

Chair of Process  
and Data Science

**RWTH**AACHEN  
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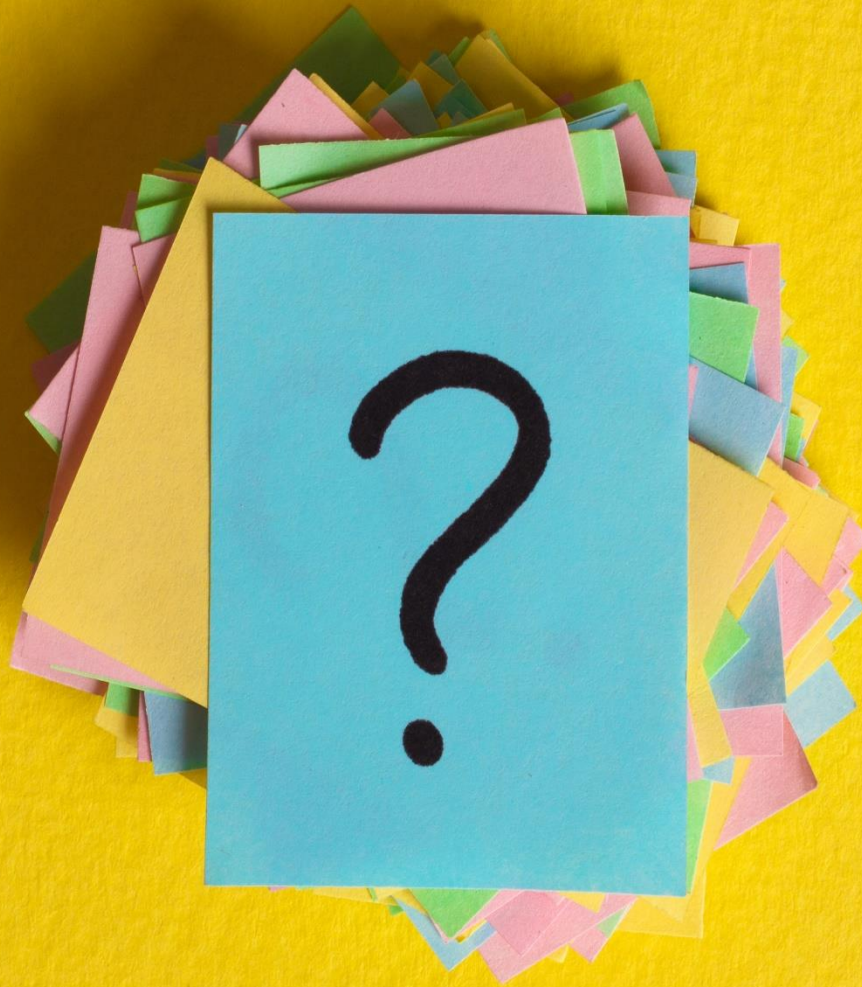
# Discovering Process Models from Uncertain Event Data

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Question:

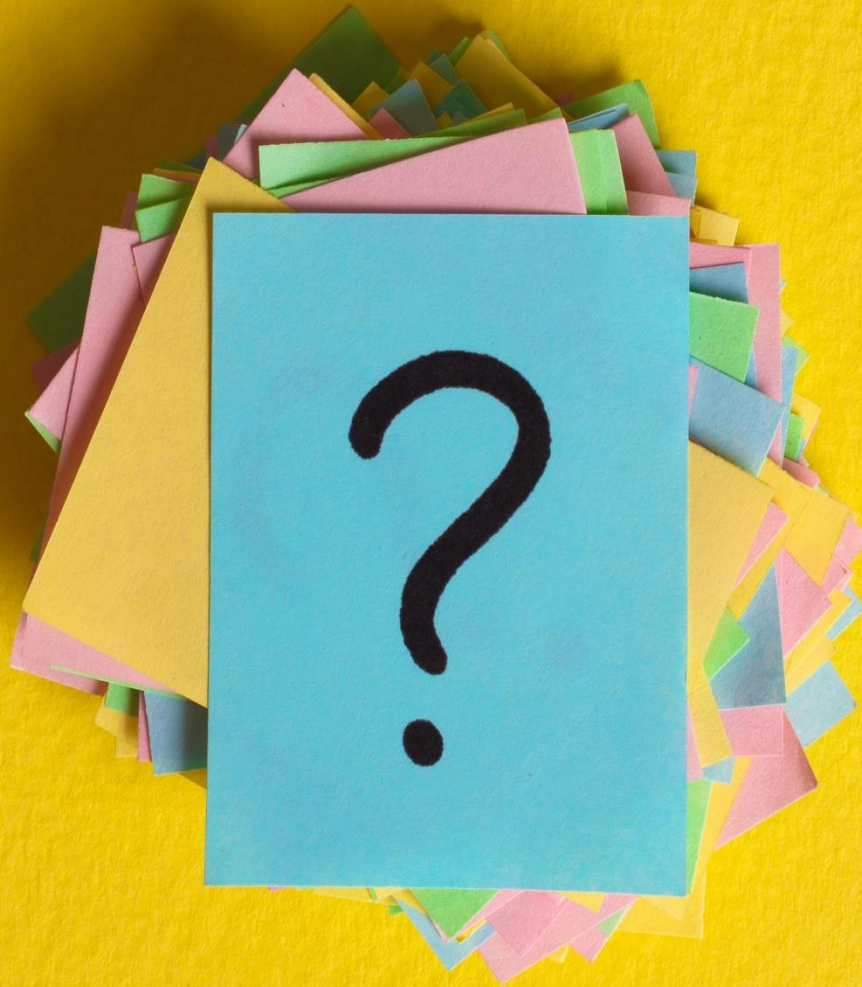
How to discover process models from uncertain event data?





## Question:

How to discover process models from uncertain event data?



## Proposal:

Utilize occurrences of activities and directly-follows relationships in uncertain event log to obtain a process model.



- Preliminaries
- Process Discovery from Uncertain Event Data
- Results
- Conclusion



# Uncertainty in event logs<sup>[1]</sup>

Uncertainty caused by  
incorrectness, coarseness,  
and ambiguity.

Assumption:  
Uncertainty is contained  
in the event log.

Control-flow perspective:  
Case id, activity, timestamp.

Define uncertainty on:  
Attribute level and event level.



UNCERTAIN

<sup>[1]</sup> M. Pegoraro and W. M. P. van der Aalst, "Mining Uncertain Event Data in Process Mining," *2019 International Conference on Process Mining (ICPM)*, Aachen, Germany, 2019, pp. 89-96. doi: 10.1109/ICPM.2019.00023 .



Did the event happen?



# Representation of uncertainty

---

Event ID	Case ID	Timestamp	Activity	Did it happen?
e <sub>1</sub>	0	05.12.2011	A	yes
e <sub>2</sub>	0	07.12.2011	{B, C}	yes
e <sub>3</sub>	0	<b>[06.12.2011, 10.12.2011]</b>	D	yes
e <sub>4</sub>	0	09.12.2011	{A, C}	yes
e <sub>5</sub>	0	11.12.2011	E	maybe

**Continuous attributes:** Represent uncertainty by an **interval**.

Example: “Timestamp”.

**Discrete attributes:** Represent uncertainty by a set of possible values.

Example: “Activity”.



# Representation of uncertainty

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e <sub>5</sub>	0	11.12.2011	E	maybe

Continuous attributes: Represent uncertainty by an interval.  
Example: “Timestamp”.

Discrete attributes: Represent uncertainty by a set of possible values.  
Example: “Activity”.

