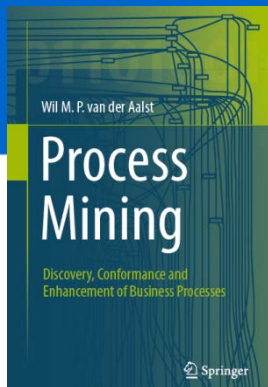


Process Mining: Data Science in Action

Four Quality Criteria for Process Discovery

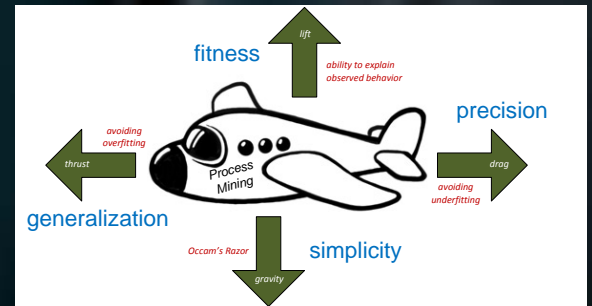
prof.dr.ir. Wil van der Aalst
www.processmining.org



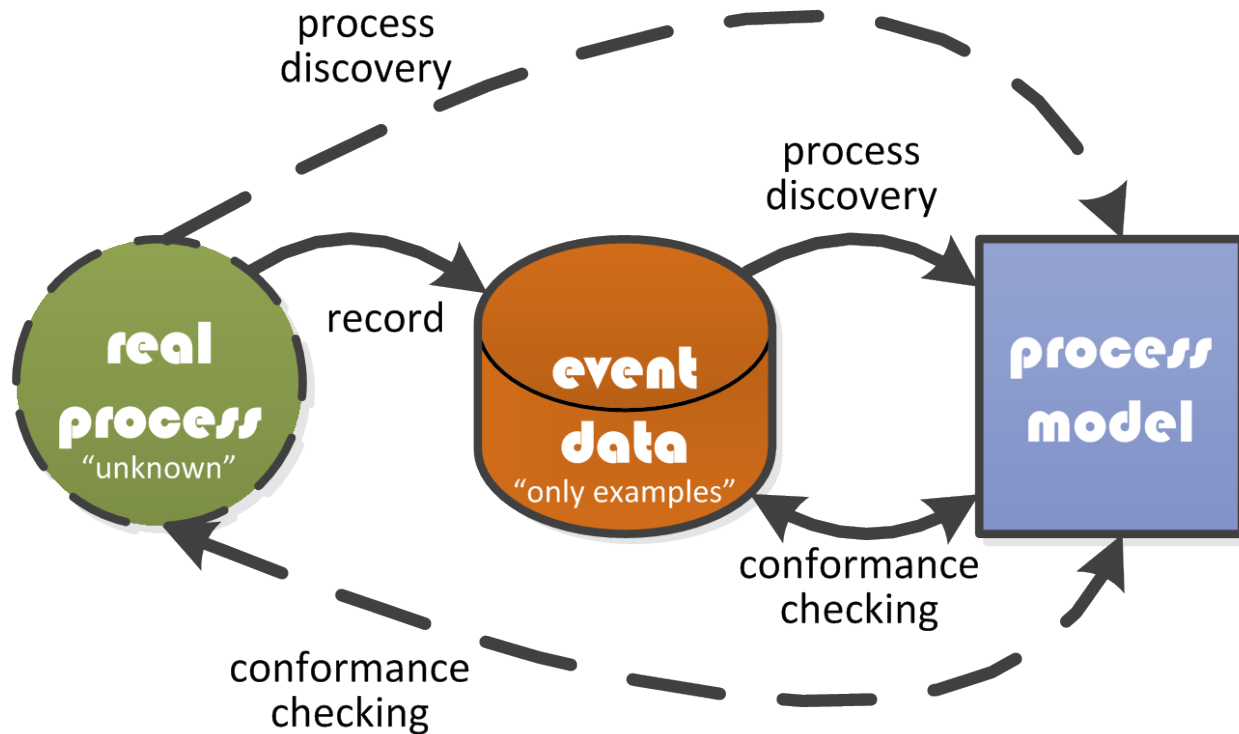
TU/e

Technische Universiteit
Eindhoven
University of Technology

Where innovation starts



Overview



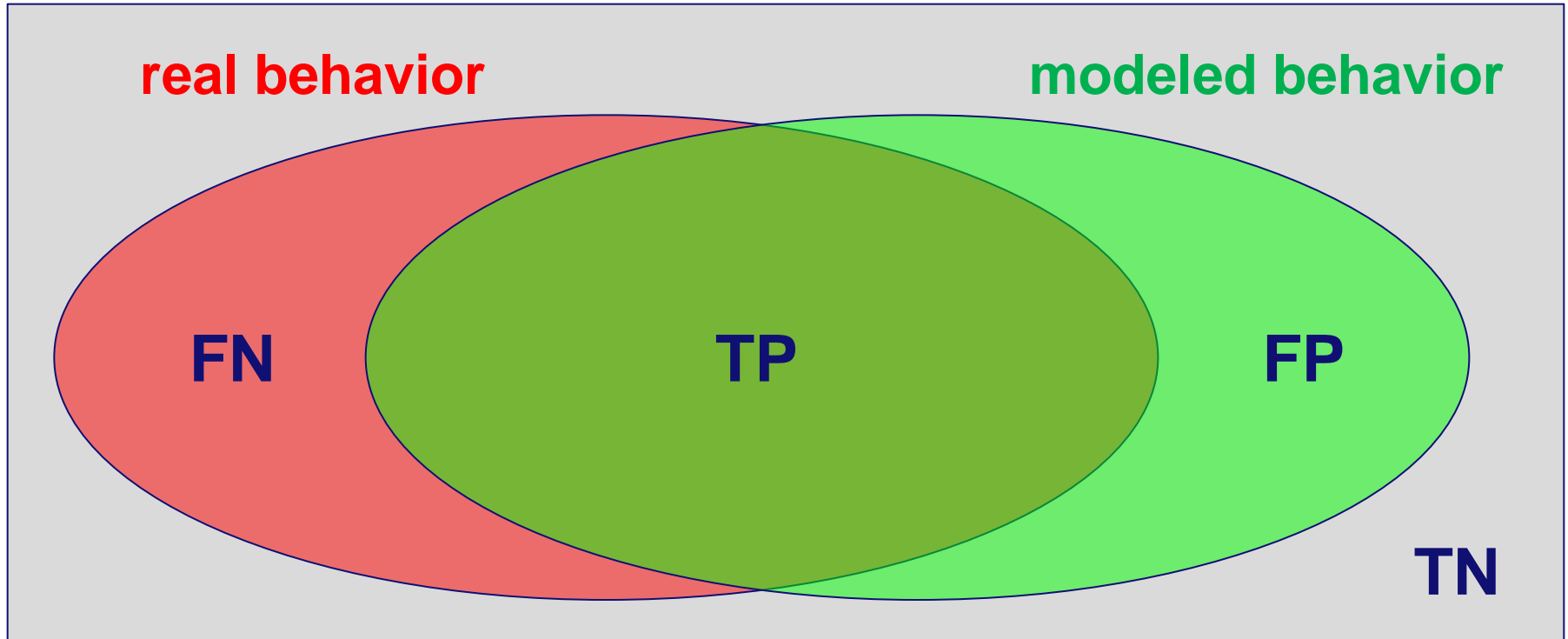
Is the process model a correct reflection of the real process?

Naïve approach based on classification

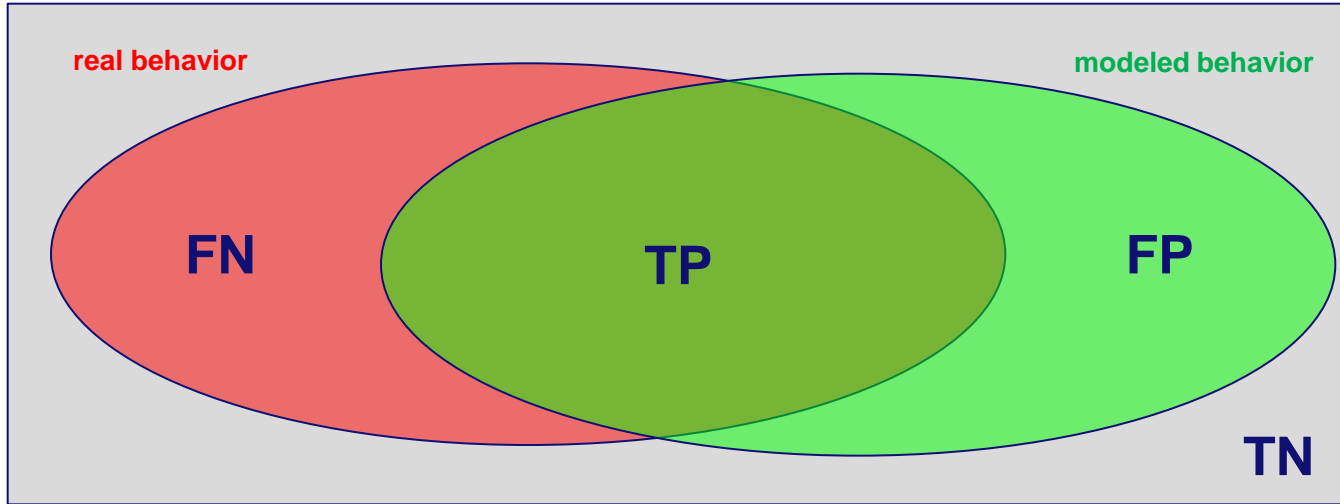
- **True Positives (TP):** traces possible in model and also possible in real process.
- **True Negatives (TN):** traces not possible in model and also not possible in real process.
- **False Positives (FP):** traces possible in model but not possible in real process.
- **False Negatives (FN):** traces not possible in model but possible in real process.

