Ludwig-Maximilians-Universität München
Lehrstuhl für Datenbanksysteme und Data Mining
Prof. Dr. Thomas Seidl

Knowledge Discovery and Data Mining 1

(Data Mining Algorithms 1)

Wintersemester 2019/20

Agenda

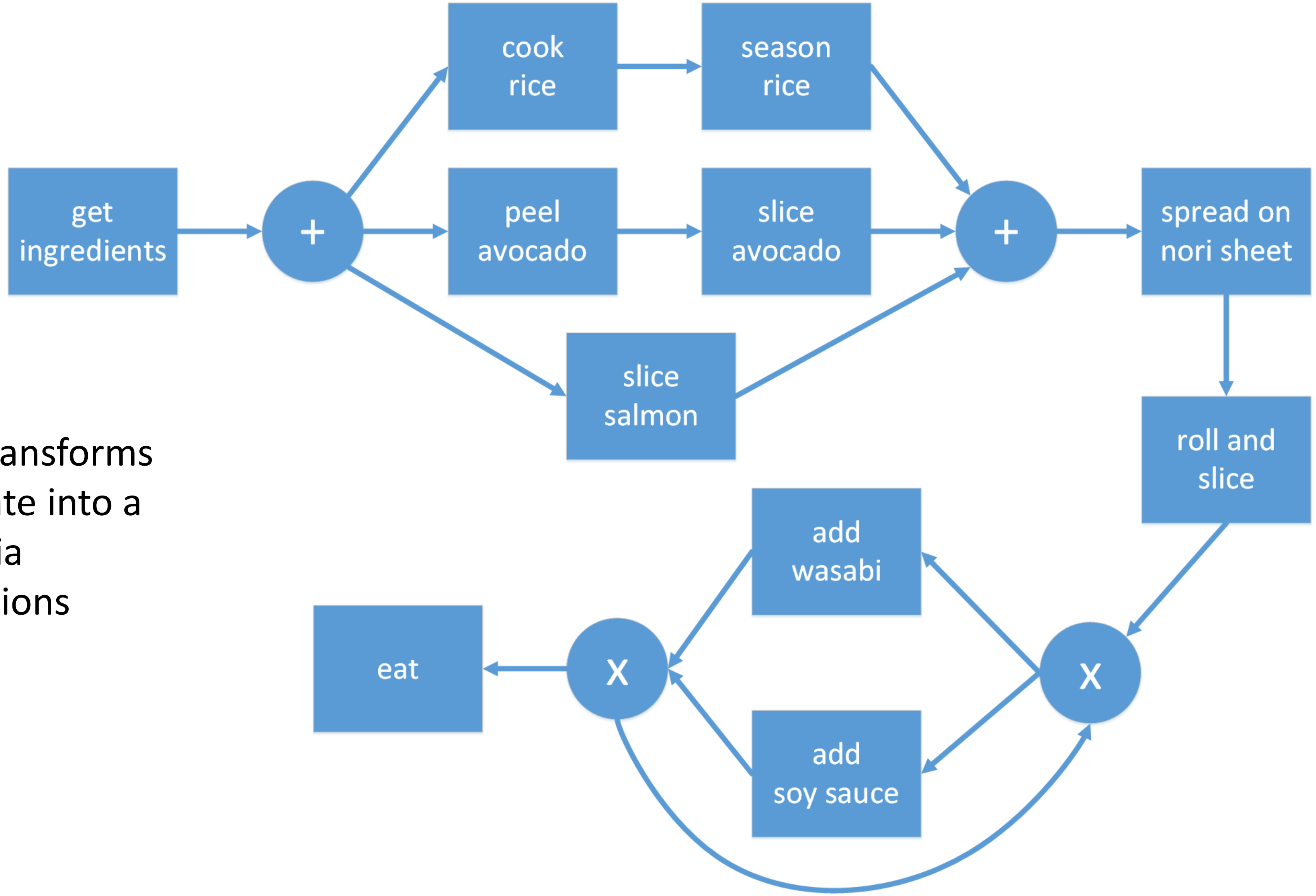
1. Introduction
2. Basics
3. Supervised Methods
4. Unsupervised Methods
5. Process Mining

5.1 Introduction
5.2 Process Models – An Overview
5.3 Process Discovery
5.4 Conformance Checking
5.5 Additional Mining Tasks

