Advanced Process Mining

Summer Semester 2020

Lecture XVII: Process Model Quality

Dr. ir. Sebastiaan J. van Zelst

> some slides borrowed from prof.dr.ir. Wil M.P. van der Aalst

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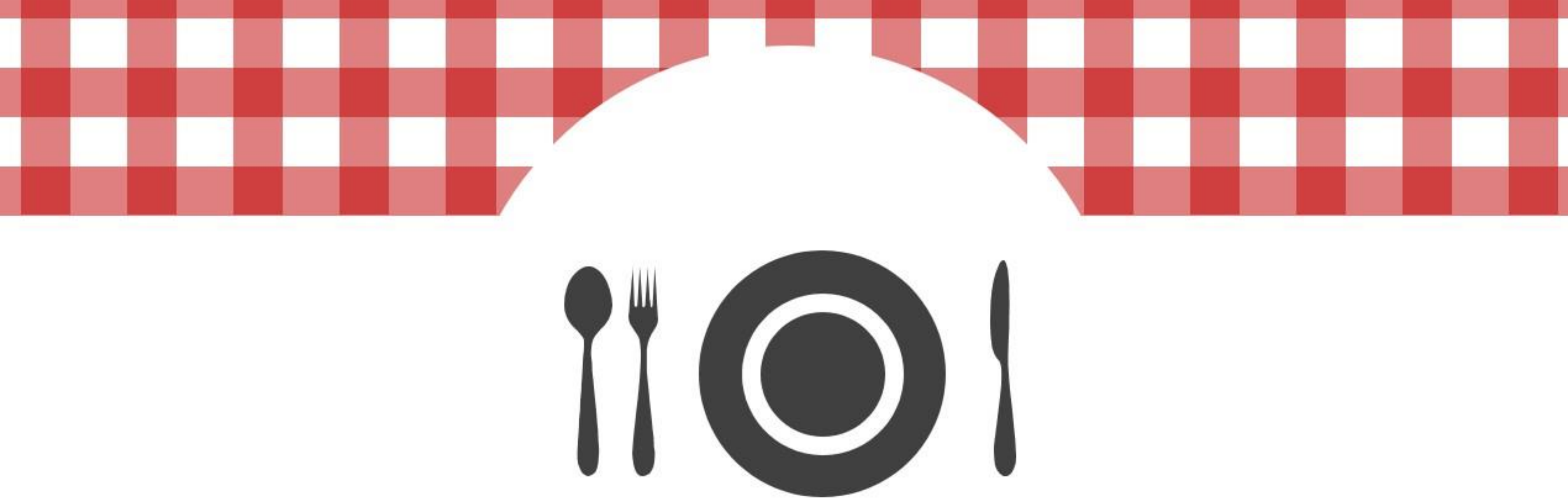

- Quality Dimensions (Recap)

- Replay-Fitness (Recap)
- Precision
- Simplicity
- Generalization

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https://giffiles.alphacoders.com/133/133737.gif

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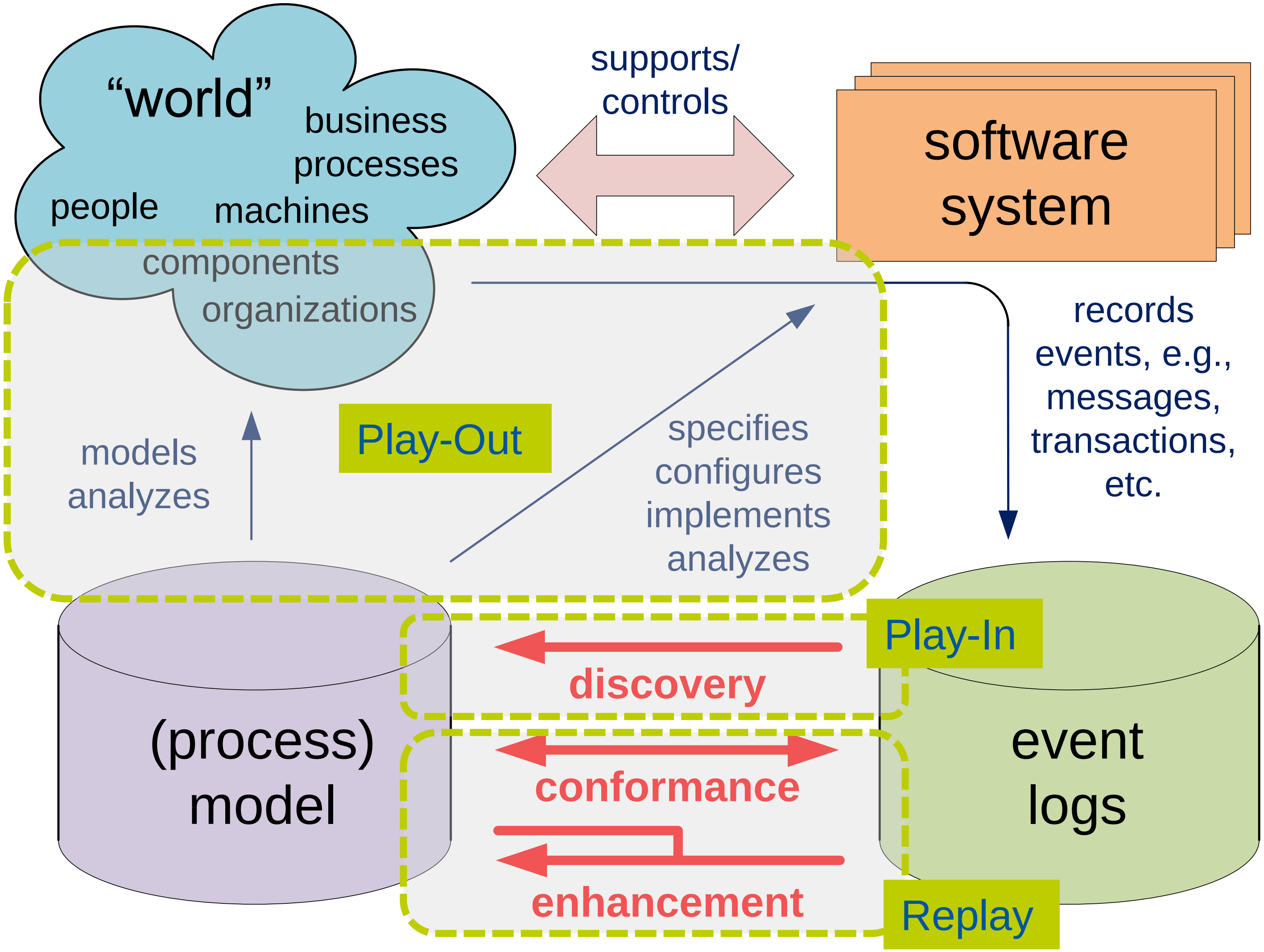
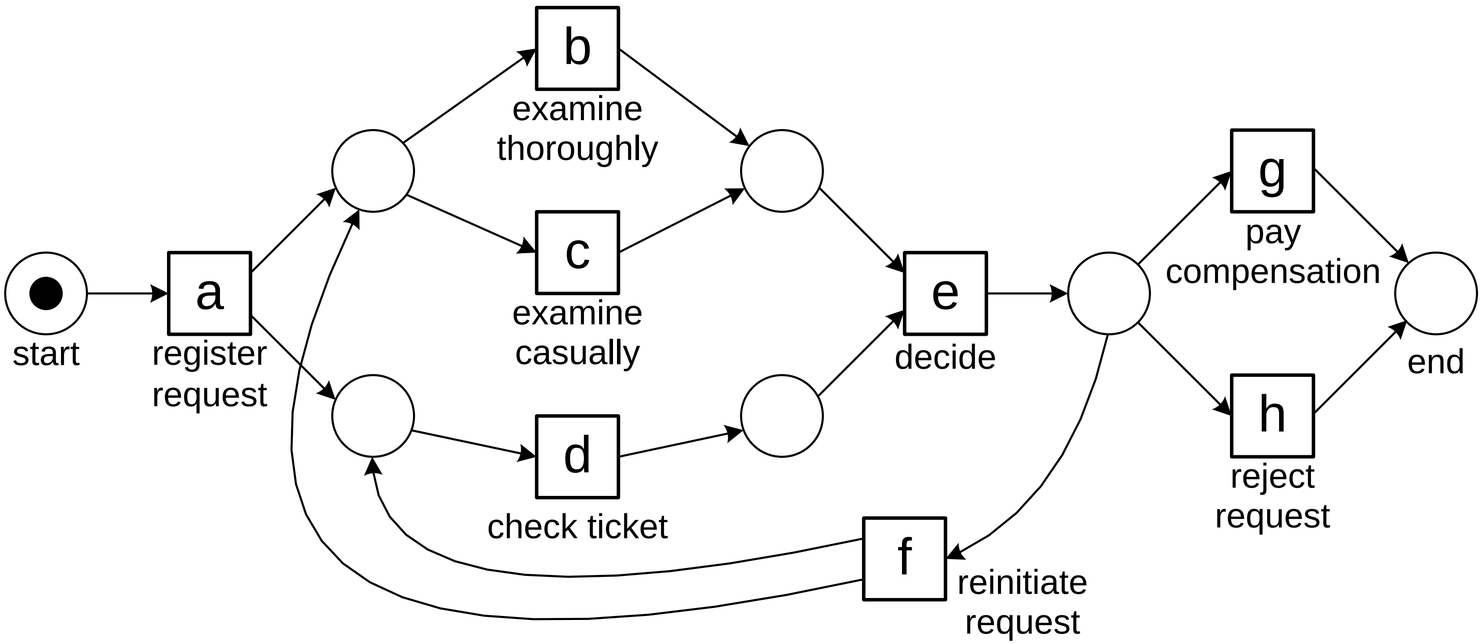
https://giffiles.alphacoders.com/133/133737.gif

Quality Dimensions

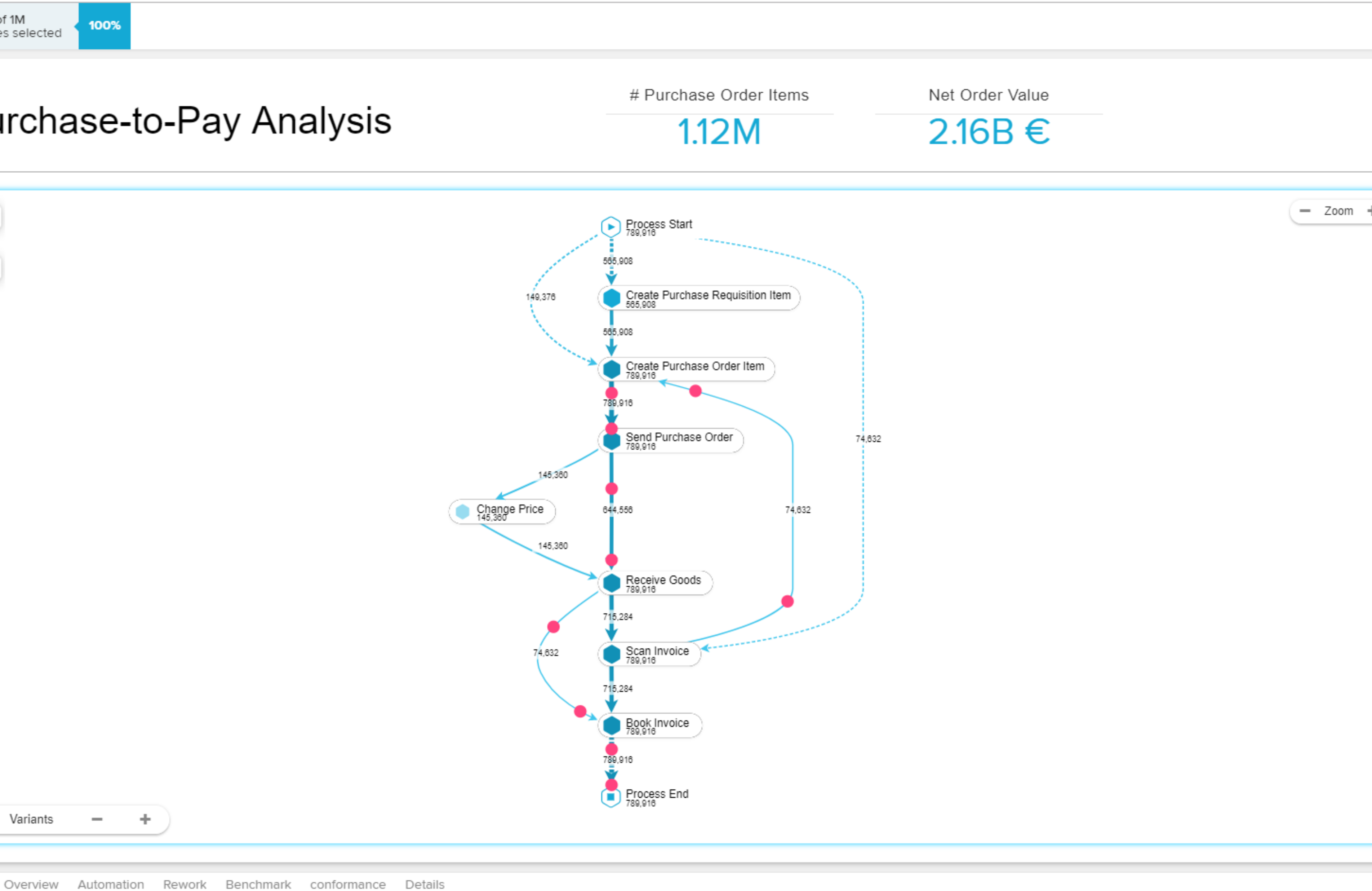
Process Mining



Process Mining (Academic)



Quality Dimensions
Process Mining (Commercial)



Models & Model Quality

- What makes a model, a good model?

Models & Model Quality

- What makes a model, a good model?

- … What is a model?

Models & Model Quality

- What makes a model, a good model?

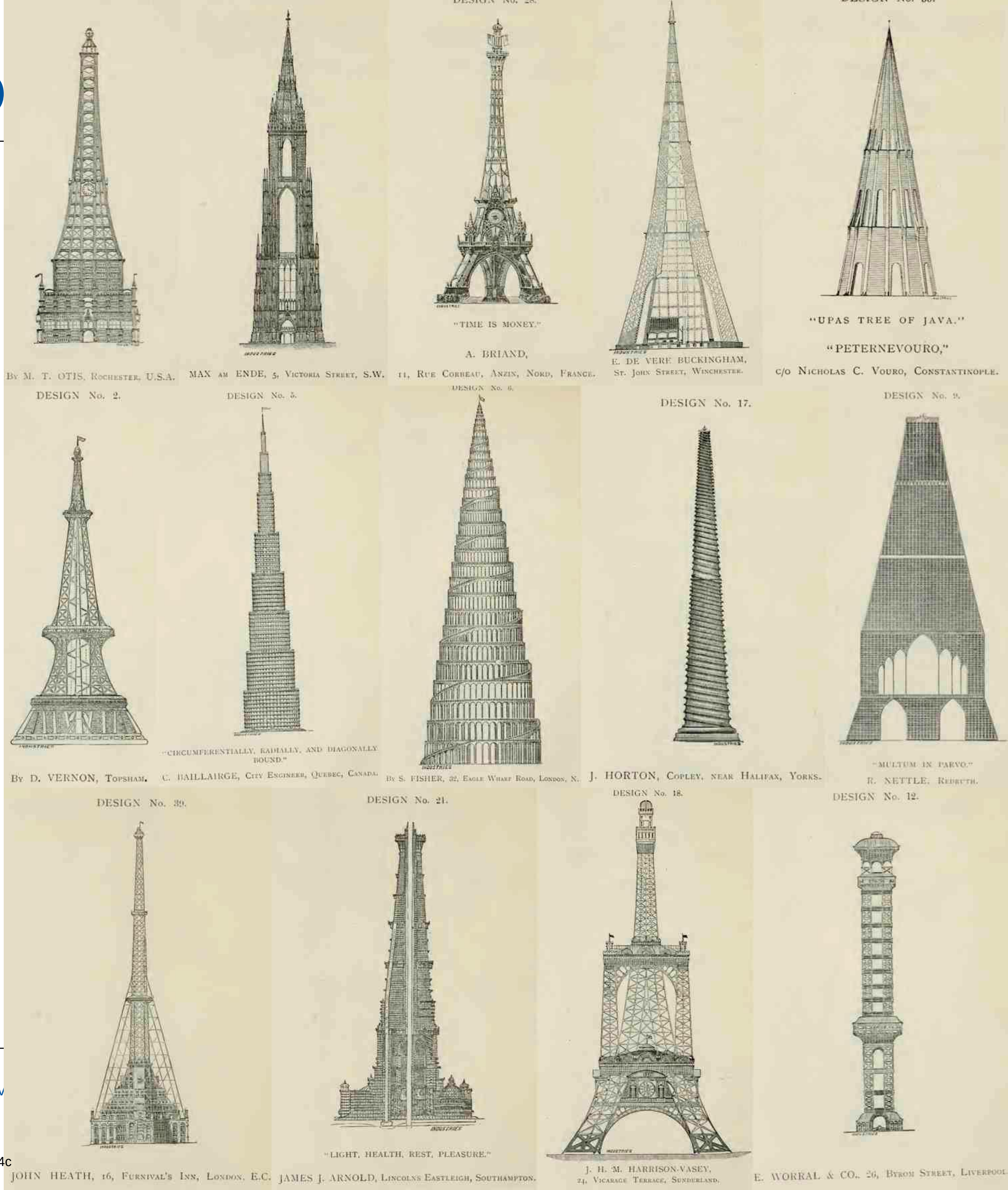
- … What is a model?
  - *A (not necessarily physical) representation of a (not necessarily physical) object*

Models & Model Quality

Models & Model Quality

https://images-na.ssl-images-amazon.com/images/I/61Sb7UkhyIL._AC_SX679_.jpg

Models & Model Q



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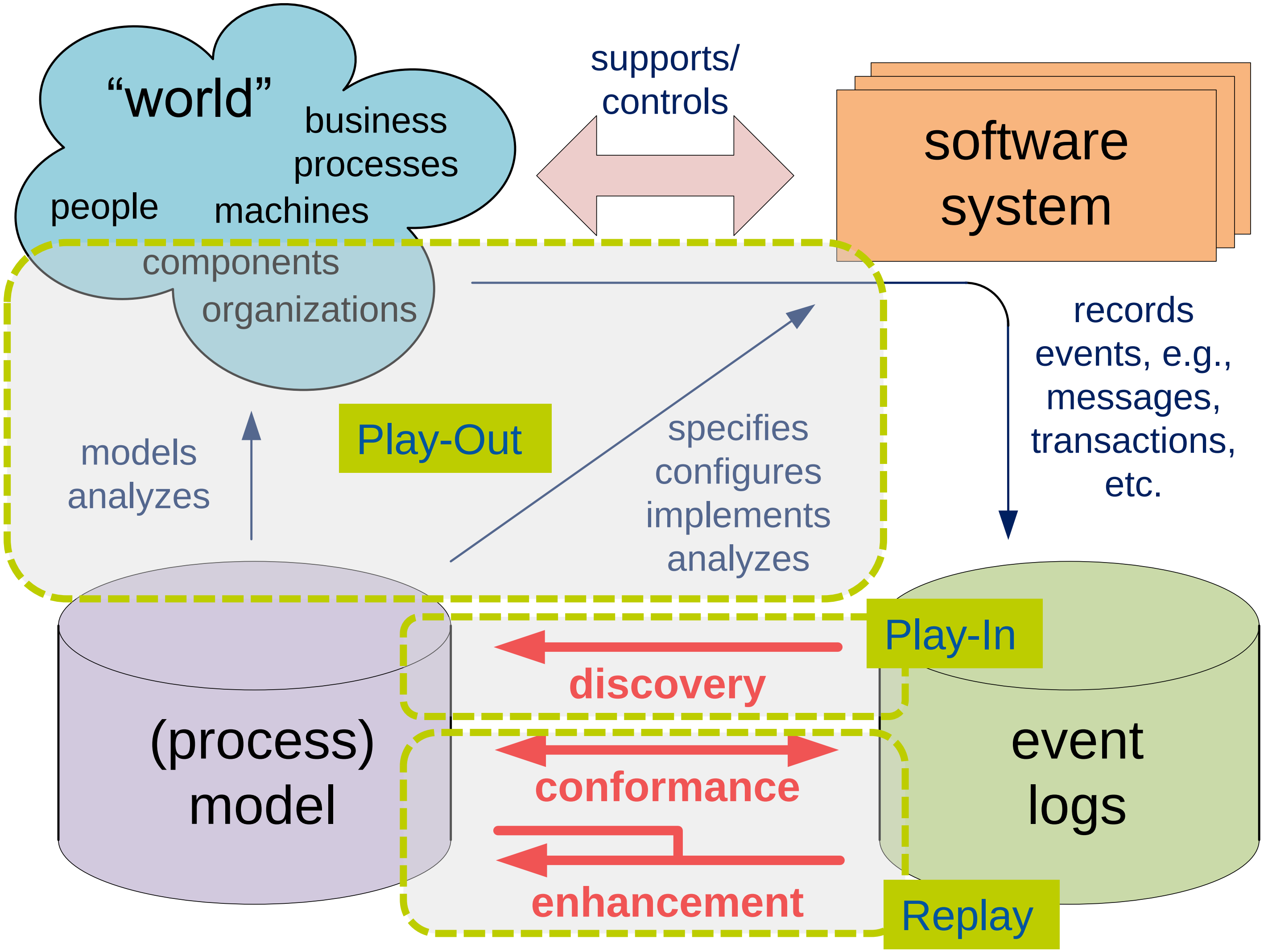
Models & Model Quality

https://www.remonline.com/wp-content/uploads/2017/01/Blueprints.jpg

Models & Model Quality



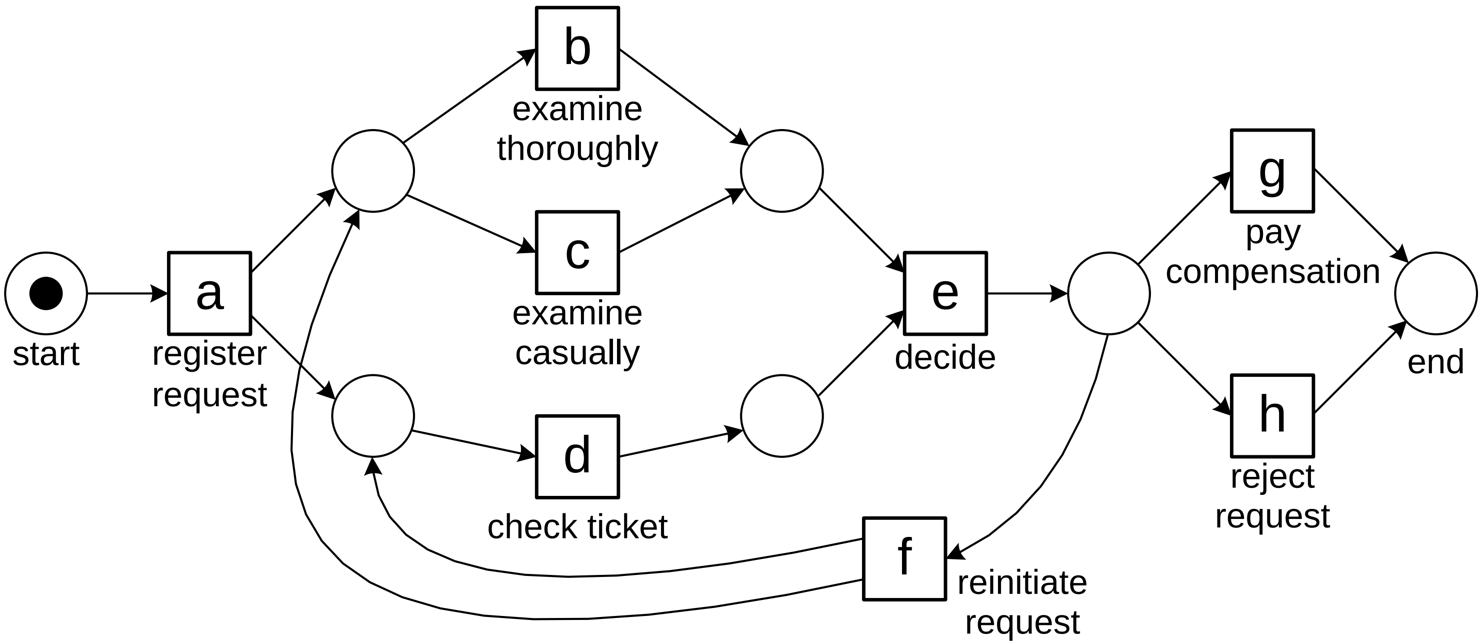
Purpose

- Why do we *model?*

https://www.devprojournal.com/wp-content/uploads/2019/09/communcation-and-culture-e1567689029626.jpg
https://www.claromentis.com/wp-content/uploads/2015/11/digital-knowledge-1024x983.jpg