		<i>predicted class</i>	
		+	-
<i>actual class</i>	+	TP	FN
	-	FP	TN

Visualization of True/False Positives/Negatives



Metrics

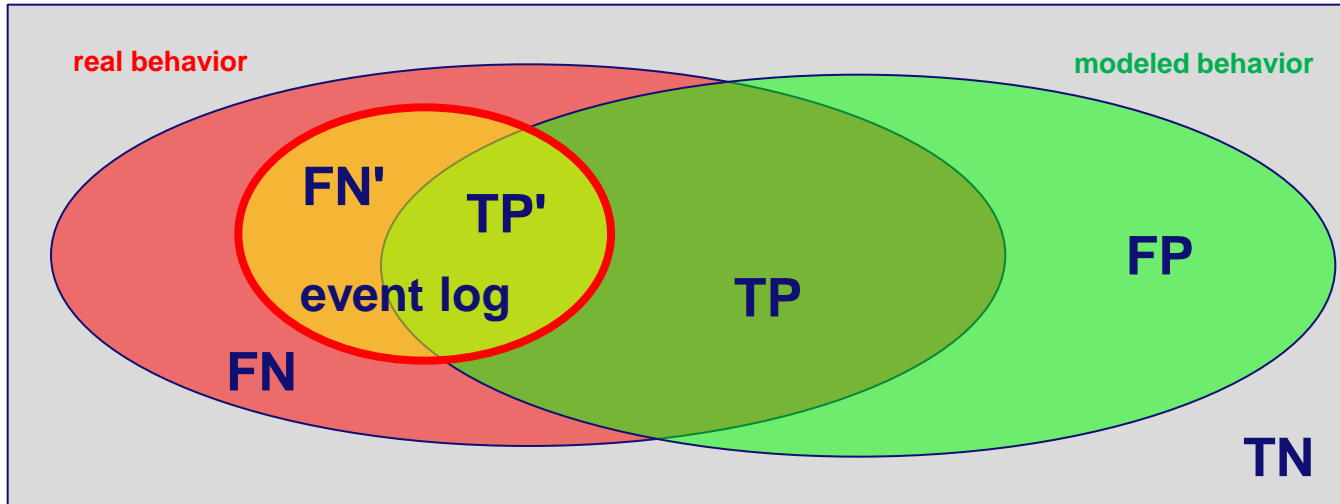


$$recall = \frac{TP}{TP + FN}$$

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

Problem

Typically the event log only shows fraction of possible traces



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

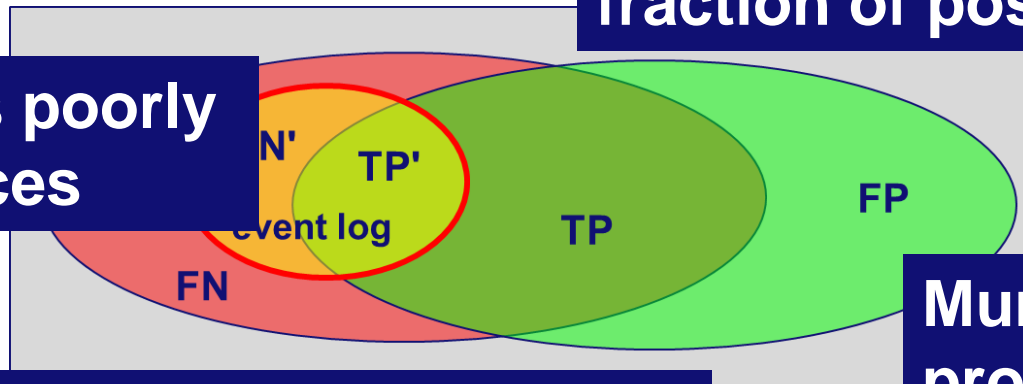
$$\text{replay_fitness} = \frac{TP'}{TP' + FN'}$$

Challenges

No negative examples
(cannot see what cannot happen)

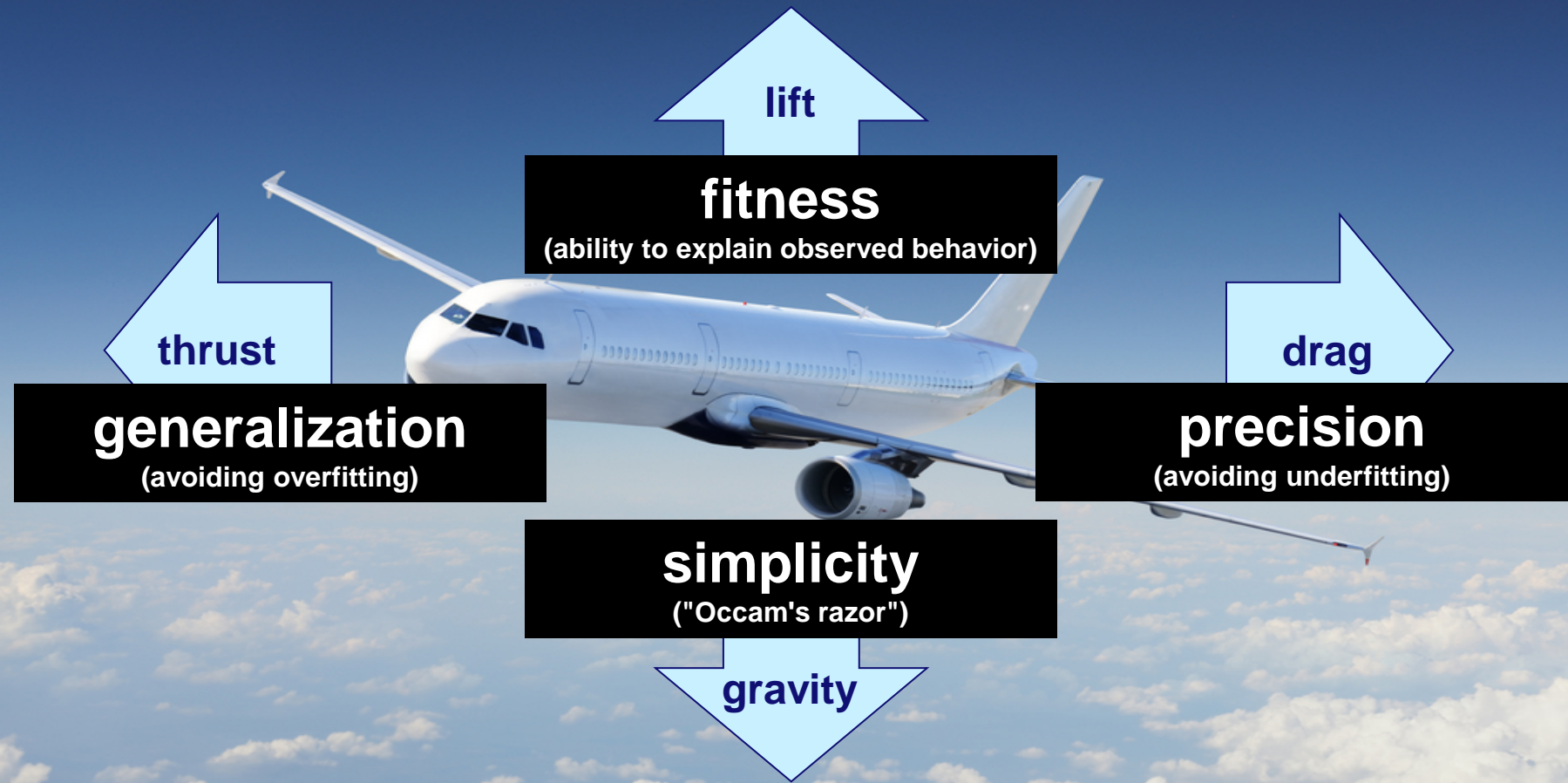
Log contains only a fraction of possible traces

Almost vs poorly fitting traces



In case of loops often infinitely many possible traces

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



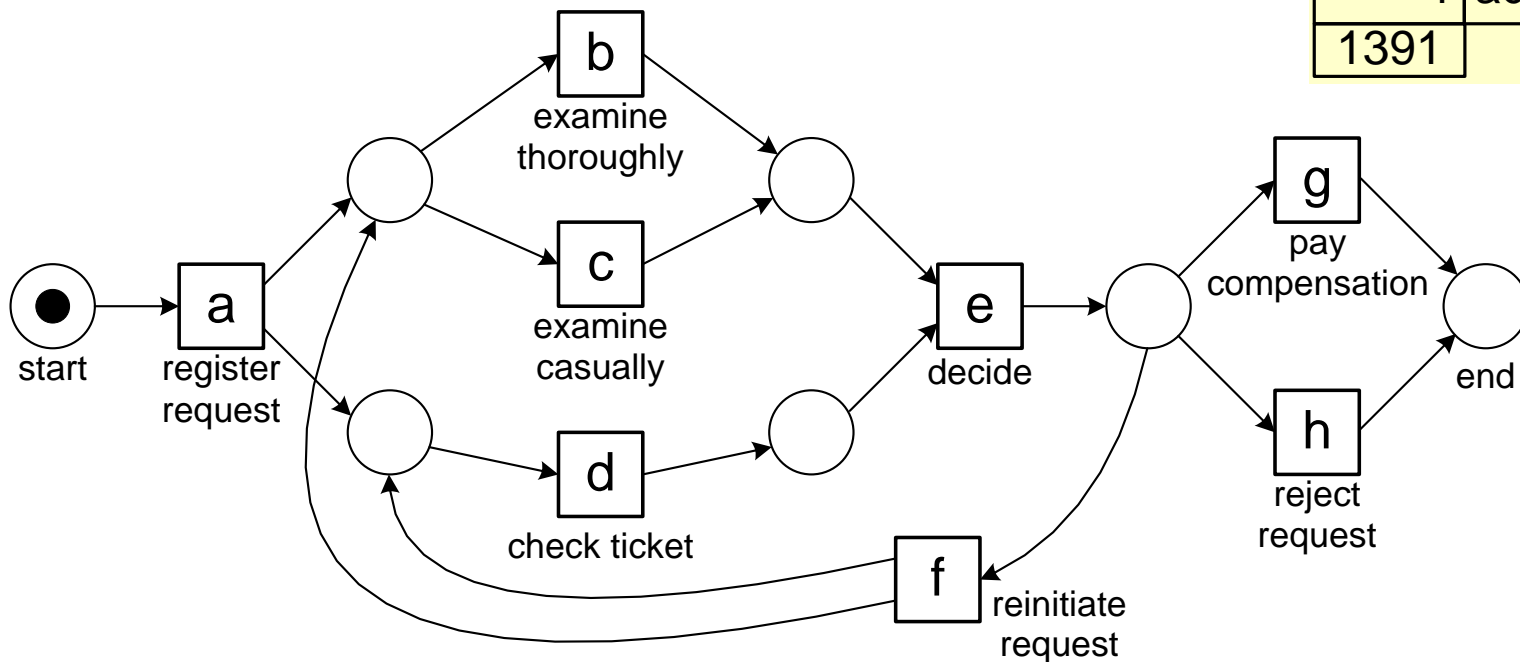
Four Forces

Example log

#	trace
455	acdeh
191	abdeg
177	adceh
144	abdeh

Model that seems to be OK ...

