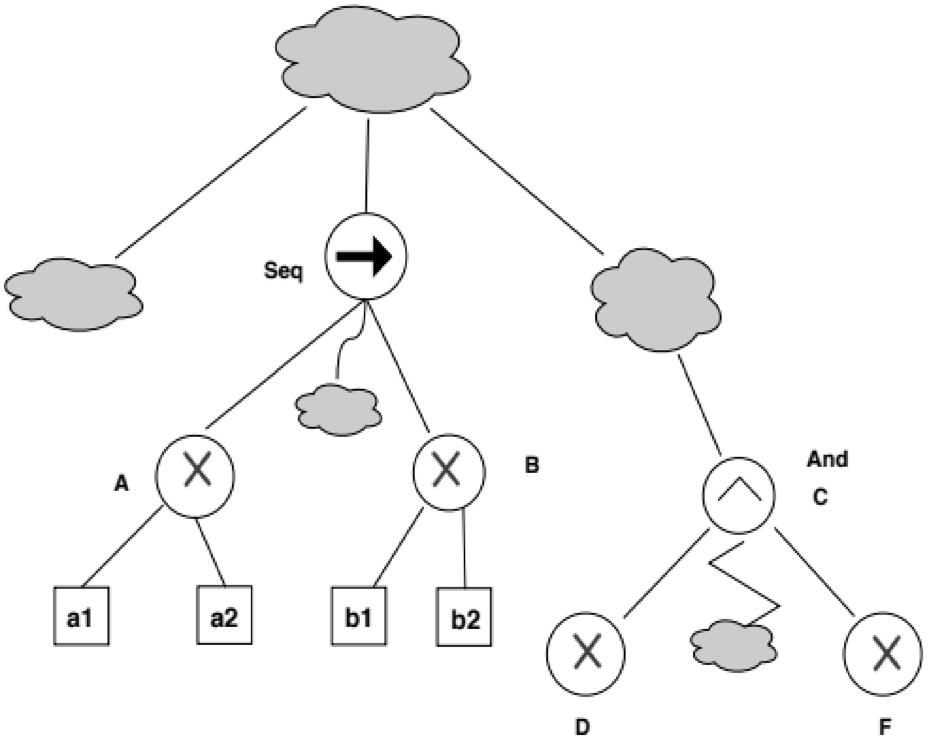
Post Process Petri net

- **Long-term dependency**
  - Exclusive choices
    - xor blocks/branches
    - In order: Least common ancestor is Seq
      A < C < B, D<F
    - In same level
      - A, B pair, D,F not pair



Post Process Petri net

- **Long-term dependency**
  - Exclusive choices
    - xor blocks/branches
    - In order: Least common ancestor is Seq
      A < C < B, D<F
    - In same level
      - A, B pair, D,F not pair
  - Strong correlation



Post Process Petri net

- **Long-term dependency**
  - Strong correlation: frequently coexist

Frequency of multiple xor branches is
$\mathrm{f}_L(x_i, y_j) = \sum_{\sigma \in L} |\{\sigma | \sigma \models x_i \wedge \sigma \models y_j\}|$

$$d^+(x_i, y_j) = \begin{cases} 0, & \text{if } \sum_{y_k \in T} f_{L^+}(x_i, y_k) = 0; \\ \frac{f_{L^+}(x_i, y_j)}{\sum_{y_k \in T} f_{L^+}(x_i, y_k)}, & \text{otherwise} \end{cases}$$

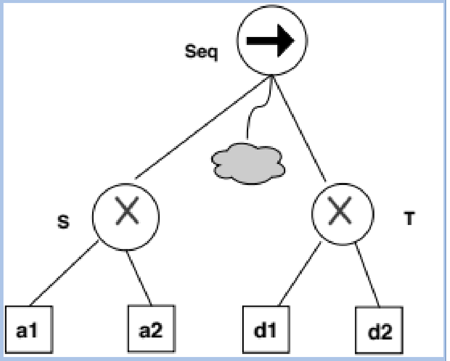
$$d^-(x_i, y_j) = \begin{cases} 0, & \text{if } \sum_{y_k \in T} f_{L^-}(x_i, y_k) = 0; \\ \frac{f_{L^-}(x_i, y_j)}{\sum_{y_k \in T} f_{L^-}(x_i, y_k)}, & \text{otherwise} \end{cases}$$

$$d(x_i, y_j) = w^+ \cdot d^+(x_i, y_j) - w^- \cdot d^-(x_i, y_j) > t$$

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

$$\begin{aligned} & \mathrm{w}^+ = 1, w^- = 1, t = 0 \\ & d(a1, d1) = d^+(a1, d1) - d^-(a1, d1) \\ & = 50/50 - 0 = 1; \\ & d(a1, d2) = d^+(a1, d2) - d^-(a1, d2) \\ & = 0 - 50/50 = -1; \\ & d(a2, d1) = -1; \\ & d(a2, d2) = 1. \end{aligned}$$

$\mathrm{LT}=\{ a1 \rightsquigarrow d1, a2 \rightsquigarrow d2\}.$



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Post Process Petri net

- **Long-term dependency**
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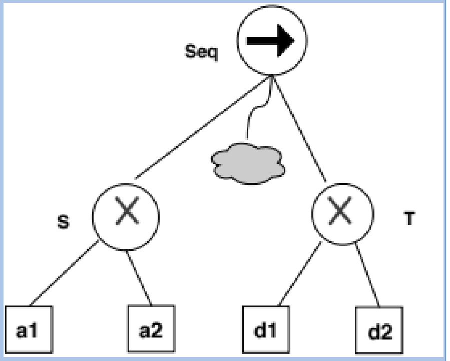
$$\begin{aligned} L_3 := \{ & < \mathbf{a1}, b, c, \mathbf{d1}, e1, e2, f >^{50,pos}, \\ & < \mathbf{a2}, b, c, \mathbf{d2}, e1, e2, f >^{50,pos}; \\ & < \mathbf{a1}, b, c, \mathbf{d2}, e1, e2, f >^{50,neg}, \\ & < \mathbf{a2}, b, c, \mathbf{d1}, e1, e2, f >^{50,neg} \} \end{aligned}$$

$$\begin{aligned} & \mathrm{w}^+ = 1, w^- = 1, t = 0 \\ & d(a1, d1) = d^+(a1, d1) - d^-(a1, d1) \\ & = 50/50 - 0 = 1; \\ & d(a1, d2) = d^+(a1, d2) - d^-(a1, d2) \\ & = 0 - 50/50 = -1; \\ & d(a2, d1) = -1; \\ & d(a2, d2) = 1. \end{aligned}$$

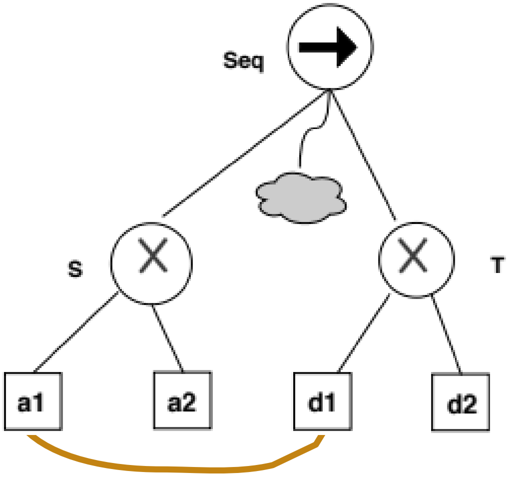
LT=$\{ a1 \rightsquigarrow d1, a2 \rightsquigarrow d2 \}$.



Algorithm – add long-term dependency

- express on process tree

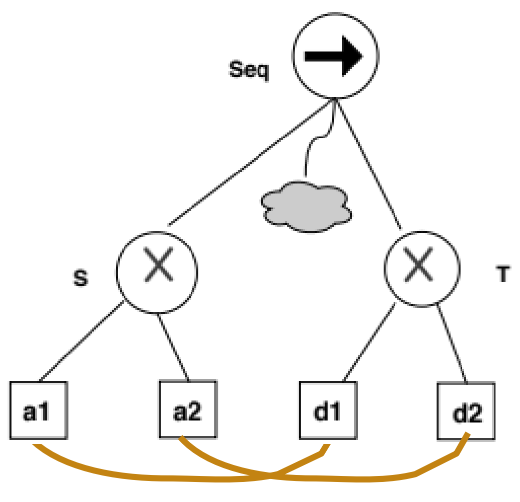
$$\mathrm{LT}=\{\ \mathrm{a1} \rightsquigarrow d1,\ a2 \rightsquigarrow d2\}.$$



Algorithm – add long-term dependency

– express on process tree

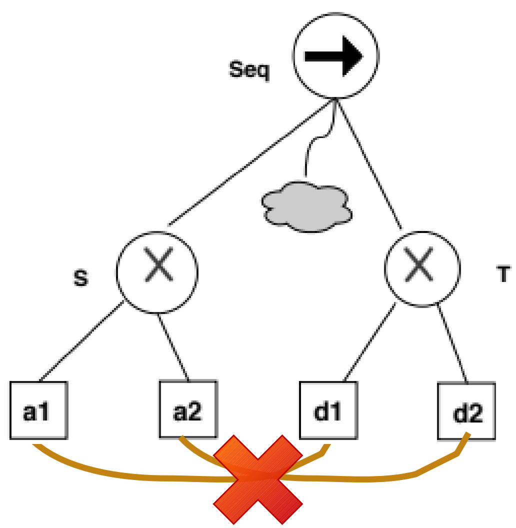
$$\mathrm{LT}=\{\ \mathrm{a1} \rightsquigarrow d1,\ a2 \rightsquigarrow d2\}.$$



Algorithm – add long-term dependency

- express on process tree

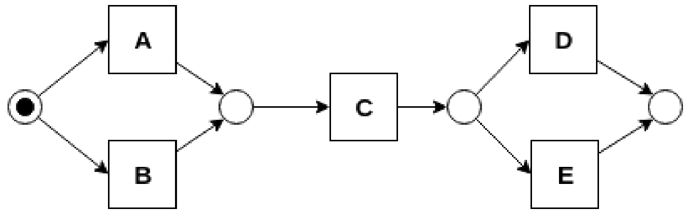
LT={ a1$\rightsquigarrow d1$,
$a2 \rightsquigarrow d2\}$.

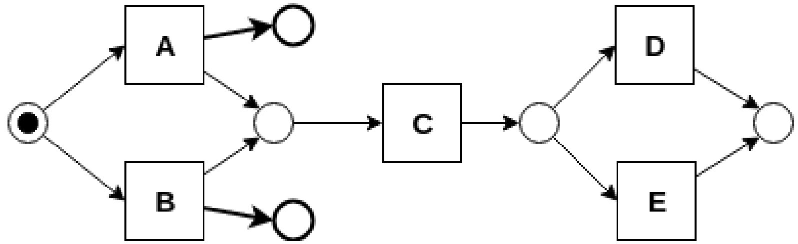


Algorithm – add long-term dependency

- express on Petri net
  - ✓ Add silent transition
    - Add control place as post-place post after S={A,B}

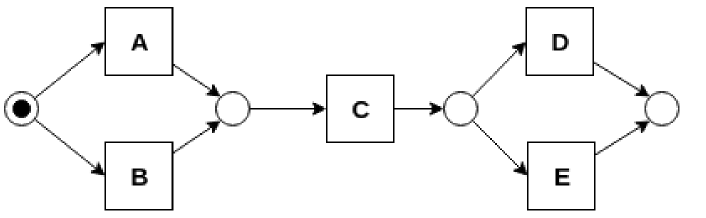
$$S = \{A, B\}, T = \{D, E\}, LT = \{A \rightsquigarrow D, A \rightsquigarrow E, B \rightsquigarrow E\}.$$



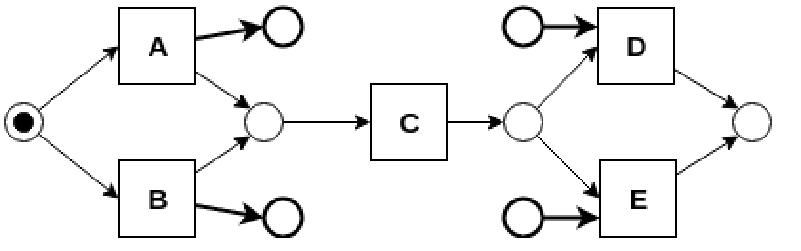


Algorithm – add long-term dependency

- How to express on Petri net
  - Add silent transition
    - Add control place as post-place post after S={A,B}
    - Add control place as pre-place before T={D,E}

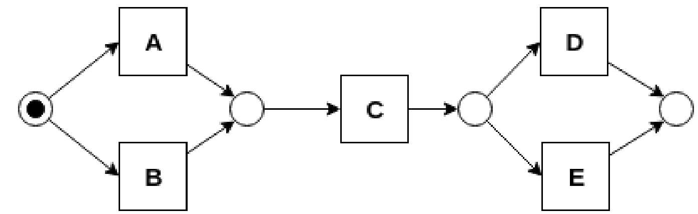


$$LT = \{A \rightsquigarrow D, A \rightsquigarrow E, B \rightsquigarrow E\}.$$

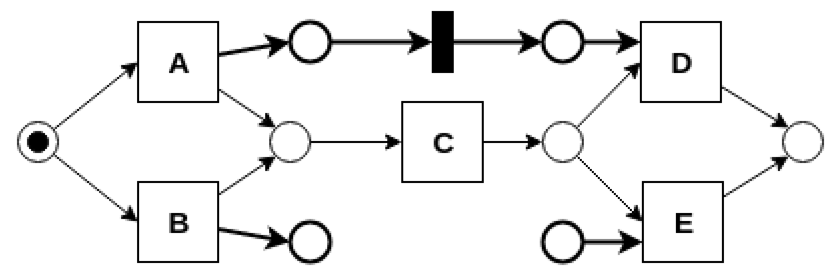


Algorithm – add long-term dependency

- How to express on Petri net
  - ✔ Add silent transition
    - Add control place as post-place post after S={A,B}
    - Add control place as pre-place before T={D,E}
    - Add silent transitions for each long-term dependency