Agenda

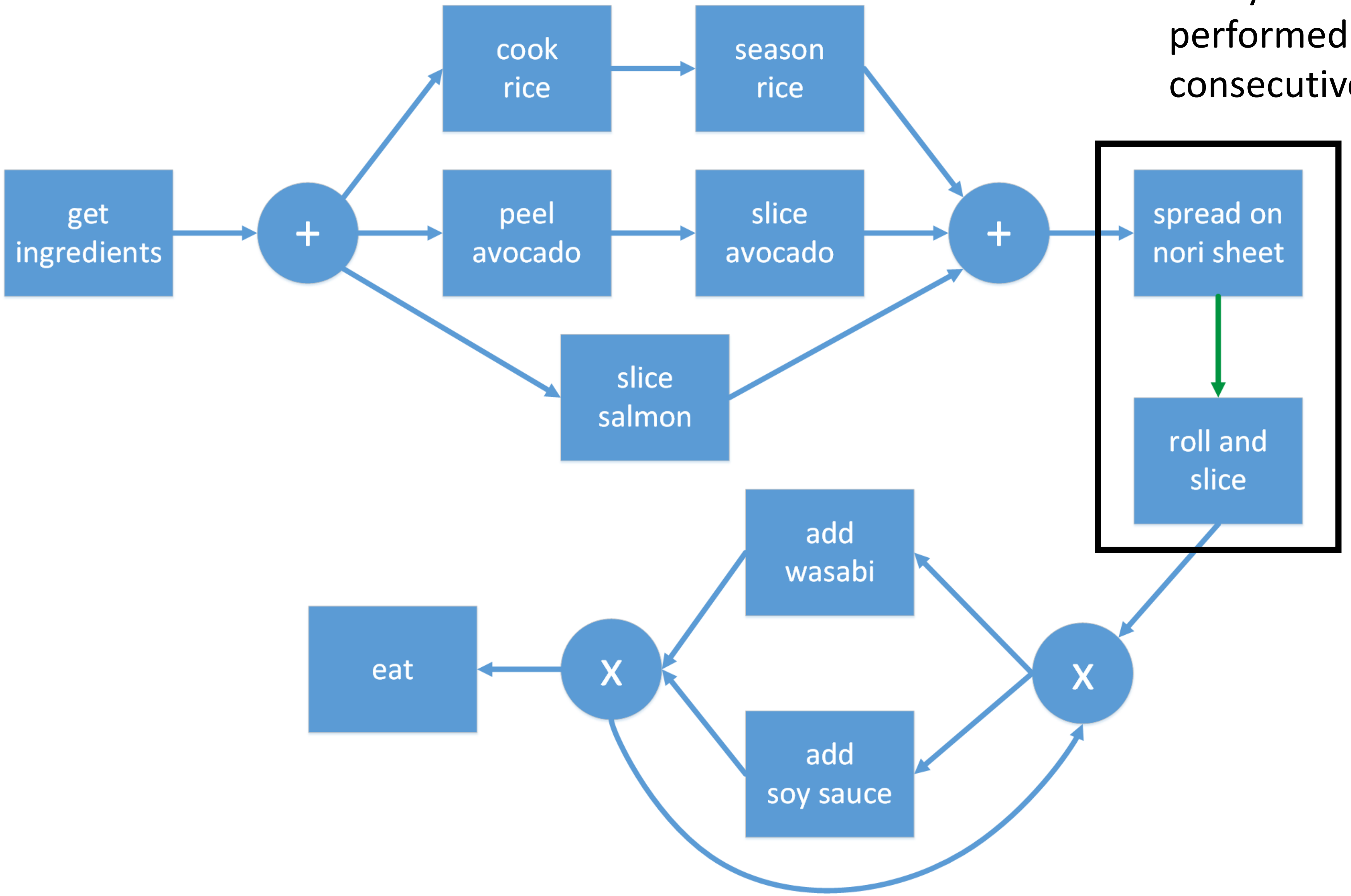
Processes in Applications

Example: The Sushi Process