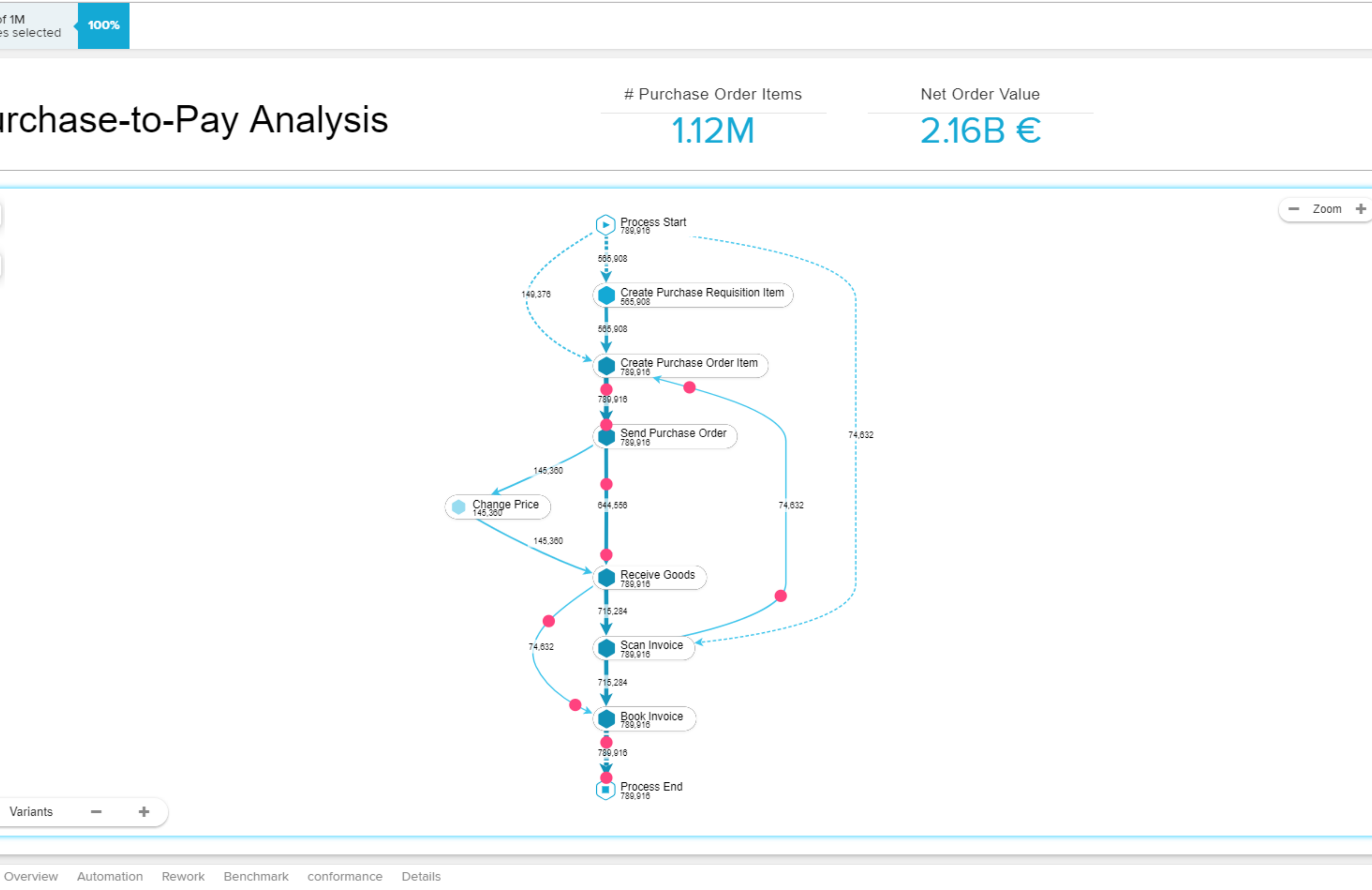
Models & Model Quality

- Models have different purposes



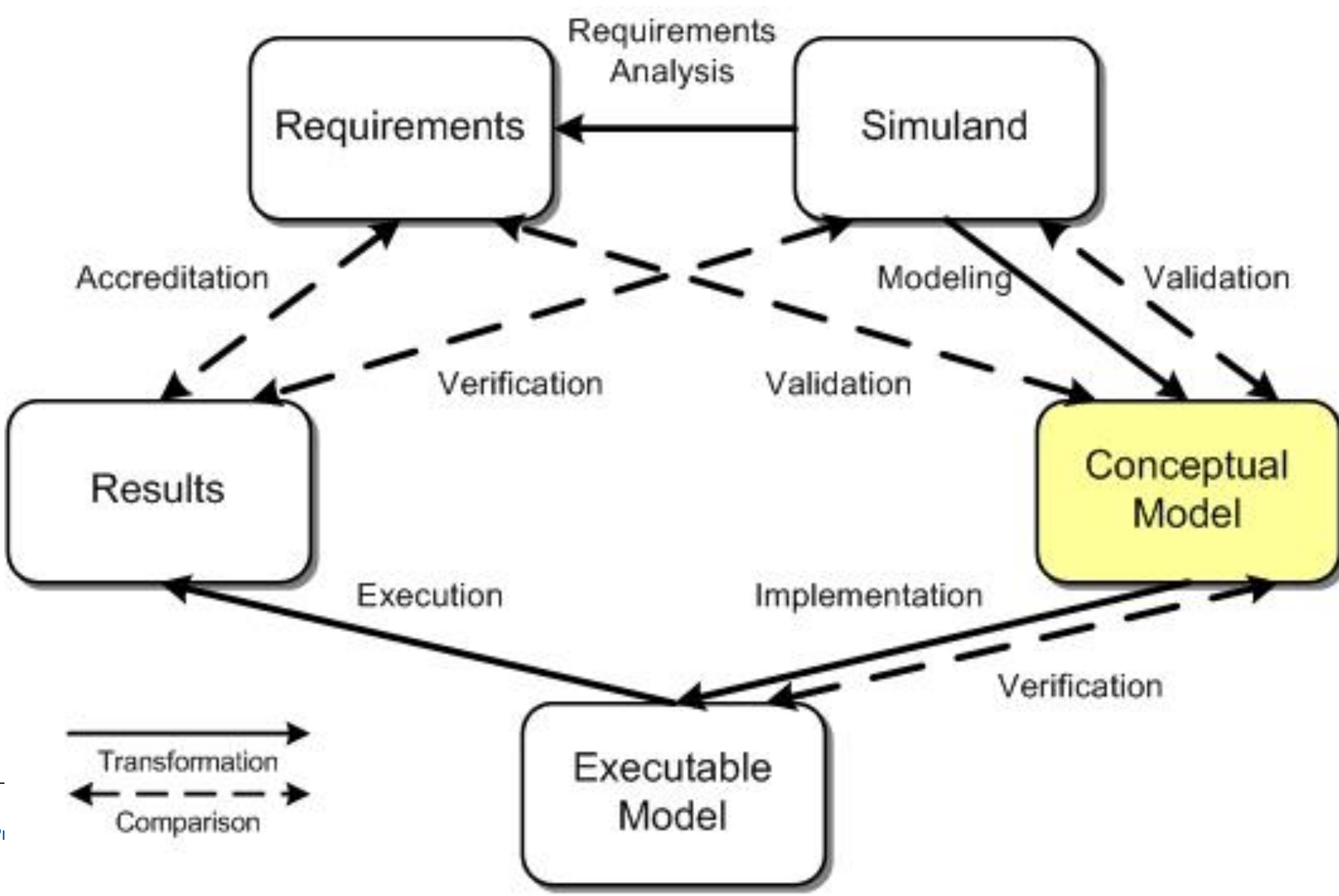
Quality Dimensions

Models & Model Quality



Models & Model Quality

- Models have different purposes



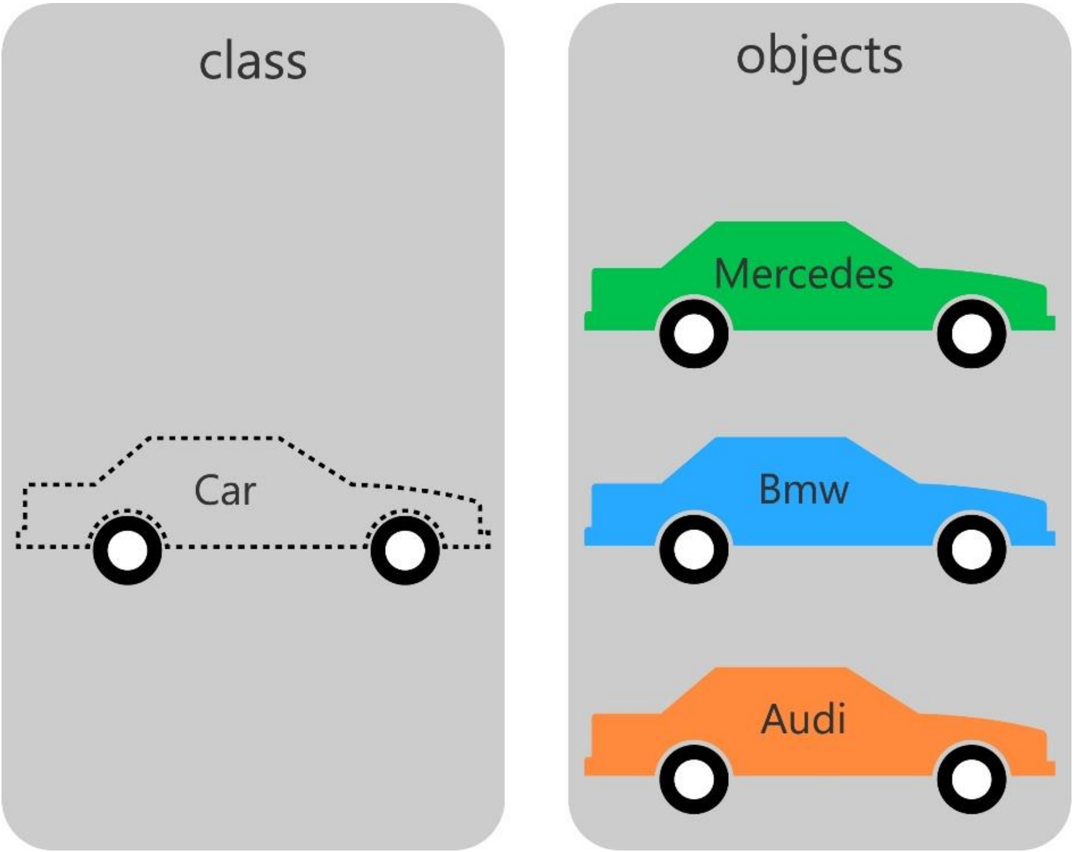
J. Sokolowski, C. Banks, Modeling and Simulation Fundamentals: Theoretical Underpinnings and Practical Domains, Wiley, 2010, pp 333

Models & Model Quality

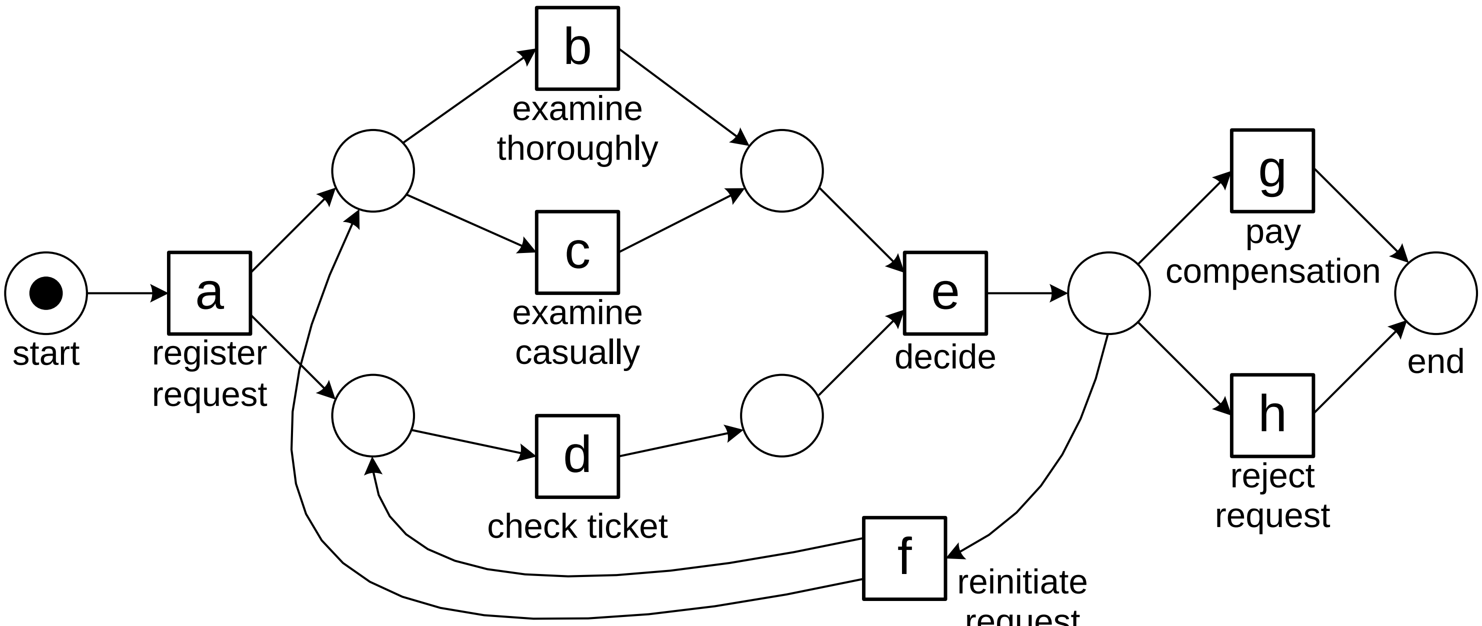
Models & Model Quality

Quality Dimensions
Models & Model Quality

Models & Model Quality

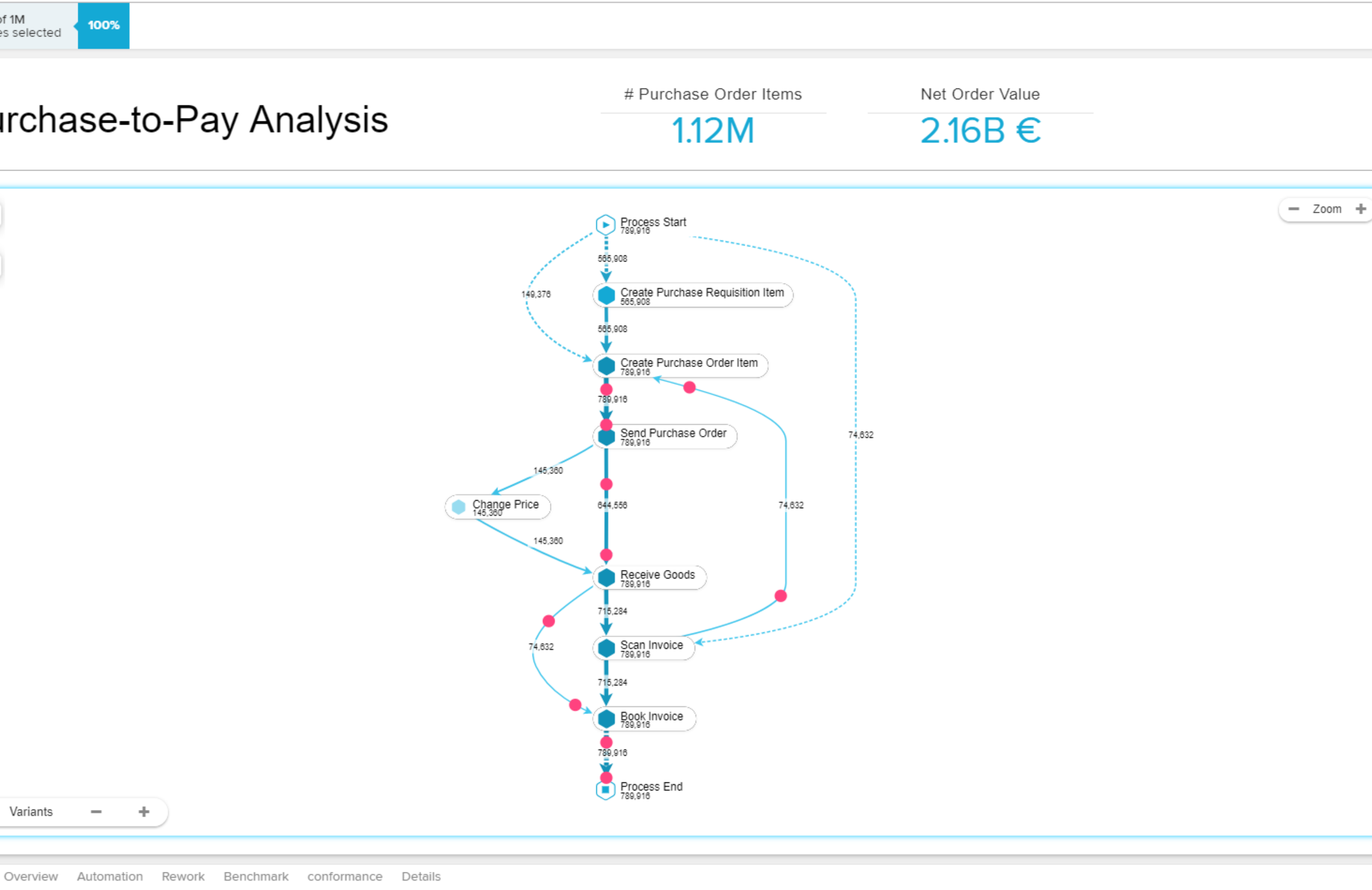


Models & Model Quality



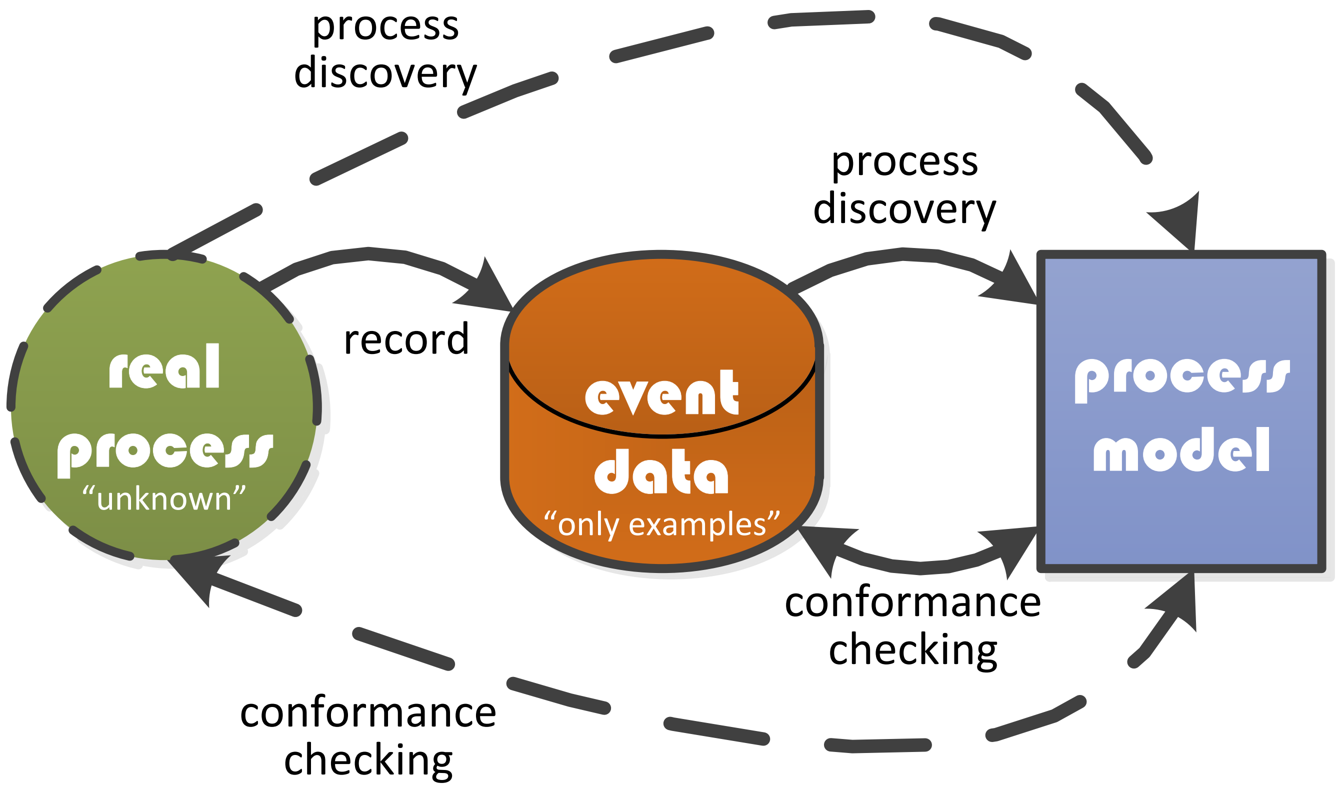
Quality Dimensions

Models & Model Quality

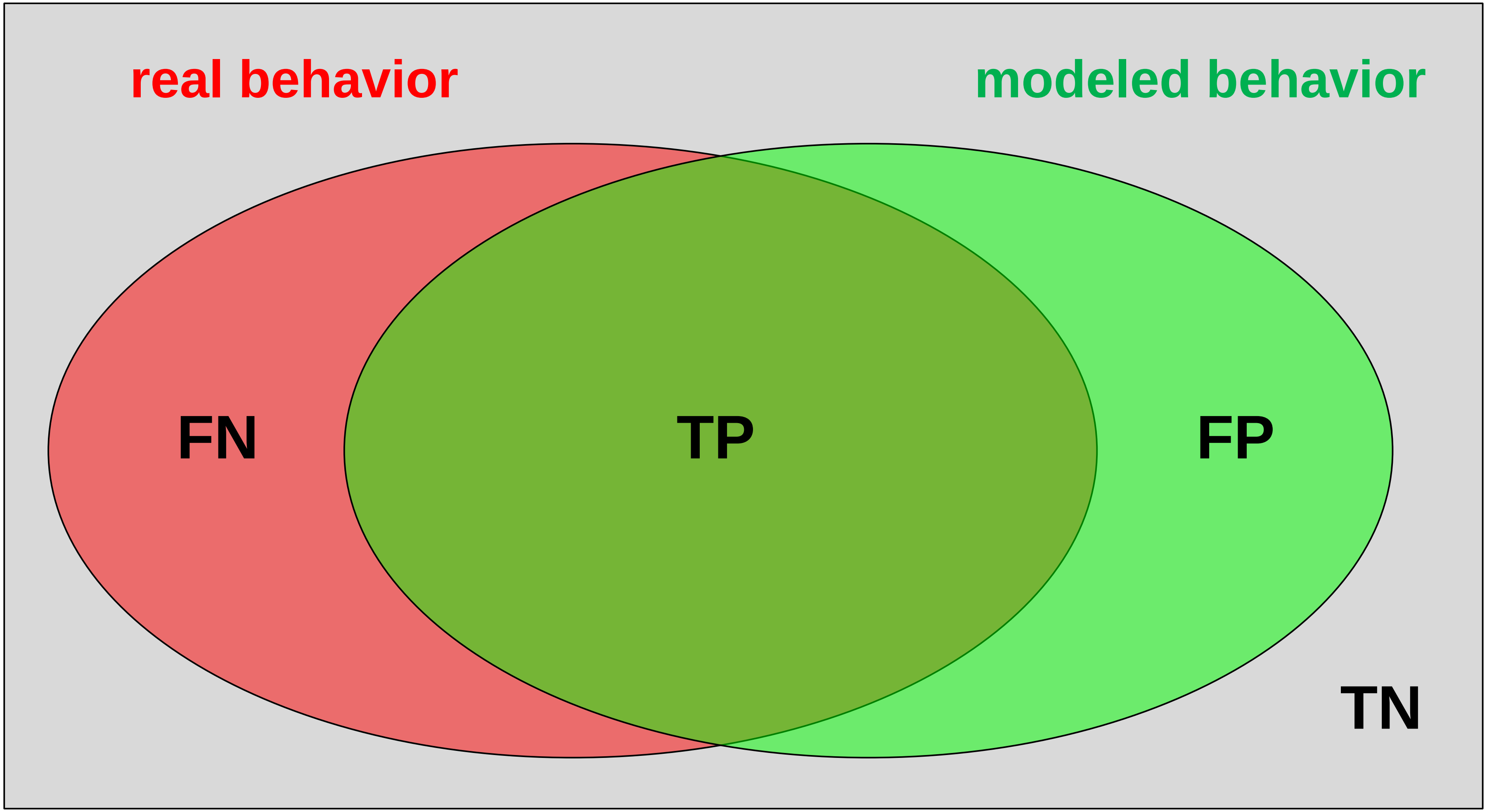


Comparing Real and Modeled Behavior

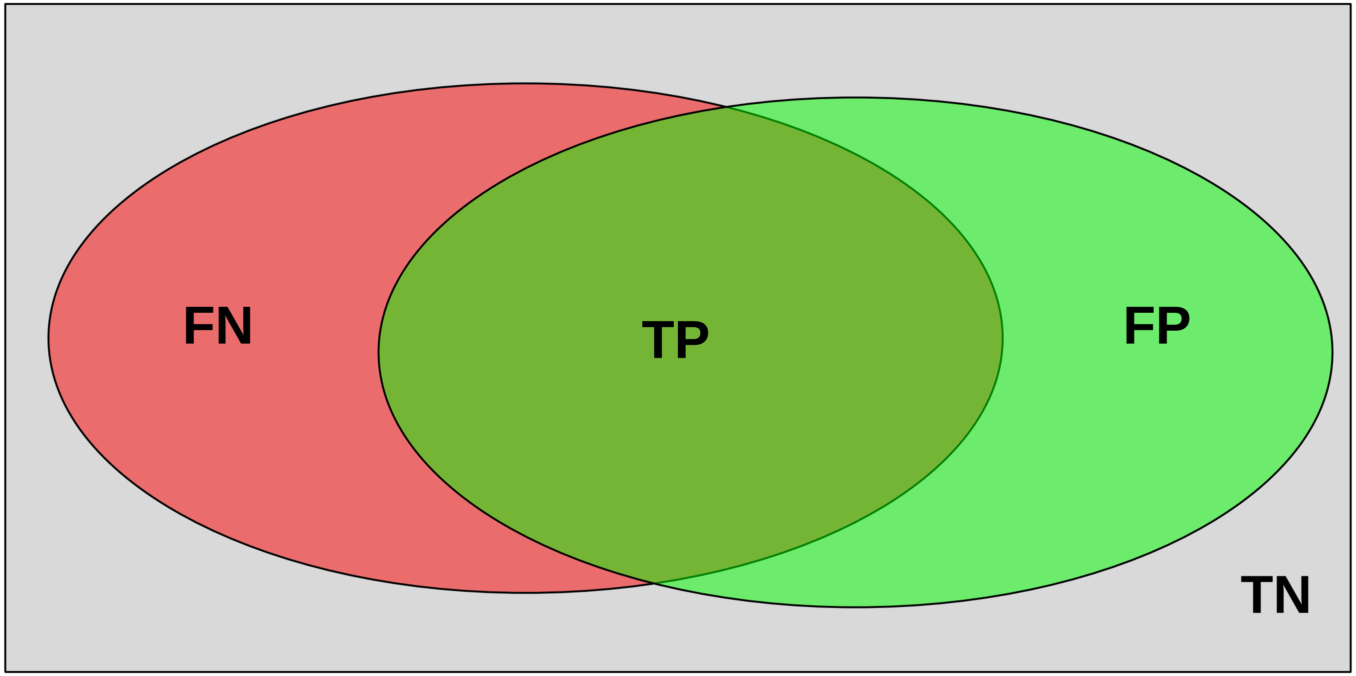
Is the process model a correct reflection of the real process?



