Reshaping ticket based services with process mining

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Contents

- Motivation for doing process mining
- The theory
  - What is process mining
  - Models and reality
  - The sketches of some common algorithms
- The experiences
  - The logs used
  - Mined process maps and interpretations
  - Practical issues
  - Some sort of insights found

Business motivation

There is a Vodafone organisational unit „X” which provides internal services to other VF units.

Individual issues are solved. They are represented by tickets in the event management system.

A small but still measurable percentage of the tickets takes too much time to solve and breaches some SLAs (Service Level Agreements).

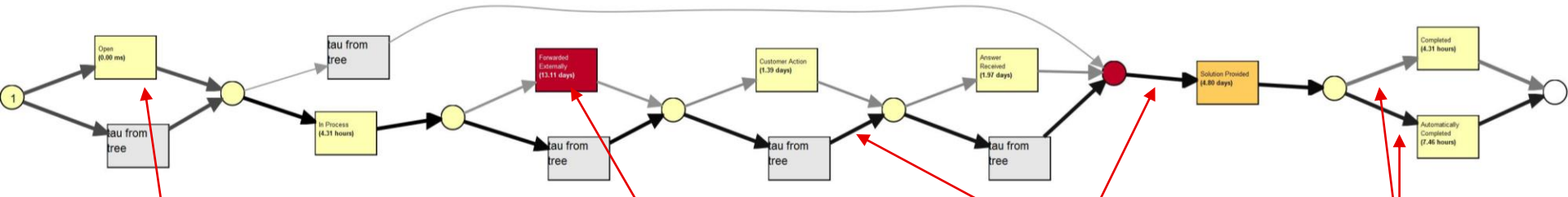
X always strives for improving its services, so wished to reduce the number of the breaches.

X wanted to see how complicated its processes are and started 6σ projects.

As a first overview, tickets for two different local markets were analysed using a process mining approach.

The fruit of the work: a process map with mean execution times

The event flow from the start to the end



Optional activities

Time waste!

Frequent path

Alternative paths

What is process mining about?

„Process mining is a process management technique that allows for the analysis of business processes based on event logs.

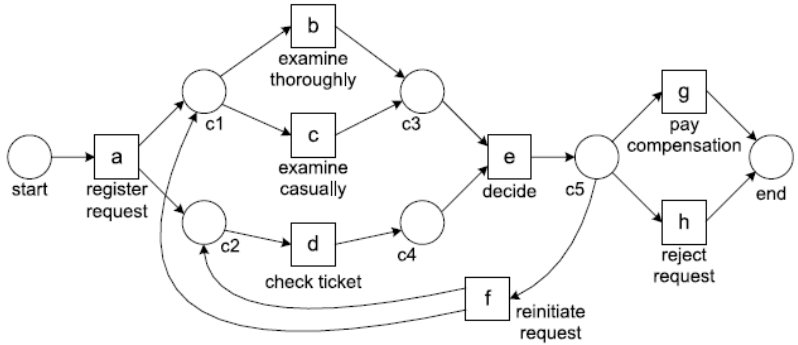
During process mining, specialized algorithms are applied to event log datasets in order to identify trends, patterns and details contained in event logs recorded by an information system. Process mining aims to improve process efficiency and understanding of processes."

Table 1.1 A fragment of some event log: each line corresponds to an event

Case id	Event id	Properties		
		Timestamp	Activity	Resource
1	35654423	30-12-2010:11.02	Register request	Pete
	35654424	31-12-2010:10.06	Examine thoroughly	Sue
	35654425	05-01-2011:15.12	Check ticket	Mike
	35654426	06-01-2011:11.18	Decide	Sara
	35654427	07-01-2011:14.24	Reject request	Pete
2	35654483	30-12-2010:11.32	Register request	Mike
	35654485	30-12-2010:12.12	Check ticket	Mike
	35654487	30-12-2010:14.16	Examine casually	Pete
	35654488	05-01-2011:11.22	Decide	Sara
	35654489	08-01-2011:12.05	Pay compensation	Ellen
	...			

A log

An idealised representation of the process, mined from the (filtered) log, usable for further analysis

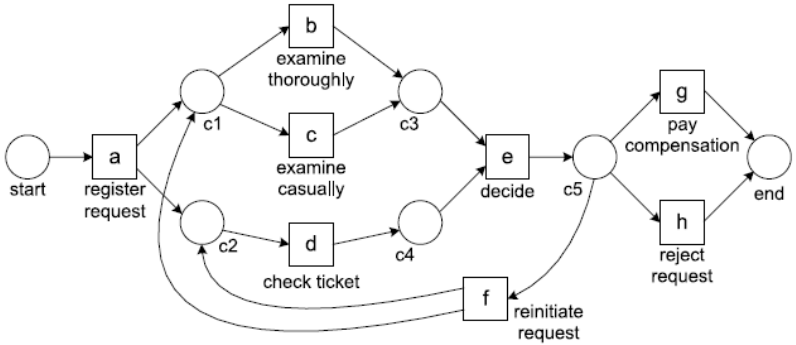


= an activity = a status enabling some activities ! Choice and parallelism possible