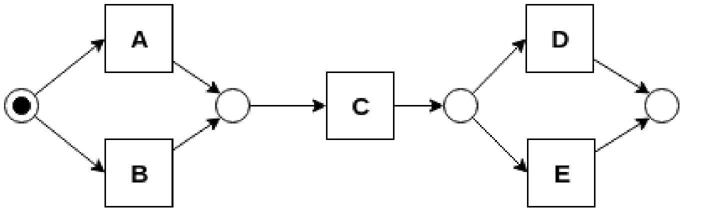


$$LT = \{A \rightsquigarrow D, A \rightsquigarrow E, B \rightsquigarrow E\}.$$

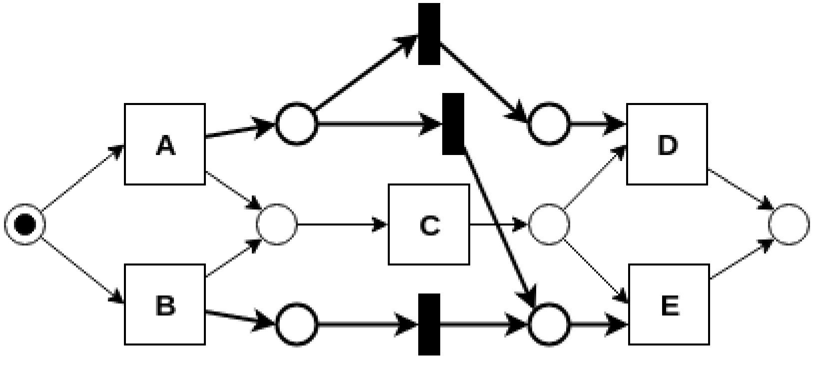


Algorithm – add long-term dependency

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



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



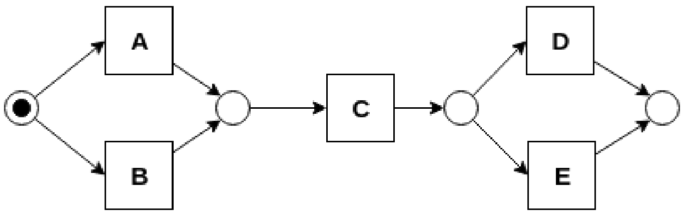
Algorithm – add long-term dependency

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

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

- **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. $LT = \emptyset$



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

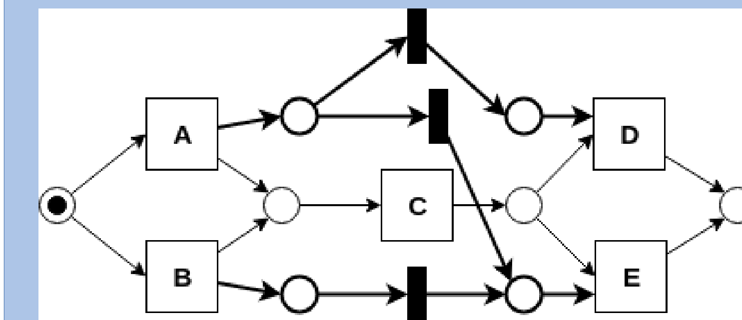
Algorithm – add long-term dependency

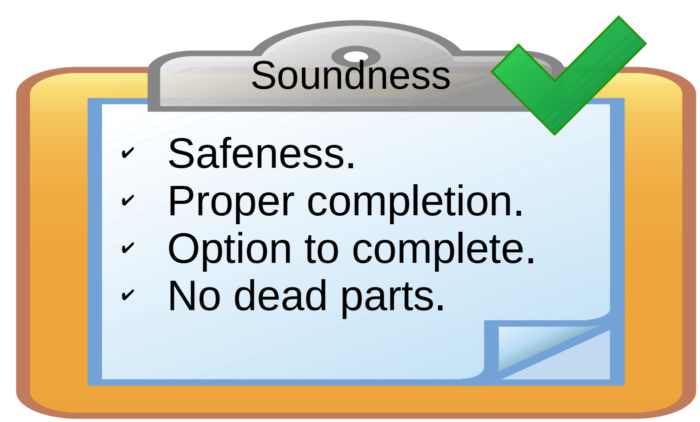
- **Long-term dependency Situations**

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. $LT = \emptyset$

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

$$LT_S = S, LT_T = T$$





Algorithm – add long-term dependency

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- **Long-term dependency Situations**

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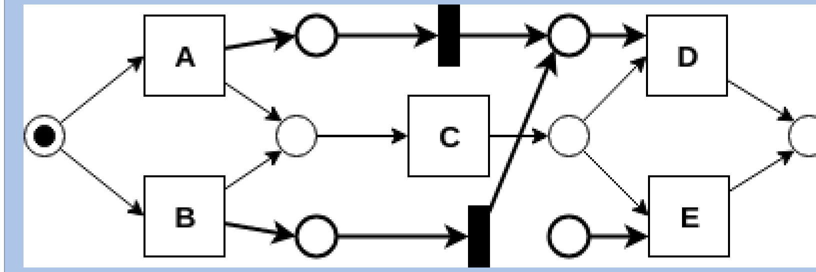
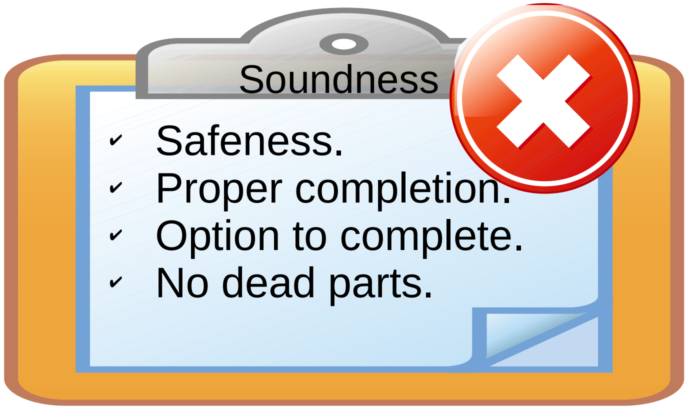
   $LT_S \subsetneq S, LT_T \subsetneq T$.
7. $LT = \emptyset$

$$LT_S \subsetneq S, LT_T \subsetneq T$$





Algorithm – add long-term dependency

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

- **Long-term dependency Situations**

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7. $LT = \emptyset$

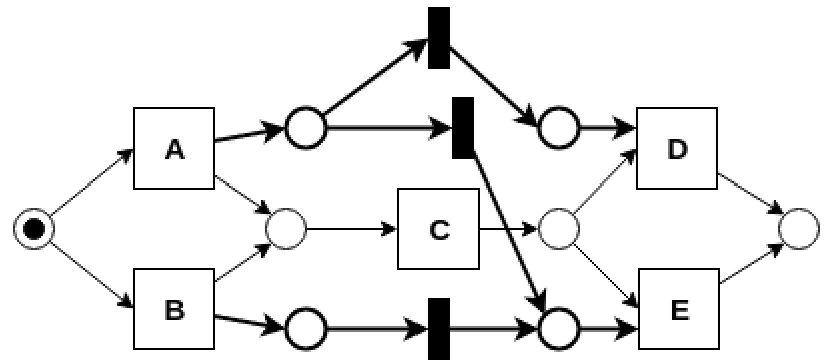
$$LT_S = S, LT_T = T, |LT| < |S| \cdot |T|$$

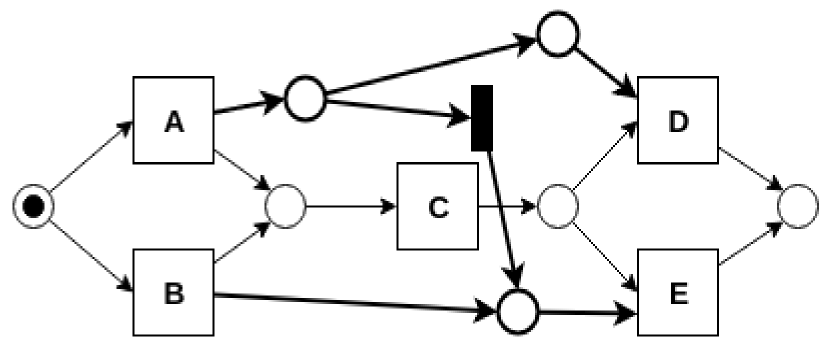
Soundness

- Safeness.
- Proper completion.
- Option to complete.
- No dead parts.