## Example of uncertain trace

Event ID	Case ID	Timestamp	Activity	Did it happen?
e <sub>1</sub>	0	05.12.2011	A	yes
e <sub>2</sub>	0	07.12.2011	{B, C}	yes
e <sub>3</sub>	0	[06.12.2011, 10.12.2011]	D	yes
e <sub>4</sub>	0	09.12.2011	{A, C}	yes
e <sub>5</sub>	0	11.12.2011	E	maybe

The exact timestamp of e<sub>3</sub>  
belongs to this interval



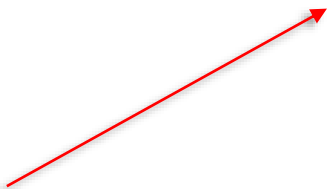
## Example of uncertain trace

Event ID	Case ID	Timestamp	Activity	Did it happen?
e <sub>1</sub>	0	05.12.2011	A	yes
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e <sub>3</sub>	0	[06.12.2011, 10.12.2011]	D	yes
e <sub>4</sub>	0	09.12.2011	{A, C}	yes
e <sub>5</sub>	0	11.12.2011	E	maybe

The events e<sub>2</sub> and e<sub>4</sub> have a set of possible activity labels

## Example of uncertain trace

Event ID	Case ID	Timestamp	Activity	Did it happen?
e <sub>1</sub>	0	05.12.2011	A	yes
e <sub>2</sub>	0	07.12.2011	{B, C}	yes
e <sub>3</sub>	0	[06.12.2011, 10.12.2011]	D	yes
e <sub>4</sub>	0	09.12.2011	{A, C}	yes
e <sub>5</sub>	0	11.12.2011	E	maybe

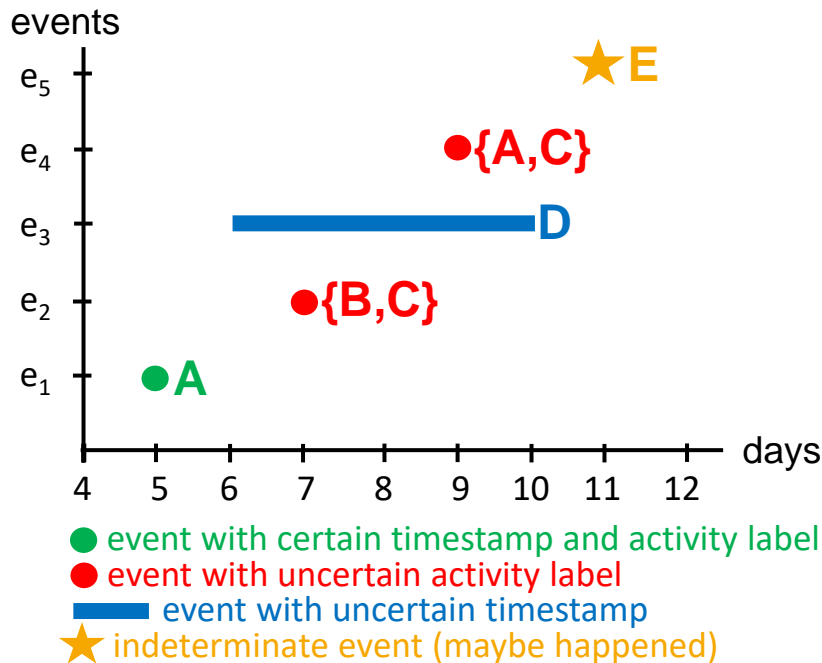


The event e<sub>5</sub> has been recorded  
but maybe it did not happen



# Realizations of an uncertain trace

Event ID	Case ID	Timestamp	Activity	Did it happen?
e <sub>1</sub>	0	05.12.2011	A	yes
e <sub>2</sub>	0	07.12.2011	{B, C}	yes
e <sub>3</sub>	0	[06.12.2011, 10.12.2011]	D	yes
e <sub>4</sub>	0	09.12.2011	{A, C}	yes
e <sub>5</sub>	0	11.12.2011	E	maybe



Example realizations:

<A, B, C, D, E>  
 <A, B, D, C, E>  
 <A, C, D, C, E>  
 <A, C, D, A, E>  
 <A, D, C, C, E>  
 <A, D, B, C>  
 <A, D, C, A>

...