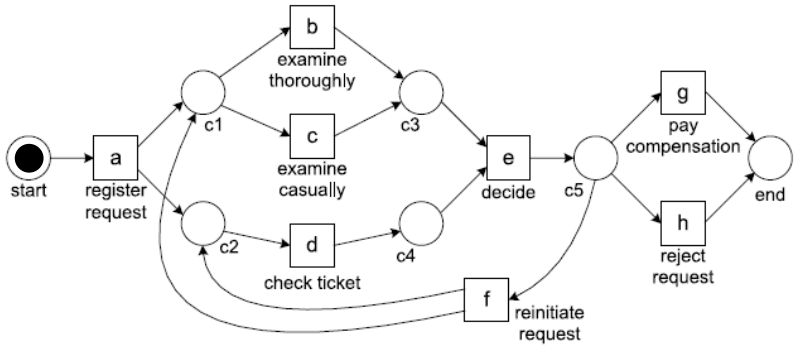
Example borrowed from: Wil M.P. van der Aalst,: Process Mining - Discovery, Conformance and Enhancement of Business Processes, Springer, 2011-2015

How does it model real event flows? – Let us replay a story!

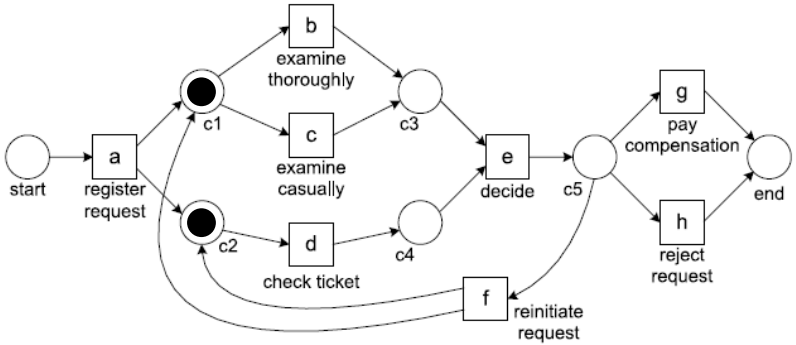
The mined model representation. „Petri Net”



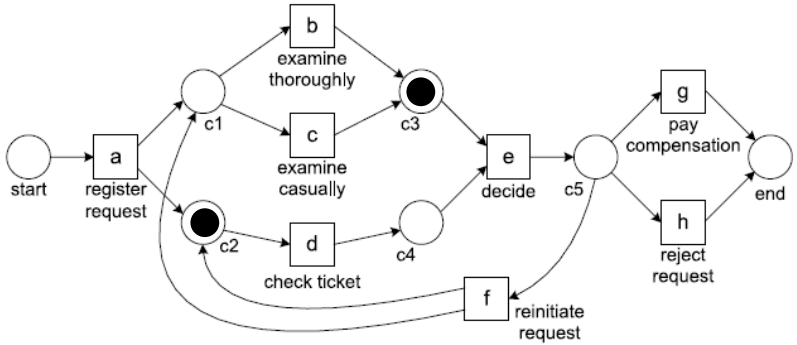
Initial state: start enabled



Register request executed – 2 branches follow – „AND”

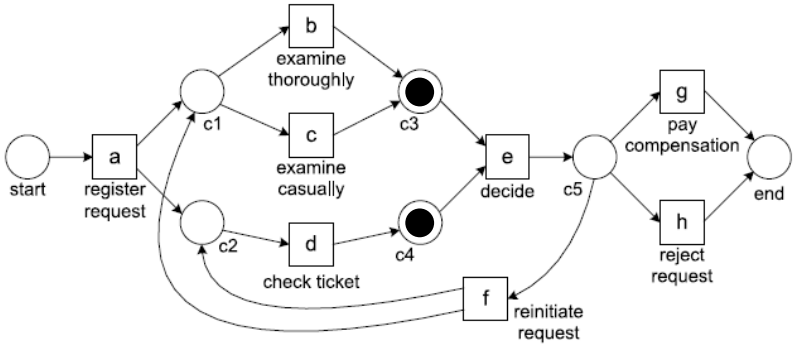


1 and only 1 examination executed – „OR”

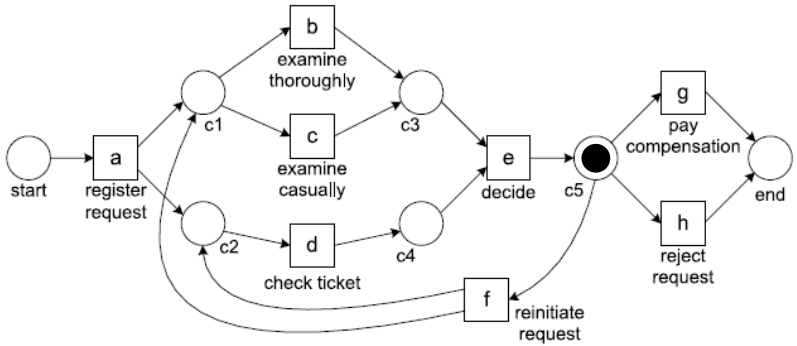


How does it model real event flows? – Replay continued.