Comparing Real and Modeled Behavior

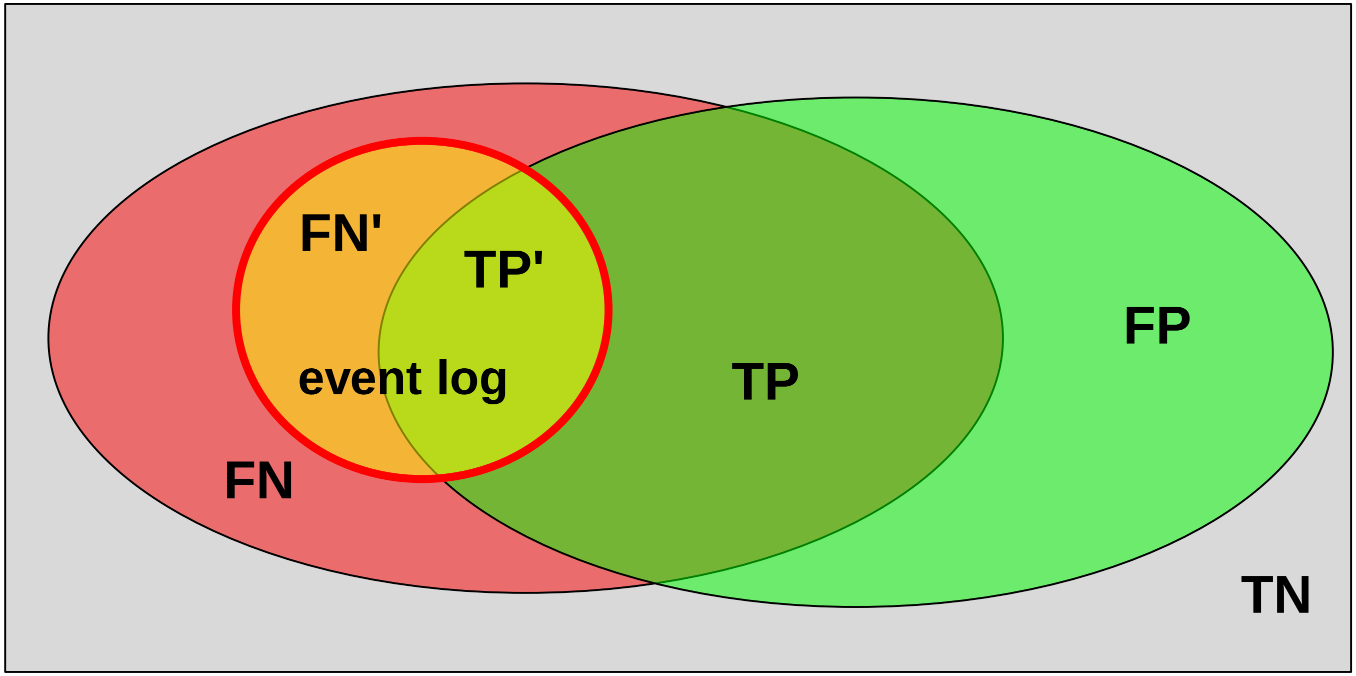


Comparing Real and Modeled Behavior



$$precision = \frac{TP}{TP + FP} \qquad recall = \frac{TP}{TP + FN}$$

Comparing Real and Modeled Behavior



$$\cancel{recall = \frac{TP}{TP + FN}}$$

$$\cancel{precision = \frac{TP}{TP + FP}}$$

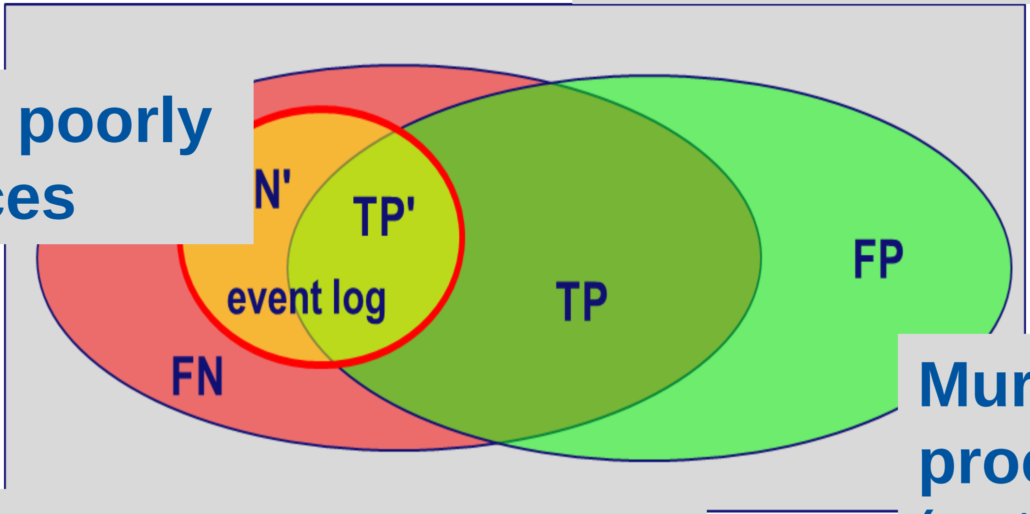
$$replay\_fitness = \frac{TP'}{TP' + FN'}$$

Comparing Real and Modeled Behavior

No negative examples
(cannot see what cannot happen)

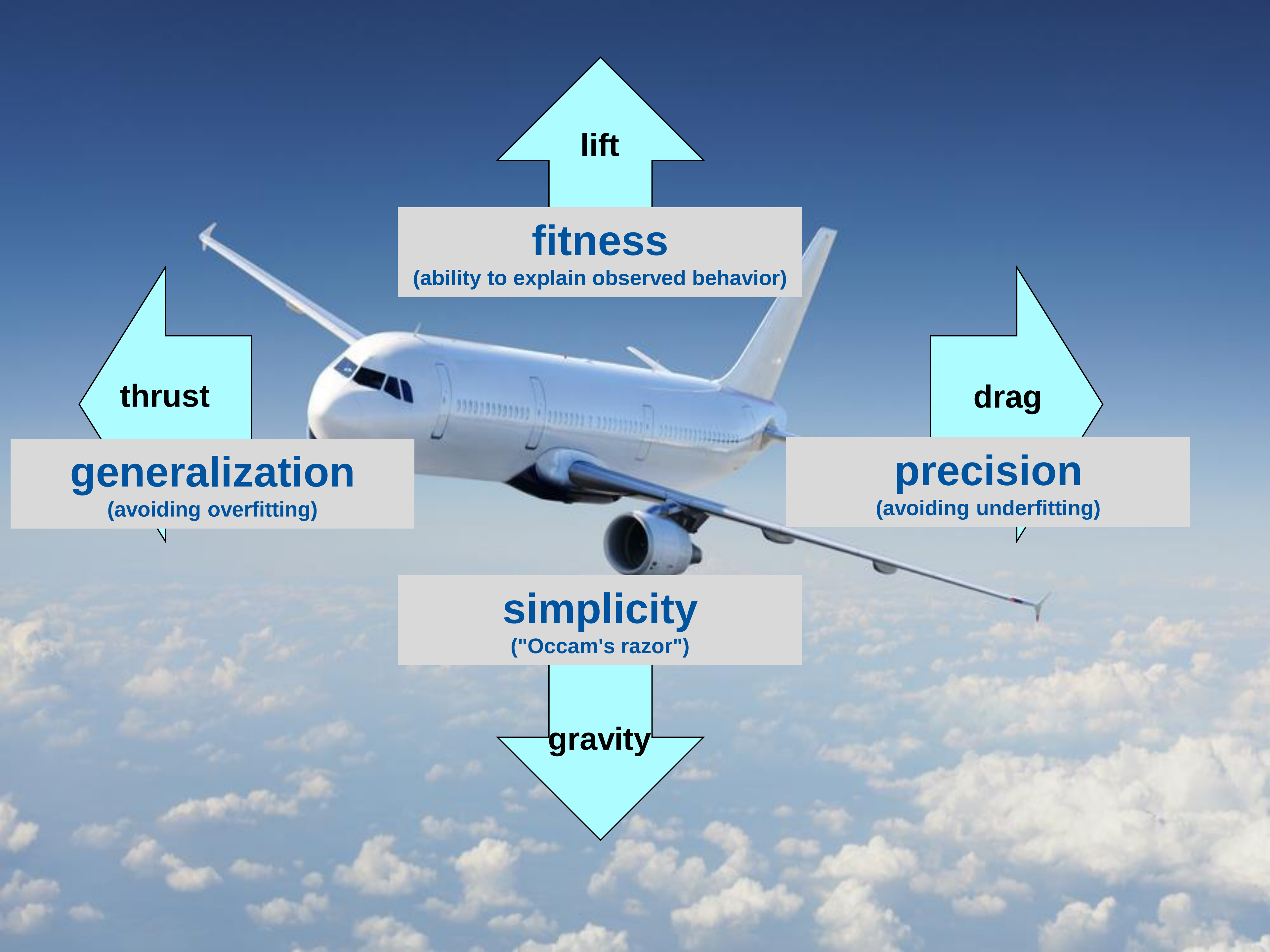
Log contains only a fraction of possible traces

Almost vs poorly fitting traces



Murphy's law for process mining
(anything is possible, so probabilities matter)

In case of loops often infinitely many possible traces

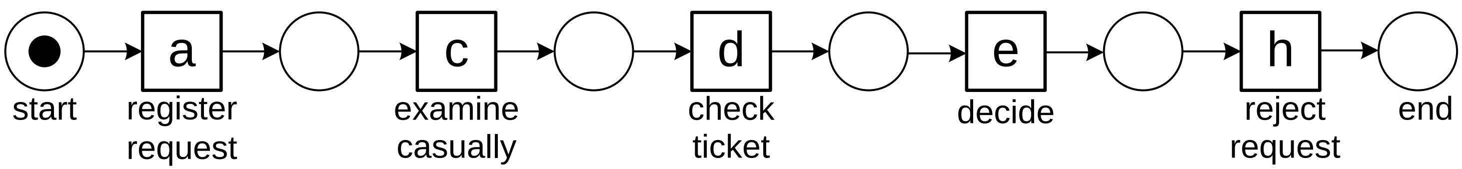

lift
fitness
(ability to explain observed behavior)
thrust
generalization
(avoiding overfitting)
drag
precision
(avoiding underfitting)
simplicity
("Occam's razor")
gravity

Process Model Quality

Comparing Real and Modeled Behavior

#	trace
455	acdeh
191	abdeg
177	adceh
144	abdeh

Comparing Real and Modeled Behavior



#	trace
455	acdeh
191	abdeg
177	adceh
144	abdeh
111	acdeg
82	adceg
56	adbeh
47	acdefdbeh
38	adbeg
33	acdefbdeh
14	acdefbdeg
11	acdefdbeg
9	adcefcdeh
8	adcefdbeh
5	adcefbdeg
3	acdefbdefdbeg
2	adcefdbeg
2	adcefbdefbdeg
1	adcefdbefbdeh
1	adbefbdefdbeg
1	adcefdbefcdefdbeg
1391	

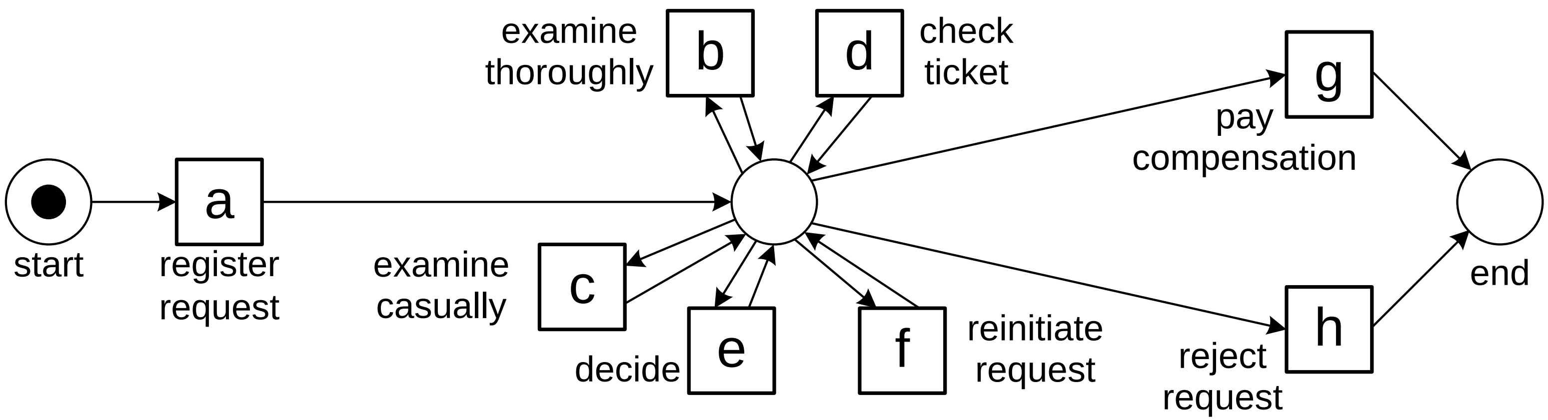
fitness
(observed behavior fits)

simplicity
("Occam's razor")

precision
(avoiding underfitting)

generalization
(avoiding overfitting)

Comparing Real and Modeled Behavior



#	trace
455	acdeh
191	abdeg
177	adceh
144	abdeh
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82	adceg
56	adbeh
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38	adbeg
33	acdefbdeh
14	acdefbdeg
11	acdefdbeg
9	adcefcdeh
8	adcefdbeh
5	adcefbdeg
3	acdefbdefdbeg
2	adcefdbeg
2	adcefbdefbdeg
1	adcefdbefbdeh
1	adbefbdefdbeg
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1391	

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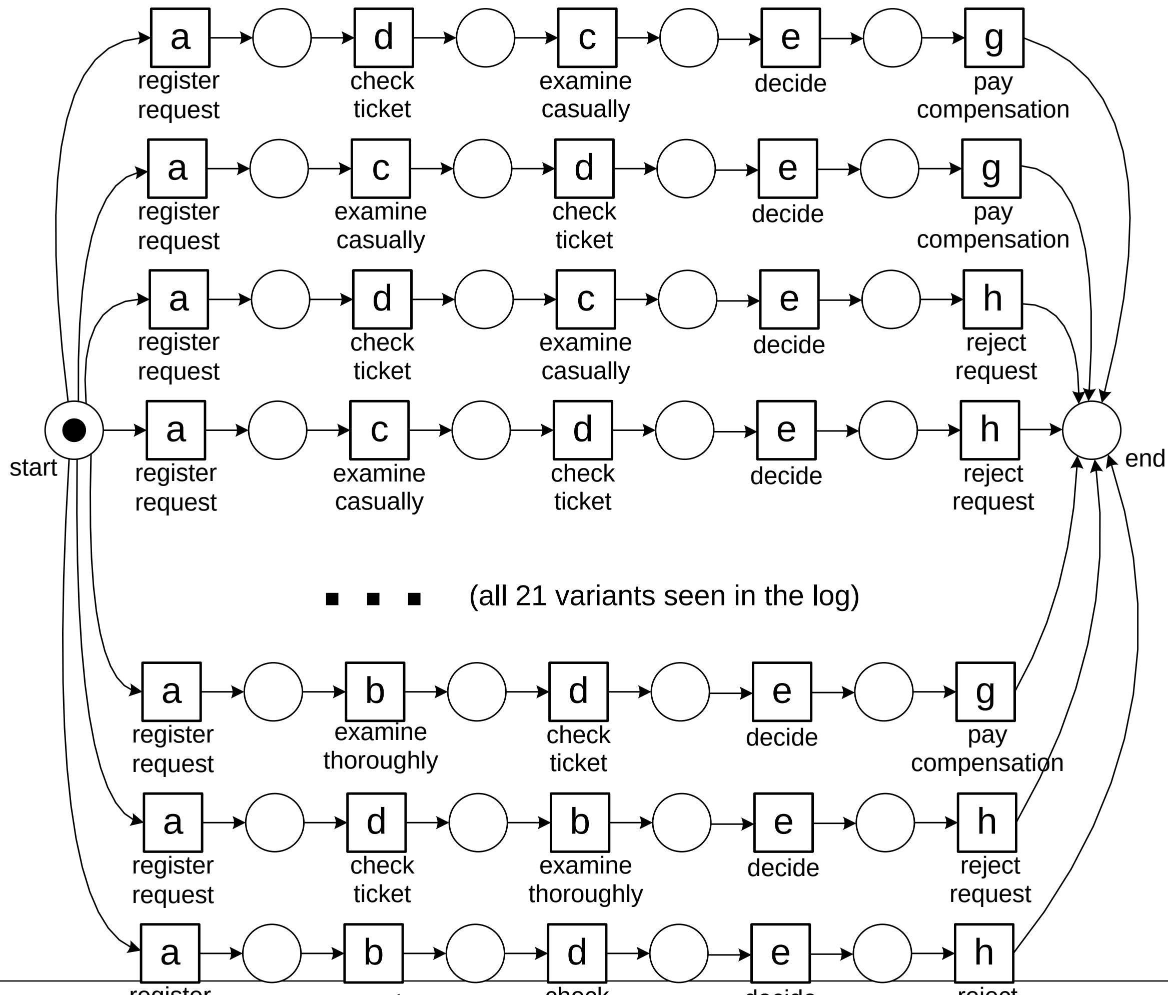

#	trace
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191	abdeg
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144	abdeh
111	acdeg
82	adceg
56	adbeh
47	acdefdbeh
38	adbeg
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14	acdefbdeg
11	acdefdbeg
9	adcefcdeh
8	adcefdbeh
5	adcefbdeg
3	acdefbdefdbeg
2	adcefdbeg
2	adcefbdefbdeg
1	adcefdbefbdeh
1	adbefbdefdbeg
1	adcefdbefcdefdbeg
1391	

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("Occam's razor")

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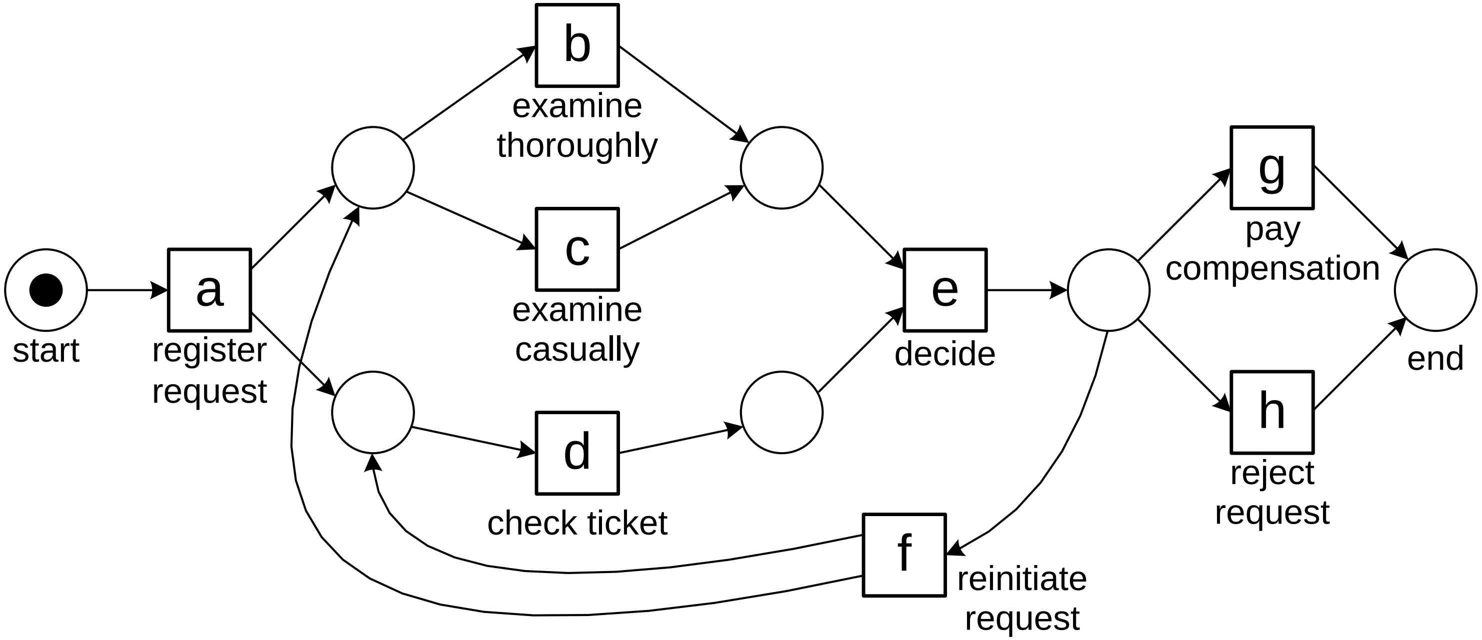
(avoiding underfitting)

generalization
(avoiding overfitting)

Process Model Quality

Comparing Real and Modeled Behavior



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455	acdeh
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177	adceh
144	abdeh
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38	adbeg
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5	adcefbdeg
3	acdefbdefdbeg
2	adcefdbeg
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1	adbefbdefdbeg
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1391	

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("Occam's razor")

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- Quality Dimensions (Recap)

- Replay-Fitness (Recap)
- Precision
- Simplicity
- Generalization

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Definition (Informal)

- Replay-Fitness
  - Quantifies to what degree a given process model describes the behavior that is also in a given event log

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  - All behavior in the log also described by the model?
    - Replay-Fitness is **perfect**! (1)
  - None of the behavior also described by the model?
    - Replay-Fitness is **bad**! (0)

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Footprint Comparison

#	trace
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56	adbeh
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38	adbeg
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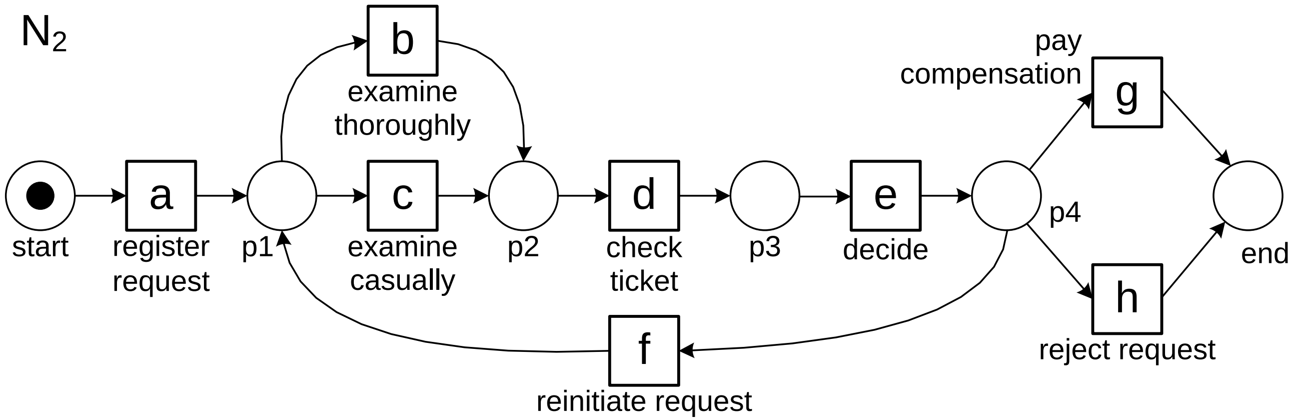
11	acdefdbeg
9	adcefcdeh
8	adcefdbeh
5	adcefbdeg
3	acdefbdefdbeg
2	adcefdbeg
2	adcefbdefbdeg
1	adcefdbefbdeh
1	adbefbdefdbeg
1	adcefdbefcdefdbeg
1391	

	a	b	c	d	e	f	g	h
a	$\#$	$\rightarrow$	$\rightarrow$	$\rightarrow$	$\#$	$\#$	$\#$	$\#$
b	$\leftarrow$	$\#$	$\#$	$\|$	$\rightarrow$	$\leftarrow$	$\#$	$\#$
c	$\leftarrow$	$\#$	$\#$	$\|$	$\rightarrow$	$\leftarrow$	$\#$	$\#$
d	$\leftarrow$	$\|$	$\|$	$\#$	$\rightarrow$	$\leftarrow$	$\#$	$\#$
e	$\#$	$\leftarrow$	$\leftarrow$	$\leftarrow$	$\#$	$\rightarrow$	$\rightarrow$	$\rightarrow$
f	$\#$	$\rightarrow$	$\rightarrow$	$\rightarrow$	$\leftarrow$	$\#$	$\#$	$\#$
g	$\#$	$\#$	$\#$	$\#$	$\leftarrow$	$\#$	$\#$	$\#$
h	$\#$	$\#$	$\#$	$\#$	$\leftarrow$	$\#$	$\#$	$\#$

Footprint Comparison



	a	b	c	d	e	f	g	h
a	#	$\rightarrow$	$\rightarrow$	#	#	#	#	#
b	$\leftarrow$	#	#	$\rightarrow$	#	$\leftarrow$	#	#
c	$\leftarrow$	#	#	$\rightarrow$	#	$\leftarrow$	#	#
d	#	$\leftarrow$	$\leftarrow$	#	$\rightarrow$	#	#	#
e	#	#	#	$\leftarrow$	#	$\rightarrow$	$\rightarrow$	$\rightarrow$
f	#	$\rightarrow$	$\rightarrow$	#	$\leftarrow$	#	#	#
g	#	#	#	#	$\leftarrow$	#	#	#
h	#	#	#	#	$\leftarrow$	#	#	#

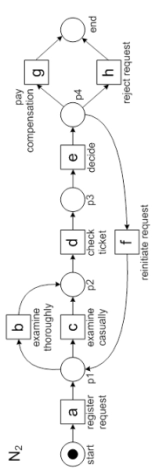
Footprint Comparison

L_{full}

#	trace
455	acdeh
191	abdeg
177	adceh
144	abdeh
111	acdeg
82	adceg
56	adbeh
47	acdefdbeh
38	adbeg
33	acdefbdeh
14	acdefbdeg
11	acdefdbeg
9	adcefcdeh
8	adcefdbeh
5	adcefbdeg
3	acdefbdefdbeg
2	adcefdbeg
2	adcefbdefbdeg
1	adcefdbefbdeh
1	adbefbdefdbeg
1	adcefdbefcdefdbeg
1391	

	a	b	c	d	e	f	g	h
a	#	→	→	→	#	#	#	#
b	←	#	#	$\|$	→	←	#	#
c	←	#	#	$\|$	→	←	#	#
d	←	$\|$	$\|$	#	→	←	#	#
e	#	←	←	←	#	→	→	→
f	#	→	→	→	←	#	#	#
g	#	#	#	#	←	#	#	#
h	#	#	#	#	←	#	#	#

N_2



	a	b	c	d	e	f	g	h
a	#	→	→	#	#	#	#	#
b	←	#	#	→	#	←	#	#
c	←	#	#	→	#	←	#	#
d	#	←	←	#	→	#	#	#
e	#	#	#	←	#	→	→	→
f	#	→	→	#	←	#	#	#
g	#	#	#	#	←	#	#	#
h	#	#	#	#	←	#	#	#

Footprint Comparison

- Formula: 1 – (#mismatches / #relations)

Log:Model	a	b	c	d	e	f	g	h
a				$\rightarrow : \#$				
b				$\| : \rightarrow$	$\rightarrow : \#$			
c				$\| : \rightarrow$	$\rightarrow : \#$			
d	$\leftarrow : \#$	$\| : \leftarrow$	$\| : \leftarrow$			$\leftarrow : \#$		
e		$\leftarrow : \#$	$\leftarrow : \#$					
f				$\rightarrow : \#$				
g								
h								

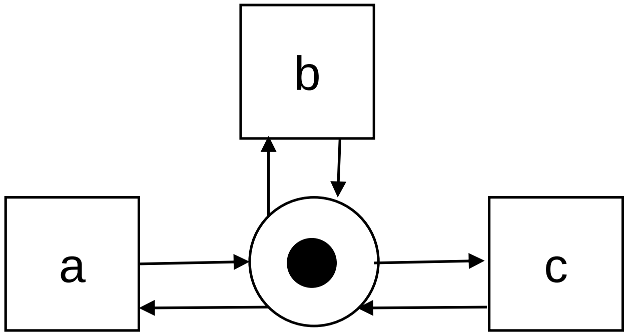
$$1 - \frac{12}{64} = 0.8125$$

(x:y where x is in log and y in N_2)

footprint-based conformance

Footprint Comparison

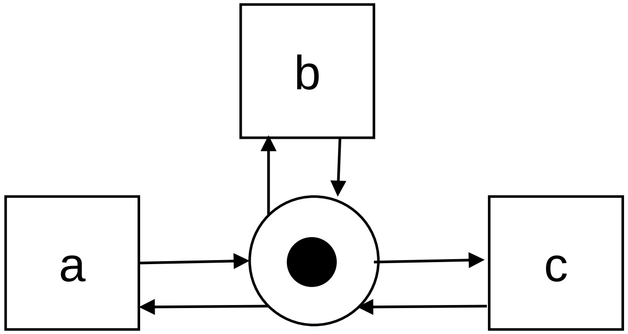
- Problem
- L = [<a,b,d>, <a,c,d>]



Footprint Comparison

- Problem
- L = [<a,b,d>, <a,c,d>]

SEVERAL MISMATCHES!



Footprint Comparison

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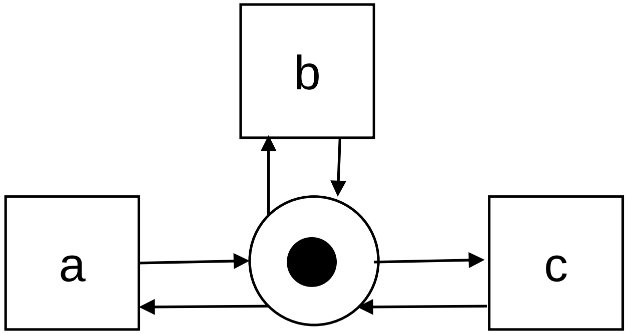
- L = [<a,b,d>, <a,c,d>]

SEVERAL MISMATCHES!