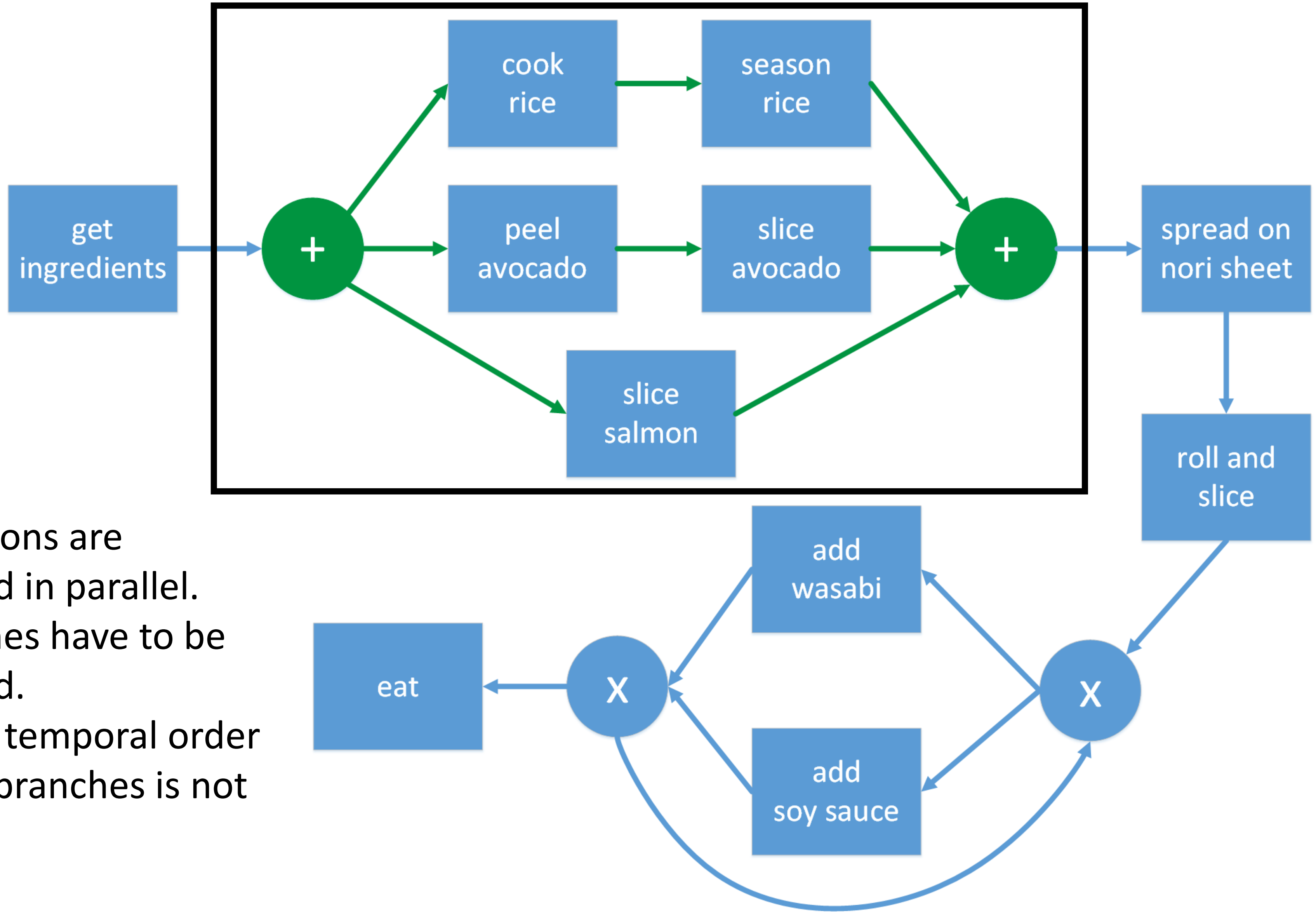
A process transforms an initial state into a final state via multiple actions