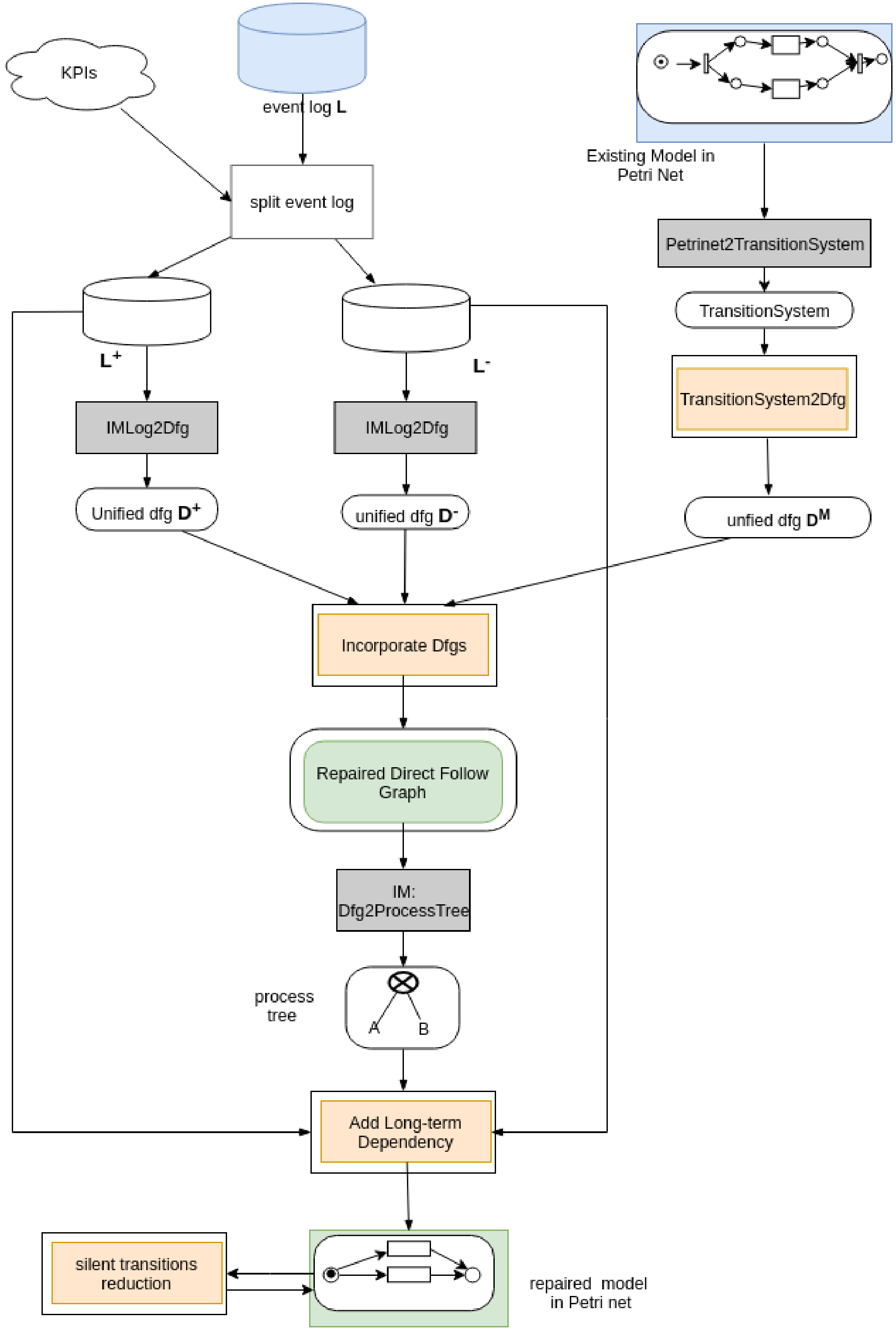
Post process

- **Delete redundant silent transitions**





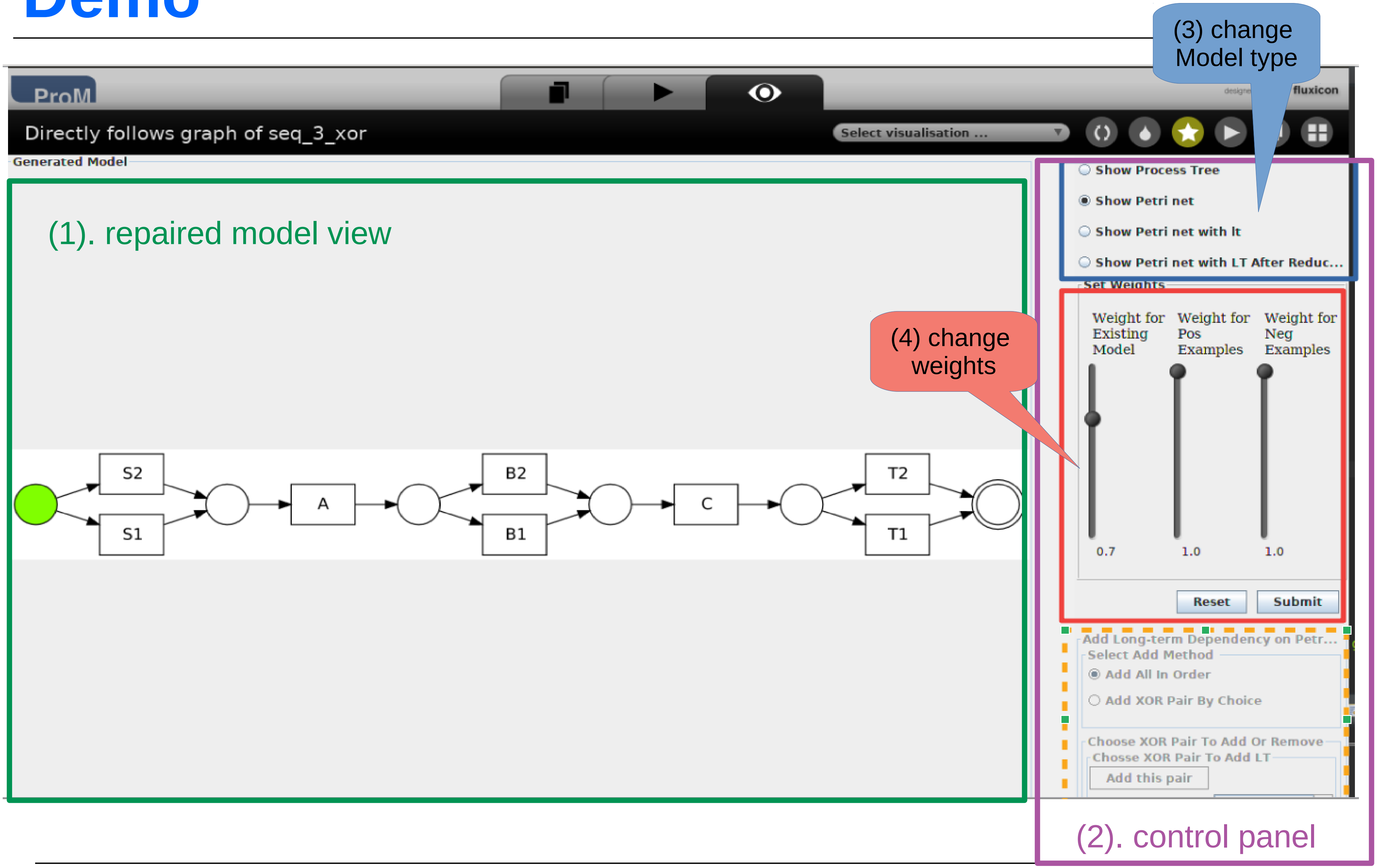
Algorithm – architecture



Outline

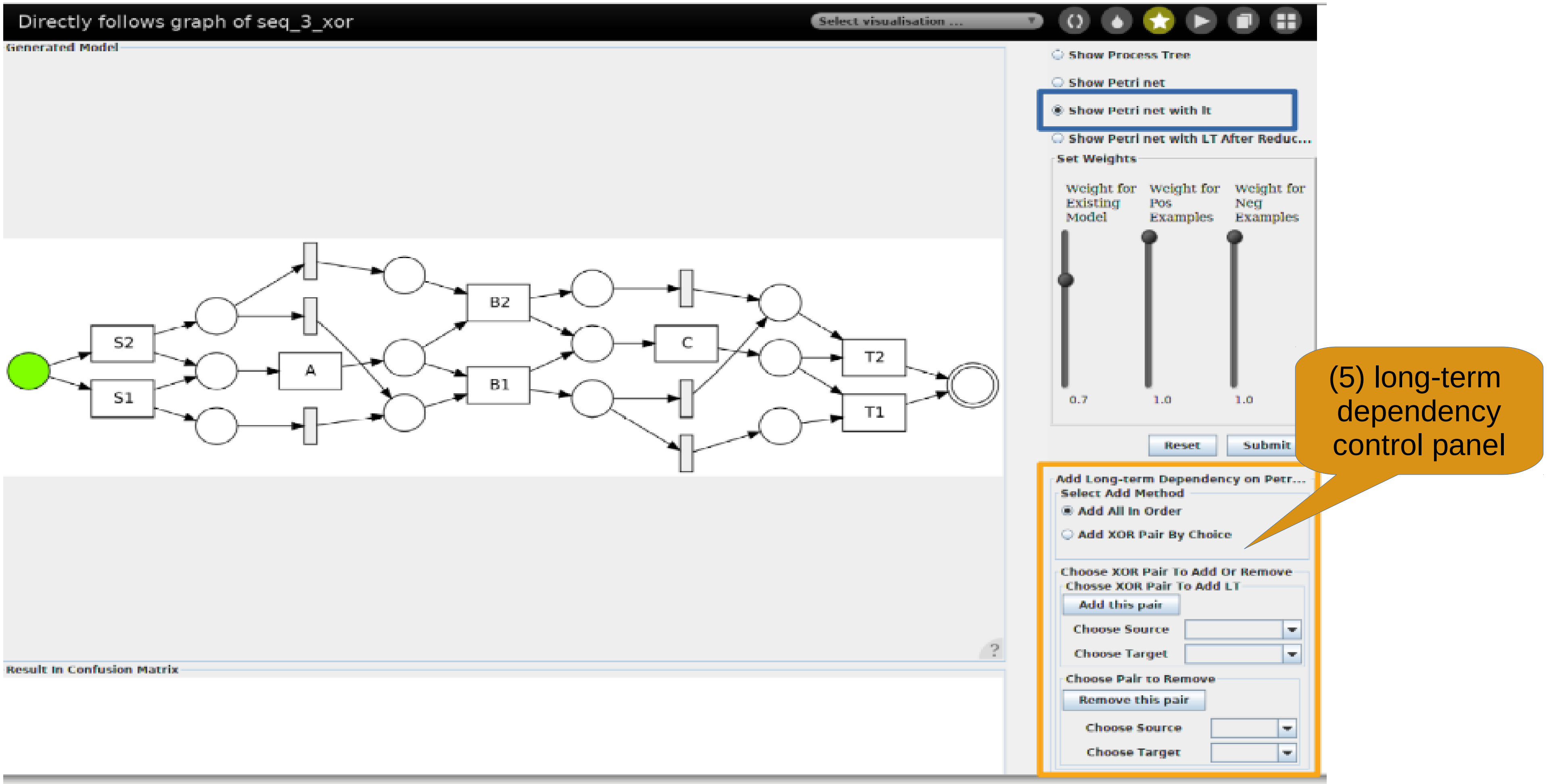
- **Motivation for Research**
- **Problem Definition**
- **Approach**
- **Demo Show**
  - ProM
  - KNIME
- **Evaluation**
- **Conclusion**

Demo



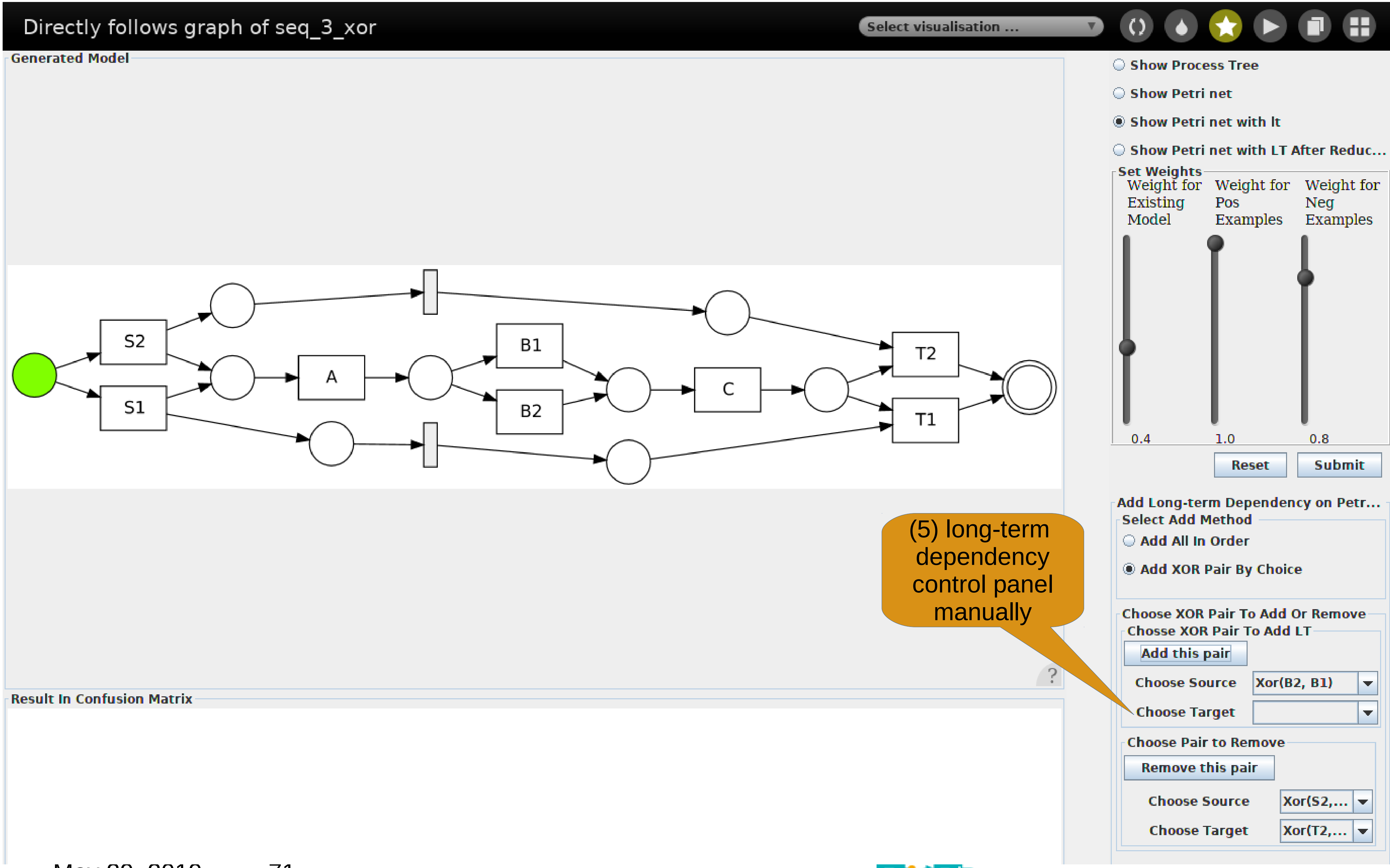
(3) change Model type
ProM
fluxicon
Directly follows graph of seq_3_xor
Select visualisation ...
Generated Model
(1). repaired model view
S2
S1
A
B2
B1
C
T2
T1
Show Process Tree
Show Petri net
Show Petri net with lt
Show Petri net with LT After Reduc...
Set Weights
Weight for Existing Model
Weight for Pos Examples
Weight for Neg Examples
0.7
1.0
1.0
Reset
Submit
(4) change weights
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
Chosse XOR Pair To Add LT
Add this pair
(2). control panel

Demo



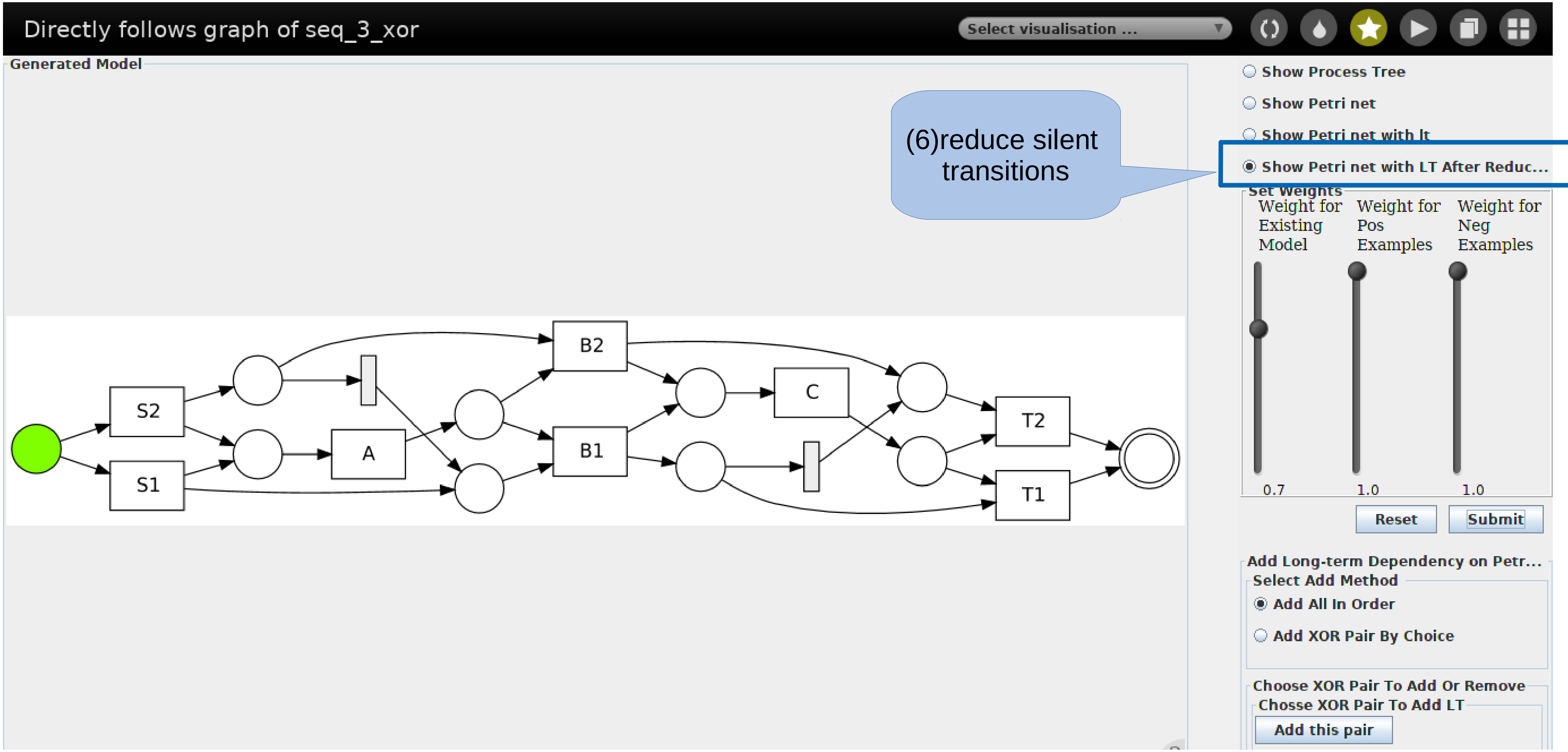
Directly follows graph of seq_3_xor
Select visualisation ...
Generated Model
S2
S1
A
B2
B1
C
T2
T1
Show Process Tree
Show Petri net
Show Petri net with lt
Show Petri net with LT After Reduc...
Set Weights
Weight for Existing Model
Weight for Pos Examples
Weight for Neg Examples
0.7
1.0
1.0
Reset
Submit
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
Chosse XOR Pair To Add LT
Add this pair
Choose Source
Choose Target
Choose Pair to Remove
Remove this pair
Choose Source
Choose Target
Result In Confusion Matrix
(5) long-term dependency control panel

Demo



Directly follows graph of seq_3_xor
Select visualisation ...
Generated Model
S2
S1
A
B1
B2
C
T2
T1
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
0.4
1.0
0.8
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
Chosse XOR Pair To Add LT
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,...
(5) long-term dependency control panel manually
Result In Confusion Matrix