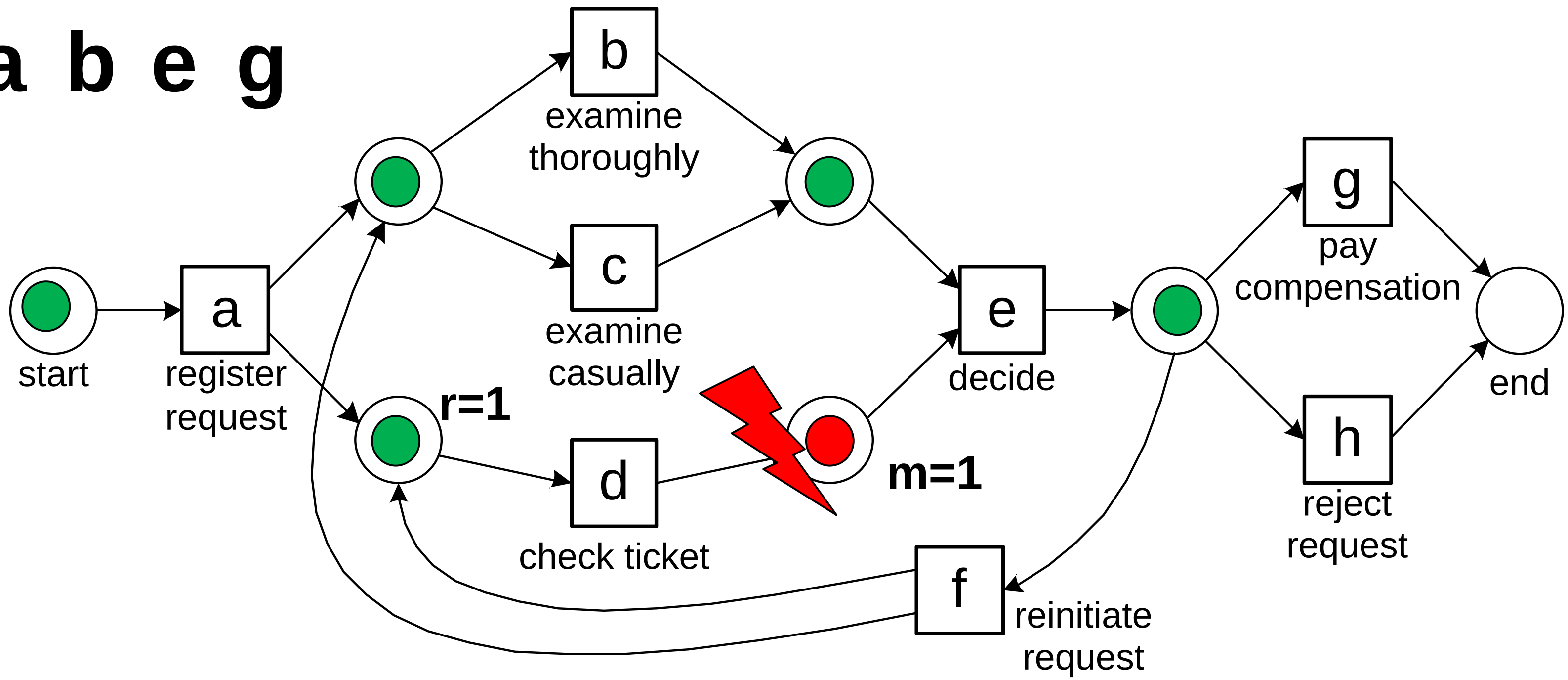
...yet the model describes L

Footprint Comparison

- Replay-Fitness
  - Quantifies to what degree a given process model describes a given event log
    - Footprint Comparison -> Treats model and log ‘equal’

Token-Based Replay

a b e g



$$fitness(\sigma, N) = \frac{1}{2}\left(1 - \frac{1}{6}\right) + \frac{1}{2}\left(1 - \frac{1}{6}\right) = 0.83333$$

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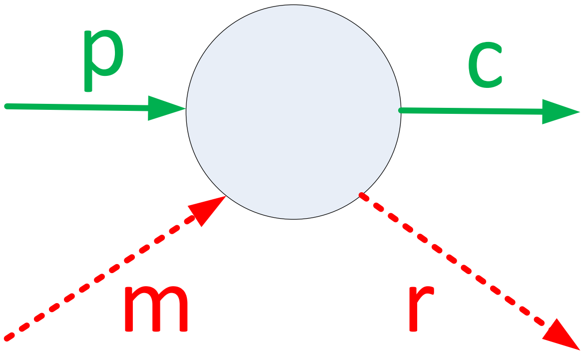
Token-Based Replay

- Use four counters:
  - p = produced tokens
  - c = consumed tokens
  - m = missing tokens
  - r = remaining tokens
- Invariants:
  - At any time: p+m ≥ c ≥ m (also per place)
  - At the end: r = p + m - c (also per place)
- Special actions:
  - In the beginning a token will be produced for the source place: p = 1.
  - At the end a token is removed from the sink place (also if not there): c' = c + 1.



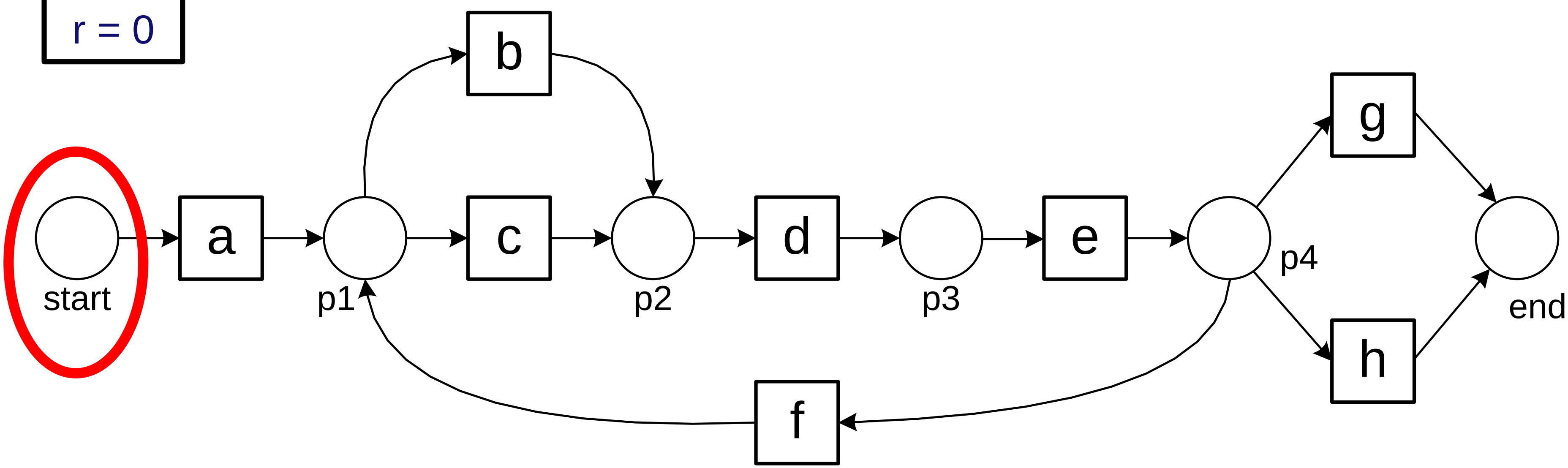
Token-Based Replay

$$fitness(L,N) = \frac{1}{2}\left(1 - \frac{\sum_{\sigma\in L} L(\sigma) \times m_{N,\sigma}}{\sum_{\sigma\in L} L(\sigma) \times c_{N,\sigma}}\right) + \frac{1}{2}\left(1 - \frac{\sum_{\sigma\in L} L(\sigma) \times r_{N,\sigma}}{\sum_{\sigma\in L} L(\sigma) \times p_{N,\sigma}}\right)$$

Token-Based Replay

$$\sigma_3 = \langle a, d, c, e, h \rangle$$

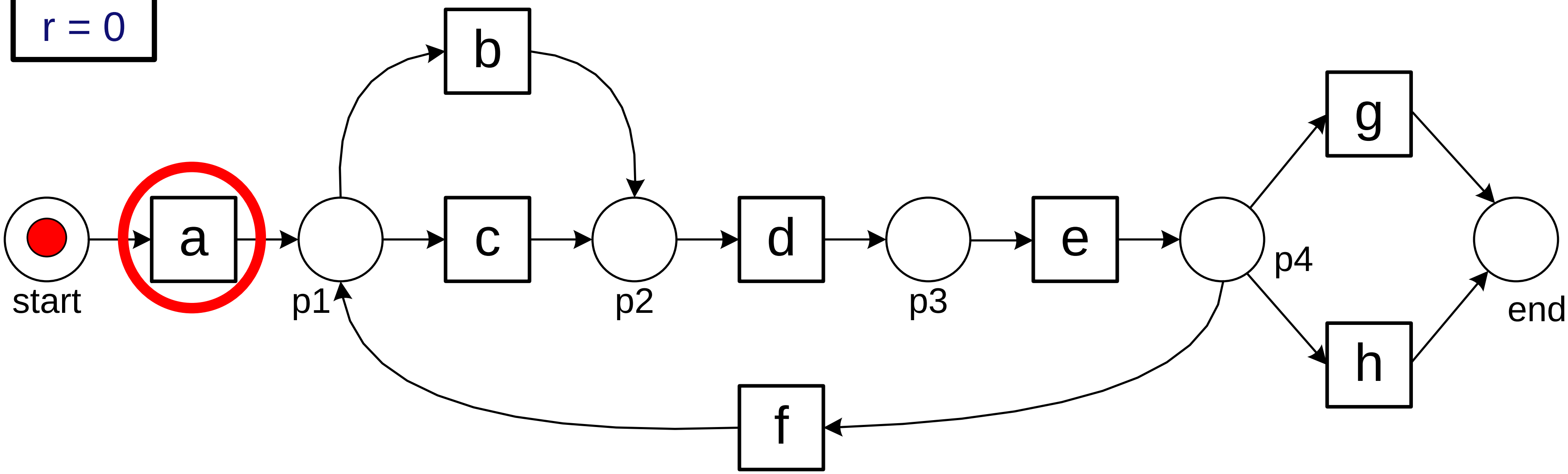
p = 0
c = 0
m = 0
r = 0



Token-Based Replay

$$\sigma_3 = \langle a, d, c, e, h \rangle$$

p = 1
c = 0
m = 0
r = 0

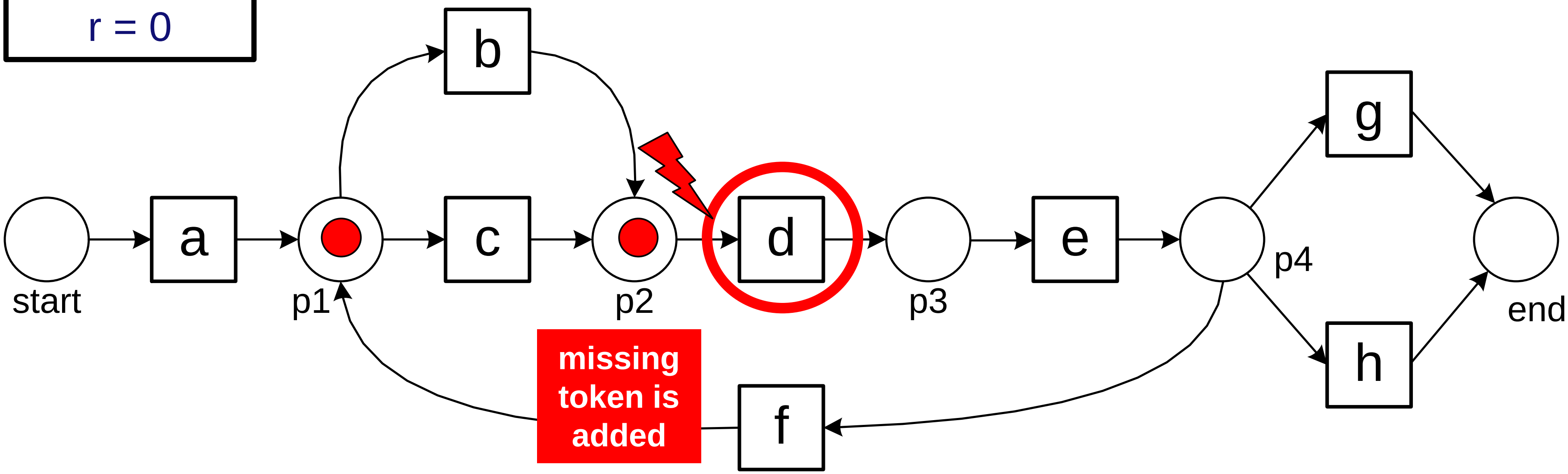


Replay-Fitness

Token-Based Replay

$$\sigma_3 = \langle a, d, c, e, h \rangle$$

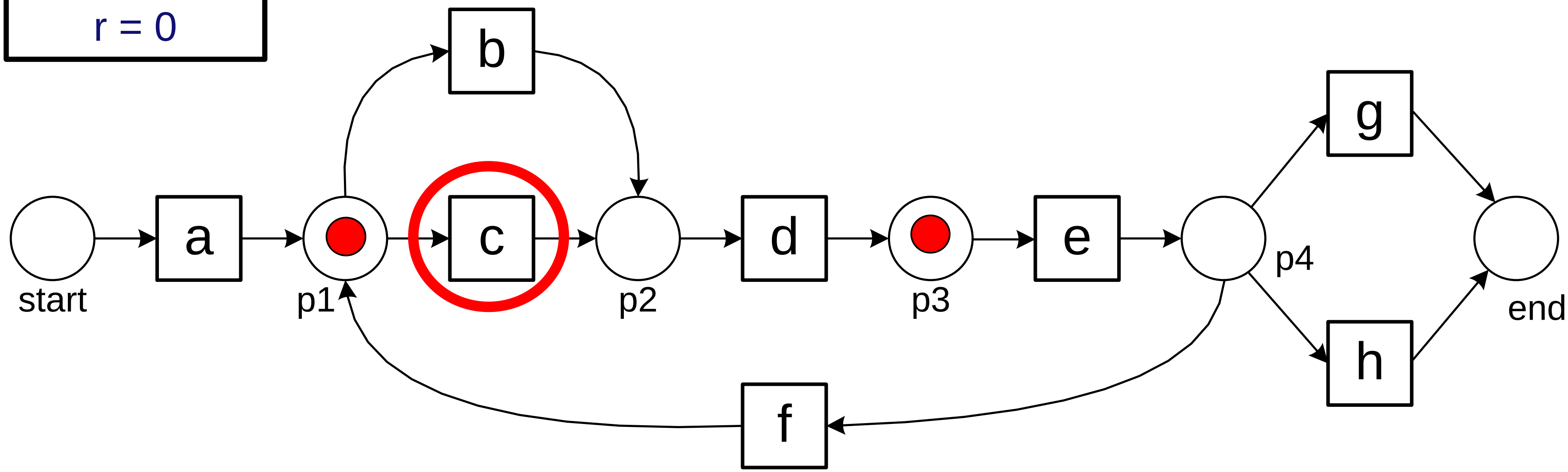
p = 1+1 = 2
c = 0+1 = 1
m = 0
r = 0



Token-Based Replay

$$\sigma_3 = \langle a, d, c, e, h \rangle$$

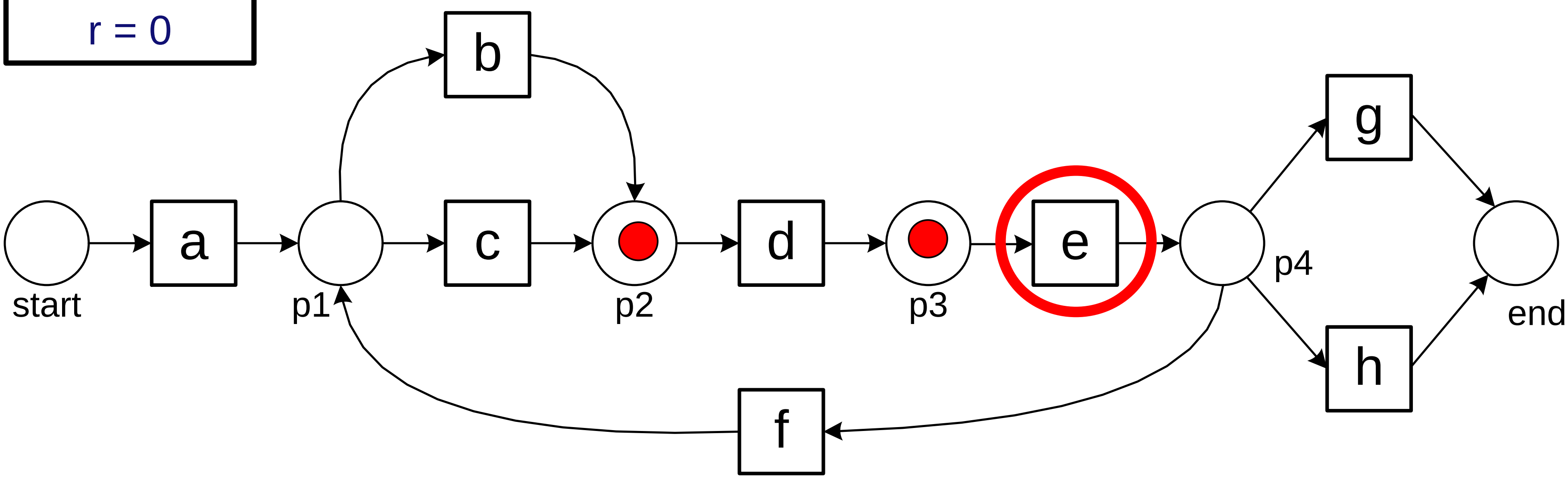
p = 2+1 = 3
c = 1+1 = 2
m = 0+1 = 1
r = 0



Token-Based Replay

$$\sigma_3 = \langle a, d, c, e, h \rangle$$

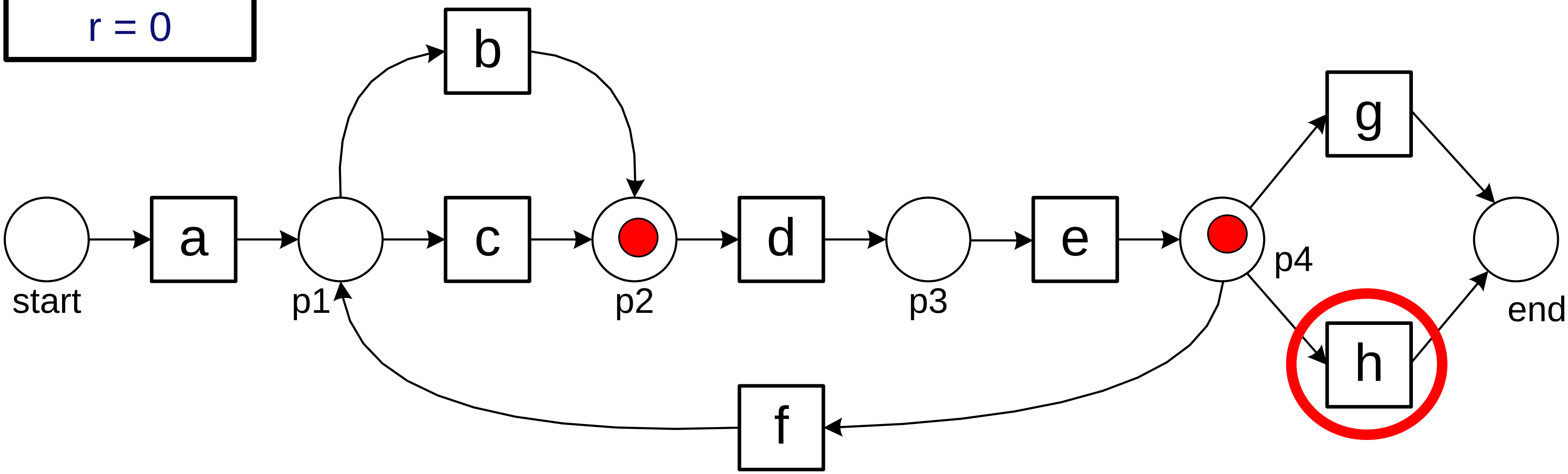
p = 3+1 = 4
c = 2+1 = 3
m = 1
r = 0



Token-Based Replay

$$\sigma_3 = \langle a, d, c, e, h \rangle$$

p = 4+1 = 5
c = 3+1 = 4
m = 1
r = 0

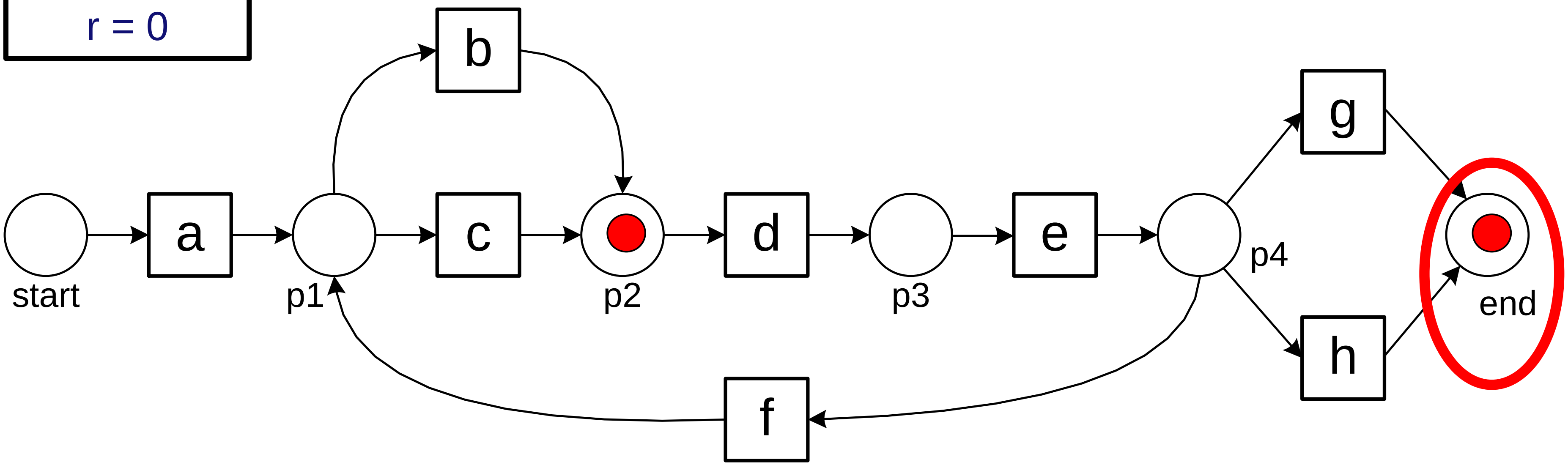


Replay-Fitness

Token-Based Replay

$$\sigma_3 = \langle a, d, c, e, h \rangle$$

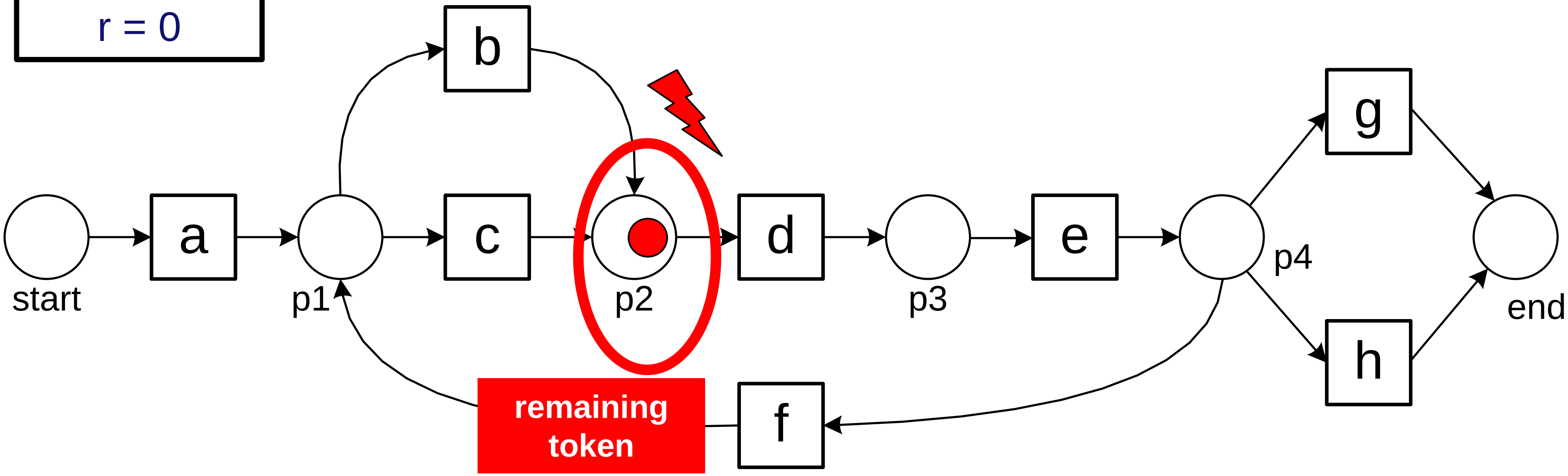
p = 5+1 = 6
c = 4+1 = 5
m = 1
r = 0



Token-Based Replay

$$\sigma_3 = \langle a, d, c, e, h \rangle$$

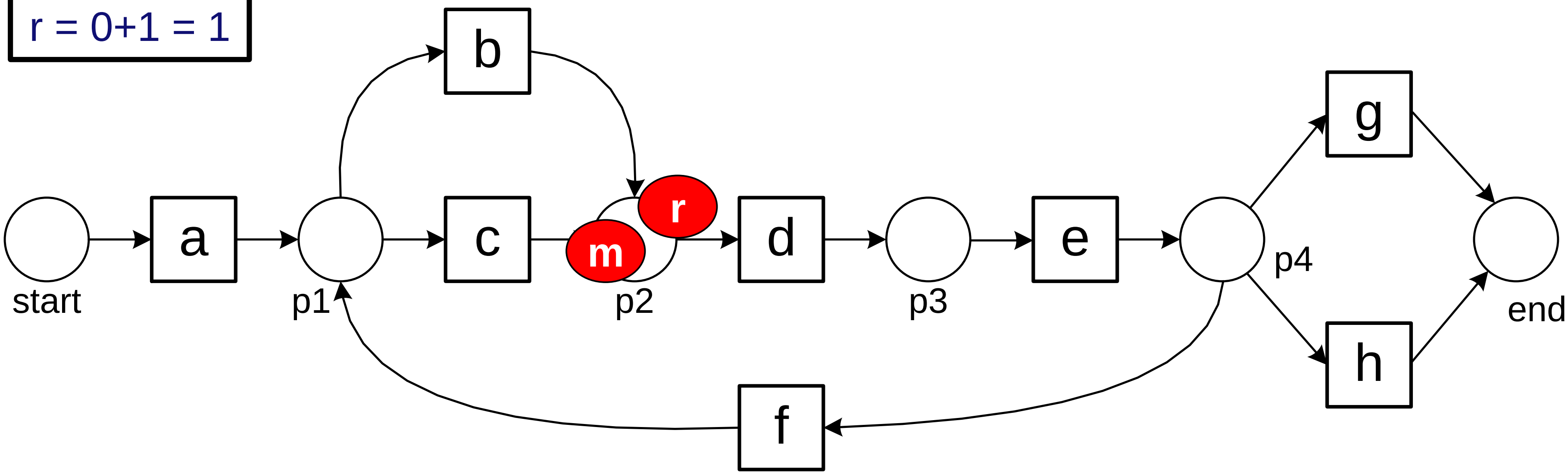
p = 6
c = 5+1 = 6
m = 1
r = 0



Token-Based Replay

$$\sigma_3 = \langle a, d, c, e, h \rangle$$

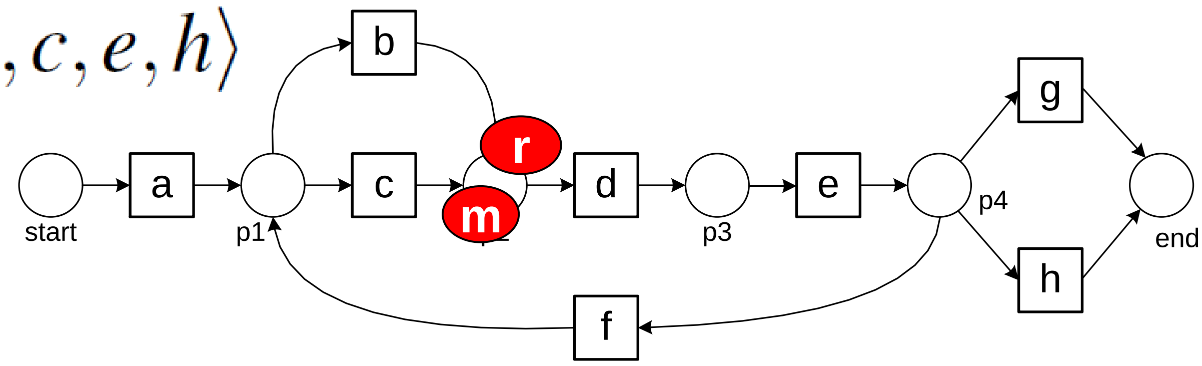
p = 6
c = 6
m = 1
r = 0+1 = 1



Token-Based Replay

p = 6
c = 6
m = 1
r = 1

$$\sigma_3 = \langle a, d, c, e, h \rangle$$

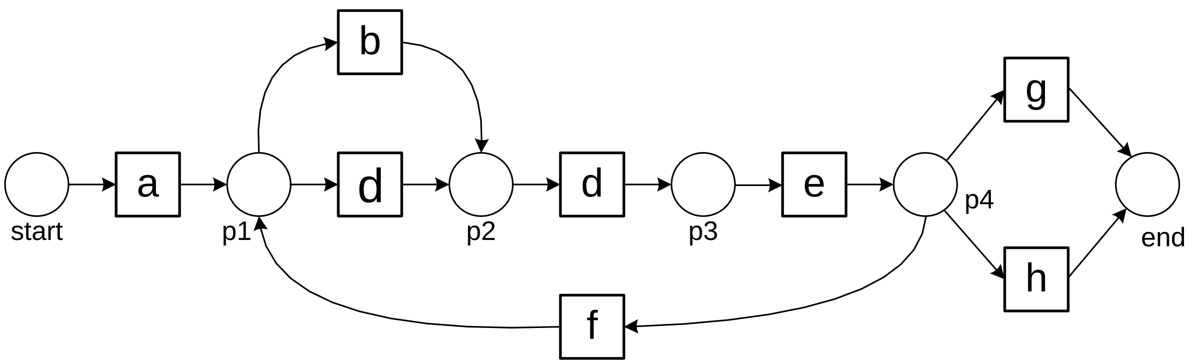


$$fitness(\sigma, N) = \frac{1}{2}\left(1 - \frac{1}{6}\right) + \frac{1}{2}\left(1 - \frac{1}{6}\right) = 0.8333$$

Chair of Process and Data Science

Token-Based Replay

- Problems
- How to handle ‘duplicate labels’?
- L = [<d,e,g>]

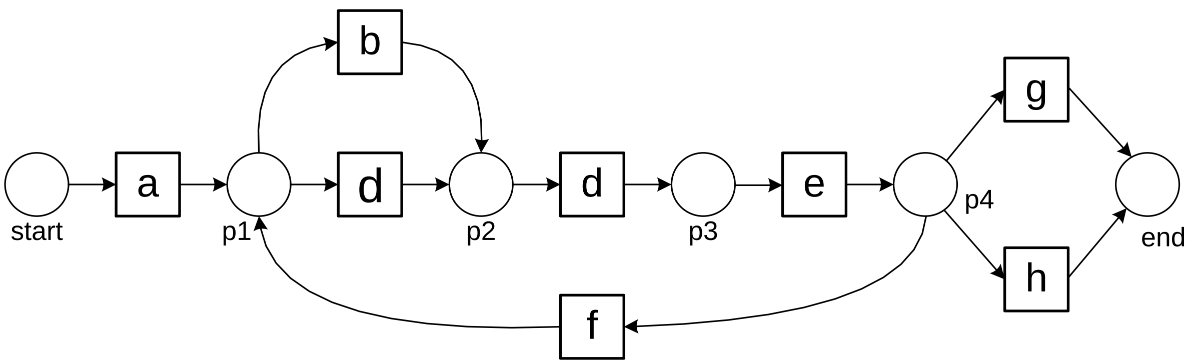


Token-Based Replay

- Problems

- How to handle ‘duplicate labels’?