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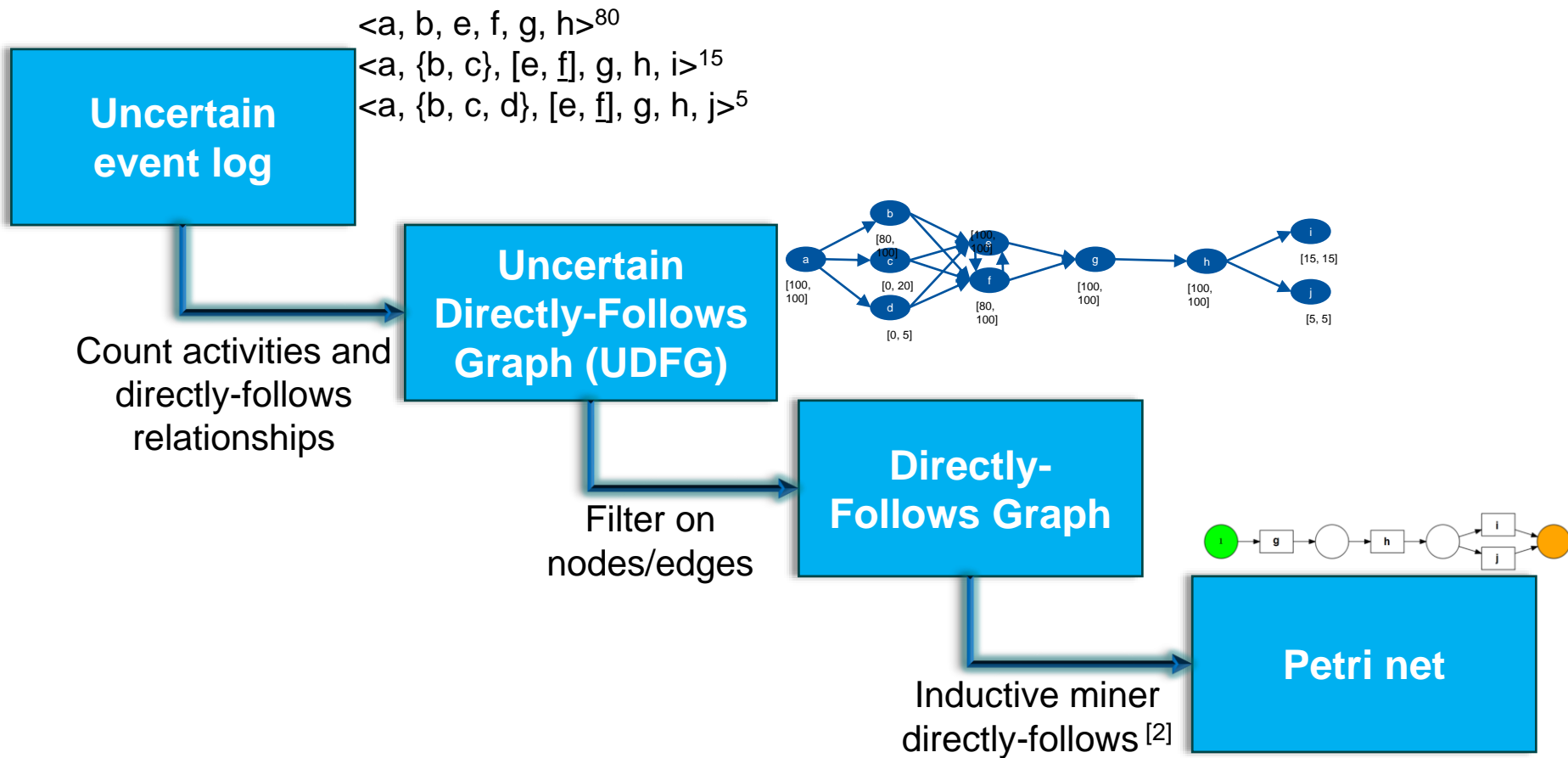
**Recall question:** How to discover process models from uncertain event data?



**Method:**

Use **minimum and maximum** number of times an activity or a directly-follows relationship can appear in the realizations of the event log.

# “Big picture”



[2] Sander J.J. Leemans, Dirk Fahland, and Wil M.P. van der Aalst. "Scalable process discovery and conformance checking." Software & Systems Modeling 17.2 (2018): 599-631.

# Formalism for uncertain event logs

---

Curly braces { } indicate uncertainty over activities.