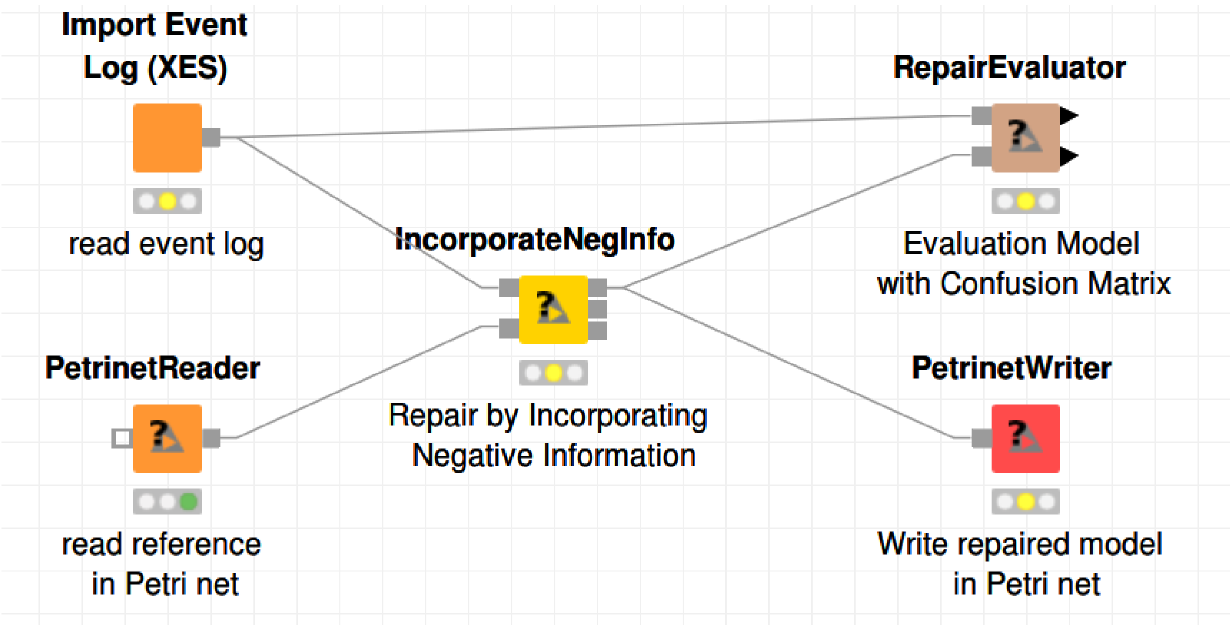
Demo



Directly follows graph of seq_3_xor
Select visualisation ...
Generated Model
(6)reduce silent transitions
S2
S1
A
B2
B1
C
T2
T1
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
Chosse XOR Pair To Add LT
Add this pair

Demo

Integration with KNIME



Chair of Process and Data Science

Outline

- **Motivation for Research**
- **Problem Definition**
- **Approach**
- **Demo**
- **Evaluation**
  - Synthetic data
  - Real life data
- **Conclusion**

Chair of Process and Data Science

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Evaluation

Confusion matrix

	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

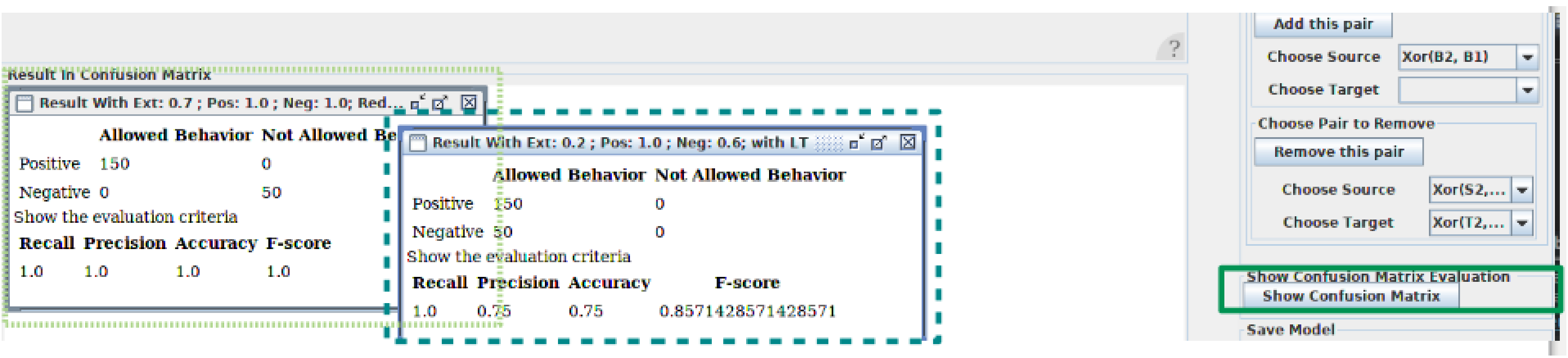
$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

  - F1

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

Evaluation --implementation

- Naive conformance checking
- Alignment-based
- External plugin & Embedded

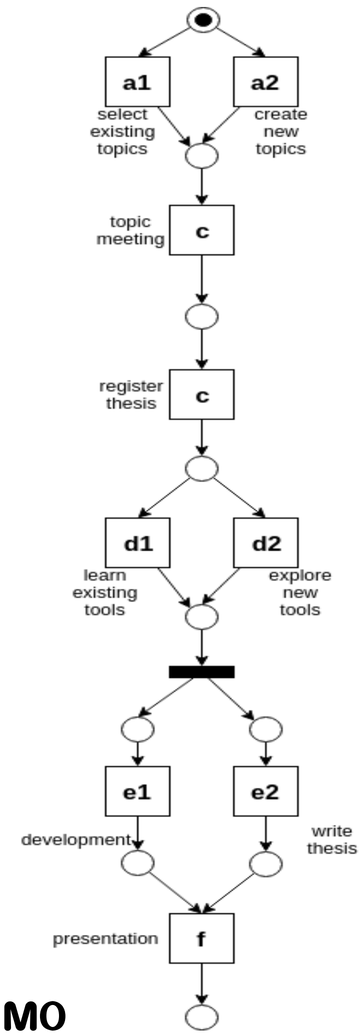


Demo --result

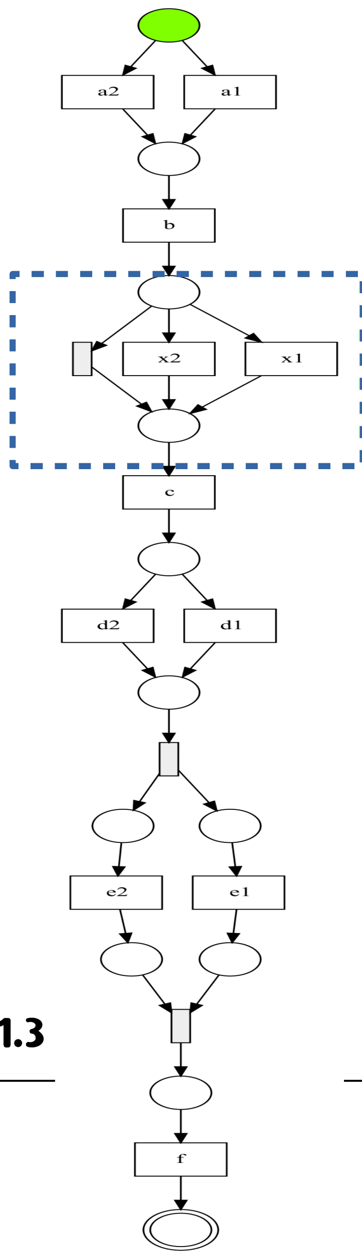
Overcome s1:
add subprocesses
as loops

Overcome s2:
unable to adapt model
With negative instances

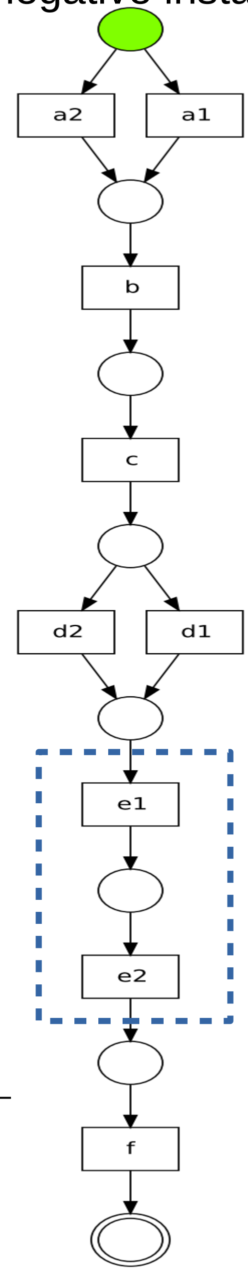
Overcome s3:
unable to detect
long-term dependency



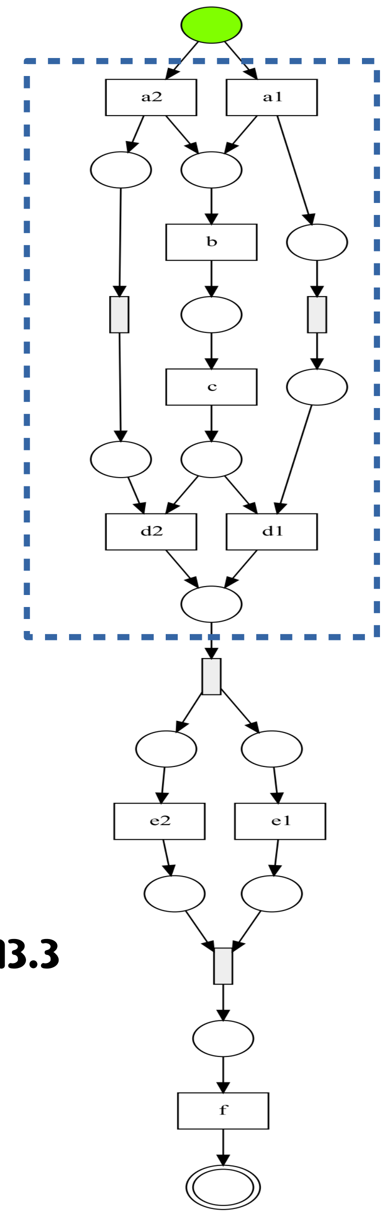
M0



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

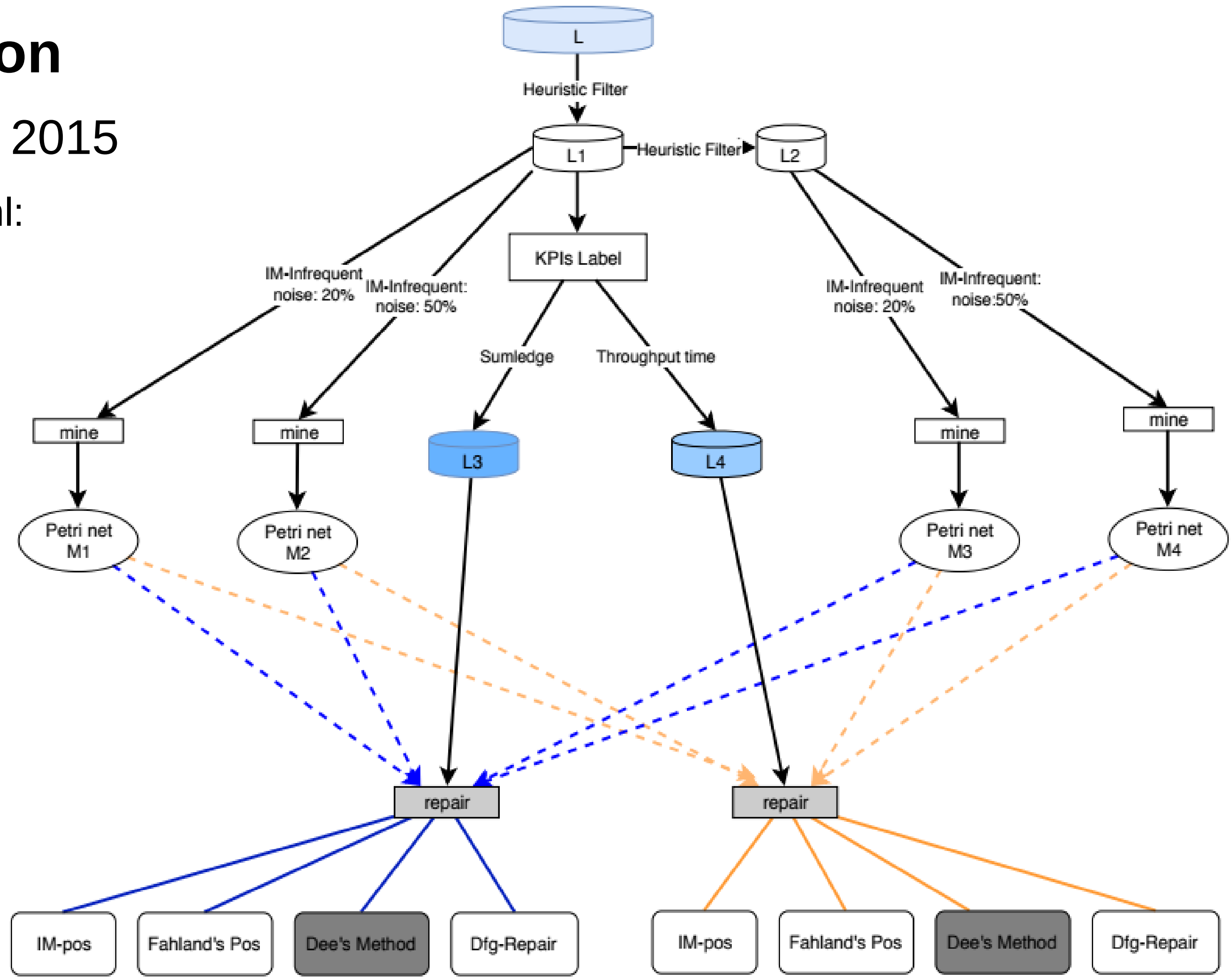
- **Data description**
  - BPI Challenge 2015

    BPIC15_1.xes.xml:

    1199 cases,

    52217 events

    398 event classes

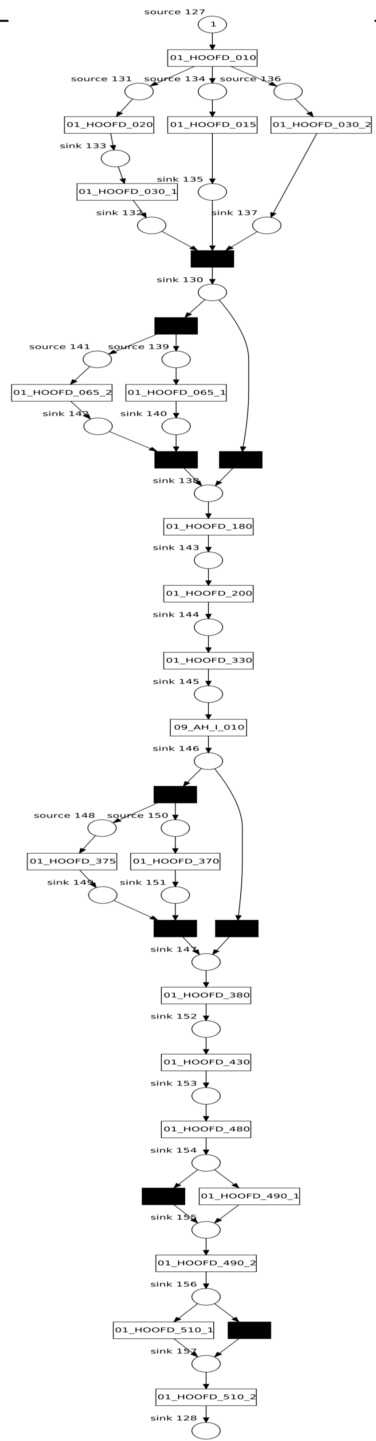


Experiments

- **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



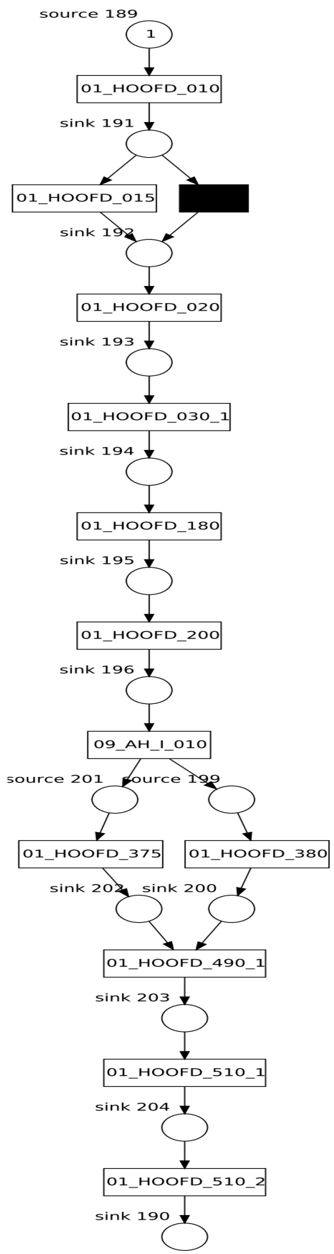
M1

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

- **Petri net Models**

M3



Model ID	Data ID	Confusion matrix							
		TP	FP	TN	FN	recall	Precision	Accuracy	F1
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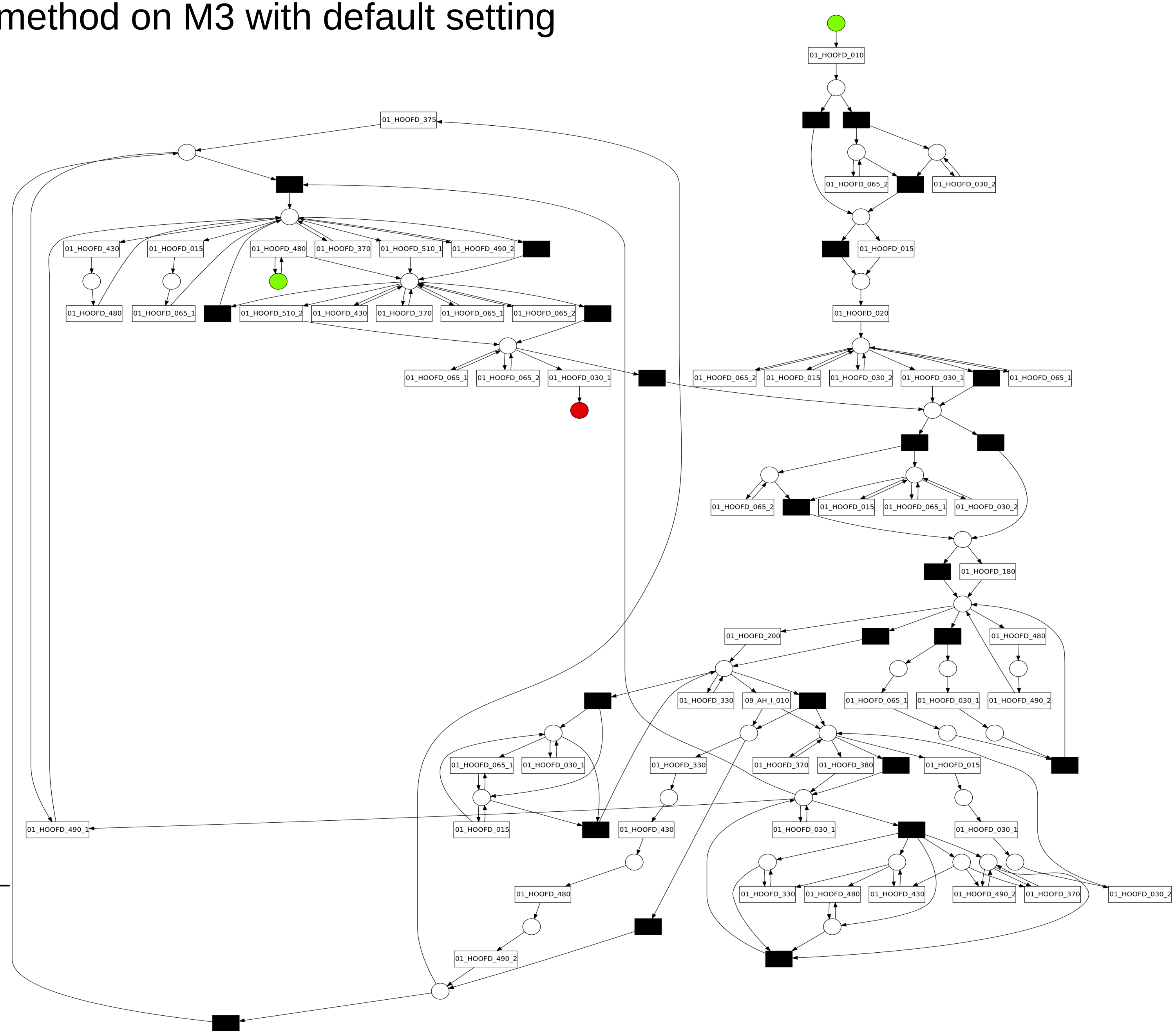
M3	D3.3	0	0	146	349	0	NaN	0.295	0
	D4.3	0	0	149	346	0	NaN	0.301	0
M4	D3.3	0	0	146	349	0	NaN	0.295	0
	D4.3	0	0	149	346	0	NaN	0.301	0

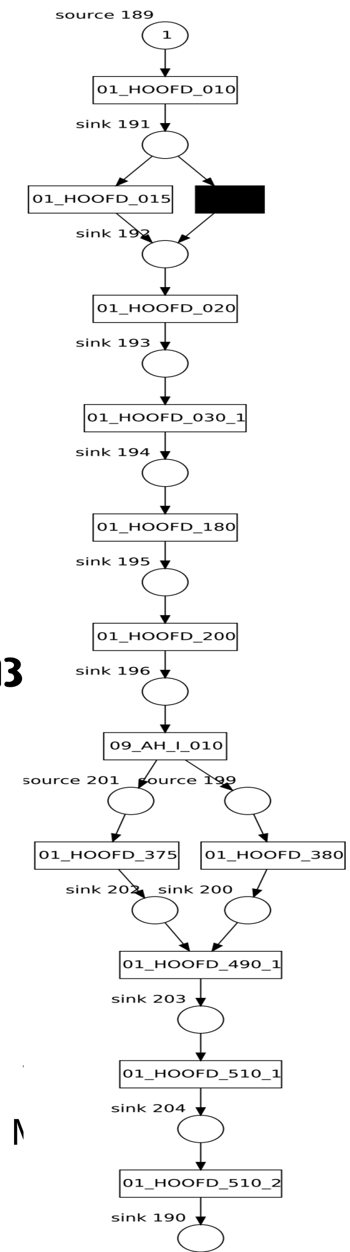
Experiments- result

Repaired model M3.2 with Fahland's method on M3 with default setting

M3.2

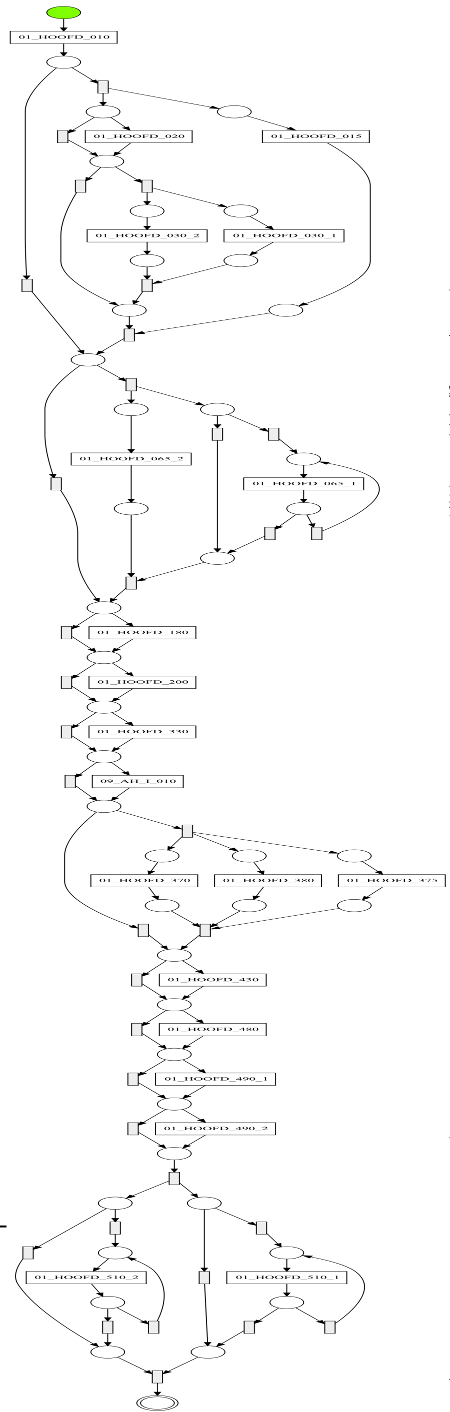


M3



Experiments results

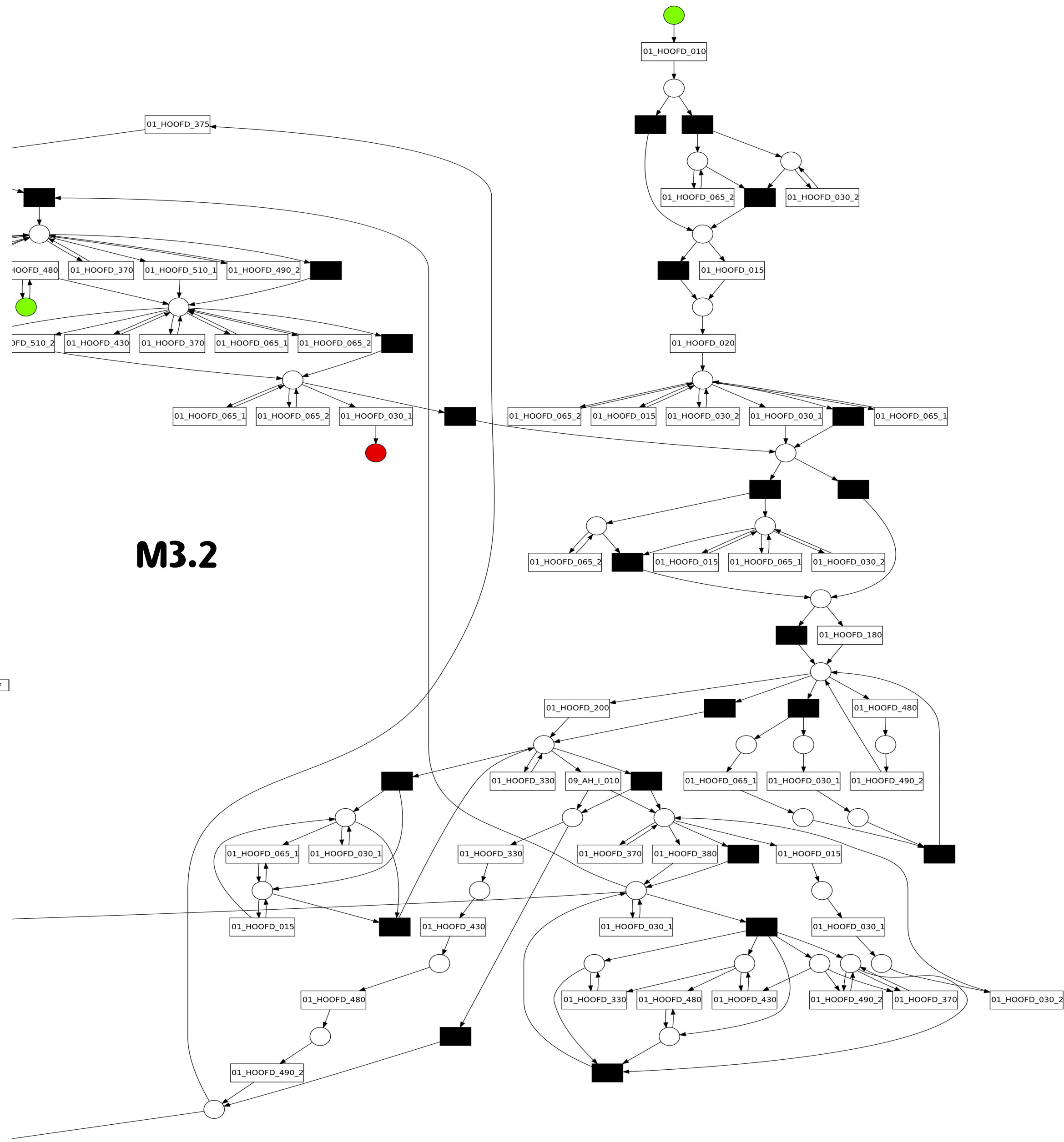
Repaired model M3.3 from dfg-repair with default setting