- L = [<d,e,g>]
- In this example, it is clear what ‘d’ to pick, in general, this decision is not trivial!



Footprint Comparison

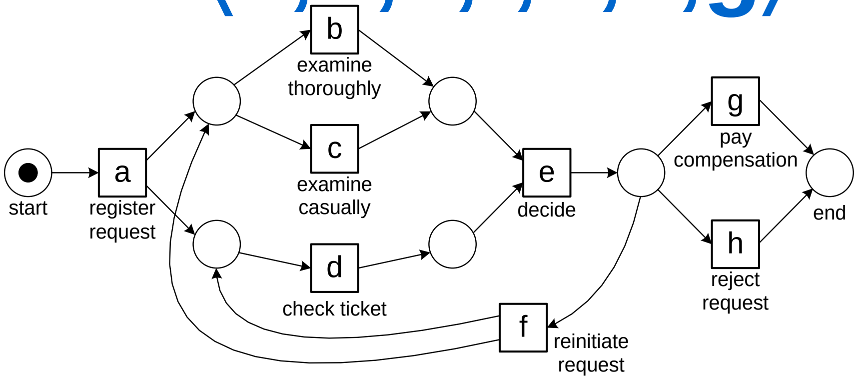
- Replay-Fitness
  - Quantifies to what degree a given process model describes a given event log
    - Footprint Comparison -> Treats model and log ‘equal’
    - Token-Based Replay -> Can lead to overestimation of non-conformance (‘token flooding’)

Alignments

a	b	e	f	d	e	g
a	b	»	»	d	e	g

1x

⟨a,b,e,f,d,e,g⟩



Alignments

alignment (sequence of moves)

move in log only

move in model only

synchronous move (move in both)

a	b	»	d	e	g
a	»	c	d	e	g

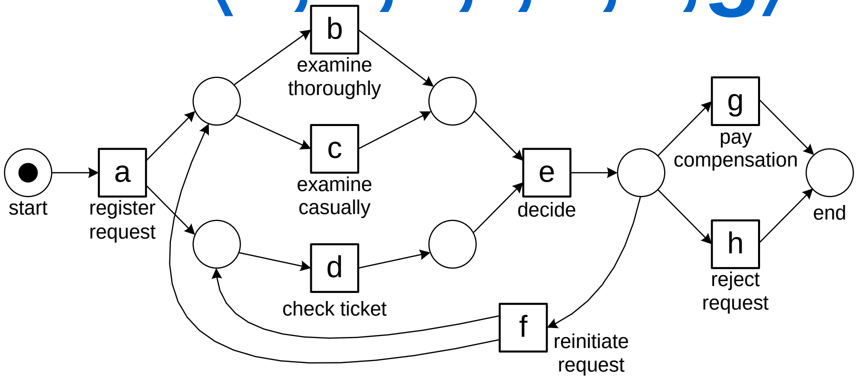
- Projection on top row (remove "no moves") corresponds to the trace in the event log.
- Projection on bottom row (remove "no moves") corresponds to a run of the model.

Alignments

a	b	e	f	d	e	g
a	b	»	»	d	e	g

1x

⟨a,b,e,f,d,e,g⟩



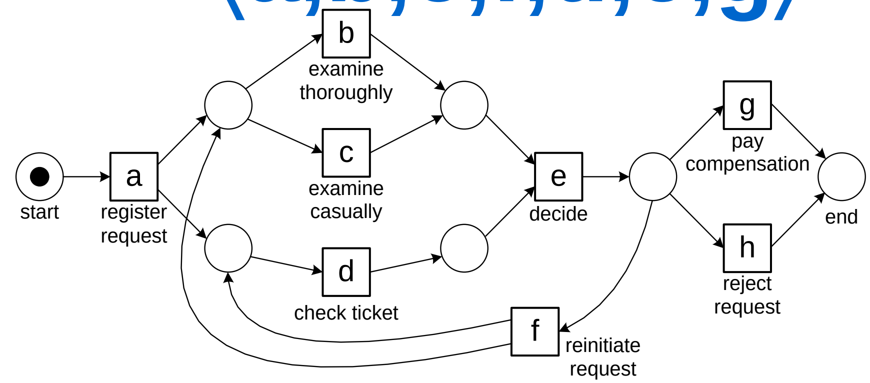
a	b	»	e	f	d	»	e	g
a	b	d	e	f	d	b	e	g

Replay-Fitness
Alignments

a	b	e	f	d	e	g
a	b	»	»	d	e	g

1x

⟨a,b,e,f,d,e,g⟩



4x

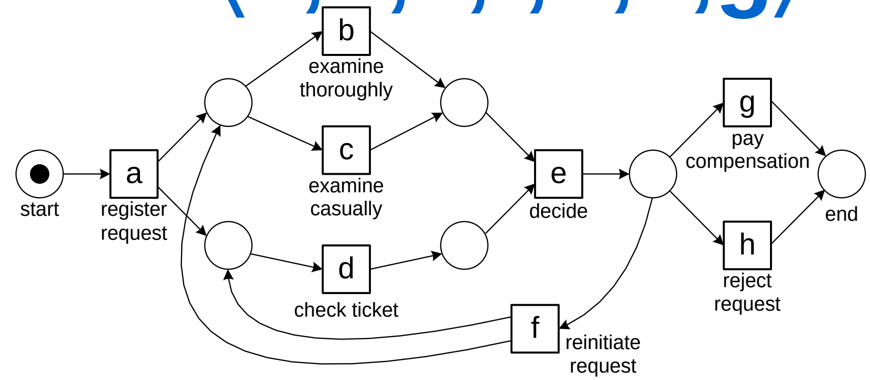
a	b	»	e	f	d	»	e	g
a	b	d	e	f	d	b	e	g

Replay-Fitness
Alignments

a	b	e	f	d	e	g
a	b	»	»	d	e	g

1x

⟨a,b,e,f,d,e,g⟩



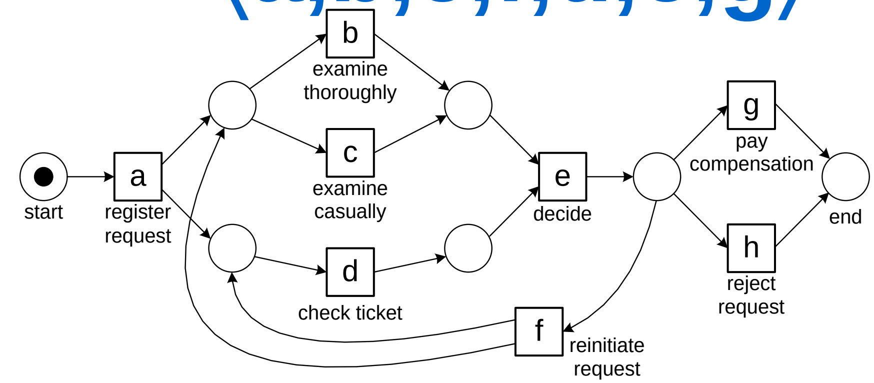
4x

a	b	»	e	f	d	»	e	g
a	b	d	e	f	d	b	e	g

a	b	»	e	f	d	»	e	g
a	b	d	e	f	d	c	e	g

Alignments

⟨a,b,e,f,d,e,g⟩



a	b	e	f	d	e	g
a	b	»	»	d	e	g

1x

a	b	»	e	f	d	»	e	g
a	b	d	e	f	d	b	e	g

4x

a	b	»	e	f	d	»	e	g
a	b	d	e	f	d	c	e	g

4x

Alignments

Fitness

- Compare the cost of an optimal alignment with a "worst case scenario" = move in log only for observed events and shortest path with only moves in model.

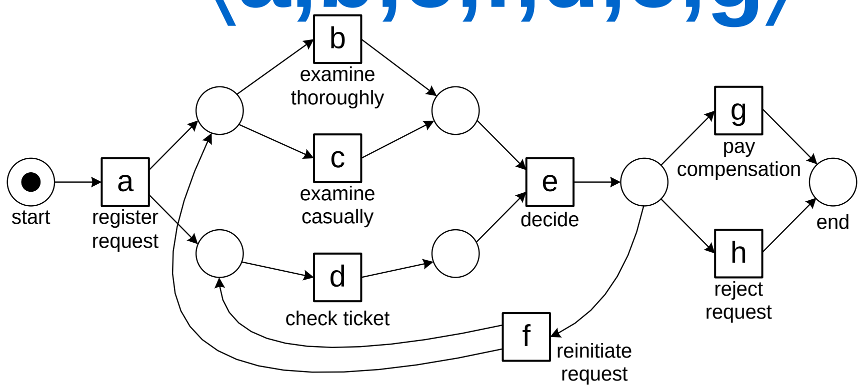
Alignments

Fitness

- Compare the cost of an optimal alignment with a "worst case scenario" = move in log only for observed events and shortest path with only moves in model.

$$1 - \frac{2}{7+5} = 0.833$$

$$\langle a,b,e,f,d,e,g \rangle$$



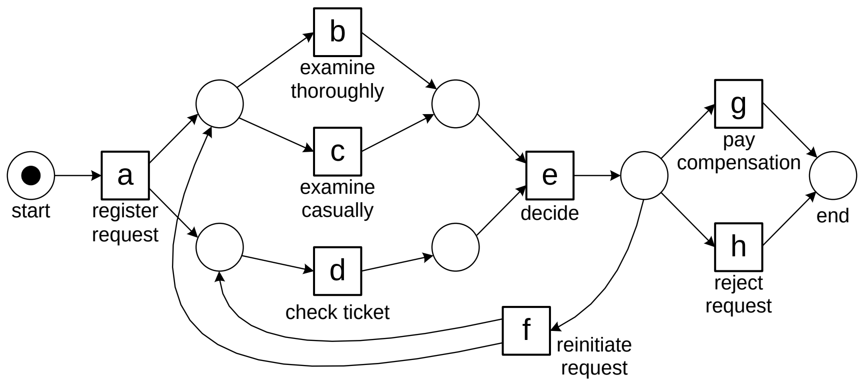
Alignments

Fitness

- Compare the cost of an optimal alignment with a "worst case scenario" = move in log only for observed events and shortest path with only moves in model.

$\langle a,b,e,f,d,e,g \rangle$

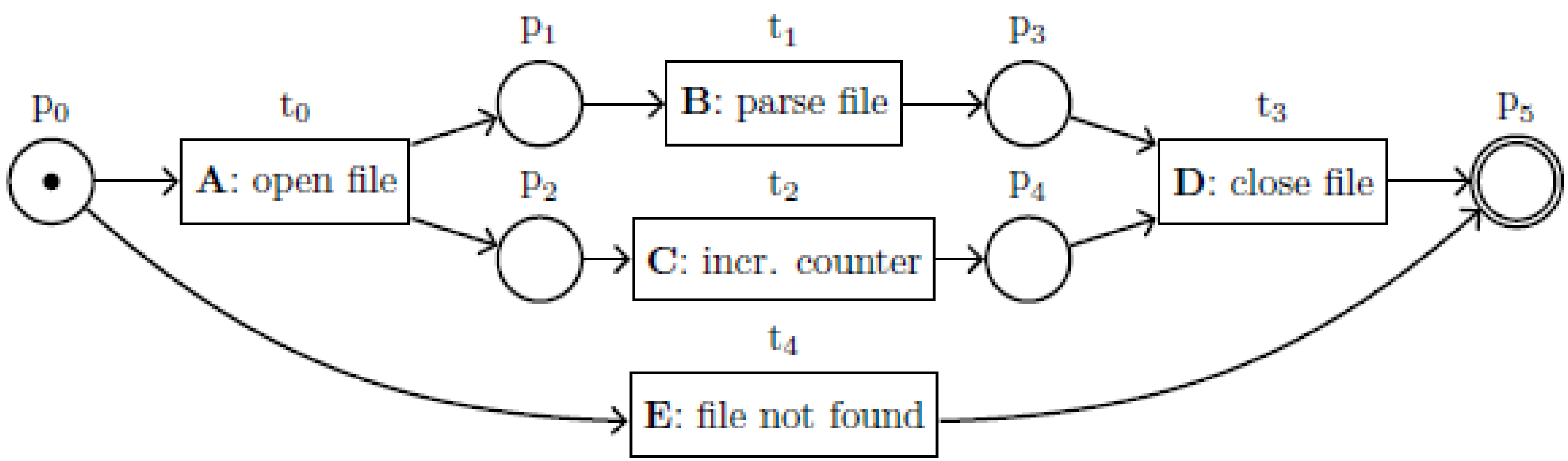
$$1 - \frac{2}{7+5} = 0.833$$



Alignments

Fitness

- Do we always want this?
  - (model by Vincent Bloemen)



Alignments

Fitness

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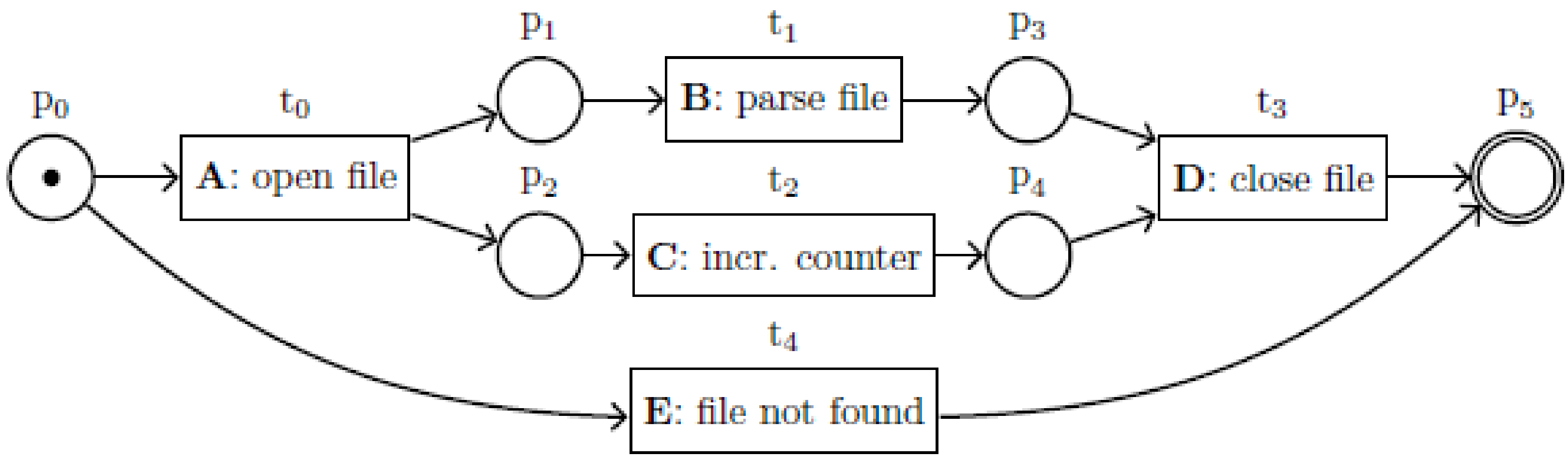
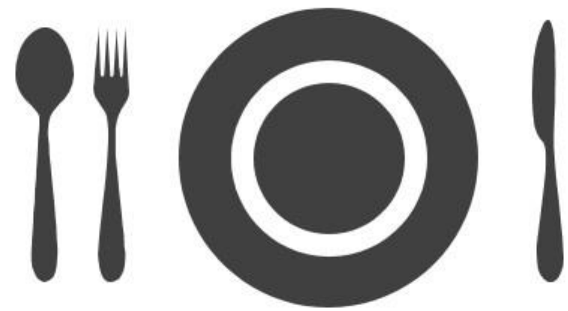
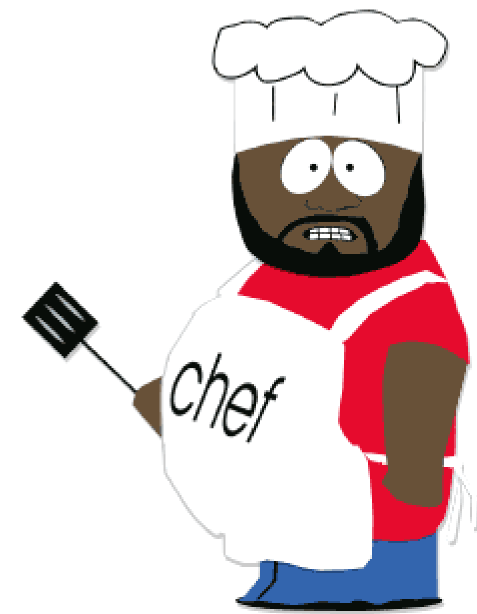


- <parse file> … optimal alignment?



- Quality Dimensions (Recap)

- Replay-Fitness (Recap)
- Precision
- Simplicity
- Generalization



https://giffiles.alphacoders.com/133/133737.gif

Definition (Informal)

- Precision
  - Quantifies to what degree a given process model describes relevant behavior given an event log

Chair of Process and Data Science

Definition (Informal)

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  - Quantifies to what degree a given process model describes relevant behavior given an event log
  - All behavior described by the model also in the log?
    - Precision is **perfect**! (1)
  - Does the model allow for more?
    - Precision is **less good**! (… the more the worse)

Definition (Informal)

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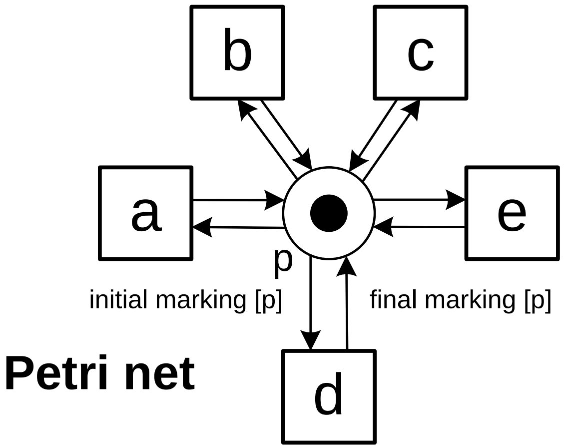
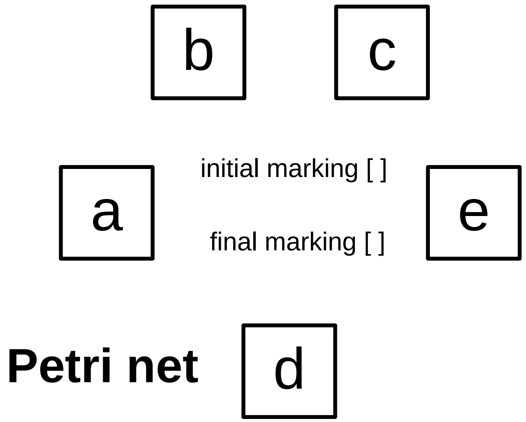
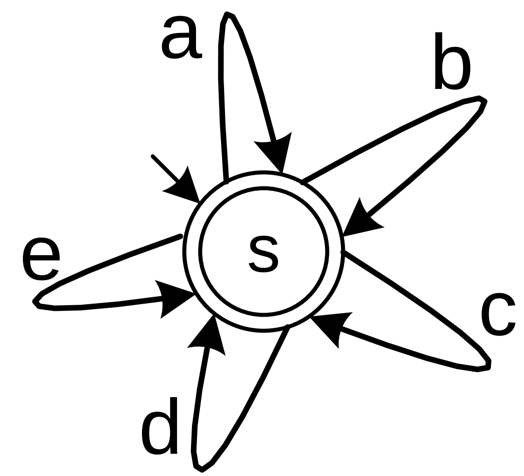
  - All behavior described by the model also in the log?
    - Precision is **perfect**! (1)
  - Does the model allow for more?
    - Precision is **less good**! (… the more the worse)

- … behavior of the model can be infinite!

Escaping Edges







$$[abde^{20}, acde^{20}, adbe^{10}]$$

$$[abcdeabcde^{50}]$$

$$[aaaaa^{20}, bbbbbb^{30}]$$

Escaping Edges

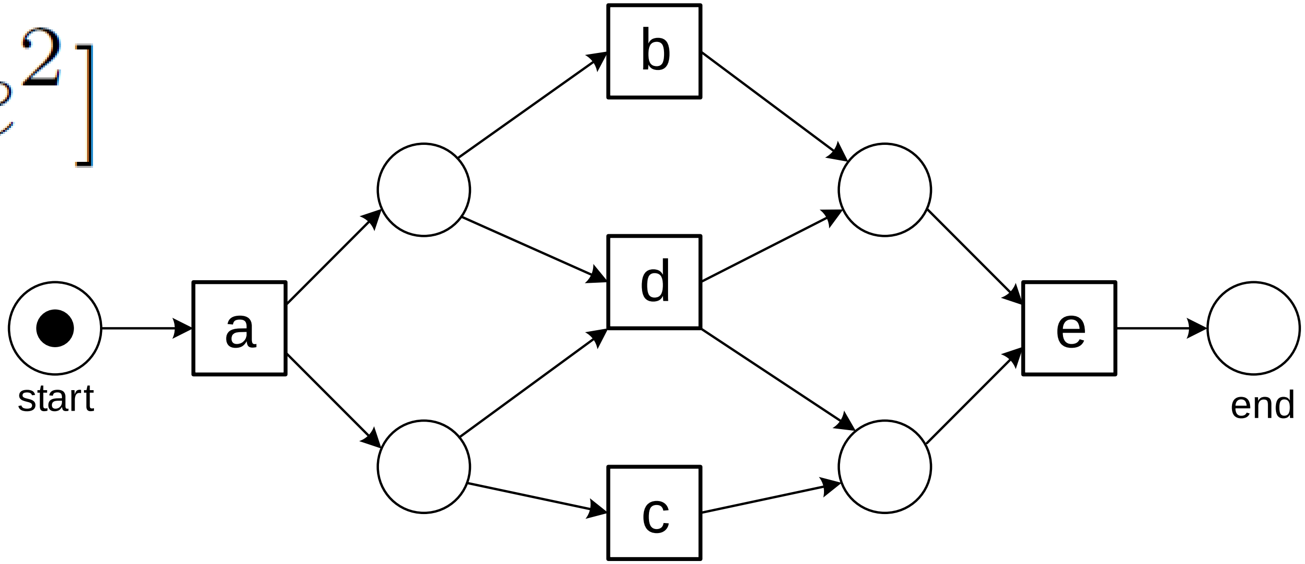
- **We consider event logs after alignment, i.e., we consider a multiset of perfectly fitting traces.**

Escaping Edges

- **We consider event logs after alignment, i.e., we consider a multiset of perfectly fitting traces.**
- We assume replay to be deterministic: only one perfect alignment per trace (just a technicality to simplify the explanation).