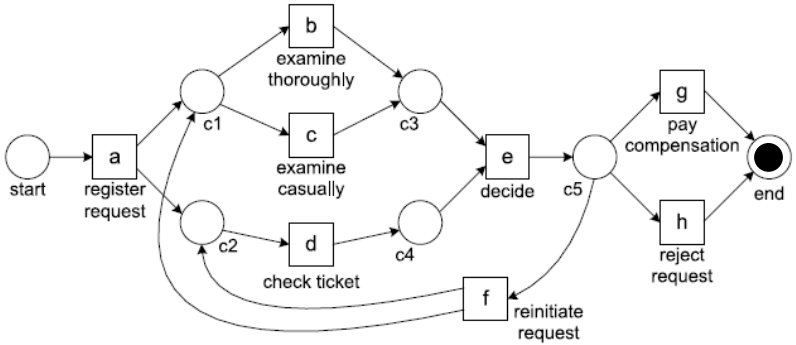
„Ticket check” MUST be executed



„Decide” executed



„Pay compensation” – End of process instance



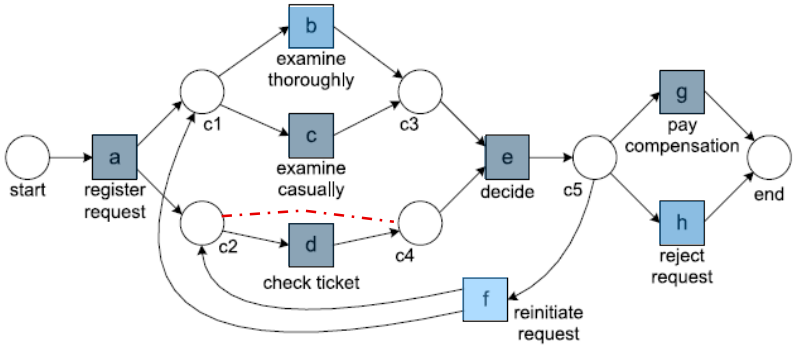
We have just replayed one trace version from many possible

1. Register request
2. Examine thoroughly
3. Check ticket
4. Decide
5. Pay compensation

Other uses of replay

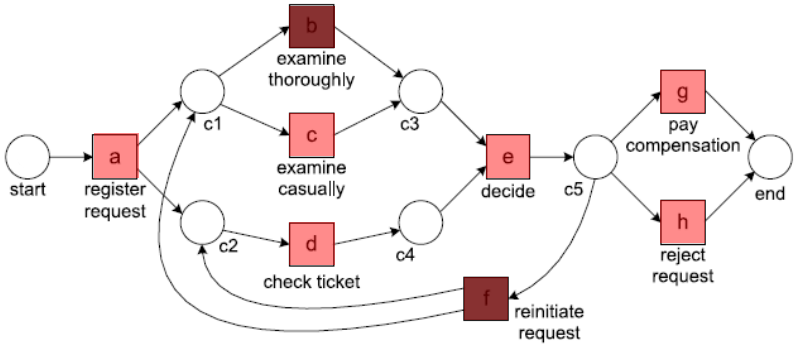
Conformance analysis

How faithfully the real traces follow the process model? If there is a prescribed event flow, where do we deviate from that?



Time analysis

Which events take much time on average to execute?

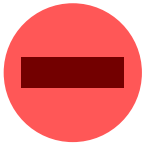


By replaying the logs one can gain some indicators of the model – real-world-log conformance.

For example, using the numbers of the tokens emerging during the replay of the log traces:

$$\text{fitness} = \frac{1}{2}\left(1 - \frac{\#missing\ tokens}{\#\ consumed\ tokens}\right) + \frac{1}{2}\left(1 - \frac{\#remaining\ tokens}{\#\ produced\ tokens}\right)$$

Belongs to data science? – A few subjective aspects

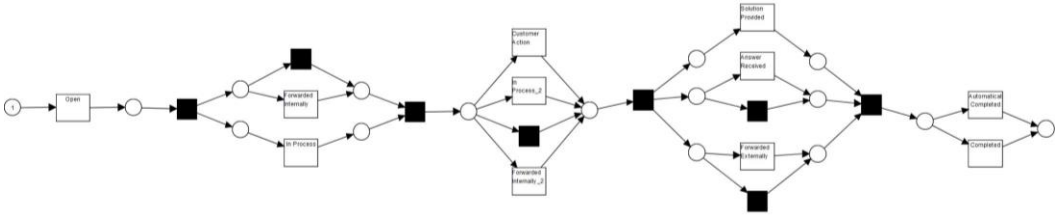


- ✓ Data based approach
- ✓ Discovery of hidden patterns
- ✓ Goal too much for humans – computer aid needed
- ✓ Sophisticated math discovery algorithms
- ✓ Well defined model performance indicators exist

- – Rather descriptive
- – Often very small data
- – Model validity may be subject to many soft criteria / beliefs
- – Model validity may be lost immediately when lessons are learned

How to create one?