M3.3

Simpler than Fahland’s method

M3.2

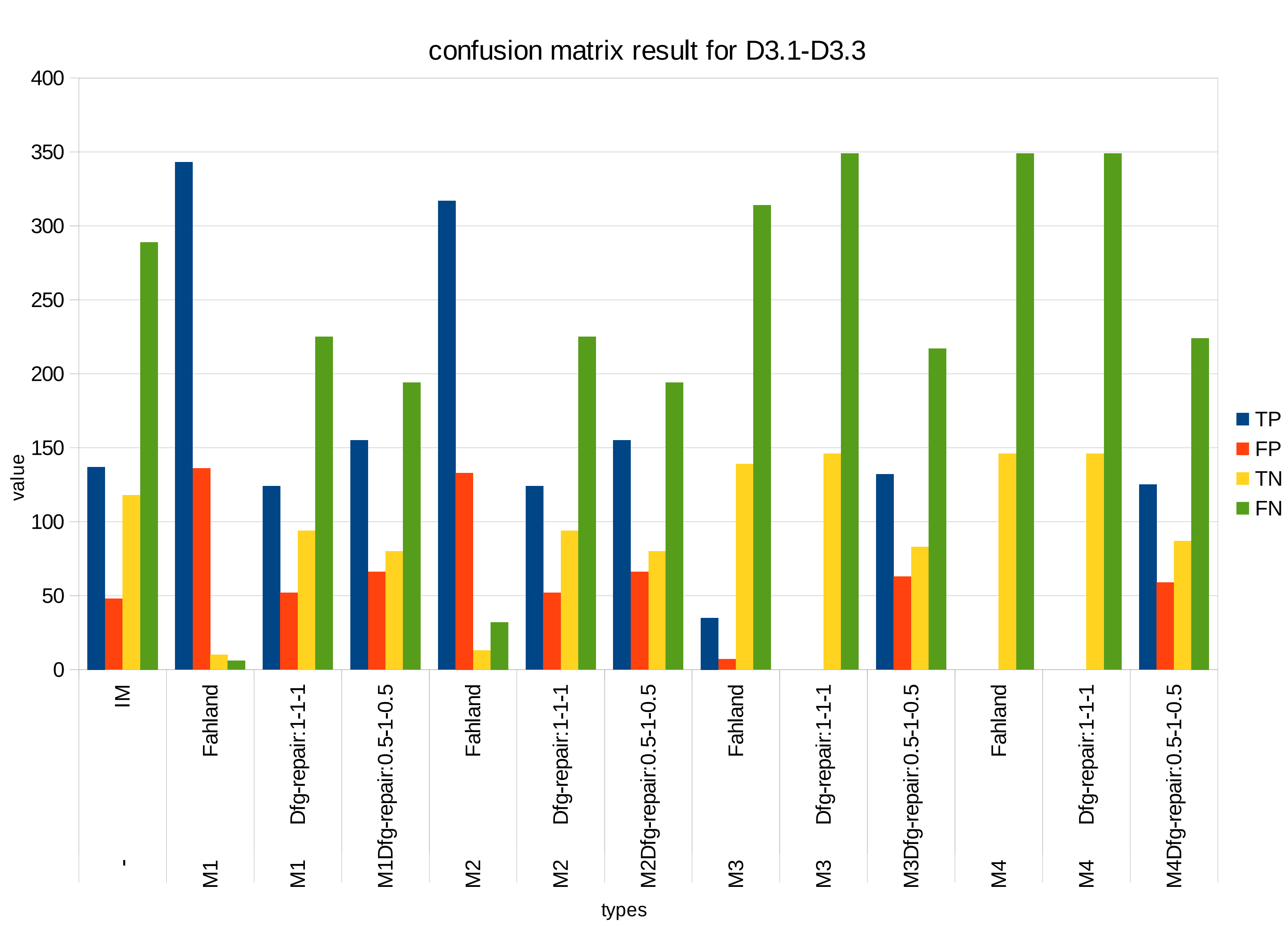


Experiment result

Table 6.5: Test Results on BPI15-M1 data

event log	reference model	method	TP	FP	TN	FN	recall	precision	accuracy	F1
			confusion matrix metrics							
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	35	7	139	314	0.100	0.833	0.352	0.179
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	0	0	146	349	0	NaN	0.294	0.0
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	10	20	129	336	0.029	0.333	0.281	0.053
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	5	14	135	341	0.014	0.263	0.283	0.027
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

Experiment result



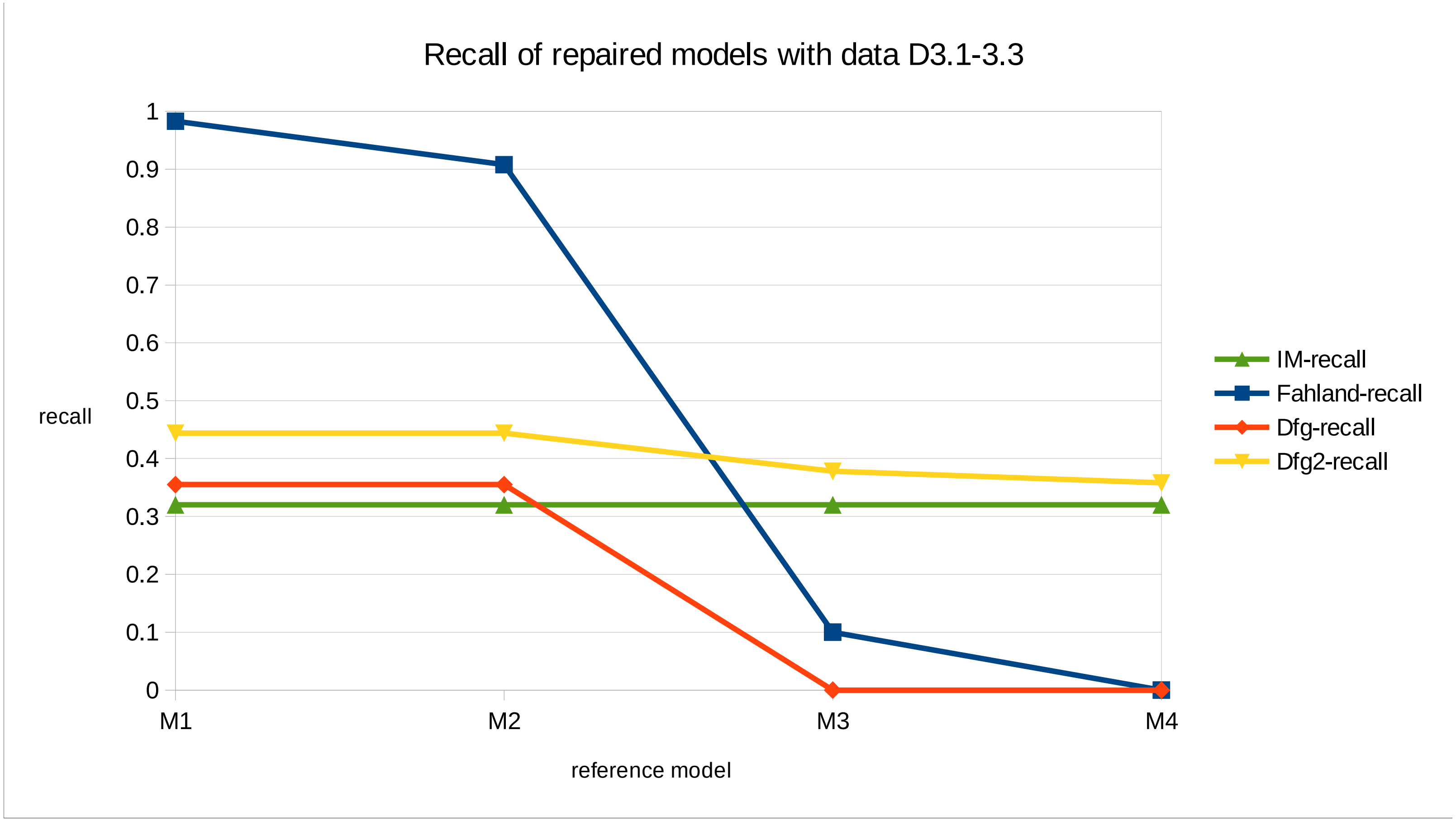
Fahland's Repair:
M1,M2
TN and FN low values
M3,M4 high values