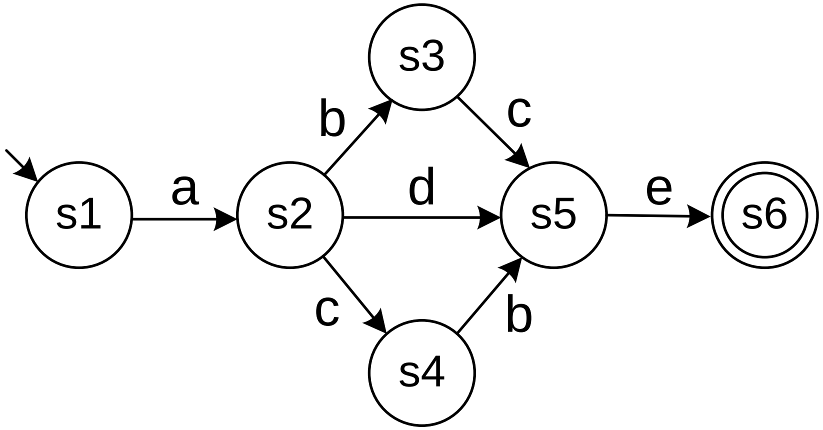
Precision
Escaping Edges

$$[abce^2, ade^2]$$



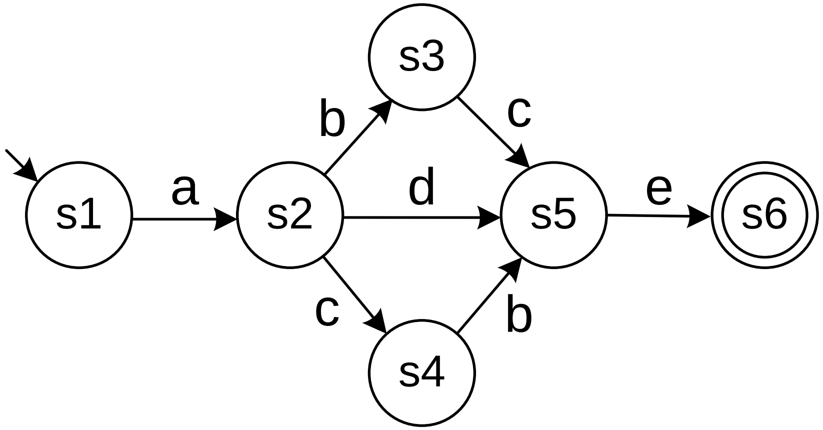
Escaping Edges

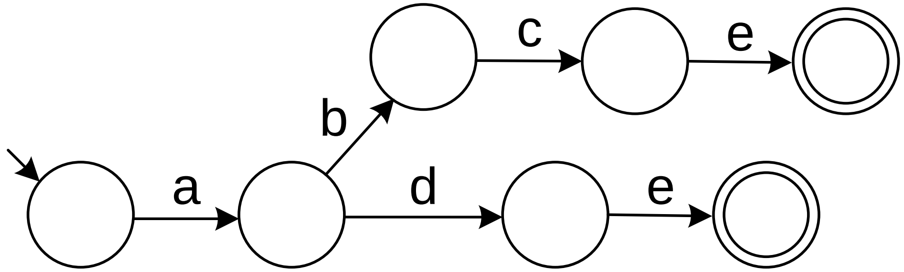
$$[abce^2, ade^2]$$



Escaping Edges

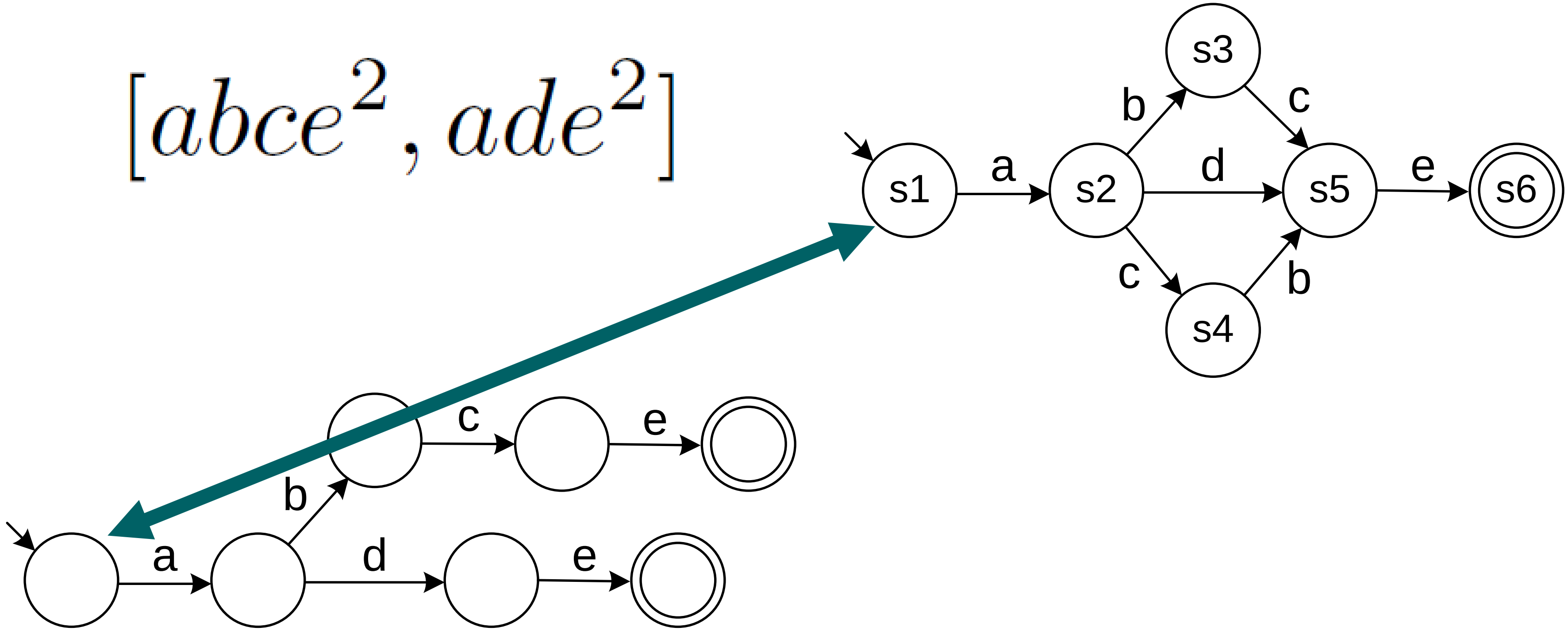
$$[abce^2, ade^2]$$





Escaping Edges

$$[abce^2, ade^2]$$

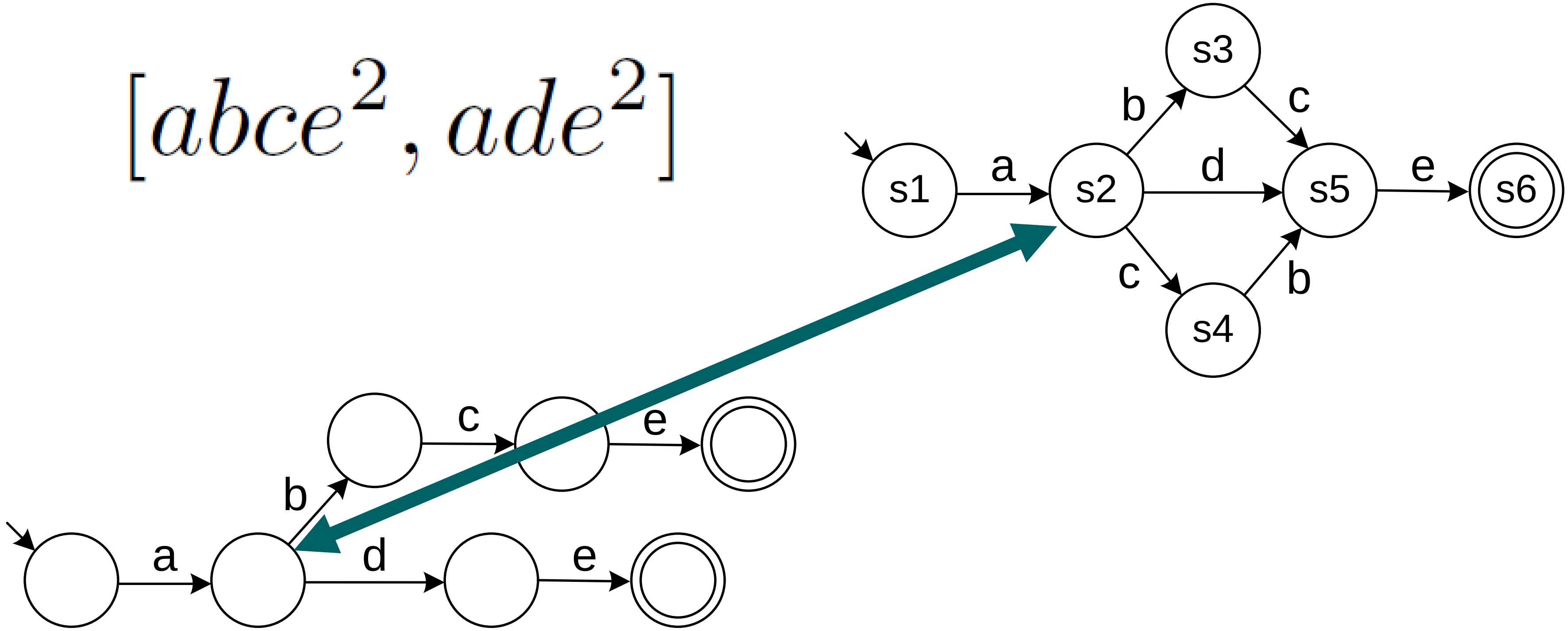


Automaton and Model ‘agree’ on what is possible!

Precision

Escaping Edges

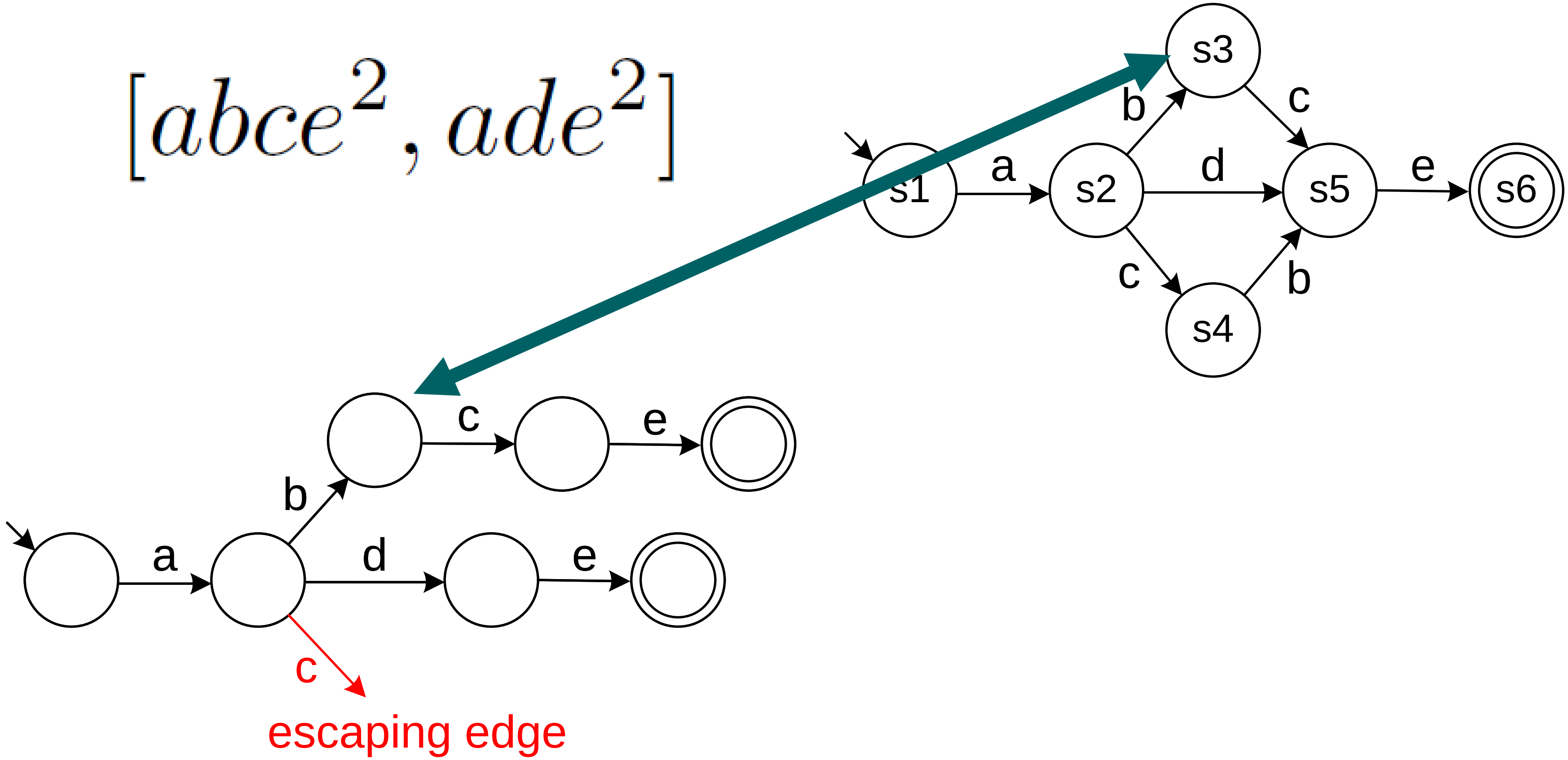
$$[abce^2, ade^2]$$



Automaton and Model do not ‘agree’ on what is possible, i.e., model describes more…

Precision
Escaping Edges

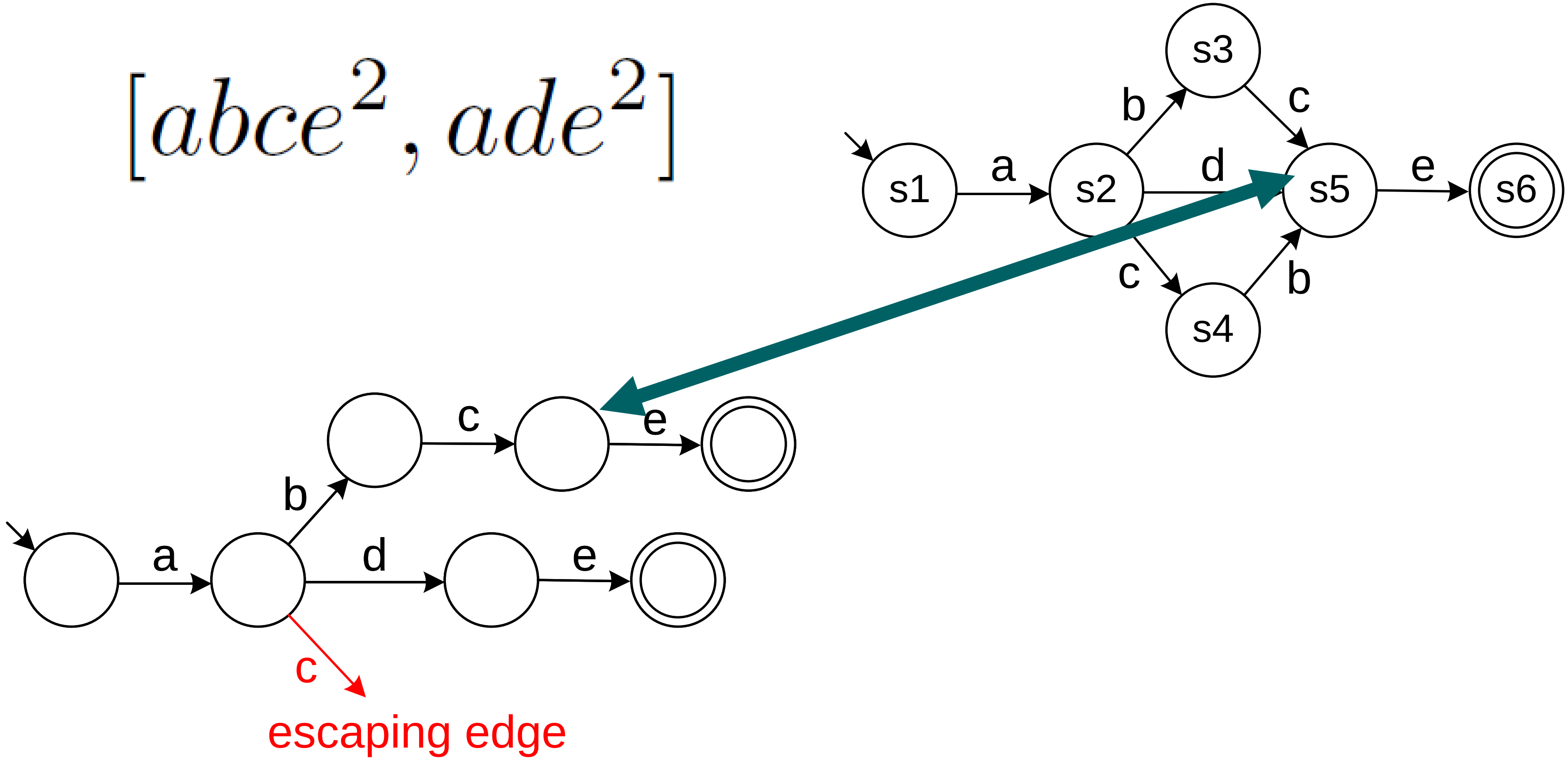
$$[abce^2, ade^2]$$



Precision

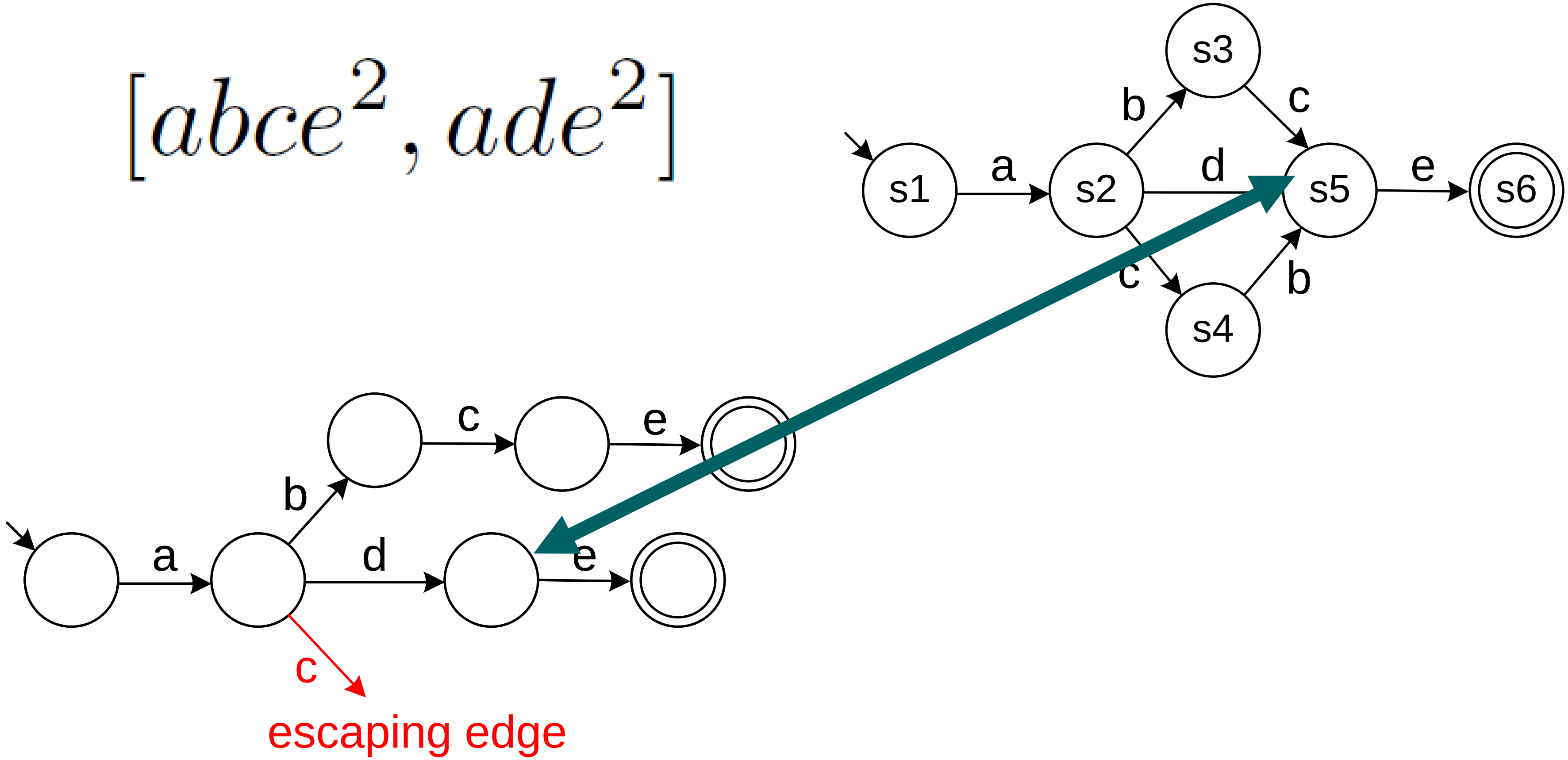
Escaping Edges

$$[abce^2, ade^2]$$



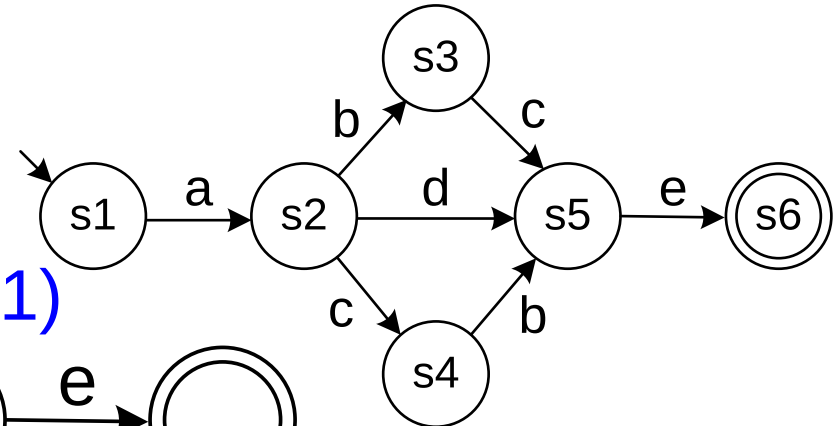
Escaping Edges

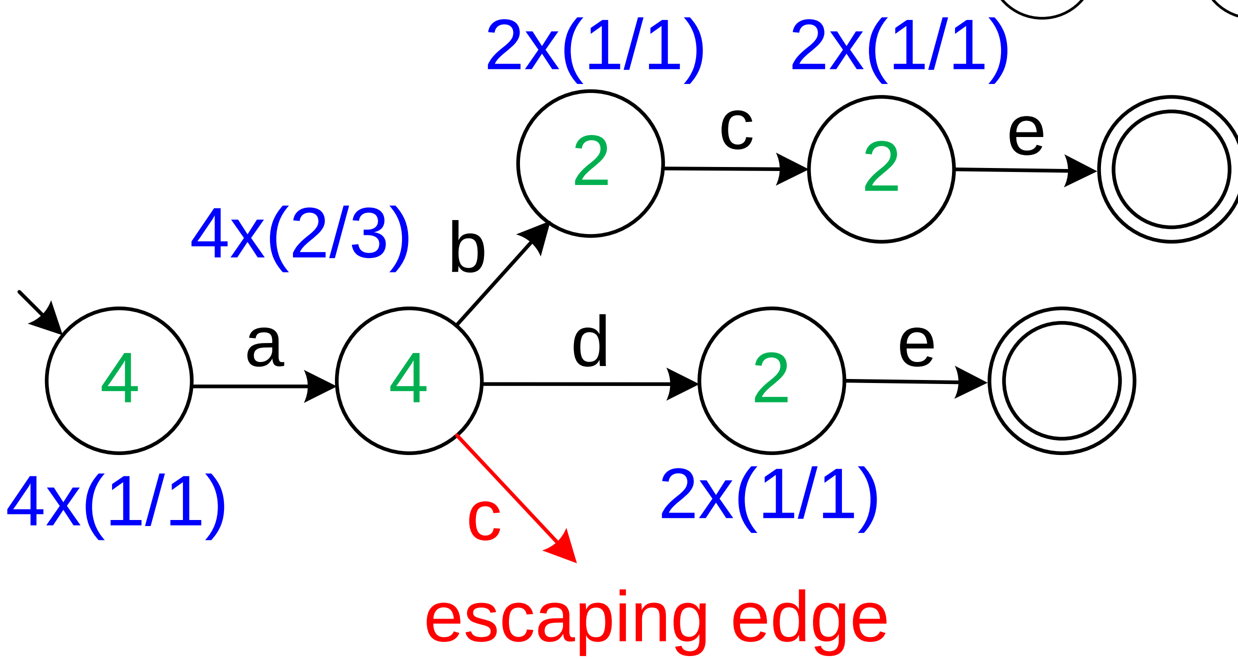
$$[abce^2, ade^2]$$



Precision
Escaping Edges

$$[abce^2, ade^2]$$



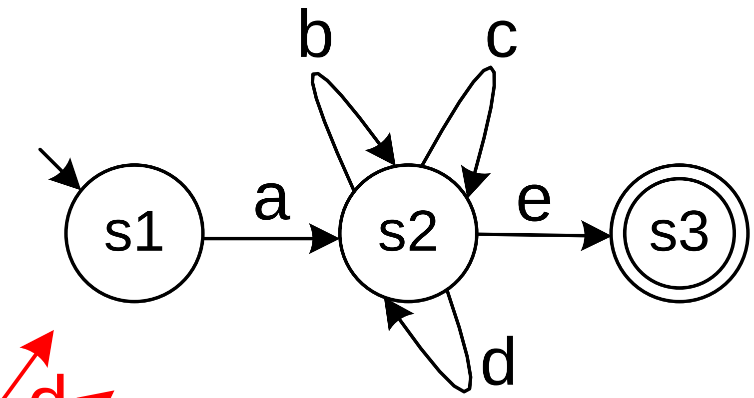


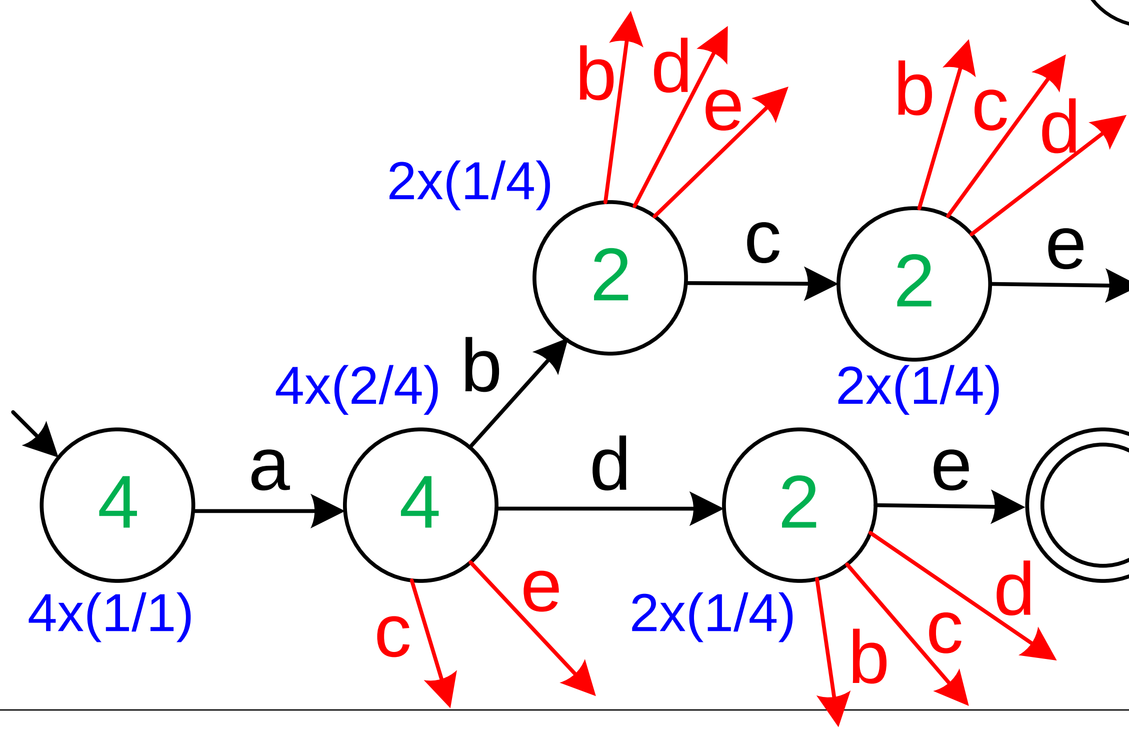
(1/14) x (4x(1/1) + 4x(2/3) + 2x(1/1) + 2x(1/1) + 2x(1/1)) = 0.905