- Several common algorithms (algorithm families) exist:
  - Alpha
  - Heuristic
  - Tree induction
  - Fuzzy
  - Integer programming based
  - Genetic approach



The Alpha algorithm

Define ordering relations for any activity pairs in a log L

Find for all activity pairs their relationship, based on the log

Define the global structure through local structures

A > B

B directly follows A at least once

A→B

B directly follows A at least once, but A never follows B

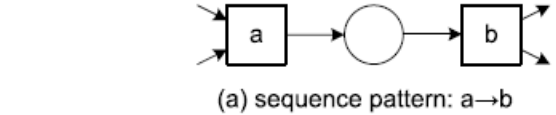
A#B:

Neither of them follows the other one directly

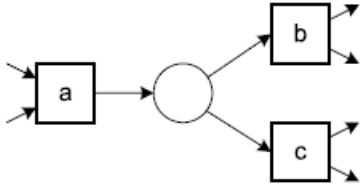
A || B:

They can follow each other in both orders

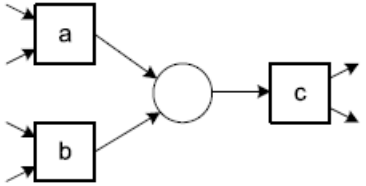
	a	b	c	d
a	#	||	→	..
b	||	#	→	..
c	←	←	#	..
d	..	..	..	..



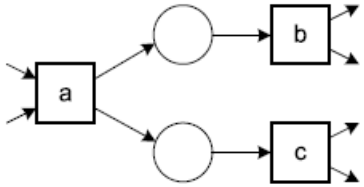
(a) sequence pattern: a→b



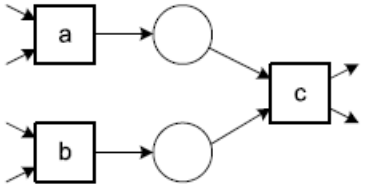
(b) XOR-split pattern:
a→b, a→c, and b#c



(c) XOR-join pattern:
a→c, b→c, and a#b



(d) AND-split pattern:
a→b, a→c, and b||c



(e) AND-join pattern:
a→c, b→c, and a||b

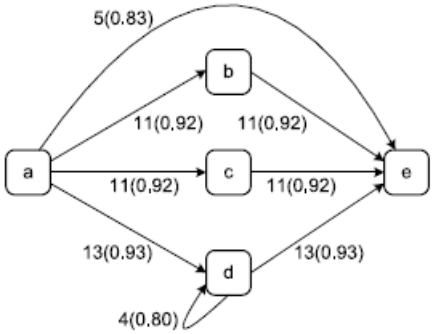
The Heuristic algorithm

Calculate an asymmetric activity dependency indicator	Create dependency graph	Filter the dependency graph	Identify splits and joins by replaying the traces
Closer to ±1, the stronger the relationship	A weighted graph, where the nodes are the activities, the edge weights are the dependency measures	By absolute number of succeeding each other and By the dependency indicator	Find optimal alignments Determine activity binding strengths Apply final filtering by frequency of input/output bindings

Number of successions $|a >_L b|$

Dependency indicator

$$|a \Rightarrow_L b| = \begin{cases} \frac{|a>_L b| - |b>_L a|}{|a>_L b| + |b>_L a| + 1} & \text{if } a \neq b \\ \frac{|a>_L a|}{|a>_L a| + 1} & \text{if } a = b \end{cases}$$



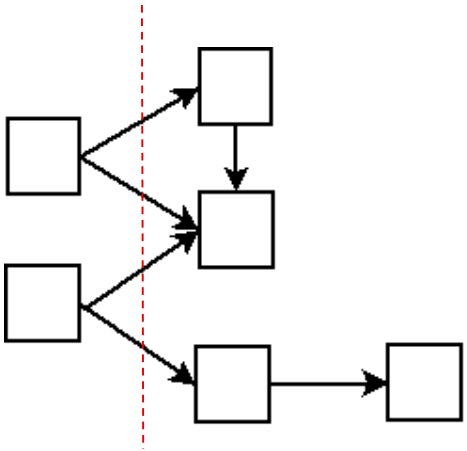
Inductive tree

Create the directly follows / eventually follows graphs weighted by occurence numbers

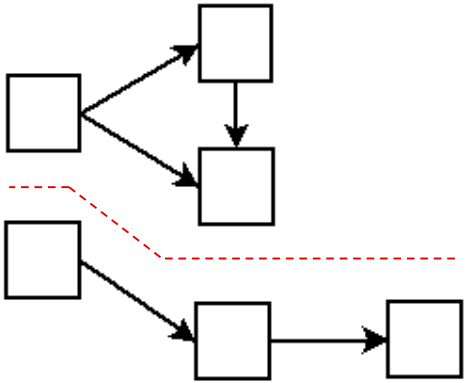
Optionally filter the graph for infrequent behavior