{b, c} indicates a single event that can be b or c.



$\langle a, \{b, c\}, [e, \underline{f}], g, h, i \rangle$



# Formalism for uncertain event logs

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Underlined events are indeterminate.  
f indicates that the event may or may not have happened.

<a, {b, c}, [e, f], g, h, i>

# Formalism for uncertain event logs

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$\langle a, \{b, c\}, [e, \underline{f}], g, h, i \rangle$



Square brackets [ ] indicate uncertainty over timestamps.  
[e, f] indicates that the order between e and f is unknown.

## Activity occurrences

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Consider the following event log L:

$\langle a, b, e, f, g, h \rangle^{80}$

$\langle a, \{b, c\}, [e, \underline{f}], g, h, i \rangle^{15}$

$\langle a, \{b, c, d\}, [e, \underline{f}], g, h, j \rangle^5$

Count the minimum and maximum number of times we observe an **activity**:

	$\langle a, b, e, f, g, h \rangle^{80}$	$\langle a, \{b, c\}, [e, \underline{f}], g, h, i \rangle^{15}$	$\langle a, \{b, c, d\}, [e, \underline{f}], g, h, j \rangle^5$	L
a	[ <b>80</b> , 80]	[ <b>15</b> , 15]	[ <b>5</b> , 5]	[ <b>100</b> , 100]
b	[80, 80]	[0, 15]	[0, 5]	[80, 100]

**$\min_a$**  and  **$\max_a$**  : Minimum and maximum number of times that **a** appears in L.



## Directly-follows relationship occurrences

Consider the following event log L:

$\langle a, b, e, f, g, h \rangle^{80}$

$\langle a, \{b, c\}, [e, f], g, h, i \rangle^{15}$

$\langle a, \{b, c, d\}, [e, f], g, h, j \rangle^5$

Count the minimum and maximum number of times we observe the **directly-follows relation**:

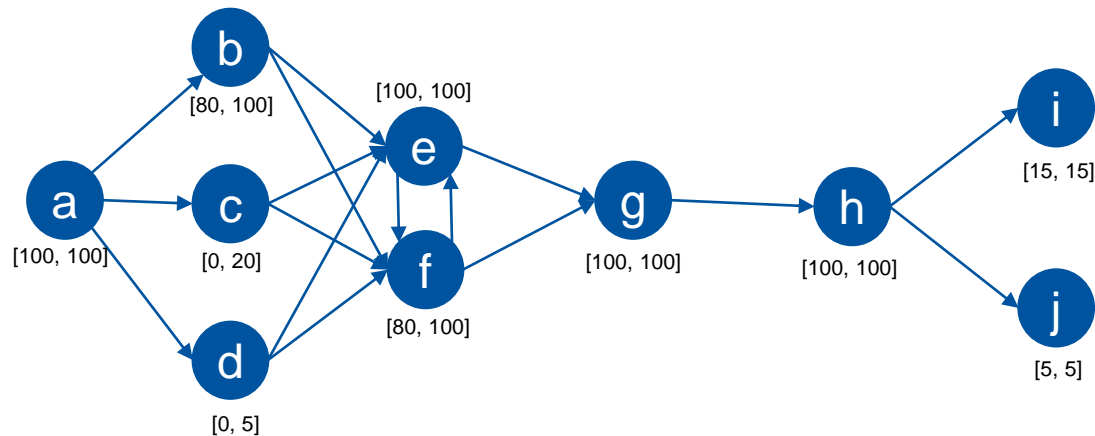
	$\langle a, b, e, f, g, h \rangle^{80}$	$\langle a, \{b, c\}, [e, f], g, h, i \rangle^{15}$	$\langle a, \{b, c, d\}, [e, f], g, h, j \rangle^5$	L
$a \rightarrow b$	[80, 80]	[0, 15]	[0, 5]	[80, 100]
$a \rightarrow c$	[0, 0]	[0, 15]	[0, 5]	[0, 20]

**$\min_{a \rightarrow b}$**  and  **$\max_{a \rightarrow b}$** : Minimum and maximum number of times the  **$a \rightarrow b$**  appears in L.