Precision

Escaping Edges

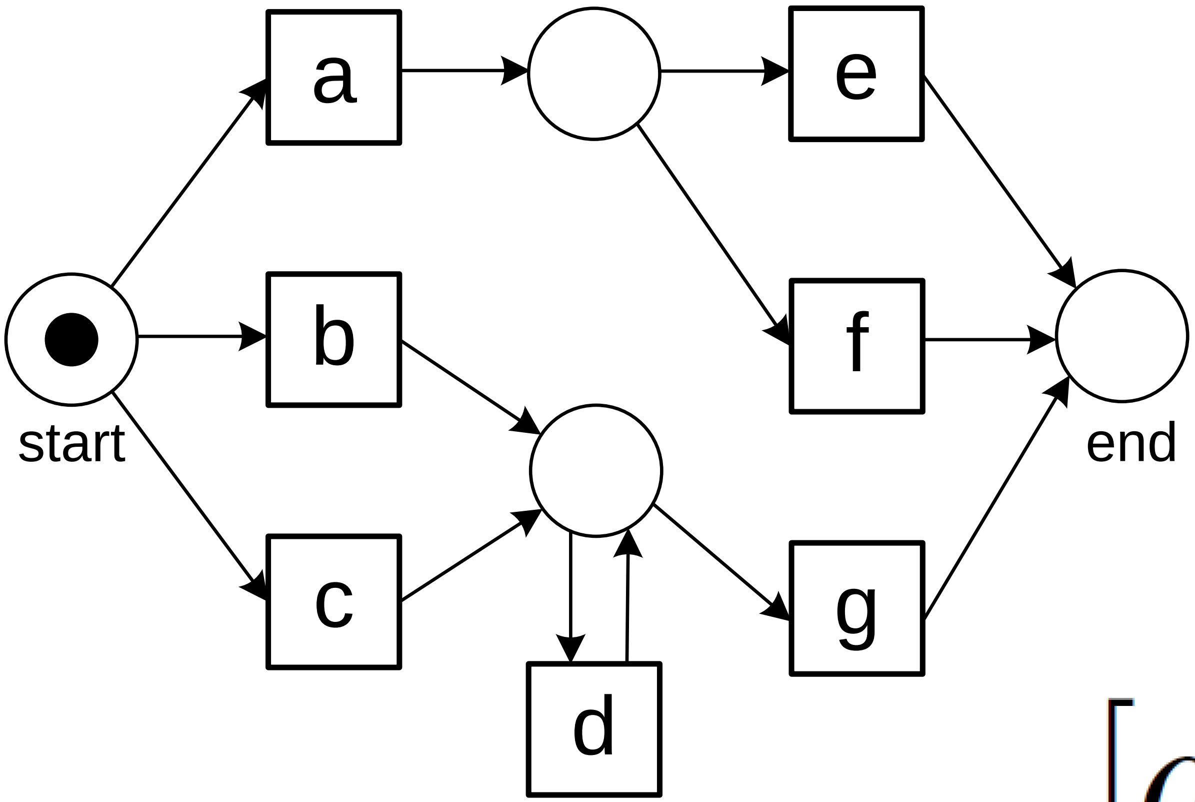
$$[abce^2, ade^2]$$





$(1/14) \times (4\times(1/1) + 4\times(2/4) + 2\times(1/4) + 2\times(1/4) + 2\times(1/4)) = 0.536$

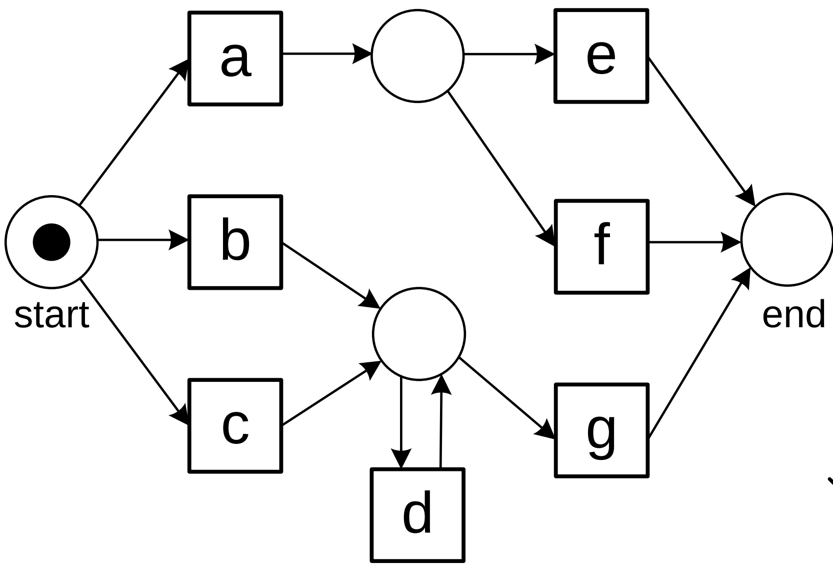
Precision
Escaping Edges



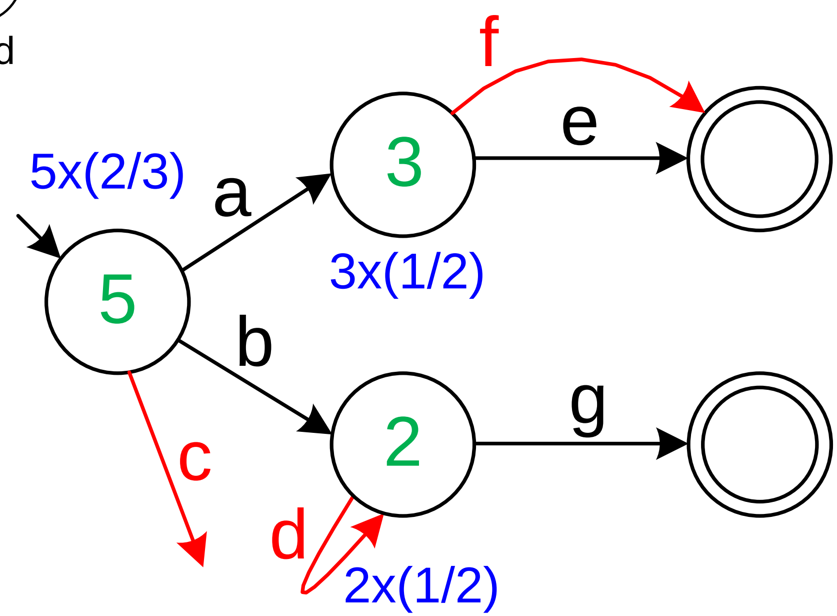
$$[ae^3, bg^2]$$

Precision

Escaping Edges

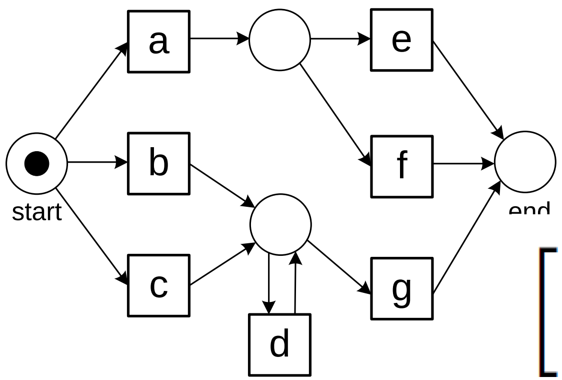


$$[ae^3, bg^2]$$

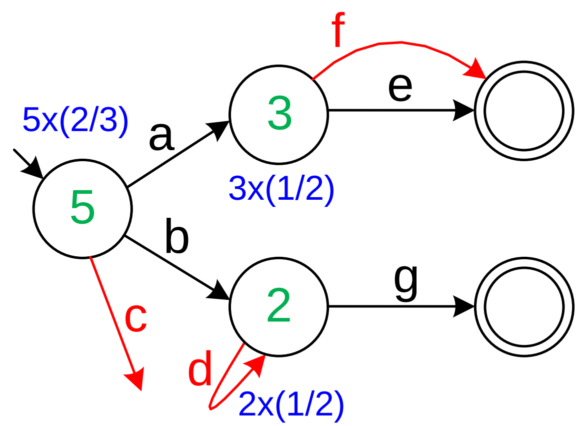


(1/10) x (5x(2/3) + 3x(1/2) + 2x(1/2)) = 7/12 = 0.58333

Escaping Edges



$$[ae^3, bg^2]$$



(1/10) x (5x(2/3) + 3x(1/2) + 2x(1/2)) = 0.58333

$$precision(L, M) = \frac{1}{|\mathcal{E}|} \sum_{e \in \mathcal{E}} \frac{|en_L(e)|}{|en_M(e)|} =$$

$$\frac{1}{|\{e_1, e_2 \ldots e_{10}\}|} \times \left(\frac{|en_L(e_1)|}{|en_M(e_1)|} + \frac{|en_L(e_2)|}{|en_M(e_2)|} + \ldots + \frac{|en_L(e_{10})|}{|en_M(e_{10})|} \right) =$$

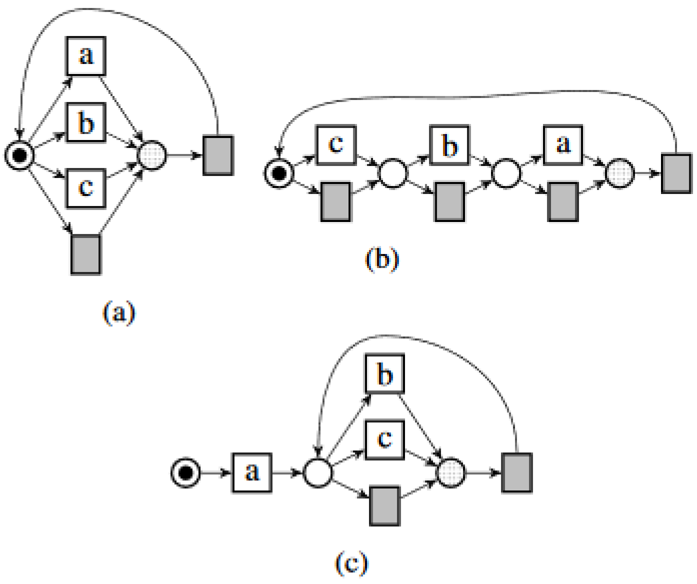
$$\frac{1}{10} \times \left(\frac{|\{a,b\}|}{|\{a,b,c\}|} + \frac{|\{e\}|}{|\{e,f\}|} + \ldots + \frac{|\{g\}|}{|\{d,g\}|} \right) =$$

$$\frac{1}{10} \times \left(\frac{2}{3} + \frac{1}{2} + \frac{2}{3} + \frac{1}{2} + \frac{2}{3} + \frac{1}{2} + \frac{2}{3} + \frac{1}{2} + \frac{2}{3} + \frac{1}{2} \right) =$$

$$\frac{15}{28} = 0.58333$$

Escaping Edges

- Consider [<a,b,c>] and the models:



Escaping Edges

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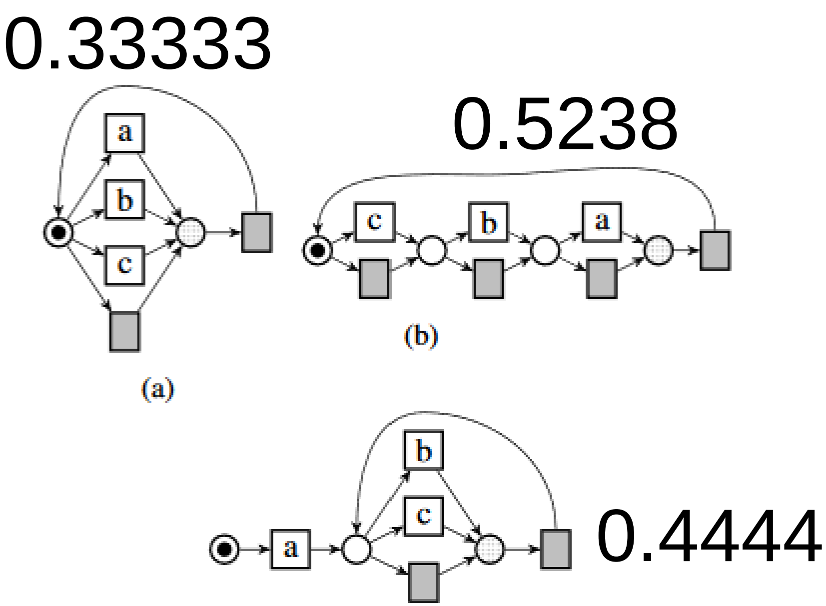


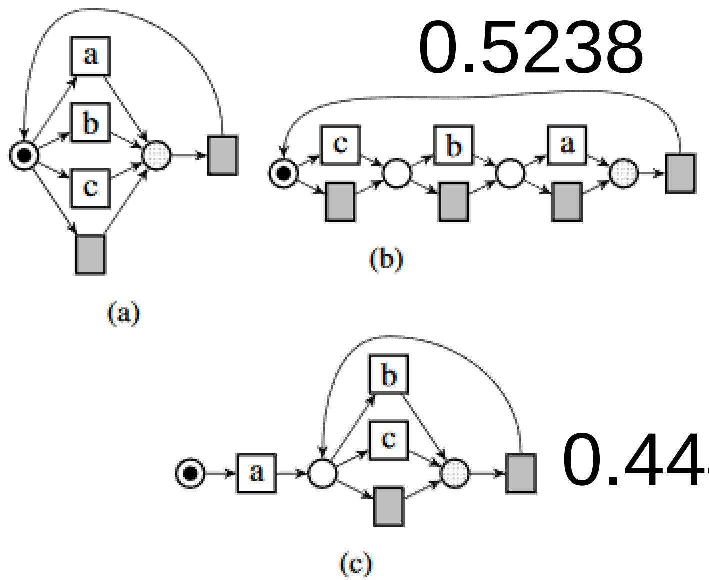
(a) (b) (c)

Escaping Edges

- Consider [<a,b,c>] and the models:
  - What model is mostly constraining the behavior?

0.33333

0.5238



0.4444

Escaping Edges

- Consider [<a,b,c>] and the models:
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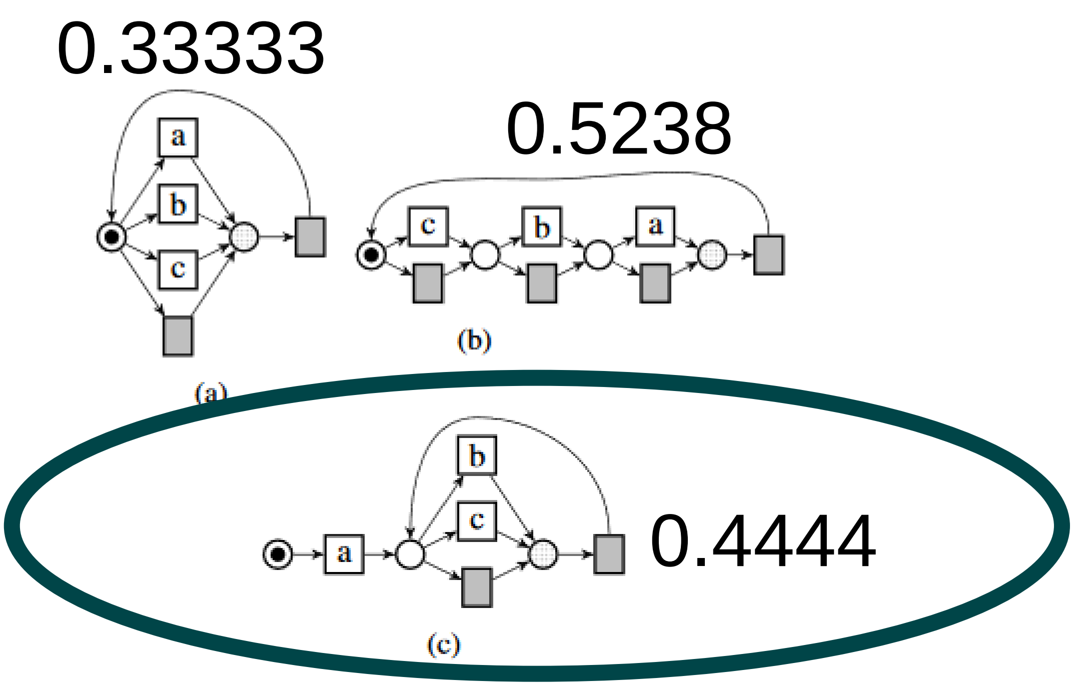


Axioms

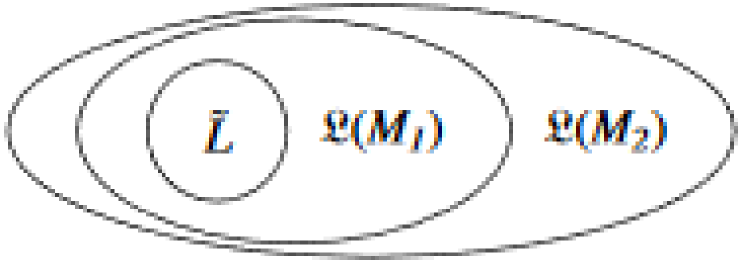
- 5 Axioms (Tax et al.)

1. A precision metric has to be deterministic

Precision

Axioms

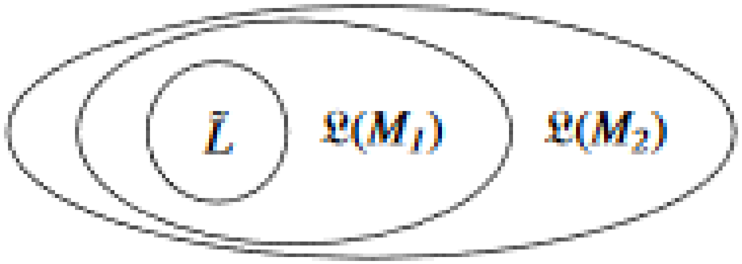
- 5 Axioms (Tax et al.)



2. If M1 and M2 (models) completely describe a log L, and if *lang(*M1) ⊆ *lang*(M2), then *prec*(M1,L) >= *prec*(M2,L), i.e., M1 is at least as precise as M2.

Axioms

- 5 Axioms (Tax et al.)



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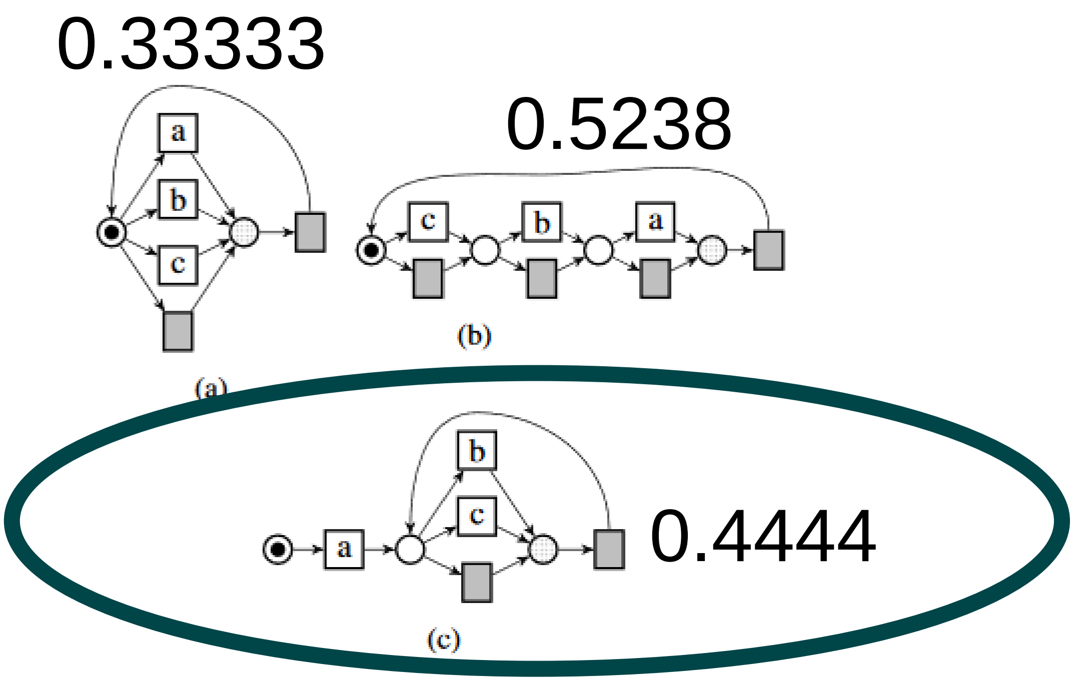
- Allows: *lang(*M1) ⊂ *lang*(M2) and *prec*(M1,L) = *prec*(M2,L)!

Escaping Edges

- Consider [<a,b,c>] and the models:
  - What model is mostly constraining the behavior?



Axioms

- 5 Axioms (Tax et al.)

3. If M1 is **not** the flower model and M2 is the flower model, then *prec*(M1,L) > *prec*(M2,L), i.e., M1 is at least as precise as M2. (for any L)

Axioms

- 5 Axioms (Tax et al.)

3. If M1 is **not** the flower model and M2 is the flower model, then *prec*(M1,L) > *prec*(M2,L), i.e., M1 is at least as precise as M2. (for any L)

- Fixes the ‘issue’ of AX 2.

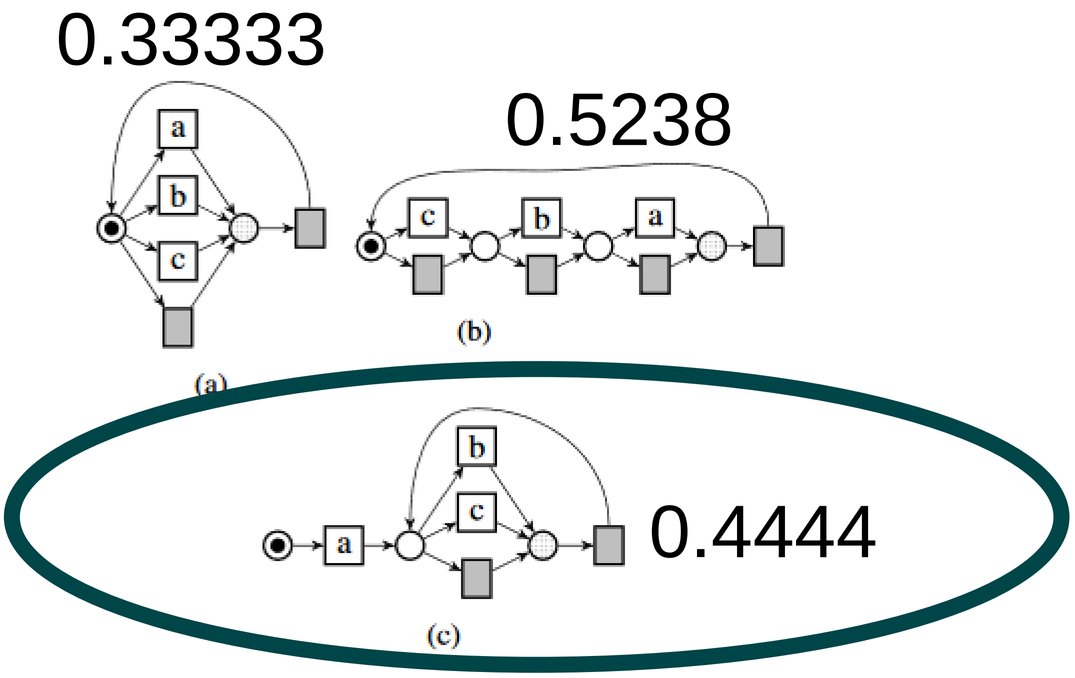
Axioms

- 5 Axioms (Tax et al.)

4. If *lang(*M1) = *lang*(M2), then *prec*(M1,L) = *prec*(M2,L), i.e., M1 is at least as precise as M2.

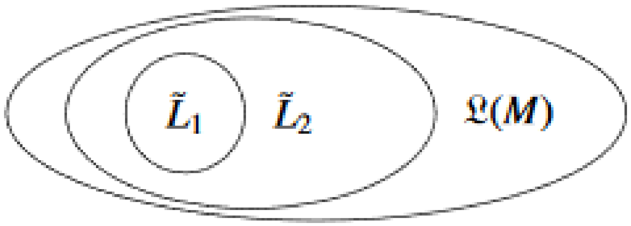
Escaping Edges

- Consider [<a,b,c>] and the models:
  - What model is mostly constraining the behavior?



Precision
Axioms

- 5 Axioms (Tax et al.)



5. If set(L1) ⊆ set(L2) ⊆ lang(M), then prec(M,L2) >= prec(M,L1)

Axioms

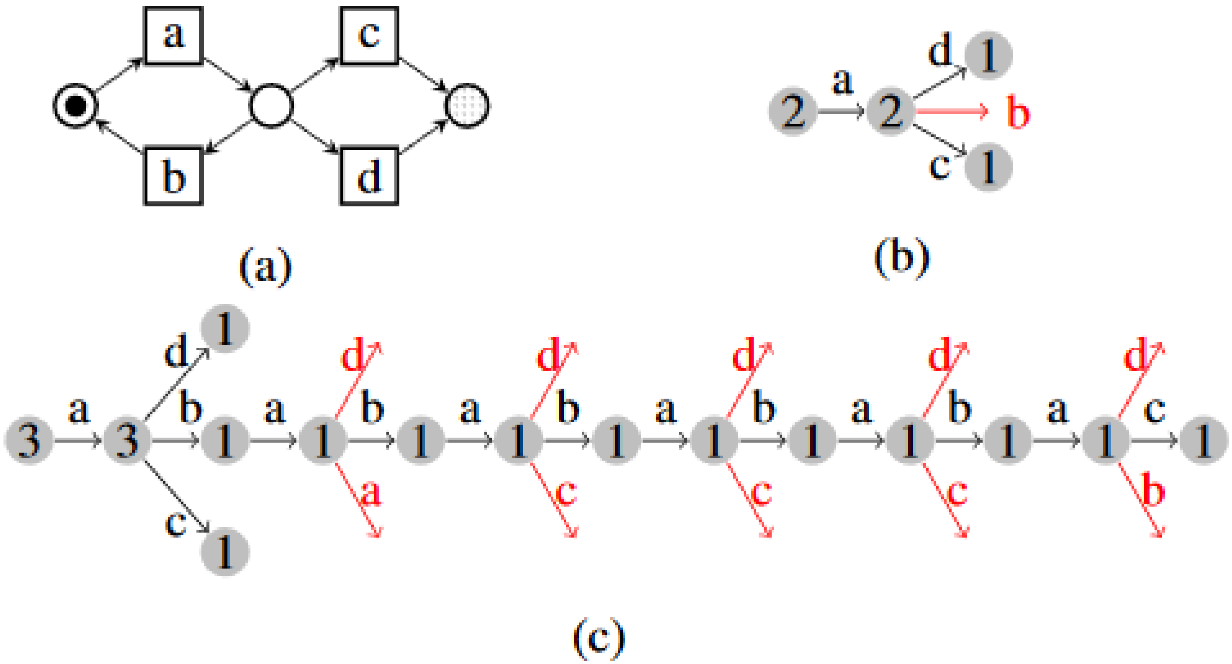


Figure 3: *(a)* Model M, and the alignment automata on Model M for *(b)* log L_1=[$\langle a,c\rangle,\langle a,d\rangle$], and for *(c)* log L_2=[$\langle a,c\rangle,\langle a,d\rangle,\langle a,b,a,b,a,b,a,b,a,b,a,c\rangle$]. Red arcs correspond to escaping edges.

Alternative Metrics (Overview)

- Artificial Negative Events (vanden Broucke et al.)

- If <a,b,c> (=positive) in event log, yet, <a,b,c,d> (=negative) is not then:
  - True Positive = trace allowed by model and in the log
  - False Positive = trace allowed by model and not in the log

  - Precision = TP / (TP + FP)

Alternative Metrics (Overview)

- Anti-Alignments (van Dongen et al.)