Find some special cut in the graph, create partitions linked in some special way to each other

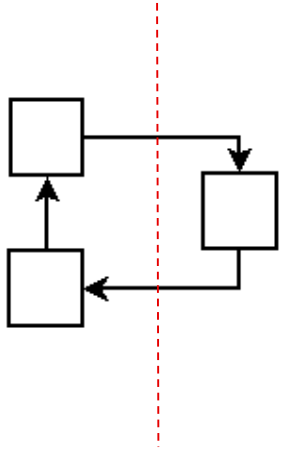
Repeat the process for the partitions until individual activities remain



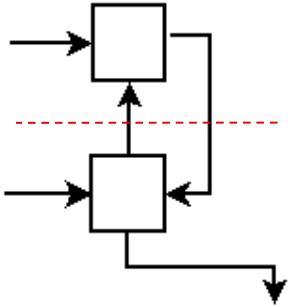
Sequence



Exclusive choice



Loop



Parallel

Now let us return to our real case – the X department

Just to recall....

„X" provides internal services to other VF units

A small but still measurable percentage of the tickets takes too much time to solve and breaches some SLAs (Service Level Agreements)

X always strives for improving its services, so wished to reduce the number of the breaches

X wanted to see how complicated its processes are and started 6σ projects

As a first overview, tickets for two different local markets were analysed using a process mining approach

A typical log from X

Event	Timestamp
Open	09.08.2016 09:34:02
In Process1	09.08.2016 09:34:28
In Process2	09.08.2016 09:37:34
In Process3	09.08.2016 14:31:11
In Process4	09.08.2016 16:45:20
In Process5	10.08.2016 12:11:06
Forwarded Externally	10.08.2016 12:11:12
Answer Received	08.09.2016 12:31:32
Completed	19.10.2016 17:28:03

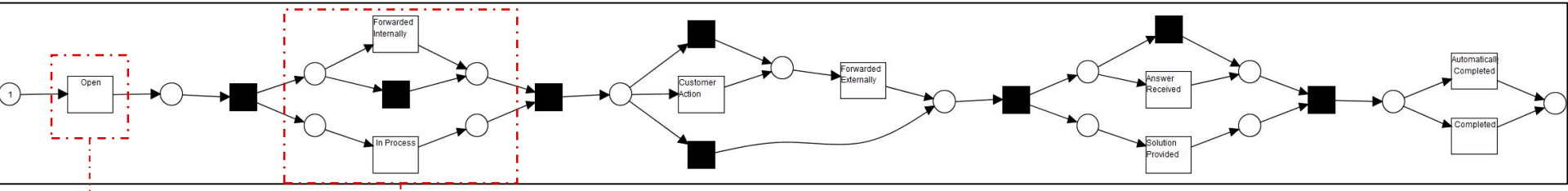
Events of the same type may follow each other.

Further possible events:

Forwarded Internally Solution provided, Automatically completed

Observation: the number of event types is low, still there is an abundance of trace variants

A mined process for some activity „Z”



The series of events starts with „Open”

Then:
- Always there is an in process step
- Perhaps there is a Forwarded internally (it may be skipped silently)
- The ordering of the In process and the Forwarding as abitrary (they are parallel)

Then:
- A „Forwarded externally” event MAY follow
- Which is preceded in some number of the cases by a „Customer action”

Then:
- Some other events MAY come

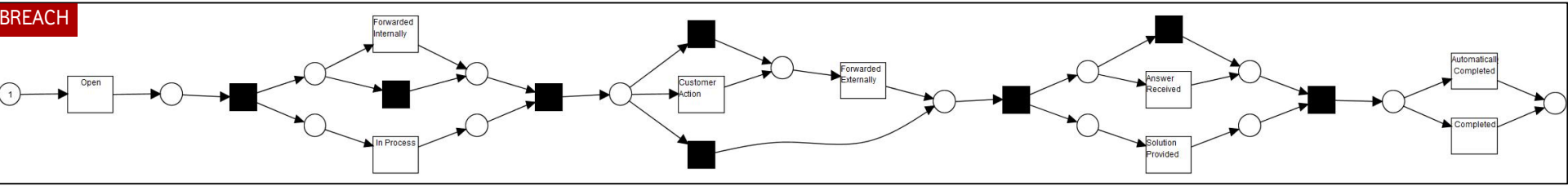
Then:
- Process is completed

We have a map – has it been worth mining it?