Process Properties: Sequence



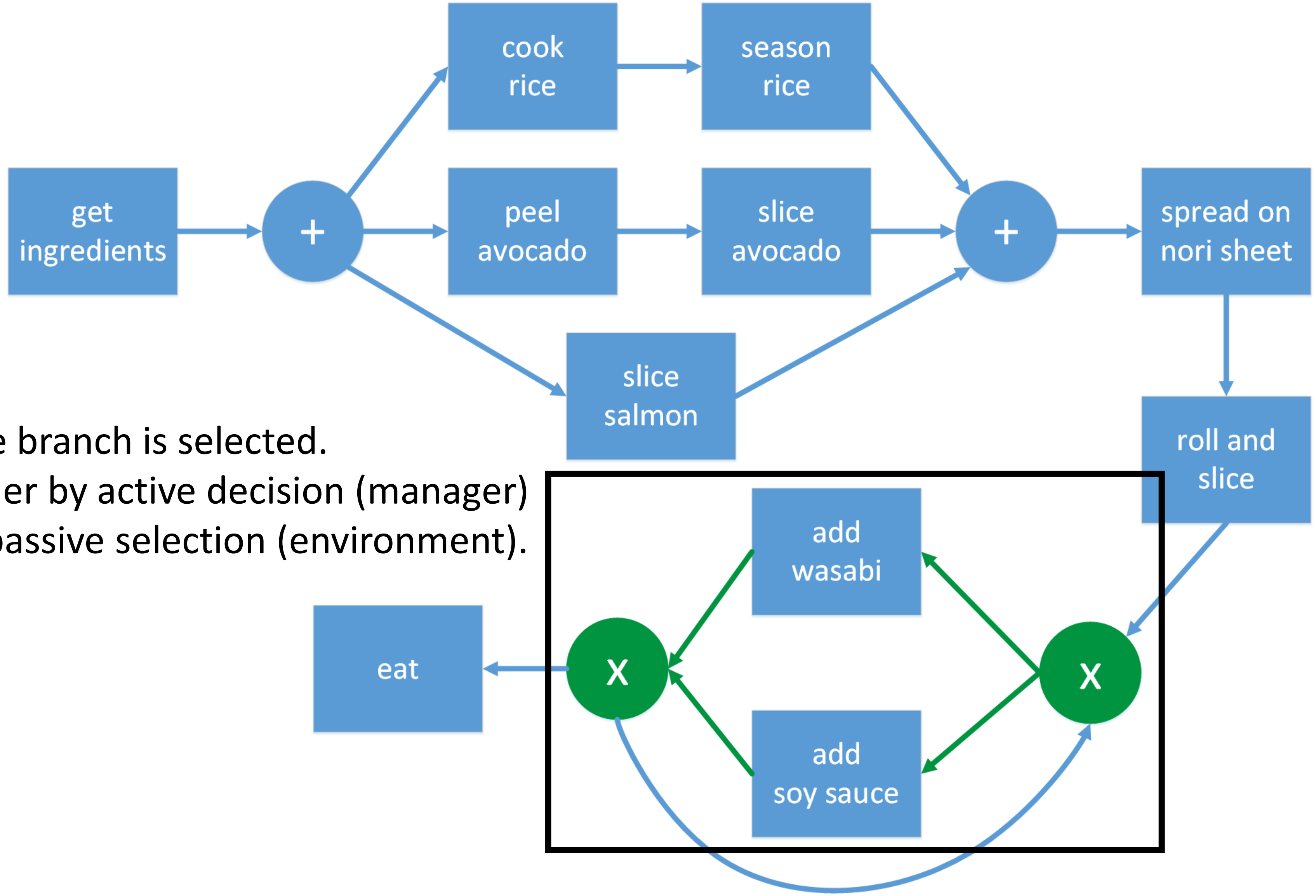
- Many actions are performed in consecutive order