Definition 3 (Anti-alignment). *A (n, δ)-anti-alignment of a model N w.r.t. a log L and a distance function d is a run $\sigma \in \mathcal{L}(N)$ such that $|\sigma| = n$ and $d(\sigma, L) \geq \delta$.*

- d(...) is a distance function
  - Levenshtein Distance (a.k.a. string edit distance)

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Alternative Metrics (Overview)

- Anti-Alignments (van Dongen et al.)

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$$\mathcal{L}^n(N) = \{\sigma \in \mathcal{L}(N) \mid m_0[\sigma\rangle m_f \wedge |\sigma| \leq n\}.$$

Definition 4 (Maximal, Complete Anti-alignments, $\Gamma_n^{d,mx}(N, L)$). *Let N be a model. We define $\Gamma_n^{d,mx}(N, L) \subseteq \mathcal{L}^n(N)$ as the set of maximal, complete anti-alignments, such that for all $\sigma \in \Gamma_n^{d,mx}(N, L)$ holds that $\nexists \sigma' \in \mathcal{L}^n(N) \setminus \Gamma_n^{d,mx}(N, L)$ with $d(\sigma', L) > d(\sigma, L)$.*

In the remainder of this paper, we write $\gamma_n^{d,mx}(N, L)$ whenever we need an arbitrary element from the set $\Gamma_n^{d,mx}(N, L)$.

Alternative Metrics (Overview)

- Anti-Alignments (van Dongen et al.)

Definition 5 (Trace-Based Precision). *Let (L, ϕ) be an event log and N a model. We define trace-based precision as follows:*

$$P_t(N, L) = 1 - \frac{1}{|L|} \cdot \sum_{\sigma \in L} d(\sigma, \gamma^{d,mx}_{|\sigma|}(N, L \setminus \{\sigma\})).$$

We assume a perfectly fitting log, i.e. $\sigma \in \mathcal{L}^{|\sigma|}(N)$ and hence $\gamma^{d,mx}_{|\sigma|}(N, L \setminus \{\sigma\})$ exists.

- Rationale: the larger the summation, the smaller precision
    - Summation gets larger if the distance, a.k.a. what is described by model versus what is in L gets larger!

Alternative Metrics (Overview)

- Anti-Alignments (van Dongen et al.)

Definition 6 (Log-Based Precision). *Let (L, ϕ) be an event log and N a model. We define Log-based precision as follows:*

$$P_l^n(N, L) = 1 - d(\gamma_n^{d,mx}(N, L), L).$$

where n represents the maximal length of the anti-alignment, typically in the order of several times the length of the longest trace in the log.

- Difference: uses 1 alignment for the whole log…

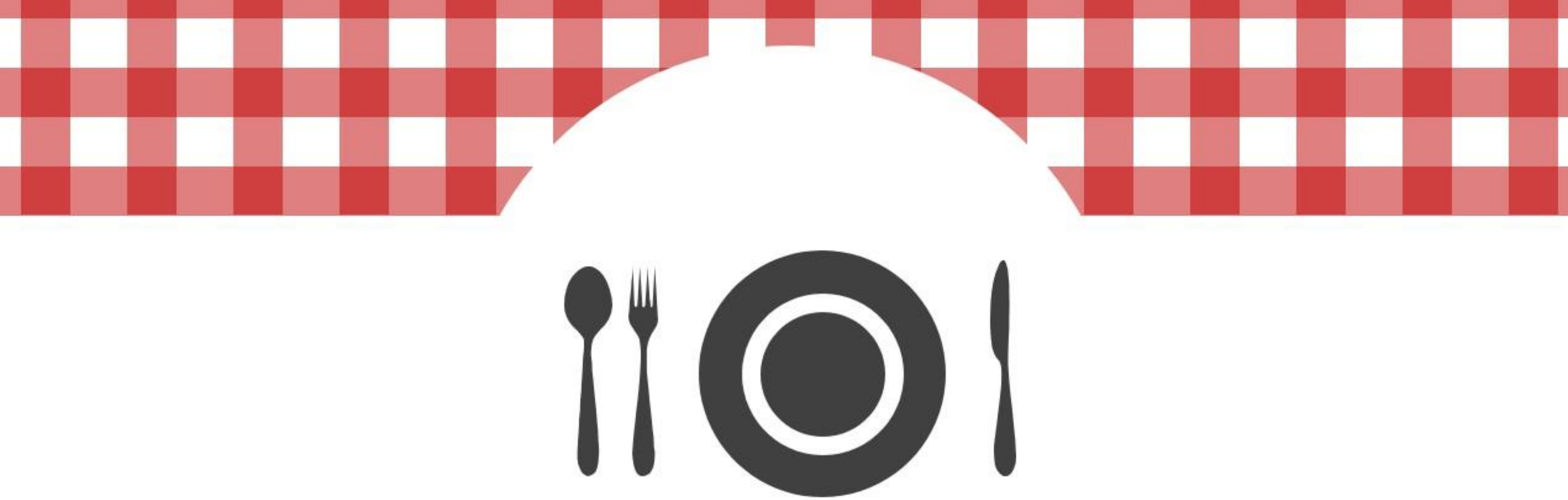
Alternative Metrics (Overview)

- Anti-Alignments (van Dongen et al.)

Definition 7 (Precision). *Let (L, ϕ) be an event log and N a model. We define anti-alignment based precision as follows:*

$$P(N, L) = \alpha P_t(N, L) + (1 - \alpha) P_l^n(N, L)$$

This definition is parameterized by α and n. In the remainder of the paper, we choose $\alpha = 0.5$ and $n = 2 \cdot \max_{\sigma \in L} |\sigma|$.



- Quality Dimensions (Recap)

- Replay-Fitness (Recap)
- Precision
- Simplicity
- Generalization

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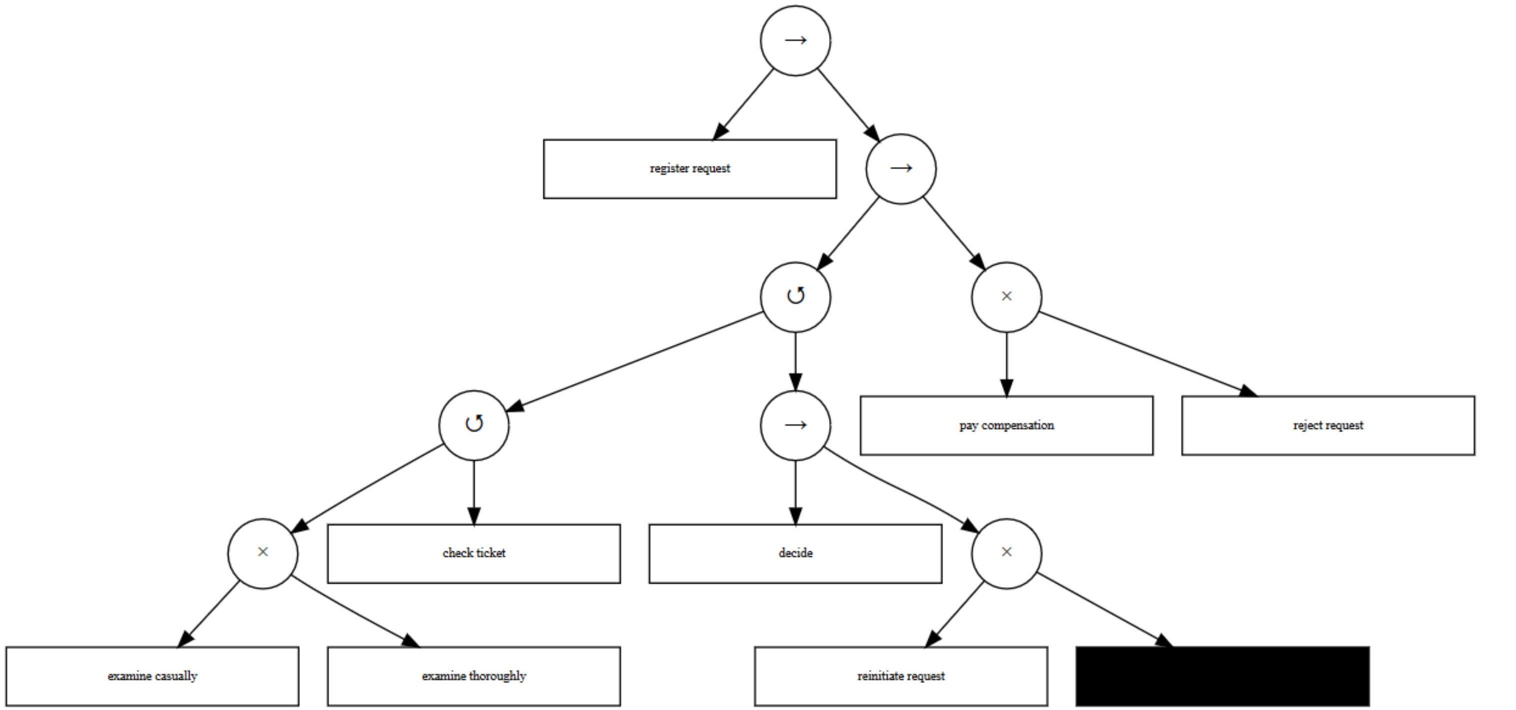
Occam’s Razor

- “Suppose there exist two explanations for an occurrence. In this case the one that requires the least speculation is usually correct. Another way of saying it is that the more assumptions you have to make, the more unlikely an explanation.”

Occam’s Razor

- Main Problem with Simplicity
- Subjective

Occam’s Razor



Can be perceived as ‘simpler’ than its corresponding Petri net representation!

Occam’s Razor

- Main Problem with Simplicity

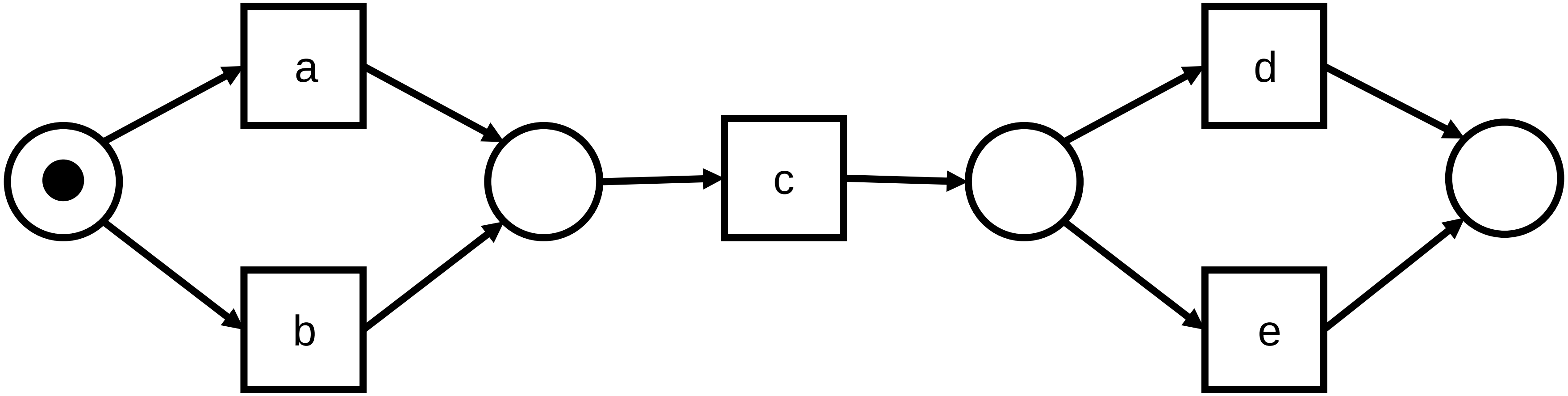
- Subjective
- Hard to express in a single number

Occam's Razor

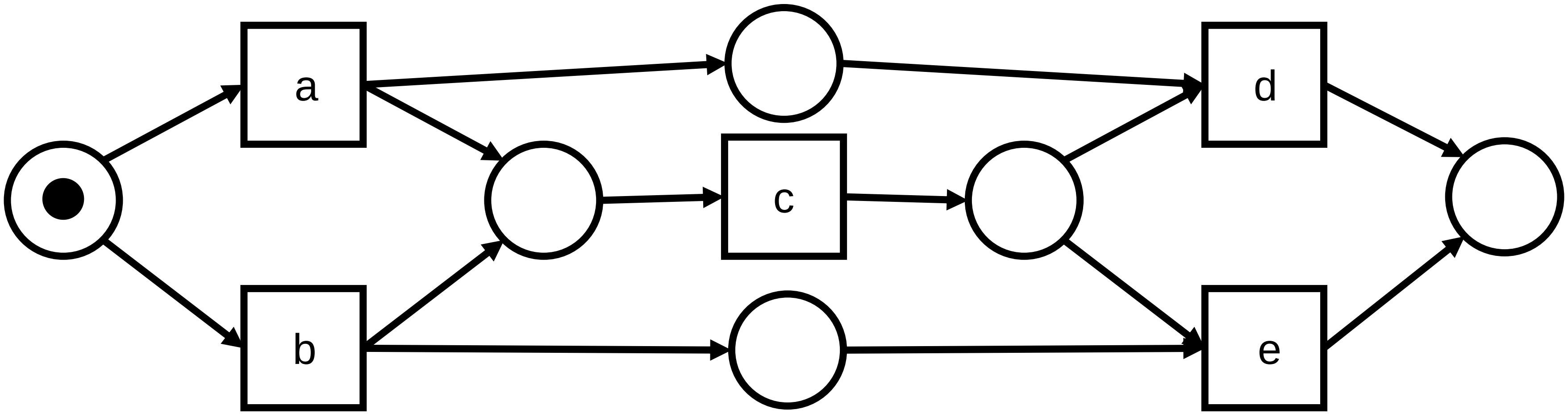
- Main Problem with Simplicity

- Subjective
- Hard to express in a single number
- Selection Bias
- …

Occam's Razor

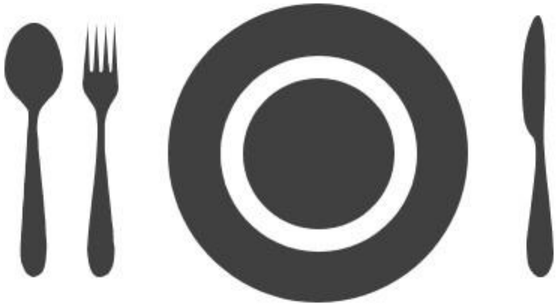


Occam's Razor



Occam's Razor

- Mendling et al.
- There is a strong correlation between existing graph complexity metrics and process model errors (e.g., unsoundness, deadlocks…)



- Quality Dimensions (Recap)
- Replay-Fitness (Recap)
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Definition (Informal)

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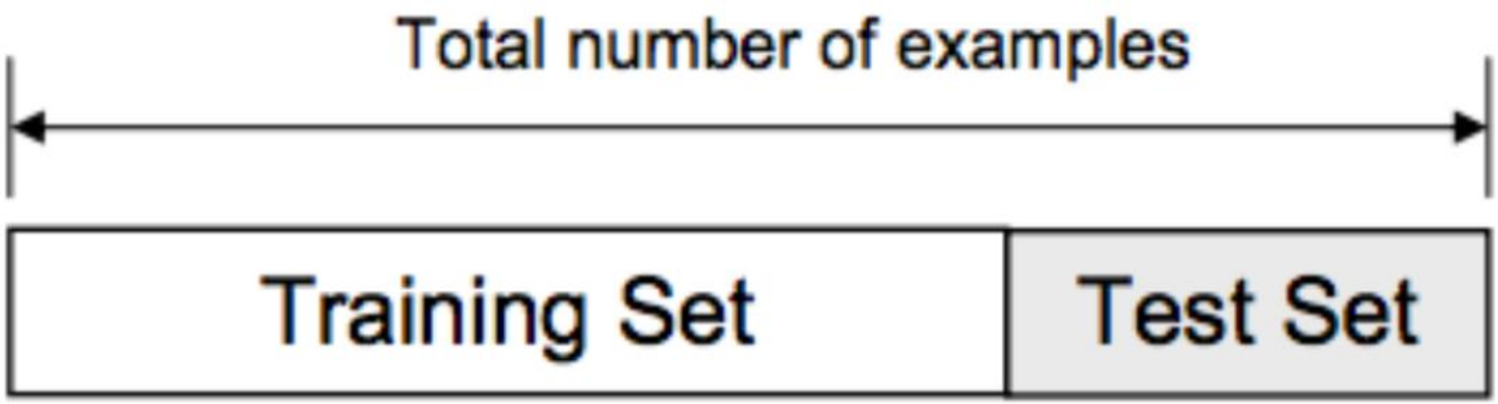
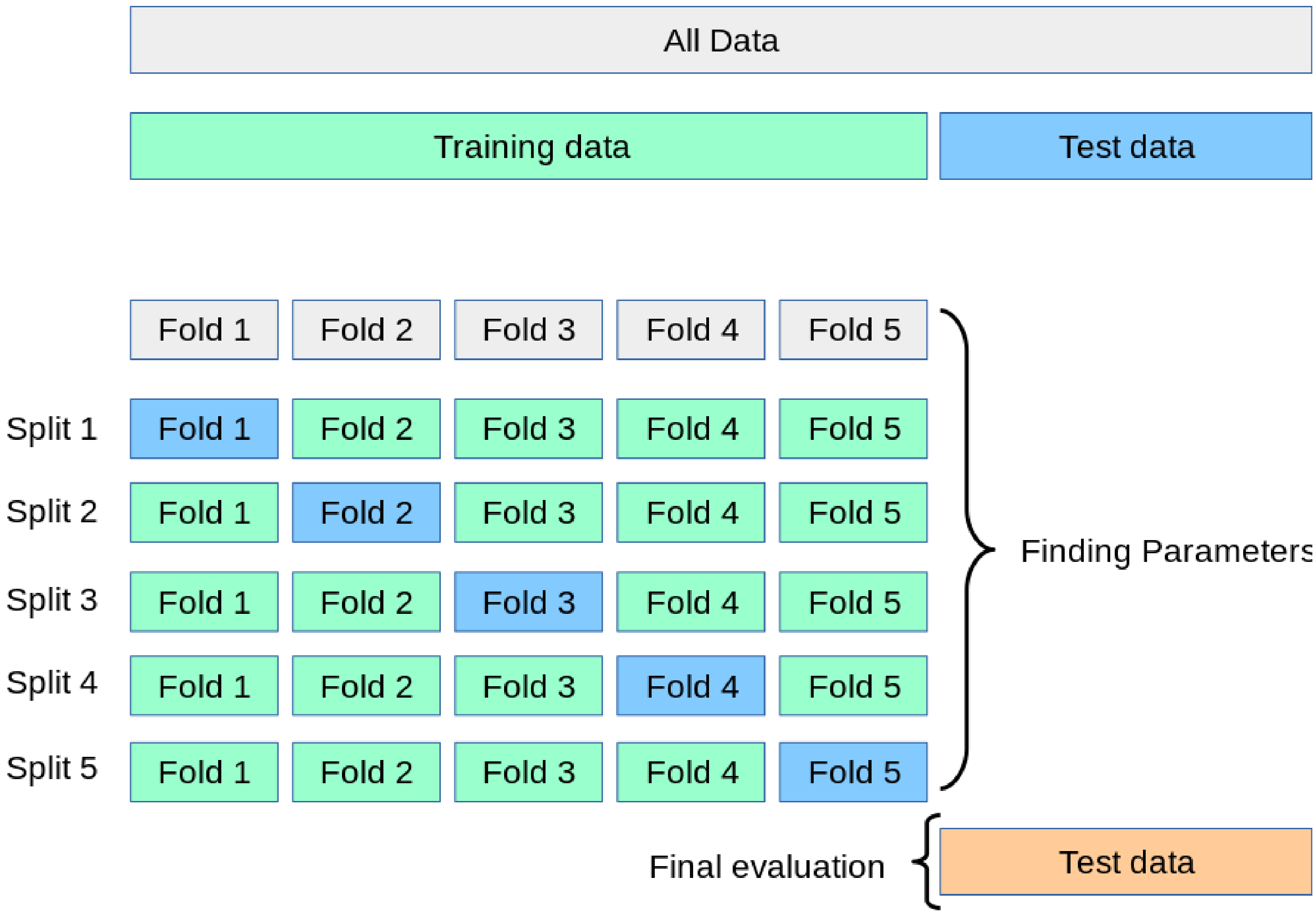
1. Does it make sense to compute generalization on the same log as the log used for training?
2. Is precision the inverse of generalization?

Definition (Informal)

- One approach:

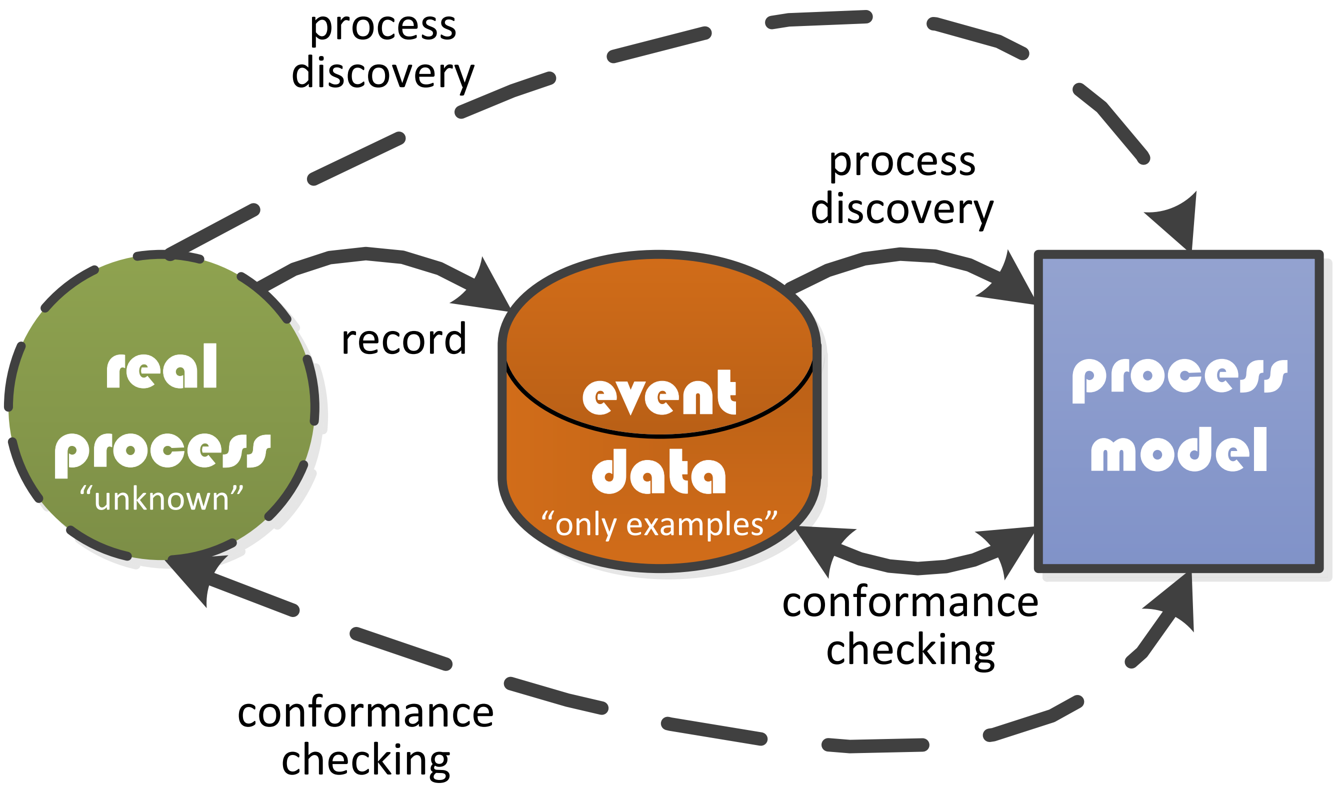


Generalization
Metrics

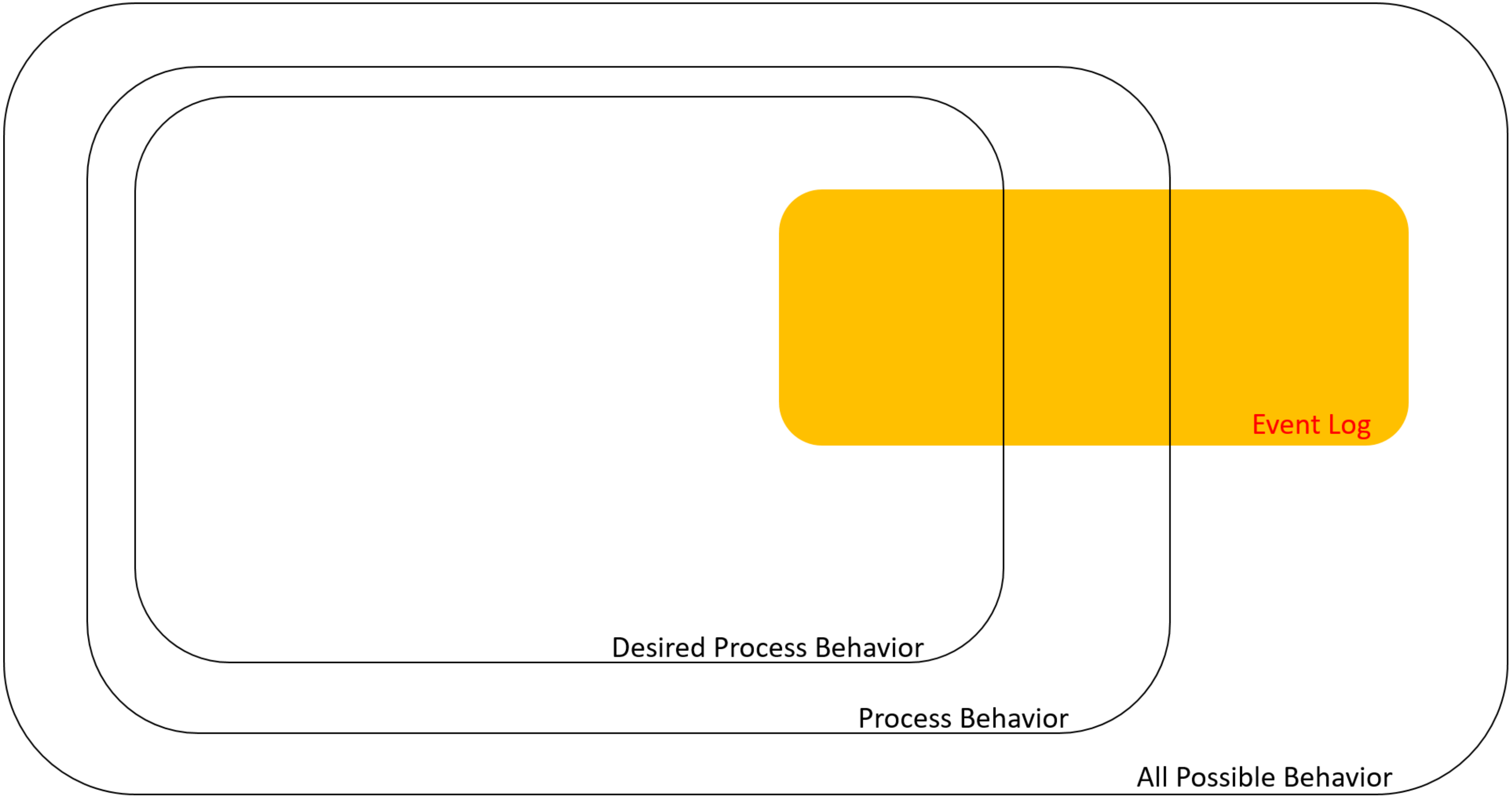


Comparing Real and Modeled Behavior

Is the process model a correct reflection of the real process?



Putting Process Mining in Perspective



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