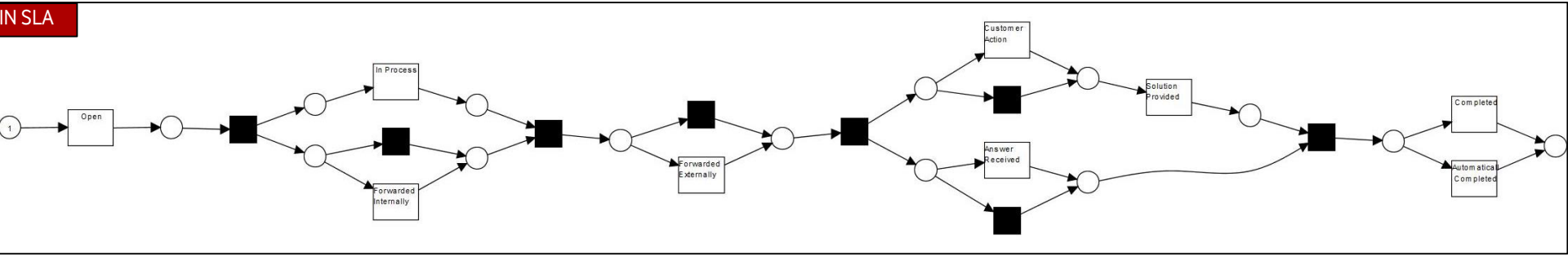
Yes, because we have got ONE description of the typical REAL process behavior albeit there were 34 trace variants in the data

What is more … two processes for the same activity Z !