# Uncertain Directly-Follows Graph (1)

An **Uncertain Directly-Follows Graph (UDFG)** is a graph labeled with the intervals.

Example of UDFG showing the labels on **activities (nodes)**:



$\langle a, b, e, f, g, h \rangle^{80}$

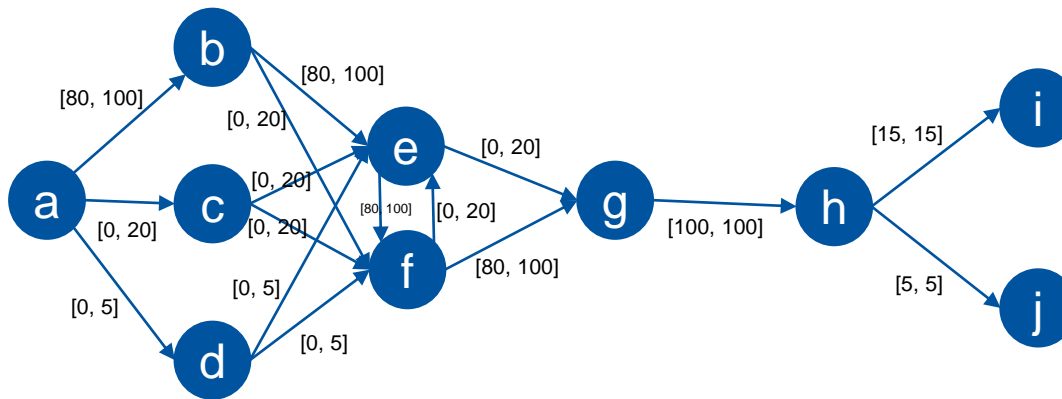
$\langle a, \{b, c\}, [e, f], g, h, i \rangle^{15}$

$\langle a, \{b, c, d\}, [e, f], g, h, j \rangle^5$

## Uncertain Directly-Follows Graph (2)

An **Uncertain Directly-Follows Graph (UDFG)** is a graph labeled with the intervals.

Example of UDFG showing the labels on **directly-follows relationships (edges)**:



$\langle a, b, e, f, g, h \rangle^{80}$

$\langle a, \{b, c\}, [e, f], g, h, i \rangle^{15}$

$\langle a, \{b, c, d\}, [e, f], g, h, j \rangle^5$



# Filtering approach

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1. Determine:

- Activity filtering parameters  **$act_{min}$**  and  **$act_{max}$**  and
- Relationship filtering parameters  **$rel_{min}$**  and  **$rel_{max}$** .

2. Keep the activities (vertices of the UDFG) for which it holds:

$$act_{min} \leq \frac{min_a}{max_a} \leq act_{max}$$

3. Keep the directly-follows relations (edges of the UDFG) for which it holds:

$$rel_{min} \leq \frac{min_{a \rightarrow b}}{max_{a \rightarrow b}} \leq rel_{max}$$

4. Perform Inductive Miner-directly-follows<sup>[2]</sup> approach on the filtered UDFG to obtain a process model.

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[2] Sander J.J. Leemans, Dirk Fahland, and Wil M.P. Van der Aalst. "Scalable process discovery and conformance checking." Software & Systems Modeling 17.2 (2018): 599-631.