Process Properties: Concurrency



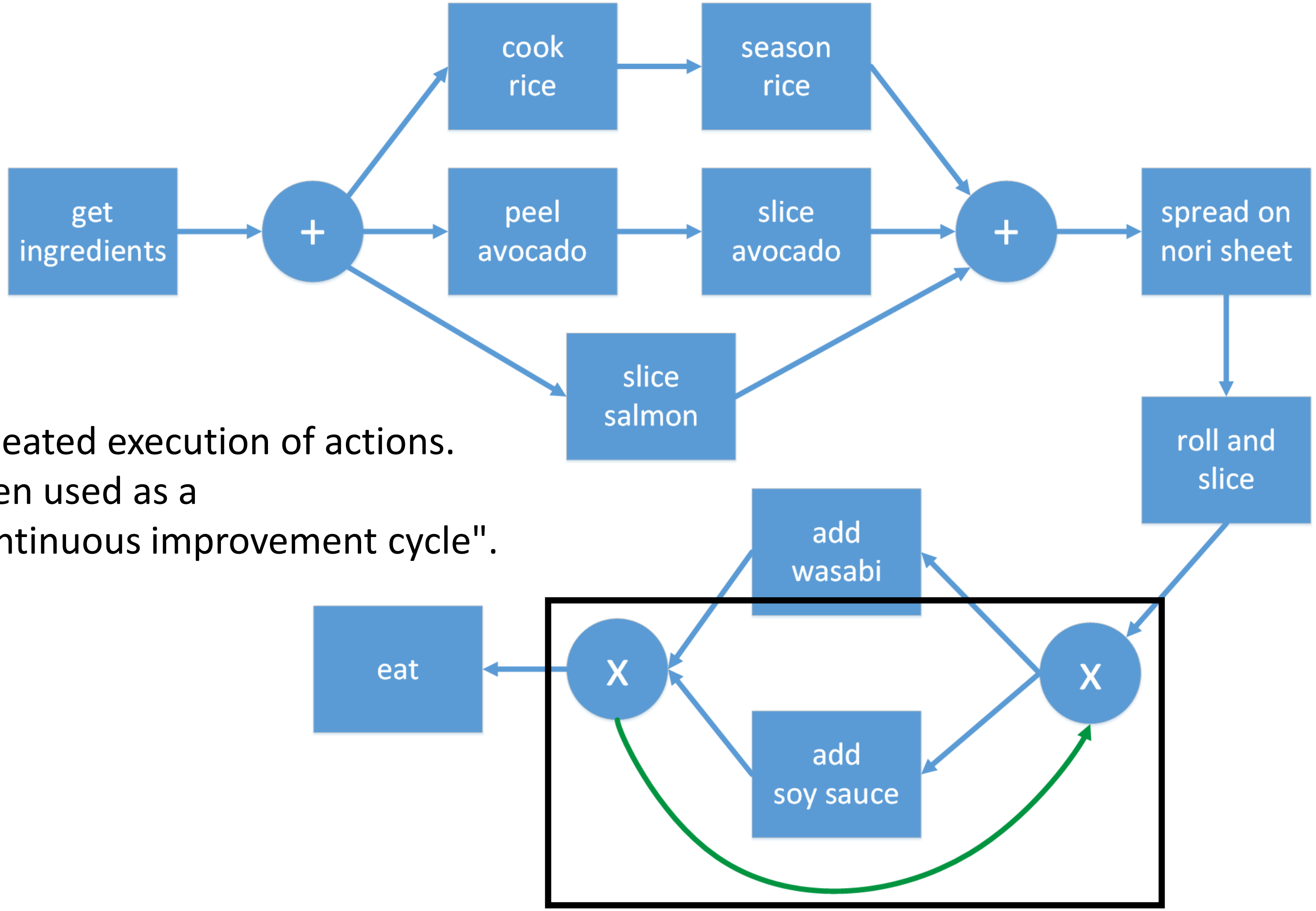
- Some actions are performed in parallel.
- All branches have to be performed.
- The exact temporal order between branches is not strict.

Process Properties: Choice



- One branch is selected.
- Either by active decision (manager) or passive selection (environment).