BREACH

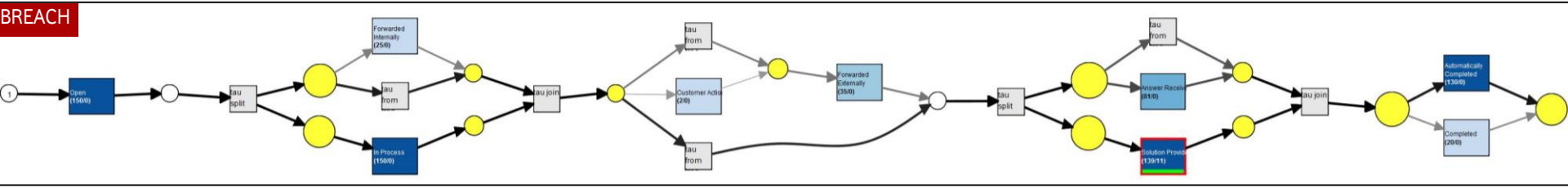


IN SLA

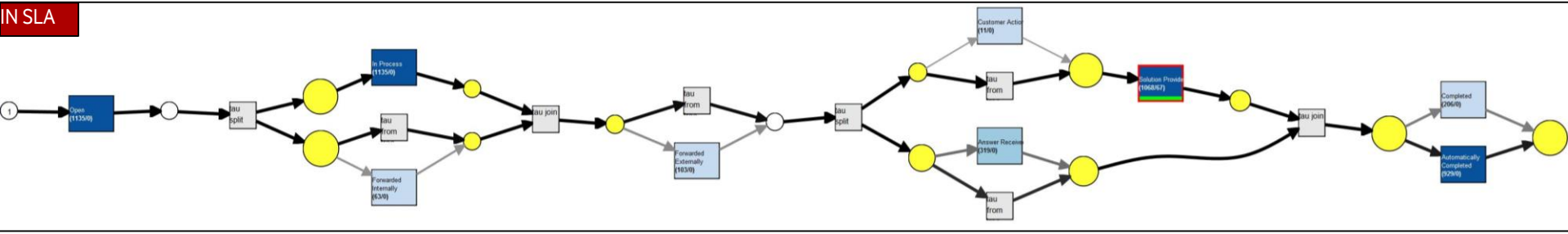


Execution frequencies…

BREACH

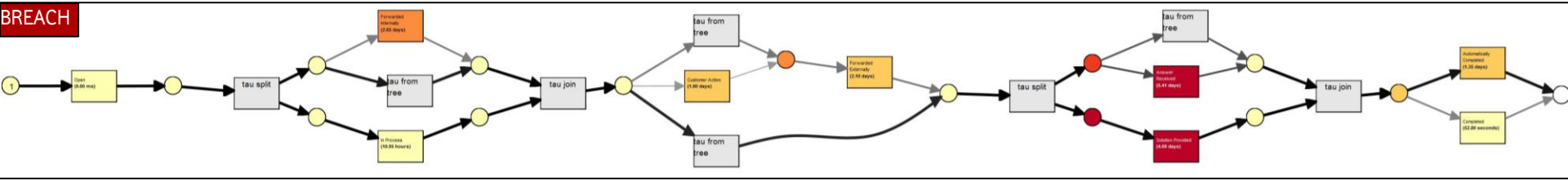


IN SLA

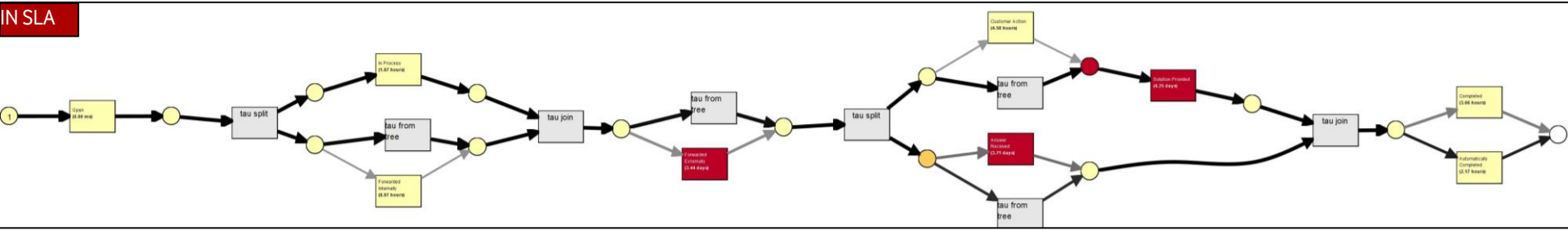


… and average execution times

BREACH

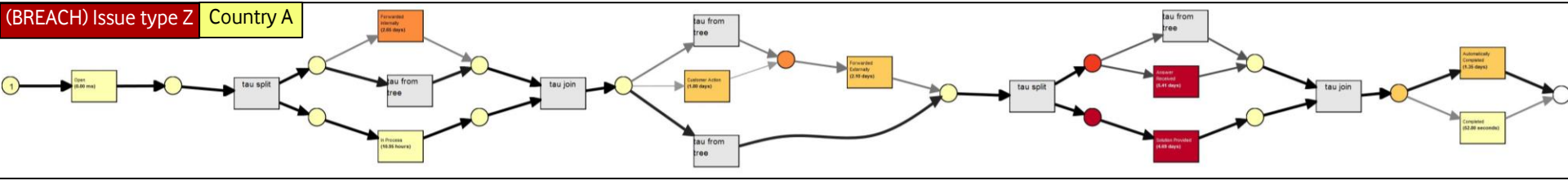


IN SLA



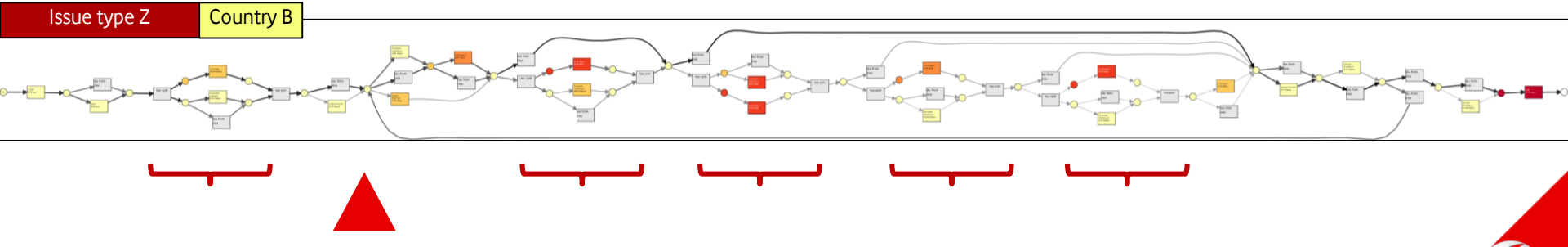
The resolution process for the same issue type Z for another country is totally different