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# Results

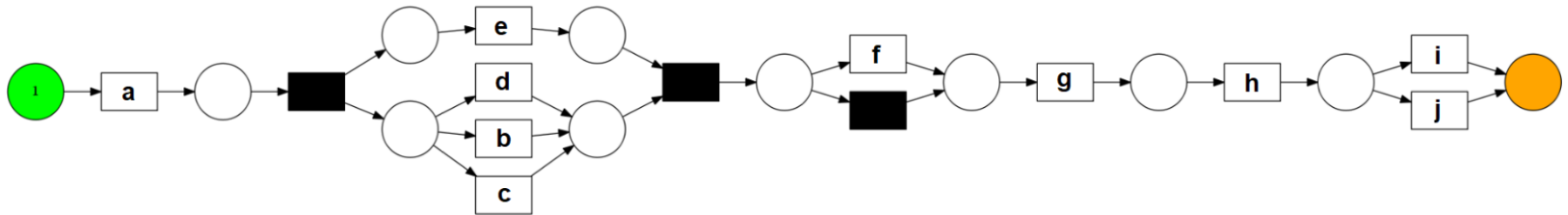
$\langle a, b, e, f, g, h \rangle^{80}$

$\langle a, [\{ b, c \}, e], \underline{f}, g, h, i \rangle^{15}$

$\langle a, [\{ b, c, d \}, e], \underline{f}, g, h, j \rangle^5$

Resulting petri net arising from **unfiltered** UDFG

i.e.  $act_{min} = 0$ ;  $act_{max} = 1$ ;  $rel_{min} = 0$ ;  $rel_{max} = 1$ :



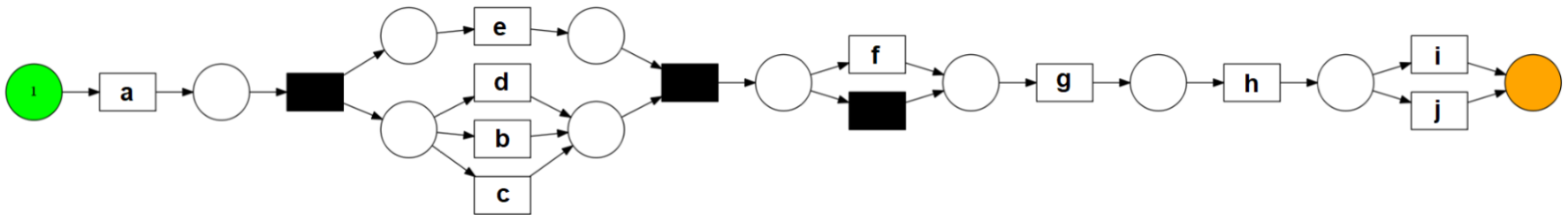
# Results

$\langle a, b, e, f, g, h \rangle^{80}$

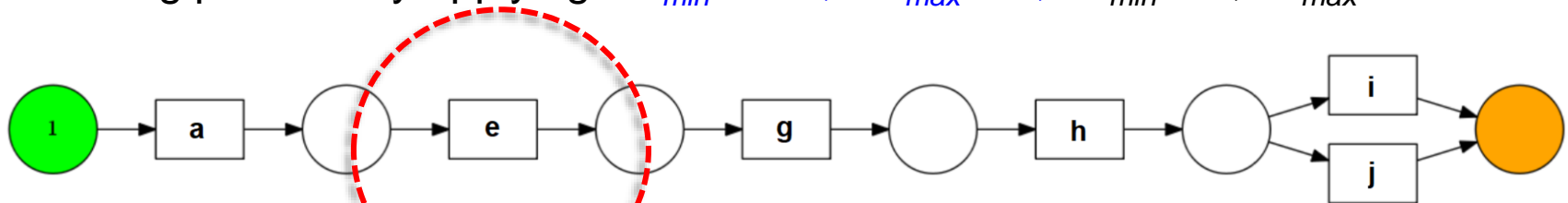
$\langle a, [\{ b, c \}, e], \underline{f}, g, h, i \rangle^{15}$

$\langle a, [\{ b, c, d \}, e], \underline{f}, g, h, j \rangle^5$

Resulting petri net arising from **unfiltered** UDFG:



Resulting petri net by applying  $act_{min} = 0.9$ ;  $act_{max} = 1$ ;  $rel_{min} = 0$ ;  $rel_{max} = 1$  to UDFG:



only completely certain activities are retained  
 $\frac{min_b}{max_b} = \frac{80}{100} = 0.8 < act_{min} = 0.9$ , thus remove b