Dfg-repair: 1-1-1
Dfg2-repair: 0.5-1-0.5

Dfg2-repair Perform better than 1-1-1

High values in TP and TN

Experiment result

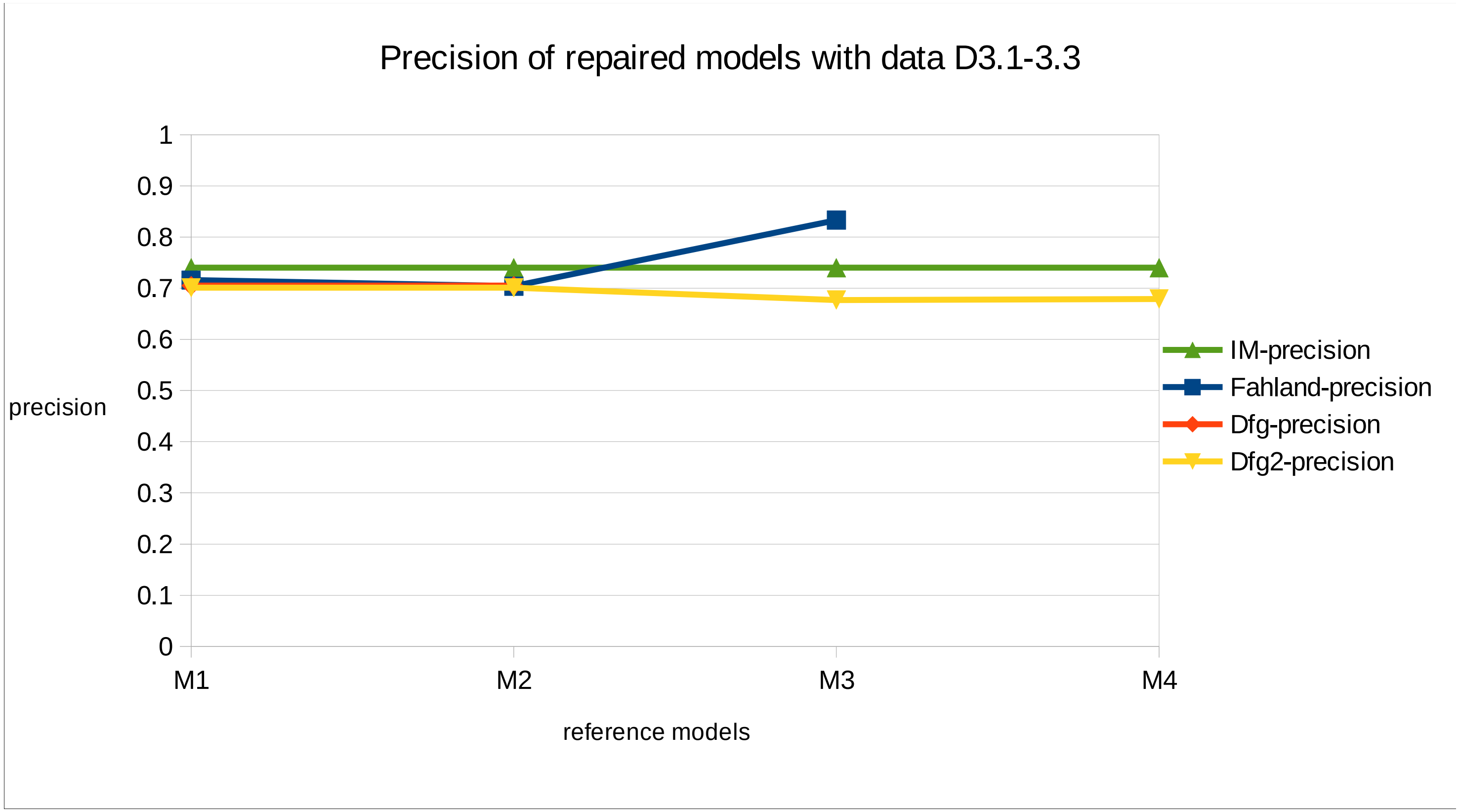


IM: Inductive Miner

Dfg-repair: 1-1-1

Dfg2-repair: 0.5-1-0.5

Experiment result

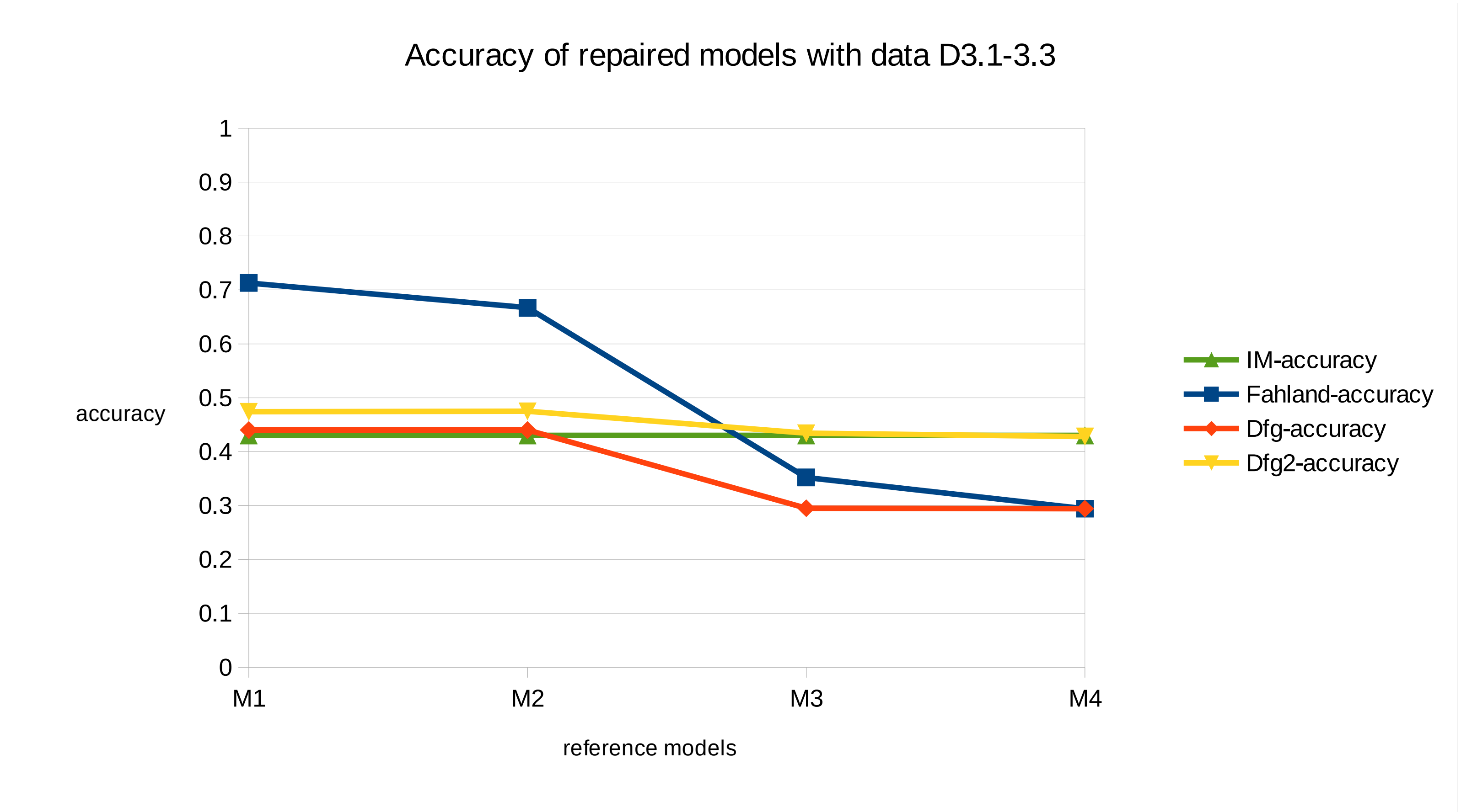


IM: Inductive Miner

Dfg-repair: 1-1-1

Dfg2-repair: 0.5-1-0.5

Experiment result



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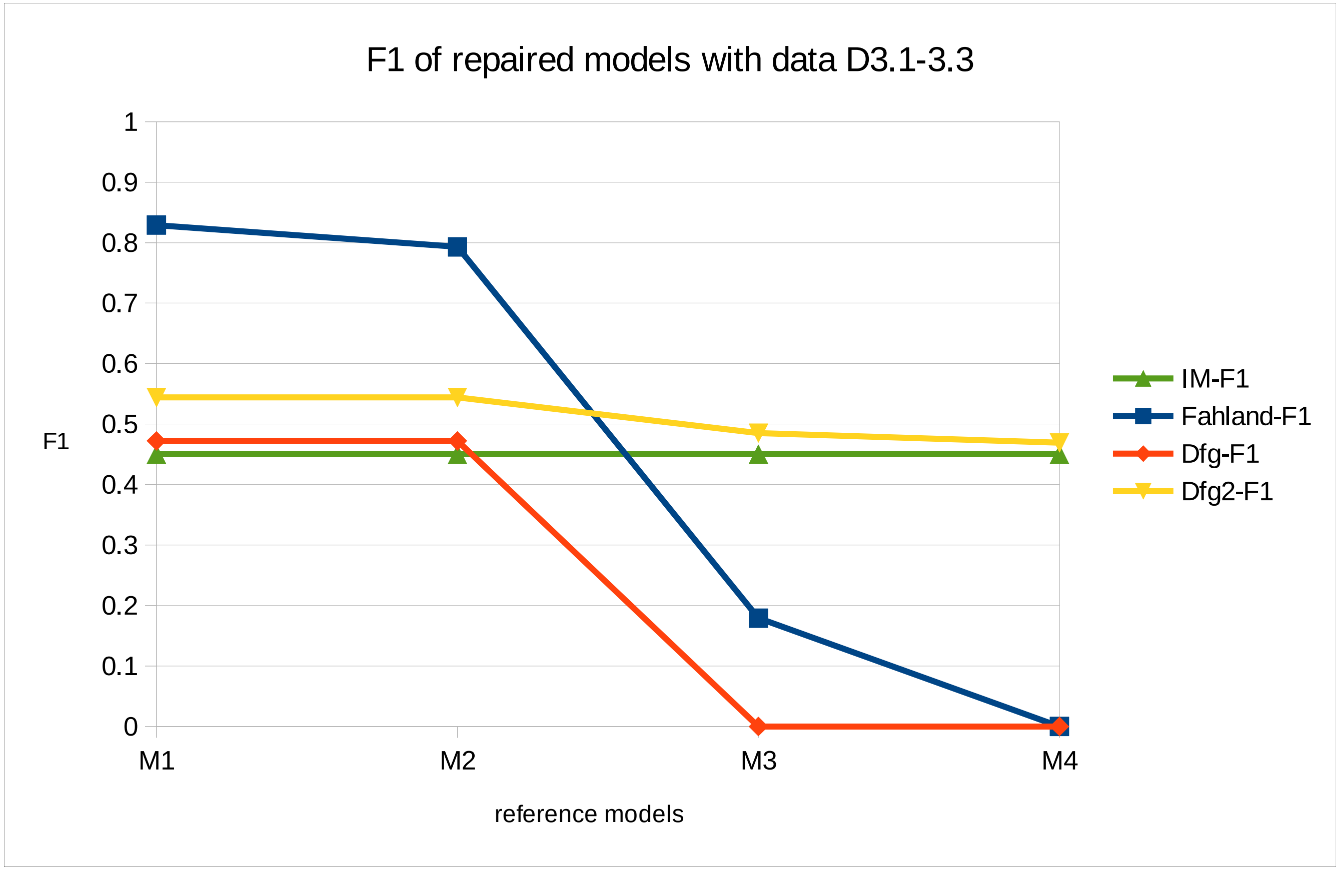
Experiment result



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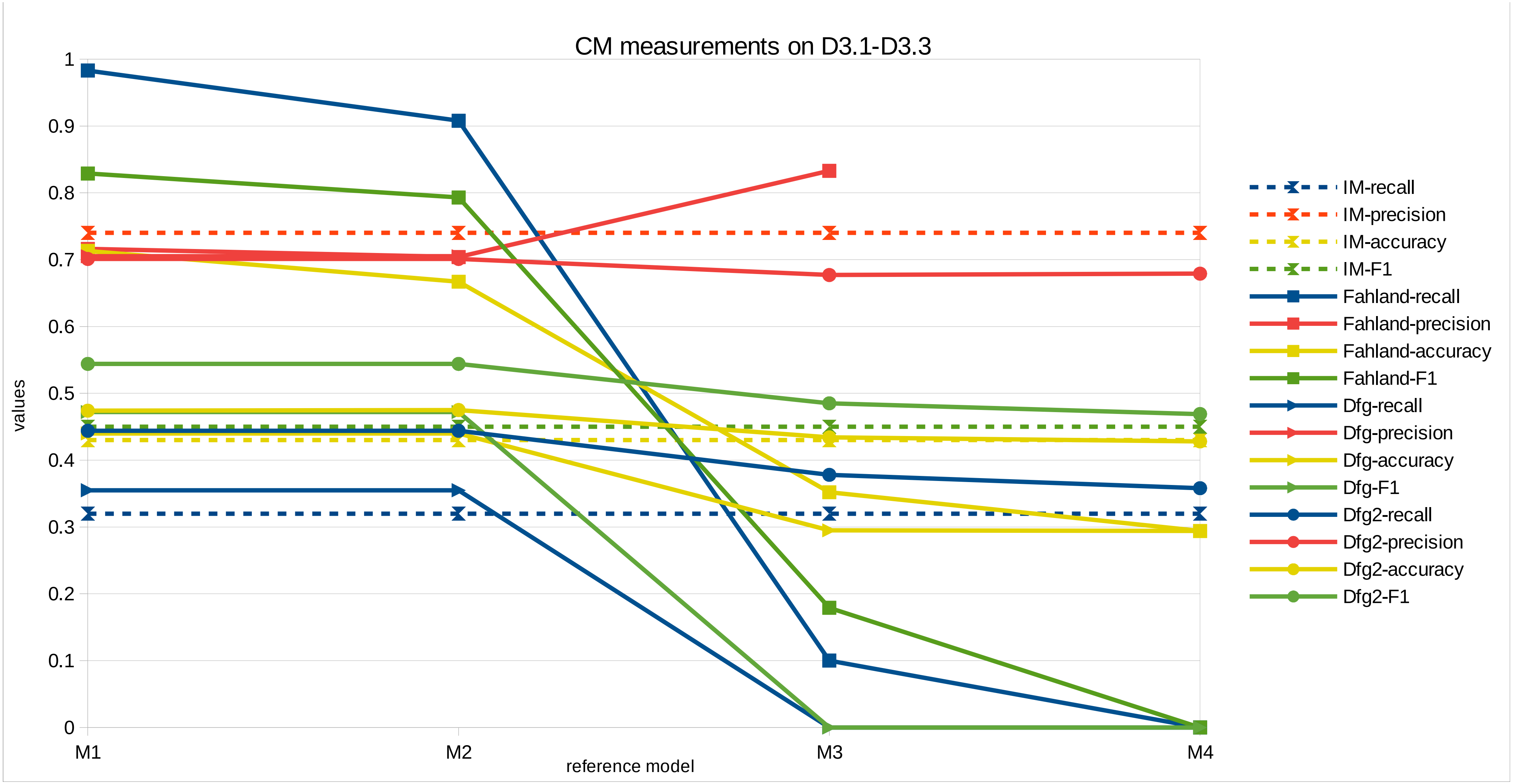
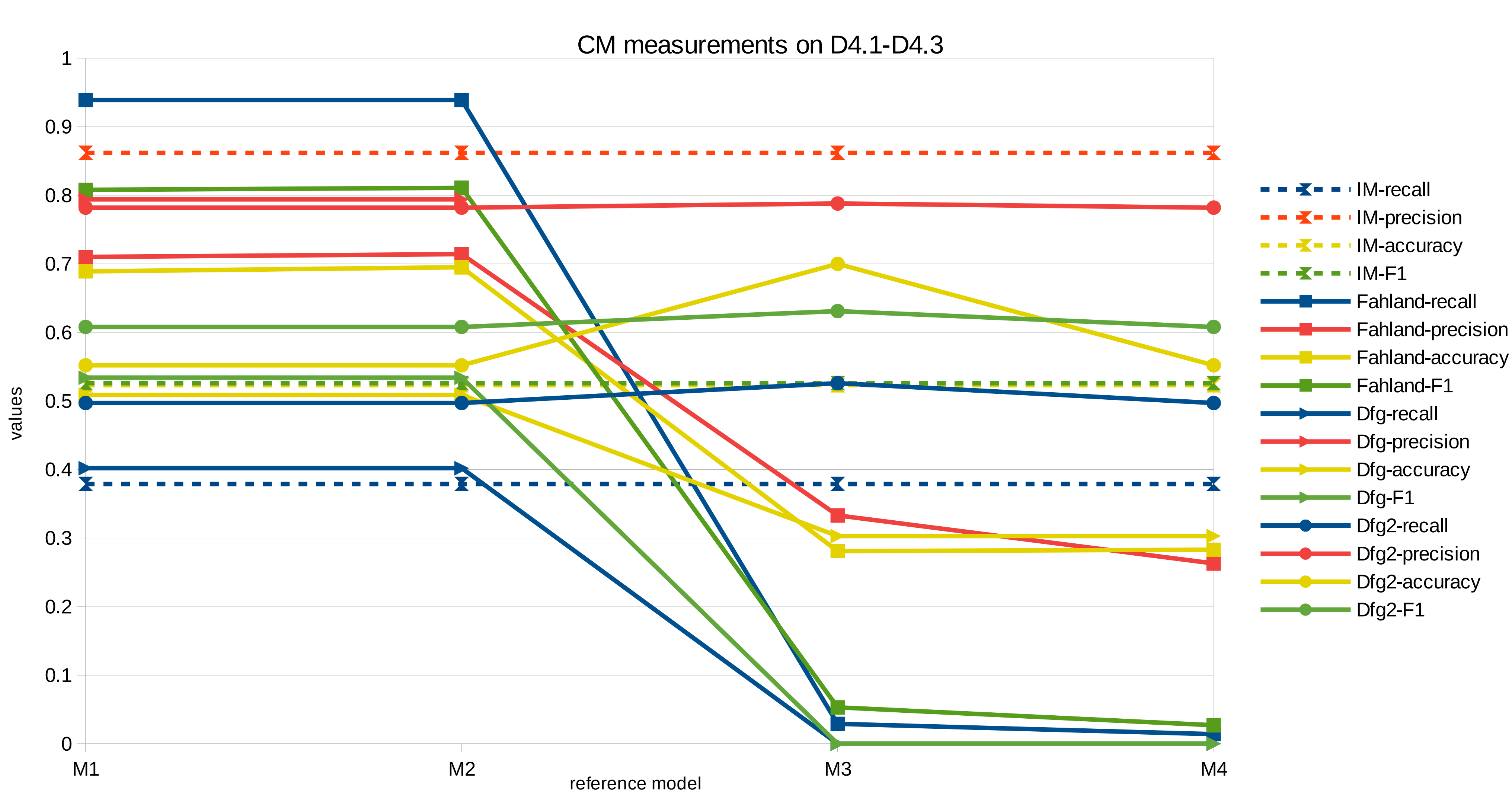
Experiment result



dfg2-repair with setting 0.5-1-0.5, rank higher in precision, accuracy and F1 than other techniques; Different setting leads to different results

Experiment result



dfg2-repair with setting 0.5-1-0.5, rank higher in precision, accuracy and F1 than other techniques; Different setting leads to different results

Outline

- **Motivation for Research**
- **Problem Definition**
- **Approach**
- **Demo**
- **Evaluation**
- **Conclusion**

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Conclusion

- **Innovative to incorporate negative instances**
- **Innovative to add long-term dependence**

- In demo, conquer the shortcomings

  repair model with better precision, accuracy, F1

- in practice, feasible to use

- In observation, repaired model simpler

  run fast

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Conclusion – Future work

- Improve the method to incorporate different data models
- Improve rules to decide long-term dependency
- Drop process tree as intermediate result
- Extend to other data models

Questions & Answers

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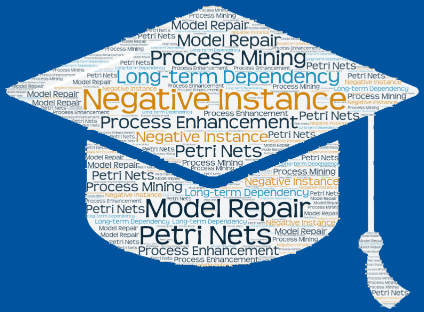
Master Thesis



Model Repair by Incorporating Negative Instances in Process Enhancement

Kefang Ding

Thank you!!!