(BREACH) Issue type Z | Country A

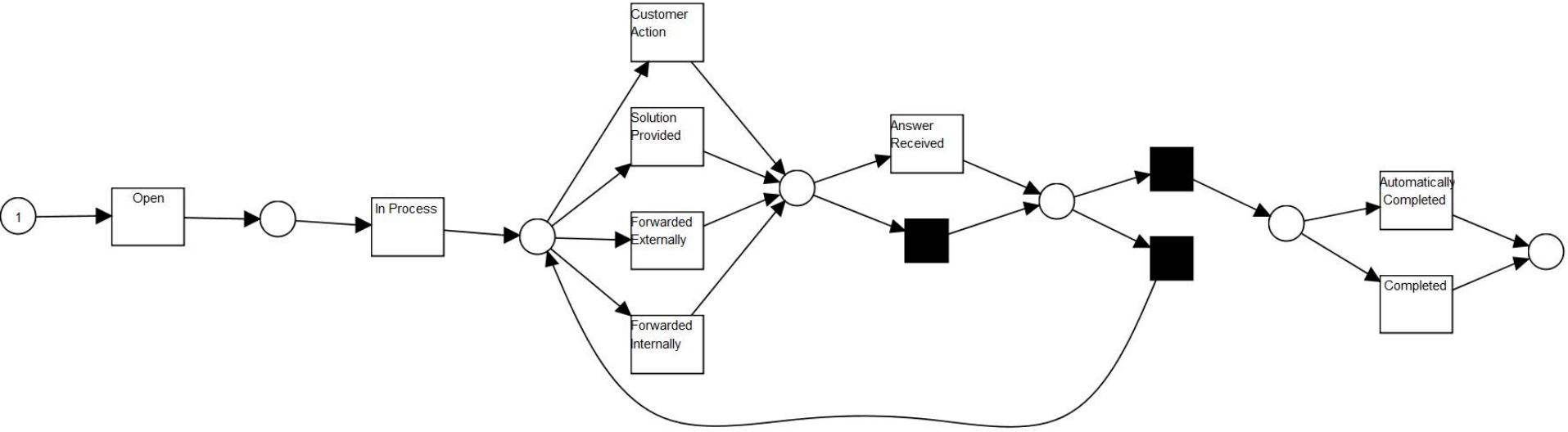


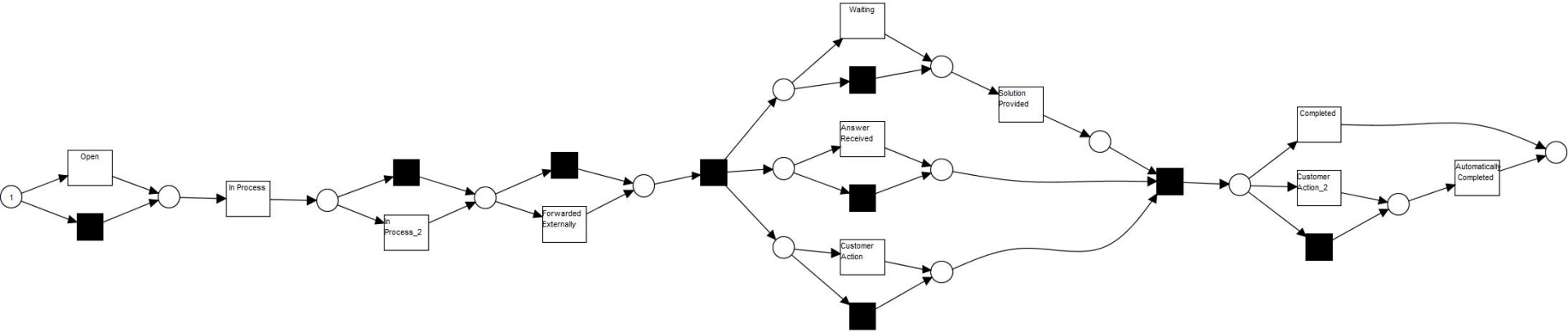
For country B separate breach – insla processes were not mined.
But it is not what makes the difference.

Issue type Z | Country B



Resolution processes for other issues – lot of differences again





Practical issues

Importance of cleaning

- Appropriate event data preparation was as influential to success than the way as the mining algorithm was used

Sensitivity to parameters

- The process graphs changed quite suddenly at some thresholds

Event sojourn times

- As there was only one (starting) time recorded for each event, sometimes it took consideration to correctly interpret elapsed times

Speed

- With the actual ticket numbers (max 1200 / issue type) speed was not an issue

Buy-in

- Although a map seems to be self-explanatory, business stakeholders need thorough explanations

Summary of the insights gained

- Presence of lots of orphan traces
- Many trace variants for one problem type
- Very long trace variants exist
- A few tickets are open for extremely long time
- Repetitions of activity blocks
- Ticket inflow rate is almost constant
- The typical process flows which are able to replay 97+% of the (not-orphan) cases
- Structural differences between the event flows for breaching and in-sla cases
- Event types taking long time for the sla breaching cases
- Reopens happen somewhat later for the breach cases than for the in-sla cases

→ Are all necessary standards in place?
Are standards known and followed?

→ Are all necessary checkpoints in place?

→ Opportunity for simple workforce planning, considering special times during the year?

→ How far these are from beliefs and standards?

→ Where can it be the easiest and most profitable to change the processes?

→ Would it useful to forego it and check fast customer opinion in cases when it is risky that there will be a reopen, in order not to waste time?

I want to do it! – Well then you need ...

A website
- WWW.PROCESSMINING.ORG

A software
- PROM
- Celonis, Disco

A book
- **van der Aalst**, Wil M.P. Process mining

An online course
- Introduction to Process Mining with ProM (FutureLearn) (Joos Buijs)
- Process Mining: Data science in Action (Coursera) (van der Aalst)

Be aware!
- There are a lot of possible topics & issues not mentioned in this presentation!

A log
- Look around!


Certificate of Achievement

Tamás Molnár

has completed the following course:

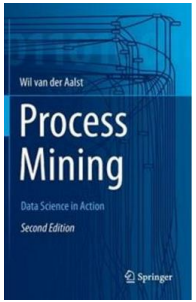
INTRODUCTION TO PROCESS MINING WITH PROM
EINDHOVEN UNIVERSITY OF TECHNOLOGY

This online course covered process mining analysis using ProM. During the course several topics were covered, from event log basics, to process discovery, process model evaluation, alignments, performance analysis and social network analysis. The course was completed with a practical assignment.

4 weeks, 3 hours per week

EDUCATORS

Joos Buijs
Assistant Professor
Eindhoven University of Technology



The author of the presentation does not claim that the here mentioned sources are the only available sources or the best ones among all possible sources. But they can be useful for sure.


Thank you!