#	trace
455	acdeh
191	abdeg
...	...
1	adcefdbefcdefdbeg
1391	



56	adbeh
47	acdefdbeh
38	adbeg
33	acdefdbdeh
14	acdefdbdeg
11	acdefdbeg
9	adcefcdeh
8	adcefdbeh
5	adcefbdeg
3	acdefdbdefdbeg
2	adcefdbeg
2	adcefbdefdbeg
1	adcefdbefdbdeh
1	adbefbdefdbeg
1	adcefdbefcdefdbeg

fitness
(observed behavior fits)

simplicity
("Occam's razor")

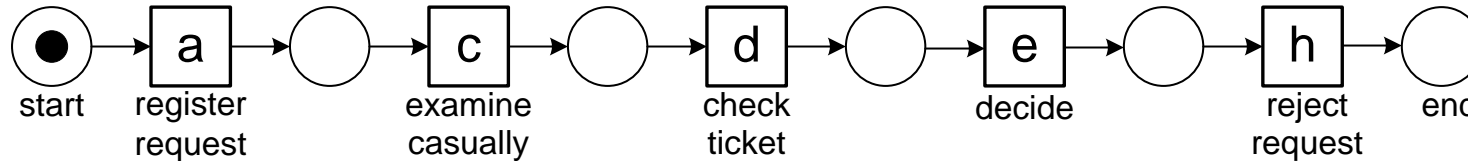
precision
(avoiding underfitting)

generalization
(avoiding overfitting)

391

Non-fitting model

#	trace
455	acdeh
191	abdeg
...	...
1	adcefdbefcdefdbeg
1391	



56	adbeh
47	acdefdbeh
38	adbeg
33	acdefdbdeh
14	acdefdbdeg
11	acdefdbeg
9	adcefcdeh
8	adcefdbeh
5	adcefbdeg
3	acdefbdefdbeg
2	adcefdbeg
2	adcefbdefdbeg
1	adcefdbefdbdeh
1	adbefbdefdbeg
1	adcefdbefcdefdbeg

fitness
(observed behavior fits)

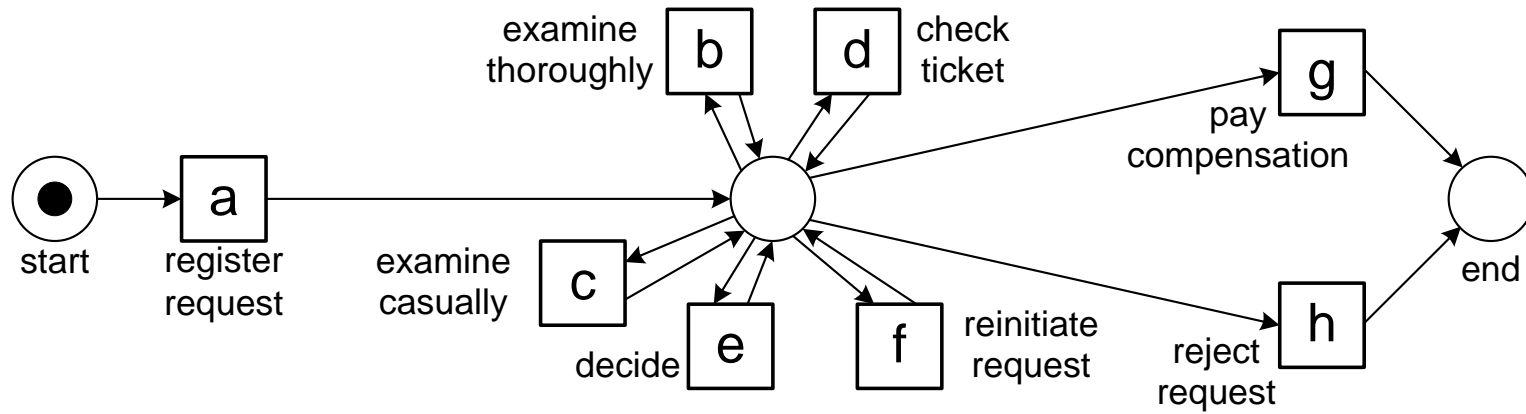
simplicity
("Occam's razor")

precision
(avoiding underfitting)

generalization
(avoiding overfitting)

391

Underfitting model



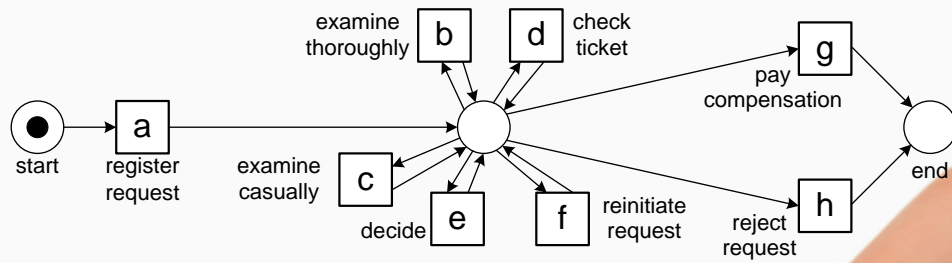
fitness
(observed behavior fits)

simplicity
("Occam's razor")

precision
(avoiding underfitting)

generalization
(avoiding overfitting)

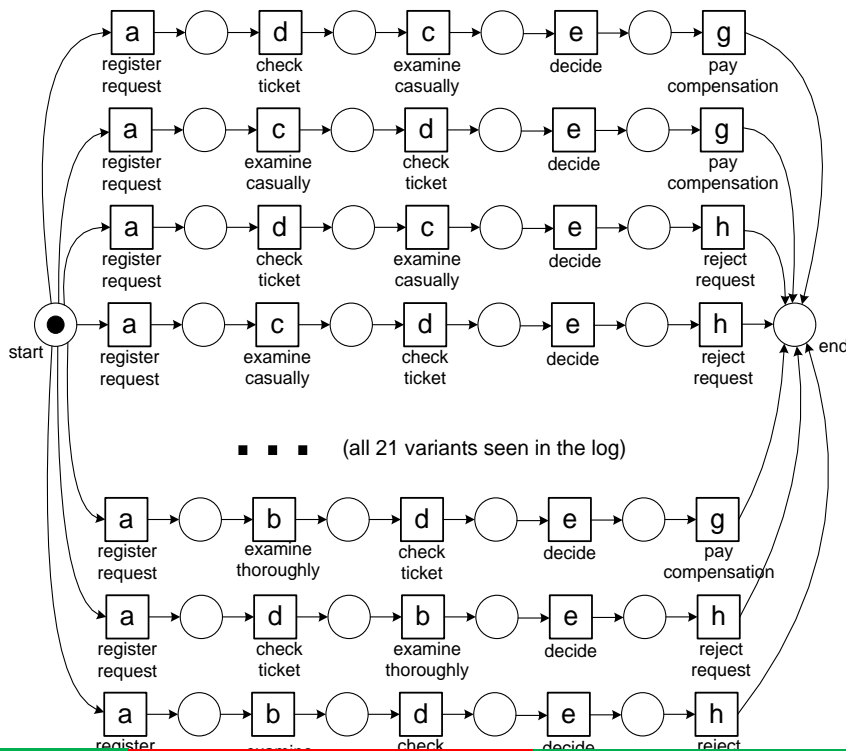
#	trace
455	acdeh
191	abdeg
177	adceh
144	abdeh
111	acdeg
82	adceg
56	adbeh
47	acdefdbeh
38	adbeg
33	acdefbdeh
14	acdefdbdeg
11	acdefdbeg
9	adcefcdeh
8	adcefdbeh
5	adcefbdeg
3	acdefbdefdbeg
2	adcefdbeg
2	adcefbdefdbeg
1	adcefdbefdbdeh
1	adbefbdefdbeg
1	adcefdbefcdefdbeg
391	



underfitting



Overfitting model



fitness
(observed behavior fits)

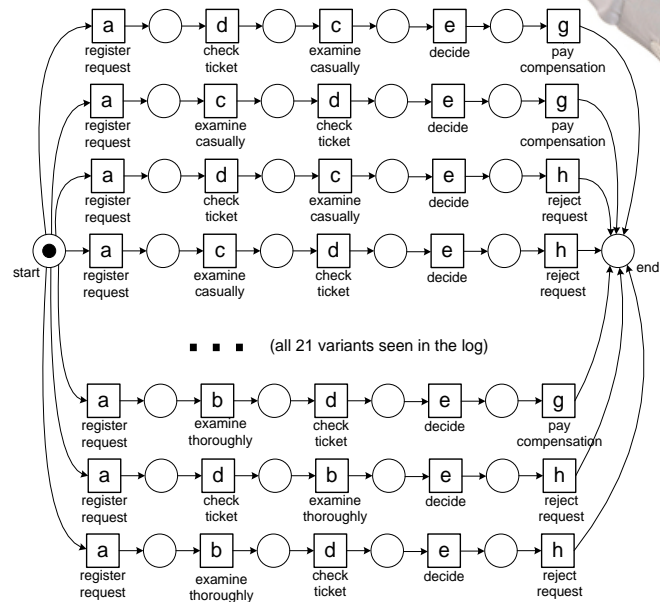
simplicity
("Occam's razor")

precision
(avoiding underfitting)