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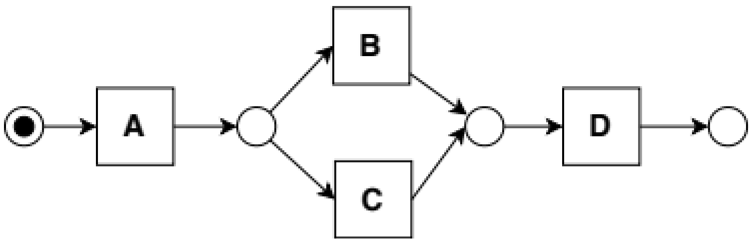
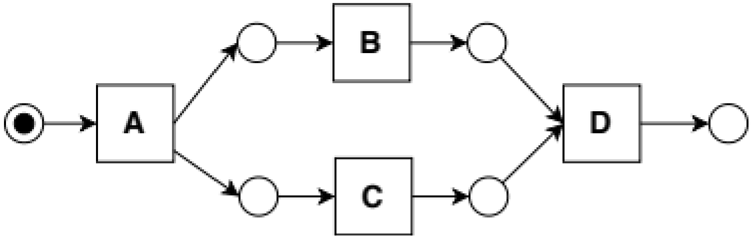
Why transition system

- **Simple extraction can't get directly-follows graph**



- **Tool exists to transform a Petri net into Transition systems**



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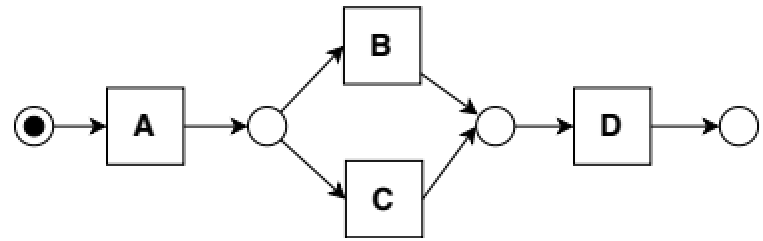

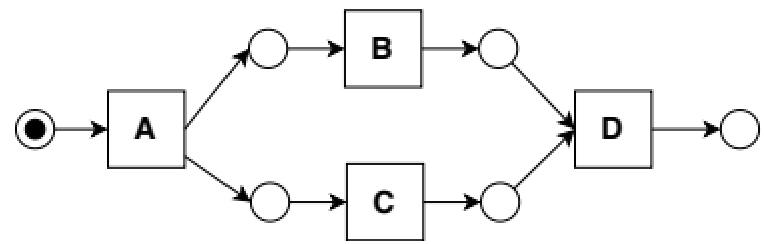

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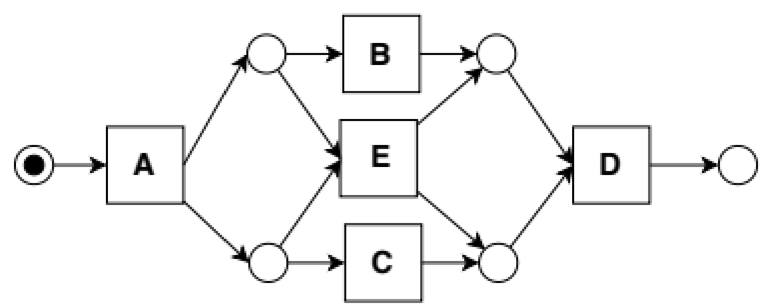
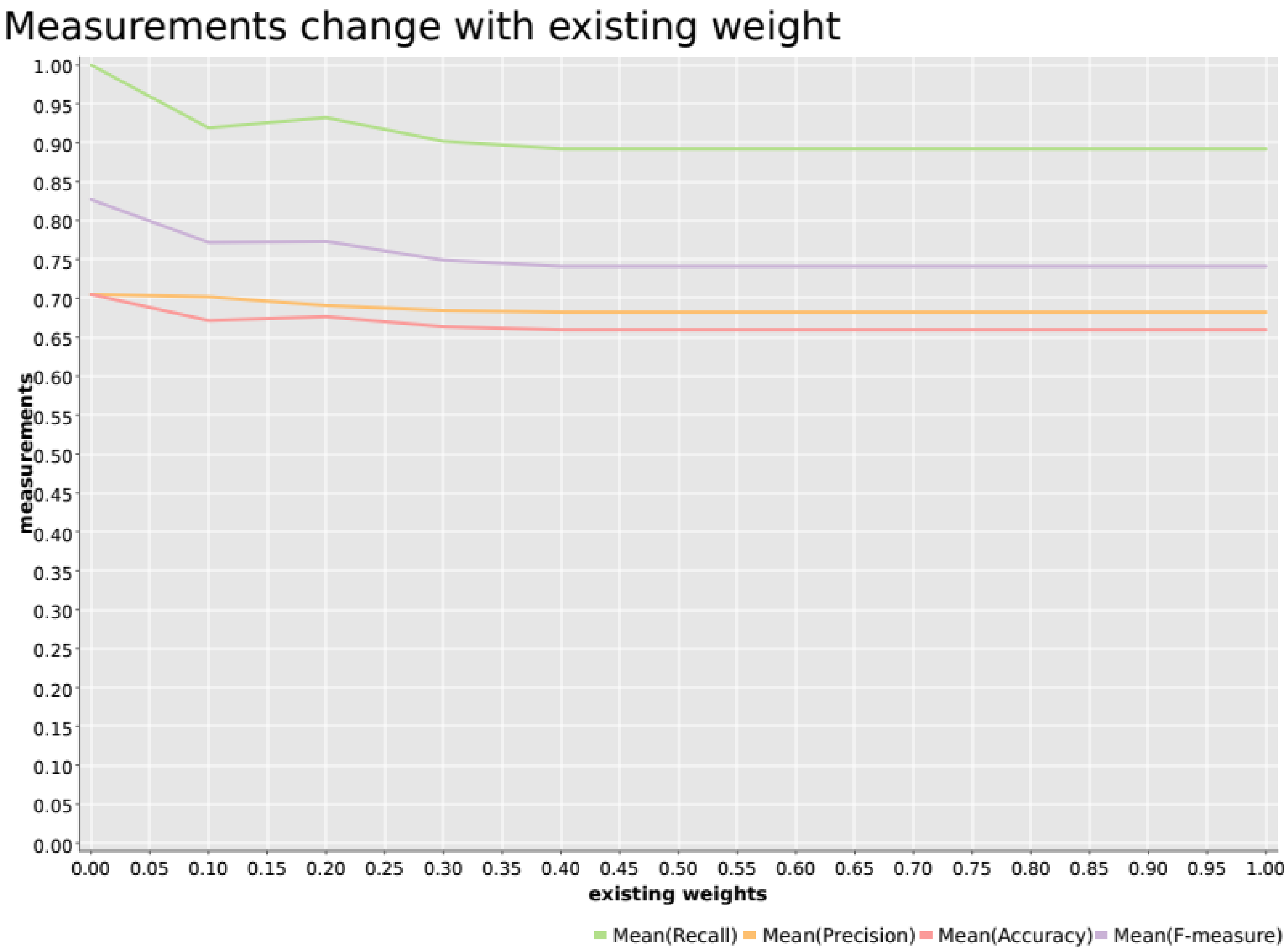


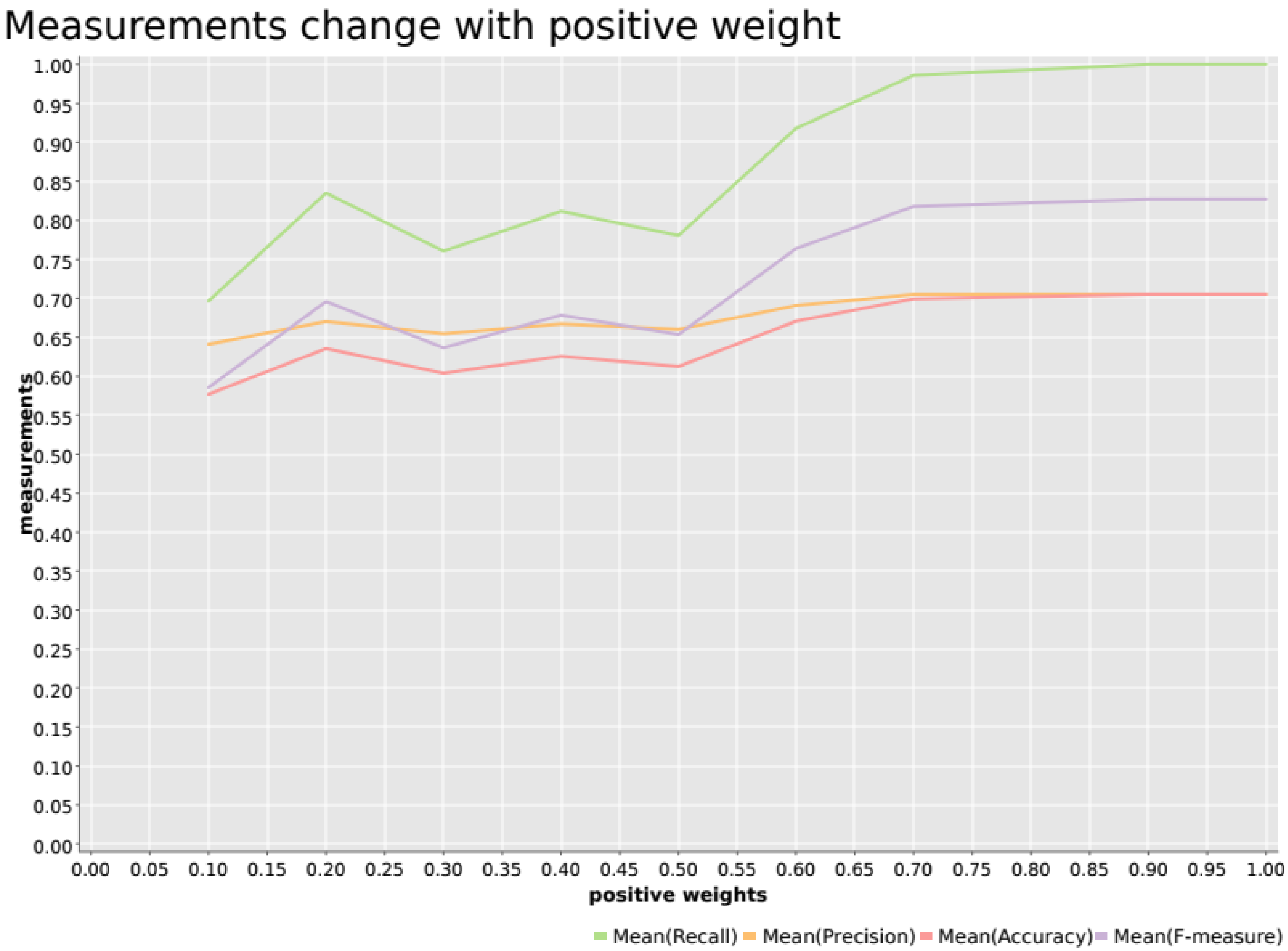
Experiment result

- **Weight for the reference model**



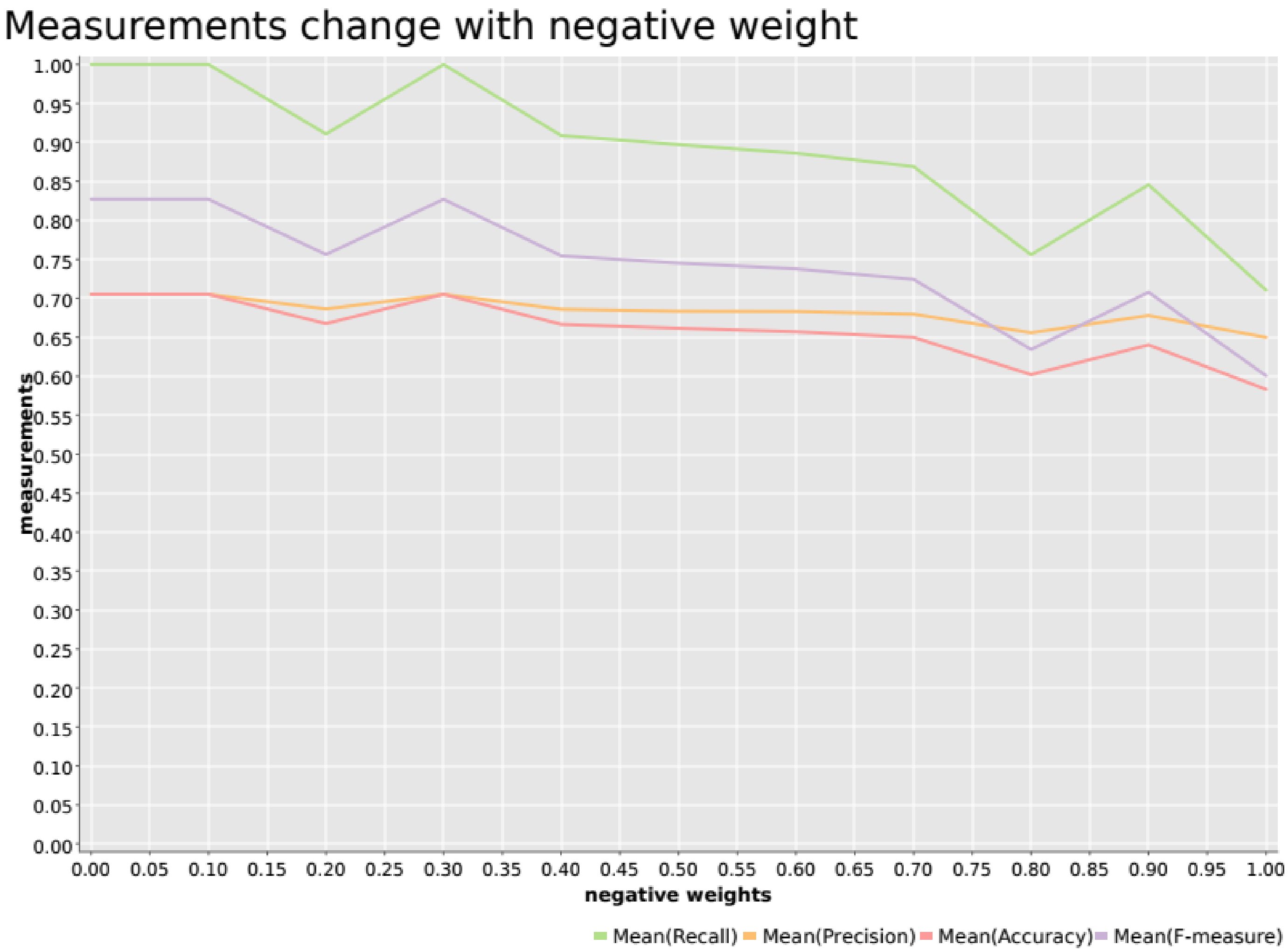
Experiment result

- **Weight for positive instance**



Experiment result

- **Weight for negative instance**



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