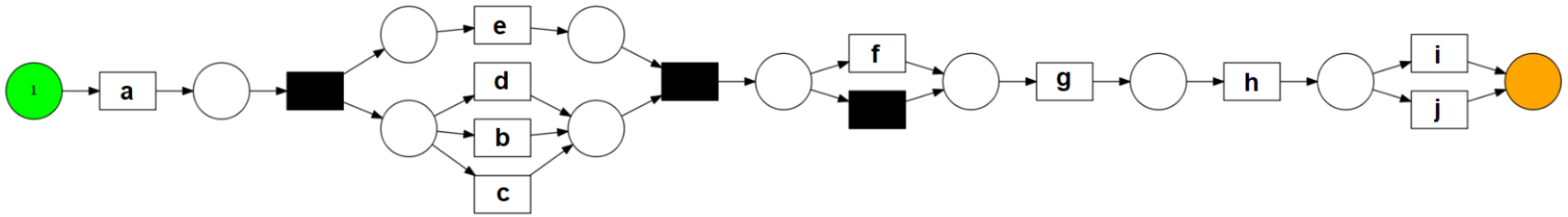
# Results

$\langle a, b, e, f, g, h \rangle^{80}$

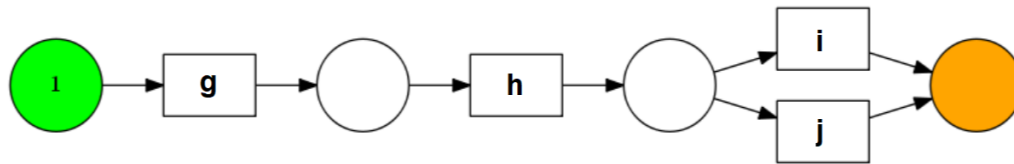
$\langle a, [\{ b, c \}, e], \underline{f}, g, h, i \rangle^{15}$

$\langle a, [\{ b, c, d \}, e], \underline{f}, g, h, j \rangle^5$

Resulting petri net arising from **unfiltered** UDFG:



Resulting petri net by applying  $act_{min} = 0$ ;  $act_{max} = 1$ ;  $rel_{min} = 0.9$ ;  $rel_{max} = 1$  to UDFG:



only the absolutely certain parts of the process are retained

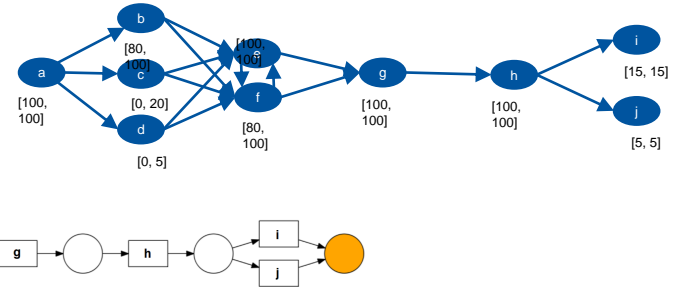
$$\frac{\min_{a \rightarrow b}}{\max_{a \rightarrow b}} = \frac{80}{100} = 0.8 < rel_{min} = 0.9, \text{ thus remove } a \rightarrow b$$

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# Conclusion

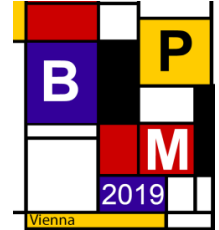
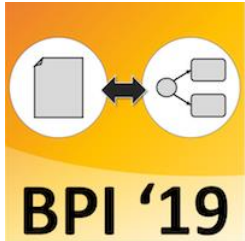
## Summary:

- Uncertain event data
- Uncertain Directly-Follows-Graph (UDFG)
- Process discovery over a UDFG
- Keep or filter out the behavior of an uncertain event log



## Future work:

- Computational cost analysis and performance optimization
- Definition of metrics and measures over uncertain event data
- Extensive experiments on real-world data



Thanks for your attention!

Any questions?



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## References

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Marco Pegoraro and Wil M.P. van der Aalst, "Mining Uncertain Event Data in Process Mining," *2019 International Conference on Process Mining (ICPM)*, Aachen, Germany, 2019, pp. 89-96. doi: 10.1109/ICPM.2019.00023 .

Sander J.J. Leemans, Dirk Fahland, and Wil M.P. van der Aalst. "*Scalable process discovery and conformance checking.*" *Software & Systems Modeling* 17.2 (2018): 599-631.