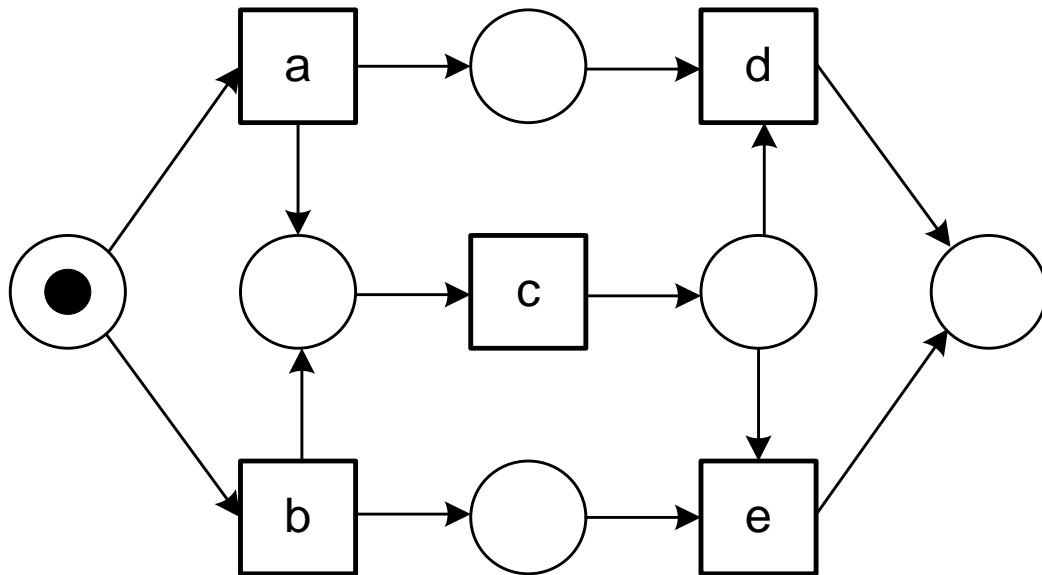
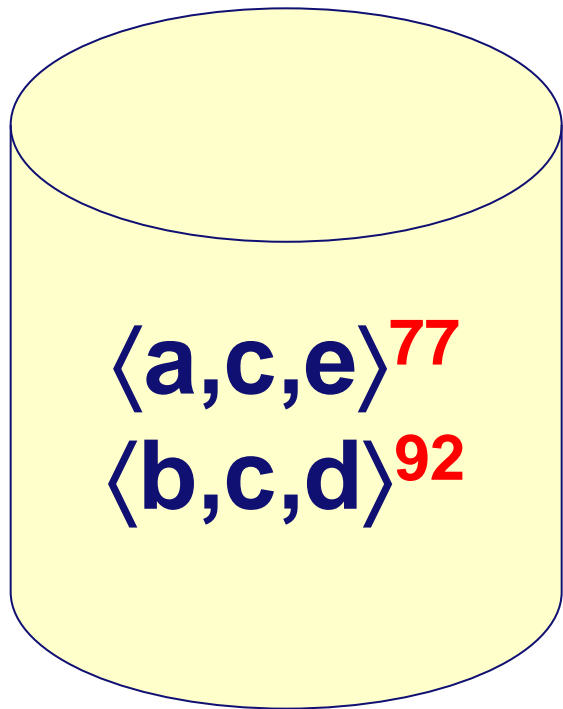
generalization
(avoiding overfitting)

#	trace
455	acdeh
191	abdeg
177	adceh
144	abdeh
111	acdeg
82	adceg
56	adbeh
47	acdefdbeh
38	adbeg
33	acdefdbdeh
14	acdefdbdeg
11	acdefdbeg
9	adcefcdeh
8	adcefdbeh
5	adcefbdeg
3	acdefbdefdbeg
2	adcefdbeg
2	adcefbdefdbeg
1	adcefdbefdbdeh
1	adbefbdefdbeg
1	adcefdbefcdefdbeg
391	

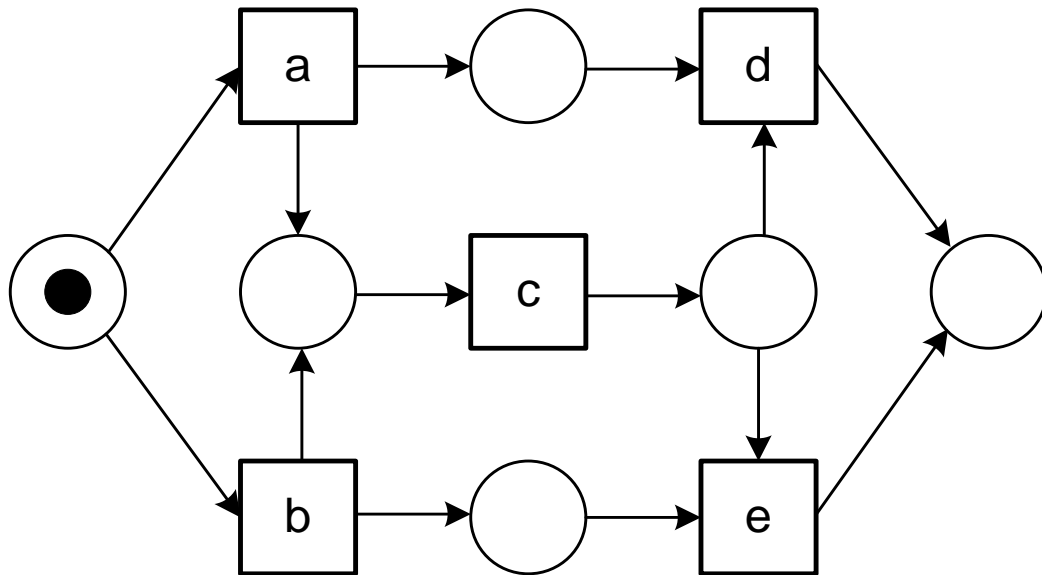
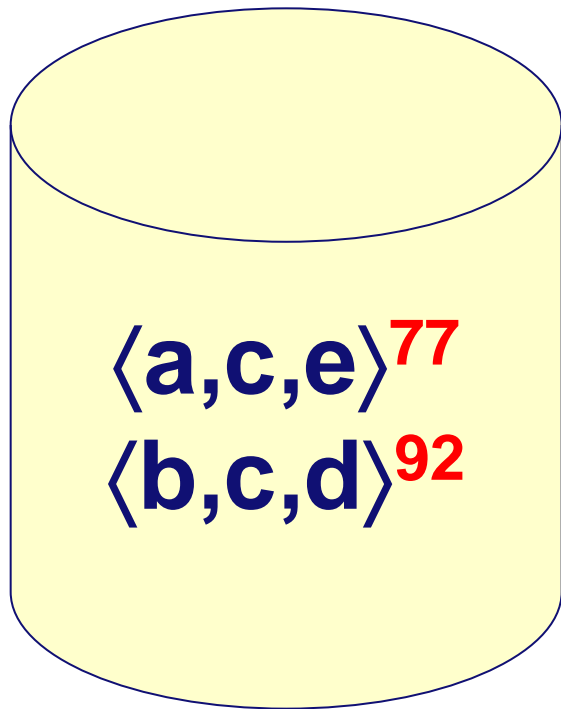
overfitting



Fitness: good or bad?

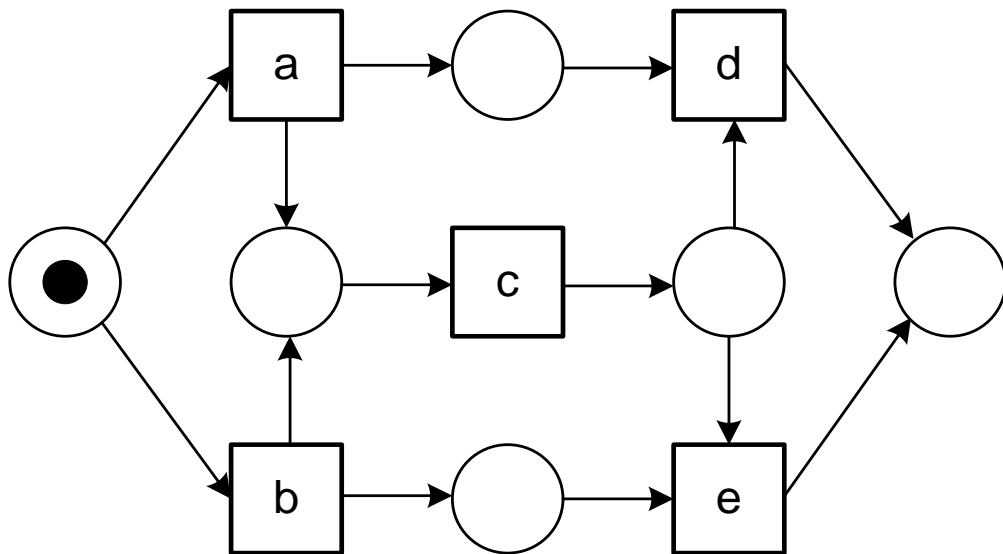
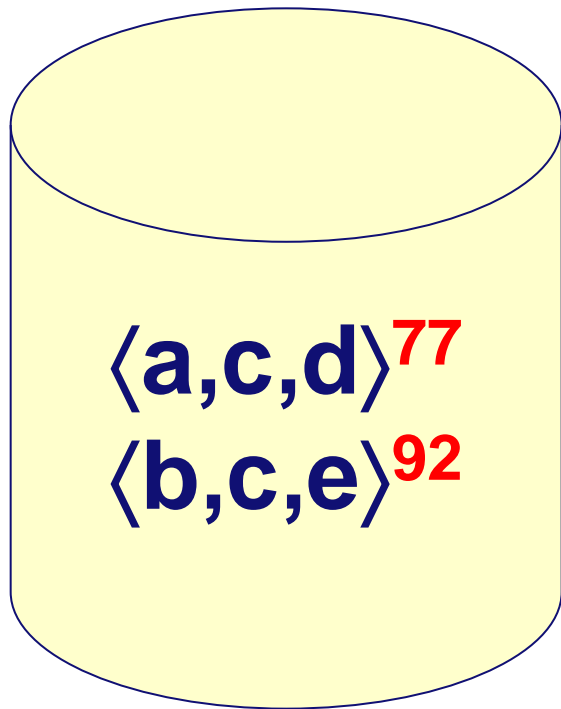


Fitness: **bad!**

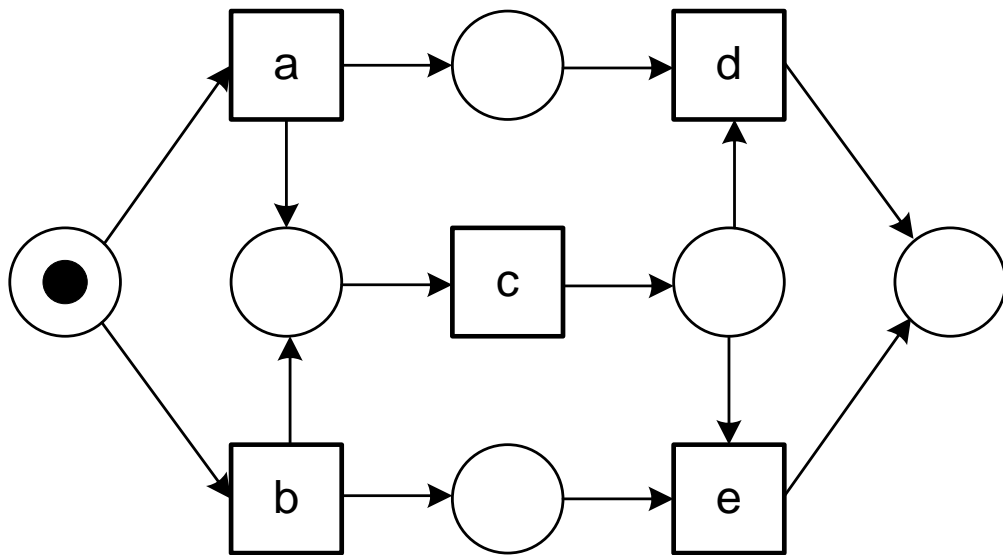
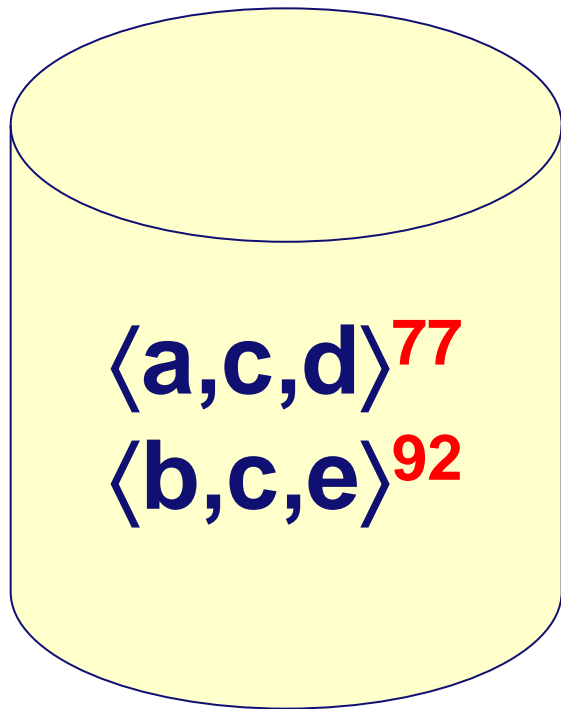


both traces do not fit ...

Precision: good or bad?

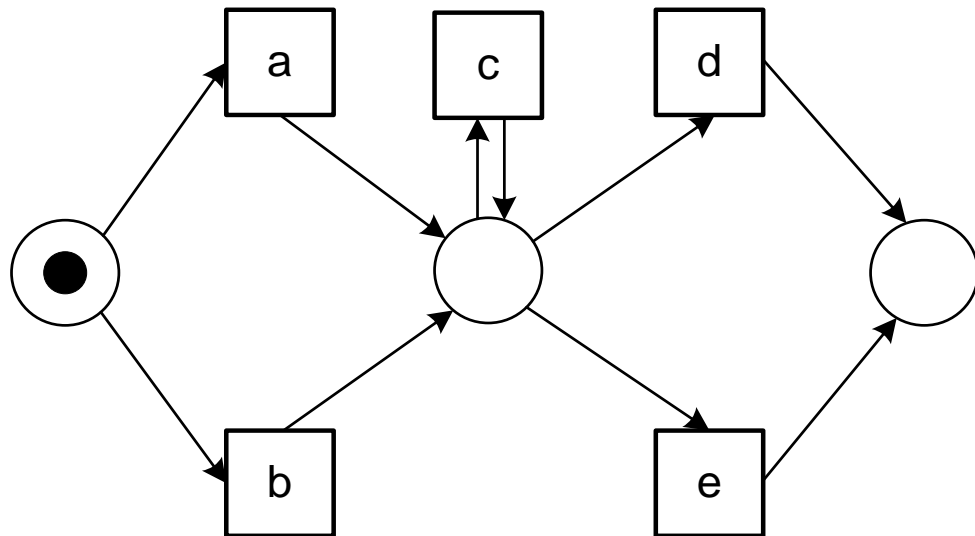
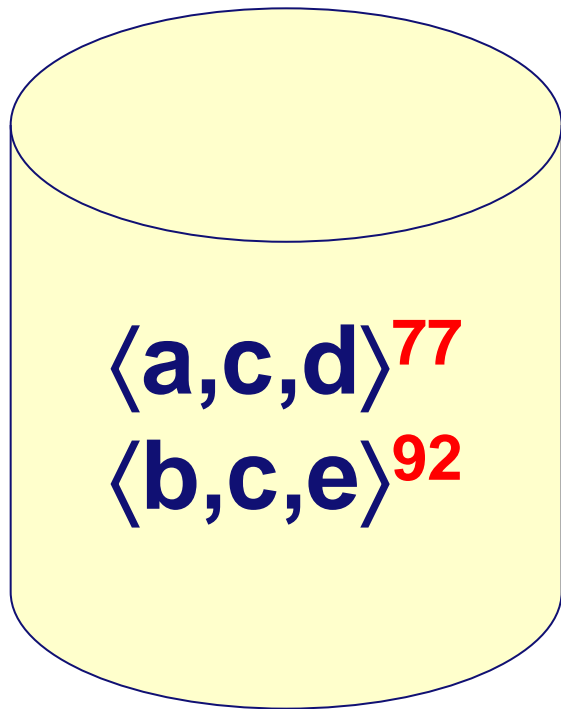


Precision: **good!**

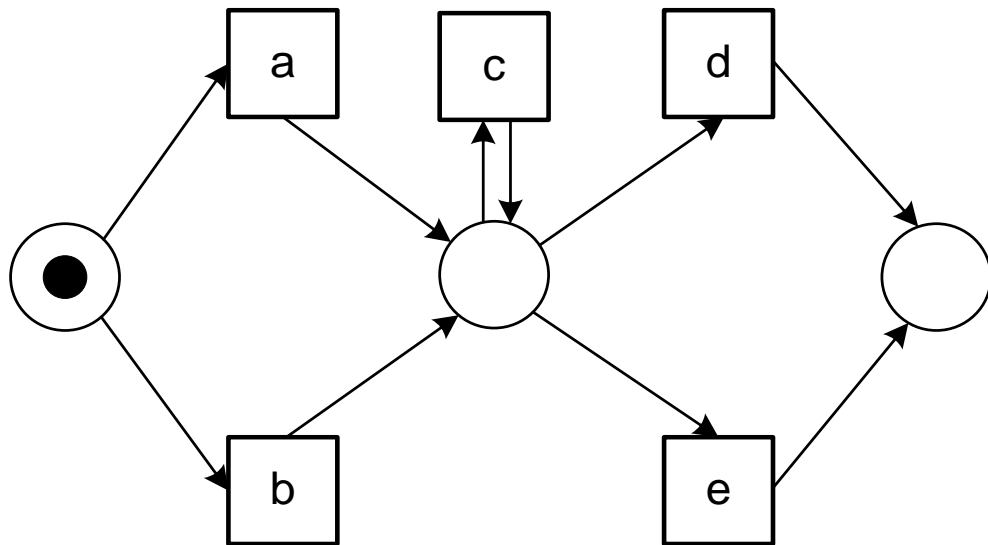
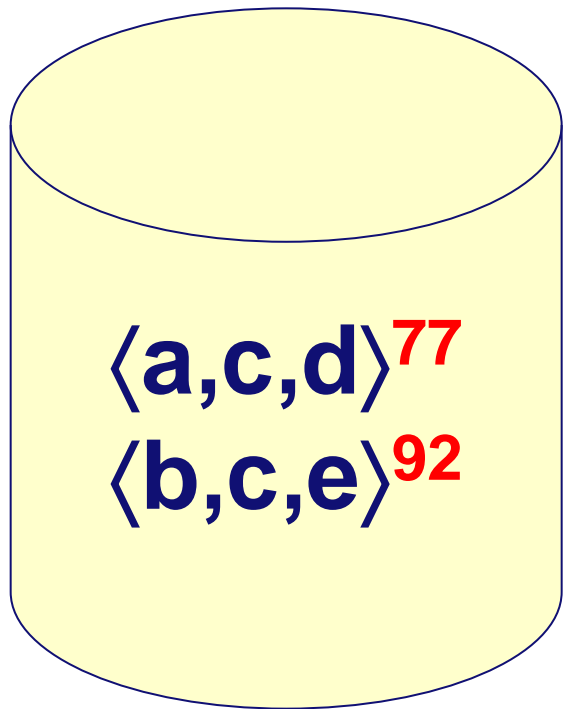


not underfitting...

Precision: good or bad?

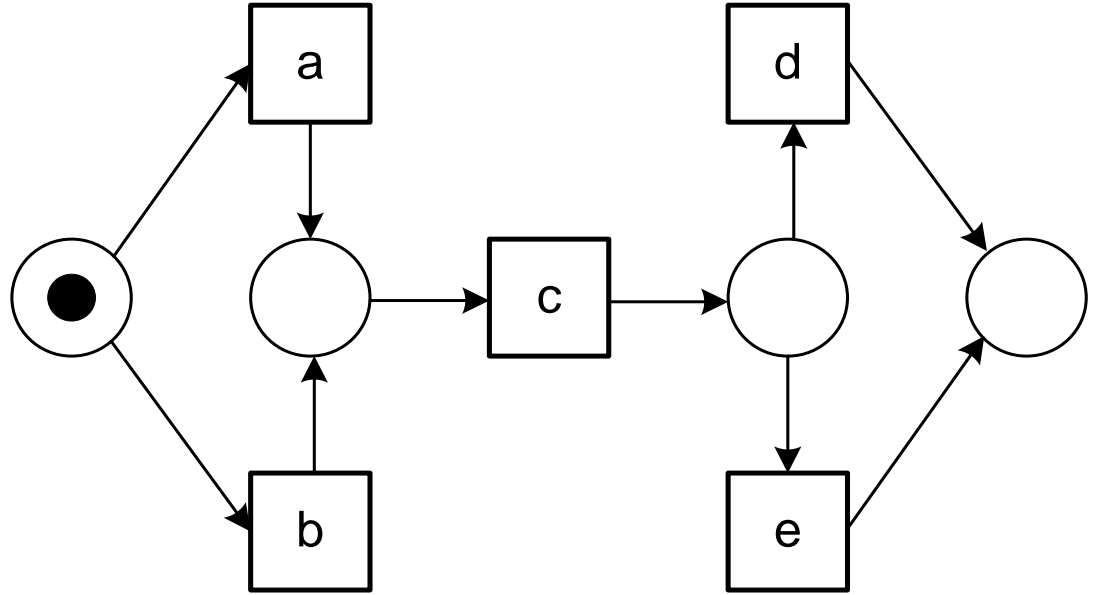
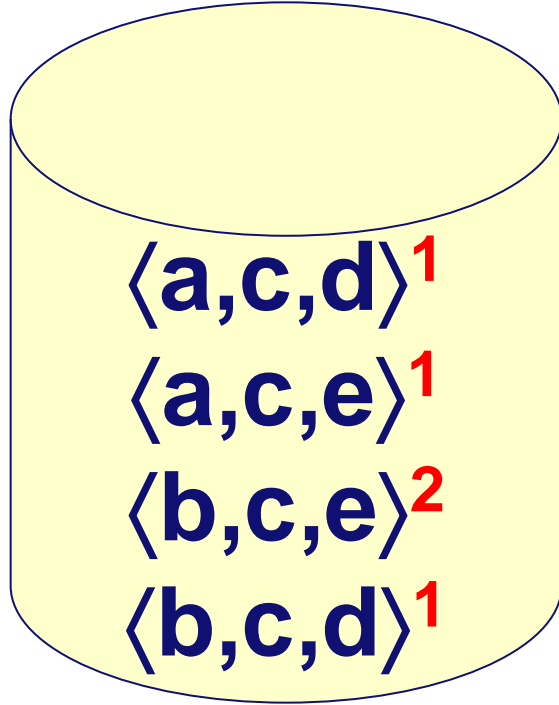


Precision: **bad!**

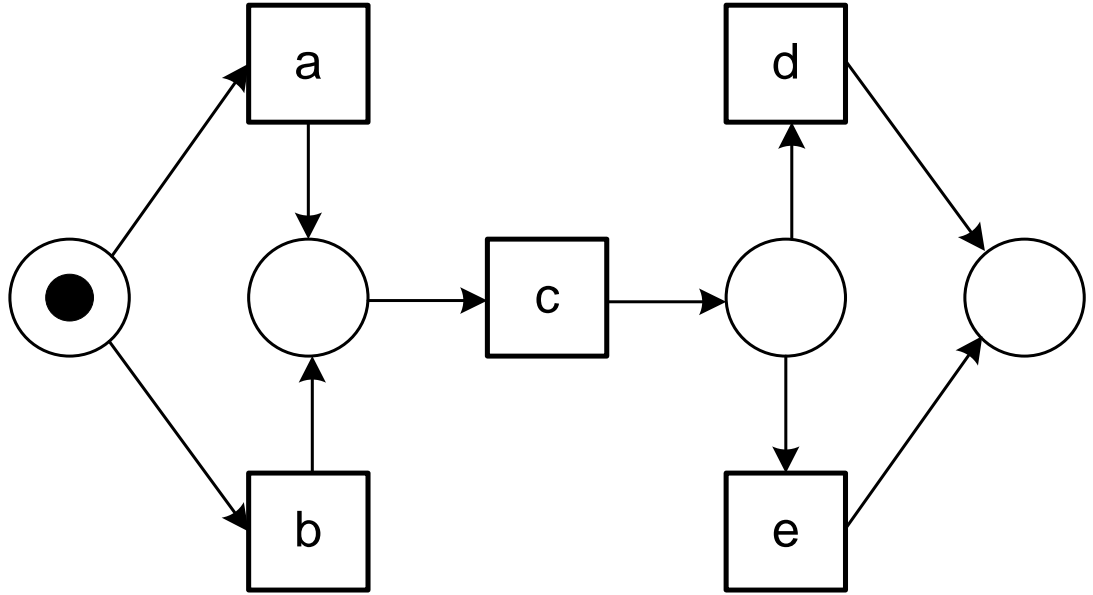
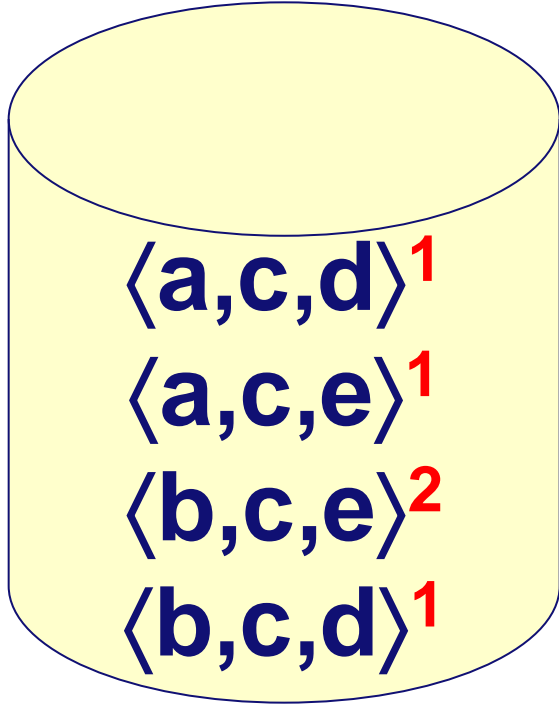


underfitting (allows for highly unlikely behavior) ...

Generalization: good or bad?

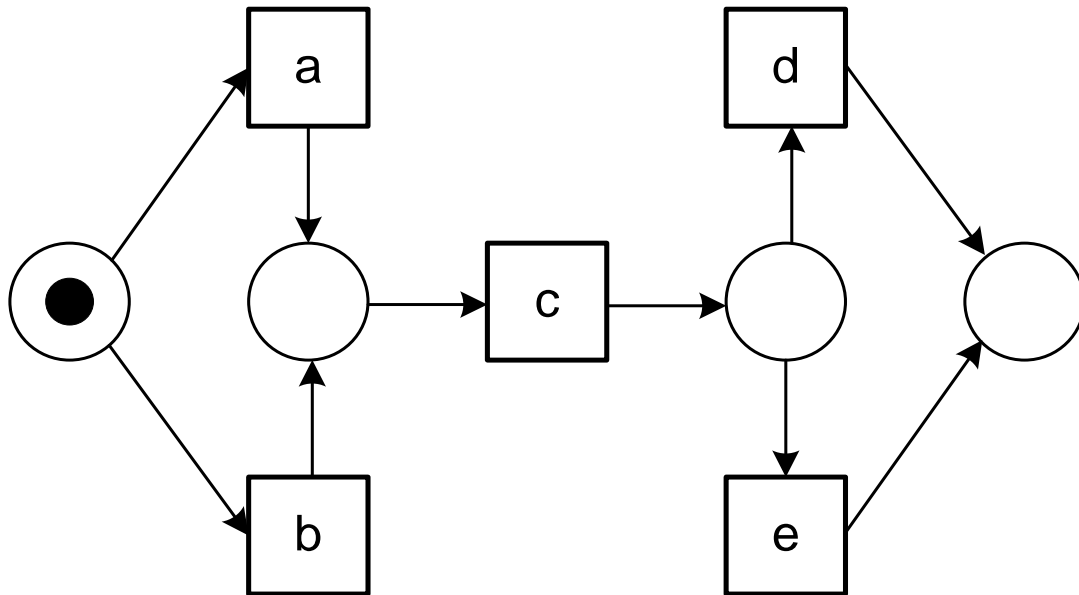
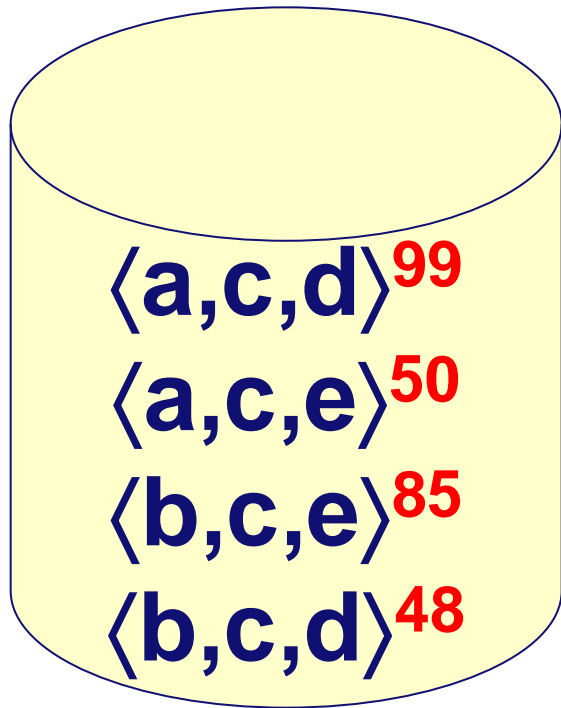


Generalization: **bad!**

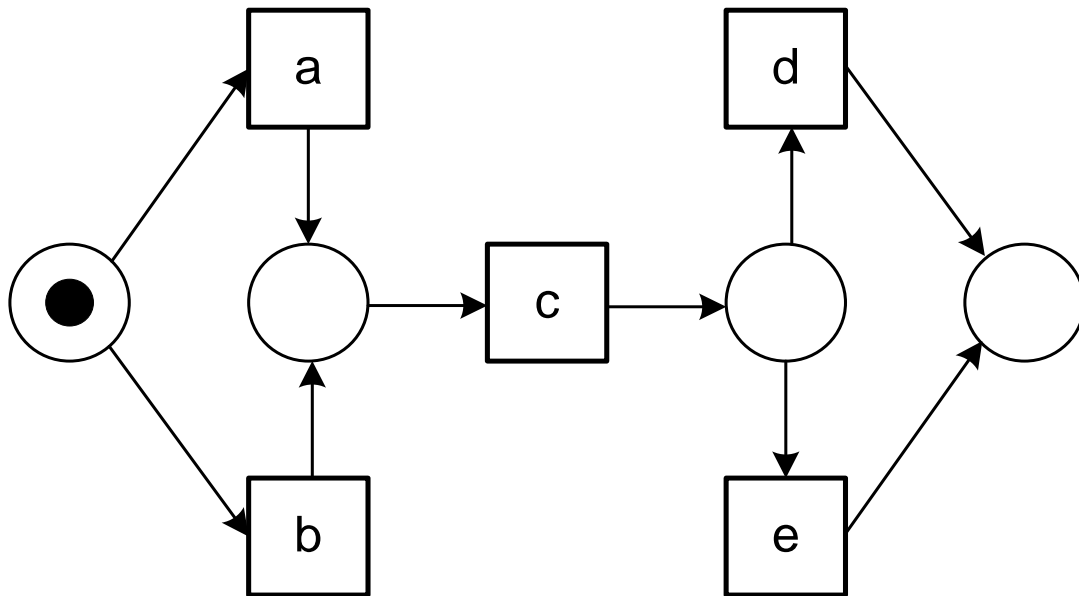
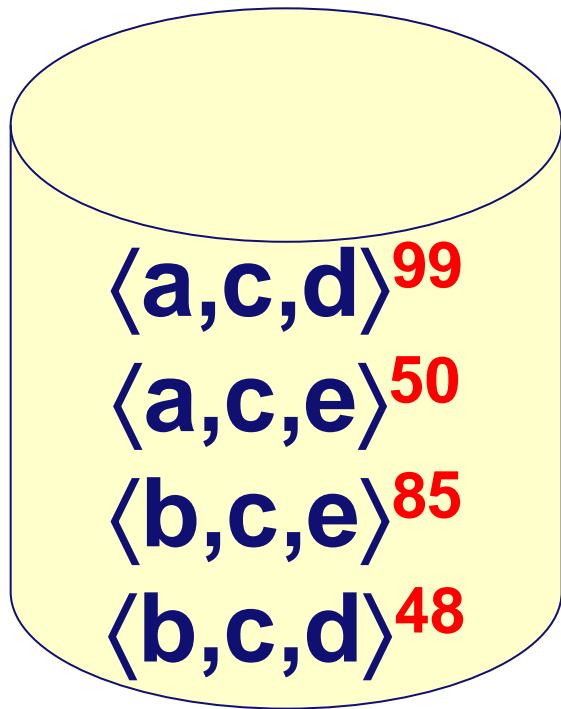


risk of overfitting on 5 example traces ...

Generalization: good or bad?



Generalization: **good!**



not overfitting...

Simplicity: good or bad?

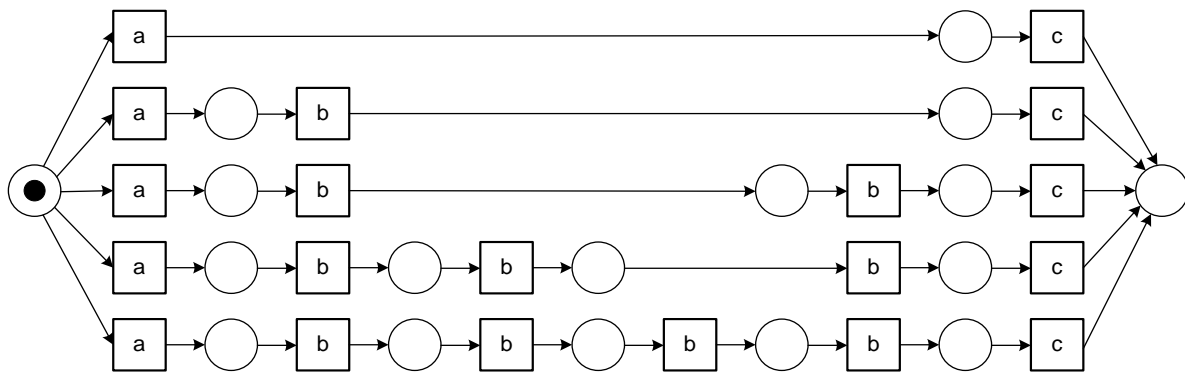
$\langle a, c \rangle^{16}$

$\langle a, b, c \rangle^8$

$\langle a, b, b, c \rangle^4$

$\langle a, b, b, b, c \rangle^2$

$\langle a, b, b, b, b, c \rangle^1$



Simplicity: **bad!**

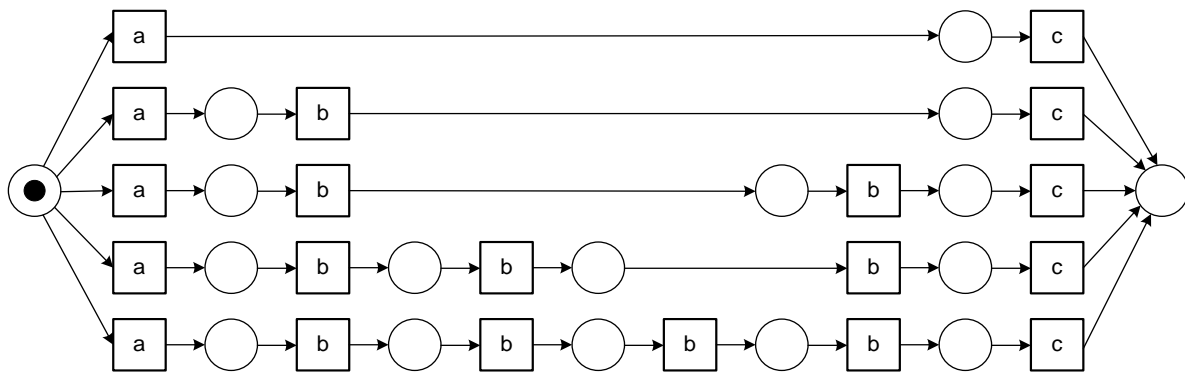
$\langle a, c \rangle^{16}$

$\langle a, b, c \rangle^8$

$\langle a, b, b, c \rangle^4$

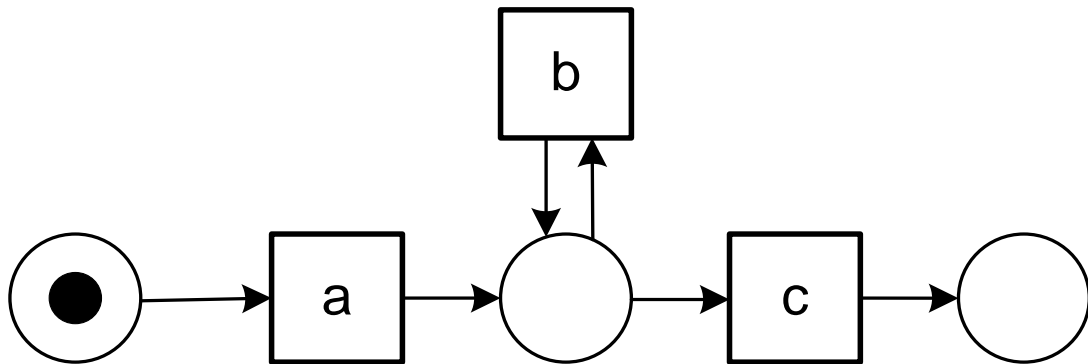
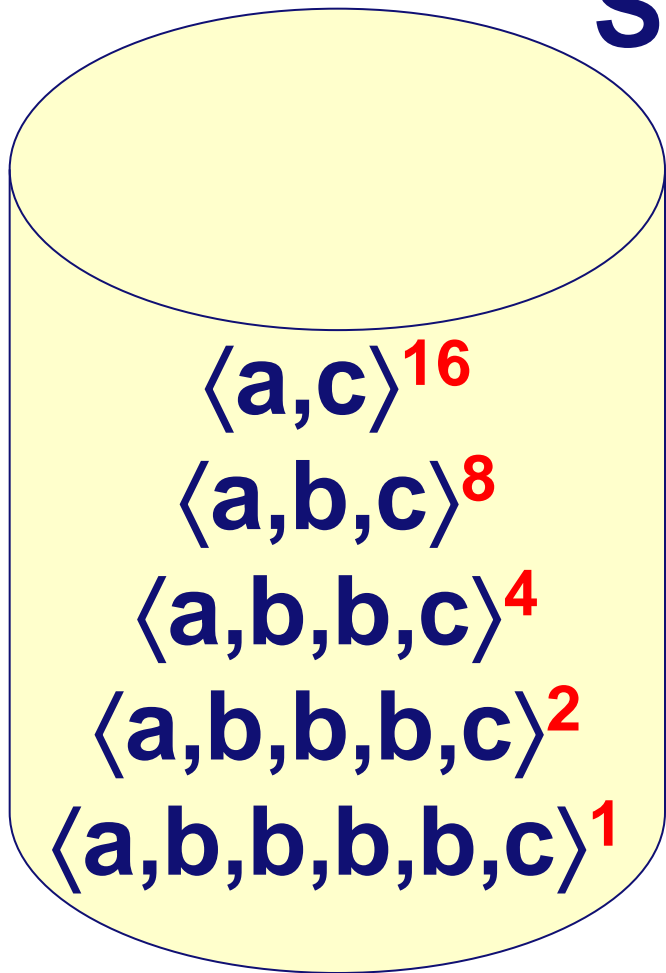
$\langle a, b, b, b, c \rangle^2$

$\langle a, b, b, b, b, c \rangle^1$

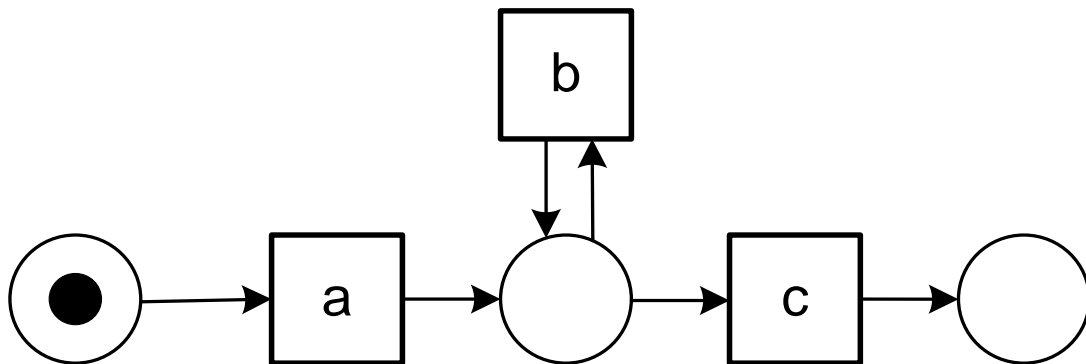
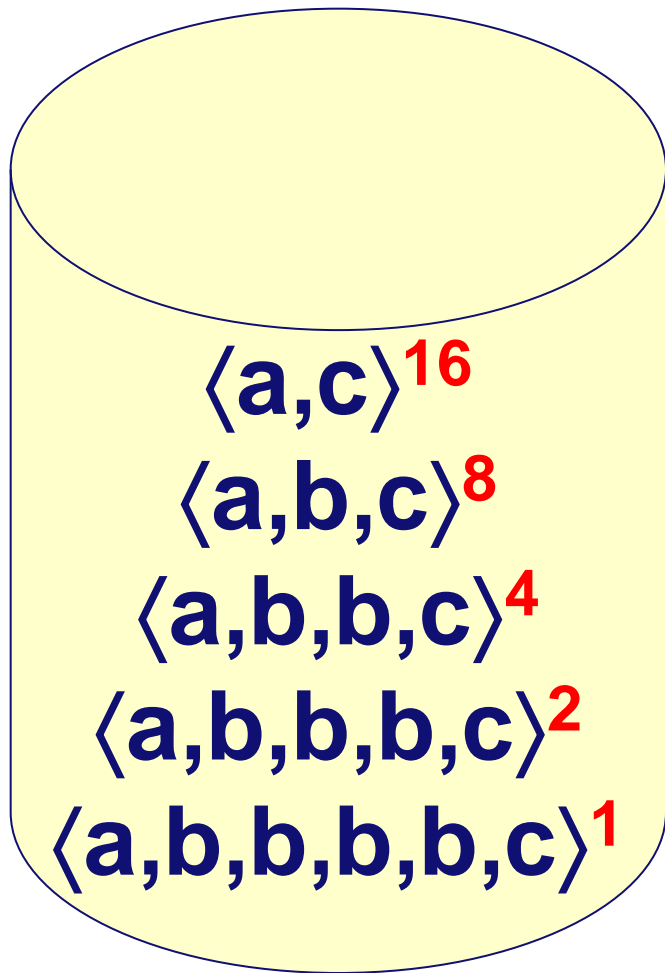


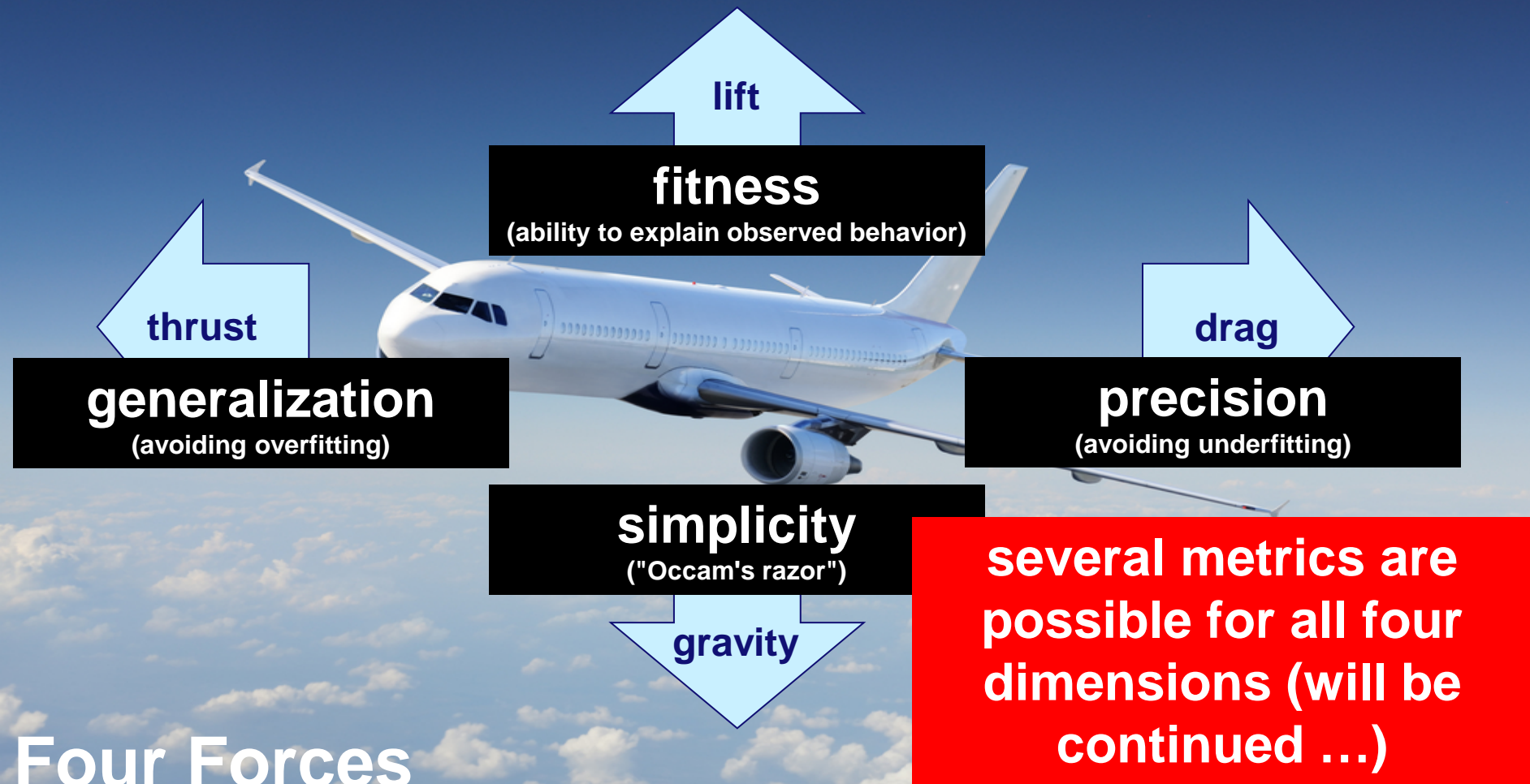
too complex/specific...

Simplicity: good or bad?



Simplicity: good!





Four Forces

modeling language provides a bias

concurrency

cancellation

OR-joins

priorities

duplicate
activities



Part I: Preliminaries

Chapter 1
Introduction

Chapter 2
Process Modeling and
Analysis

Chapter 3
Data Mining

Part III: Beyond Process Discovery

Chapter 7
Conformance
Checking

Chapter 8
Mining Additional
Perspectives

Chapter 9
Operational Support

Part II: From Event Logs to Process Models

Chapter 4
Getting the Data

Chapter 5
Process Discovery: An
Introduction

Chapter 6
Advanced Process
Discovery Techniques

Part IV: Putting Process Mining to Work

Chapter 10
Tool Support

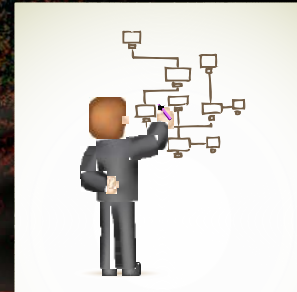
Chapter 11
Analyzing "Lasagna
Processes"

Chapter 12
Analyzing "Spaghetti
Processes"

Part V: Reflection

Chapter 13
Cartography and
Navigation

Chapter 14
Epilogue



Wil M. P. van der Aalst

Process Mining

Discovery, Conformance and
Enhancement of Business Processes

 Springer