Process Properties: Loop

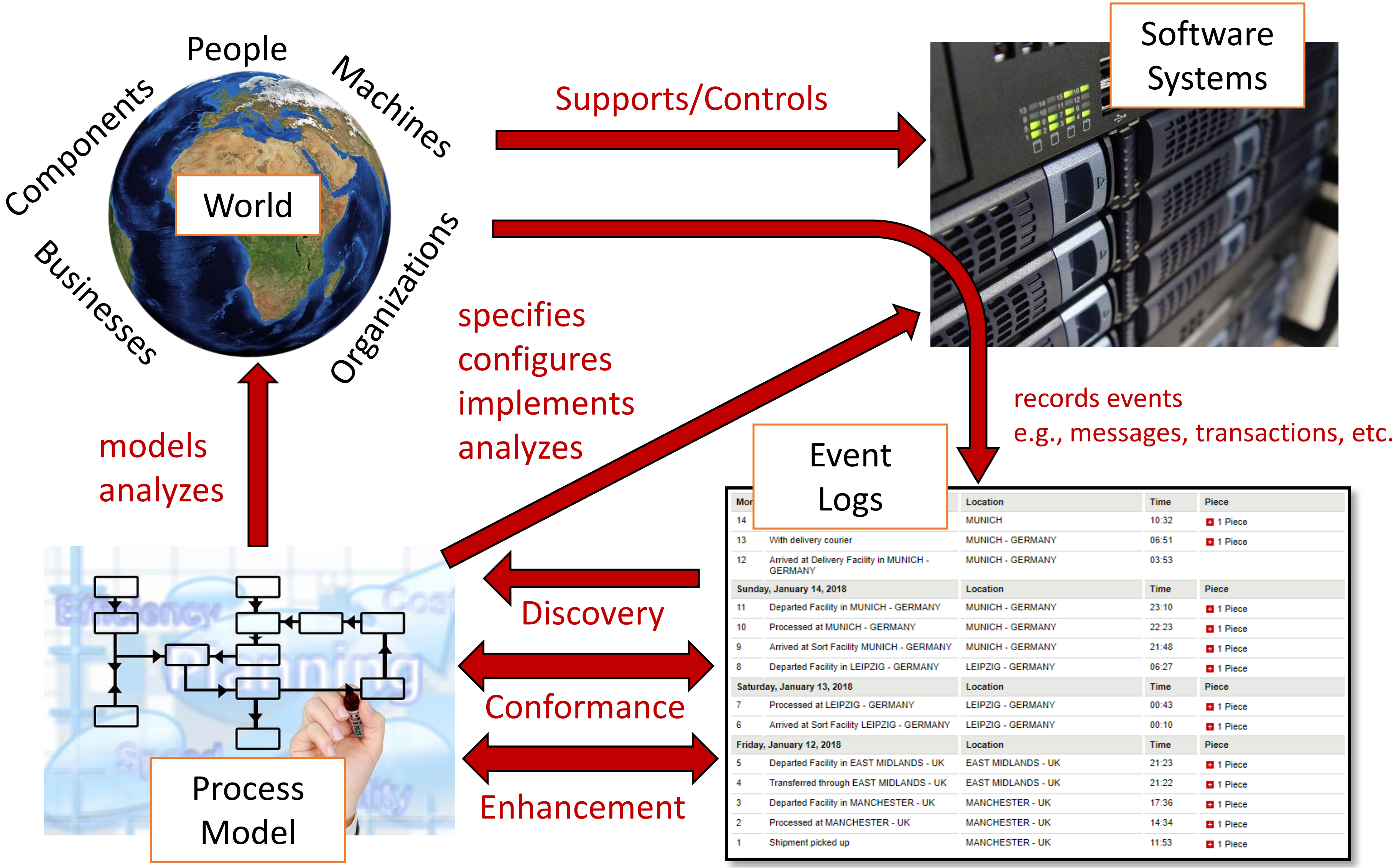


- Repeated execution of actions.
- Often used as a "continuous improvement cycle".

Benefits of Process Models

- Insights by changing perspectives and highlights.
- Specification / Documentation for certifications or legal contract purposes.
- Verification of executions to reveal problems.
- Performance analysis to identify issues like bottlenecks.
- Simulation (digital twin) to experiment virtually with changed settings.

Information Flow of Event Data



Event Logs as Starting Point

case id	activity	timestamp	resource 1	resource 2	execution quality
		…			
Sushi 113	get ingredients	09:31	Andreas	bag	good
Sushi 239	slice salmon	09:35	Bianca	knife 1	medium
Sushi 239	spread on nori sheet	09:42	Bianca		very good
Sushi 248	eat	09:43	Charlie		-
Sushi 249	get ingredients	09:47	Andreas	bag	good
Sushi 113	cook rice	09:51	Bianca	rice cooker 3	poor
Sushi 239	roll and slice	09:51	Charlie	knife 1	good
Sushi 113	peel avocado	09:53	Andreas	knife 2	poor
Sushi 239	add soy sauce	09:54	Bianca		good
Sushi 239	add soy sauce	09:55	Bianca		poor
Sushi 239	eat	09:57	Andreas		-
		…			

Event Logs Technically

- Data collection mostly fully automated.
- Process-Aware Information Systems (PAIS)
  - ERP (Enterprise-Resource Planning) [SAP, Oracle]
  - BPM (Business Process Management) [IBM BPM]
  - CRM (Customer Relationship Management)
- Popular data format: XES
  - XML-based
  - easy to understand

```xml
<?xml version="1.0" encoding="UTF-8" ?>
<log xes.version="2.0" xes.features="arbitrary-depth" xmlns="http://www.xes-standard.org
    /">
    <extension name="Concept" prefix="concept" uri="http://www.xes-standard.org/concept.
        xesext"/>
    <extension name="Time" prefix="time" uri="http://www.xes-standard.org/time.xesext"/>
    <global scope="trace">
        <string key="concept:name" value=""/>
    </global>
    <global scope="event">
        <string key="concept:name" value=""/>
        <date key="time:timestamp" value="1970-01-01T00:00:00.000+00:00"/>
        <string key="system" value=""/>
    </global>
    <classifier name="Activity" keys="concept:name"/>
    <classifier name="Another" keys="concept:name system"/>
    <float key="log attribute" value="2335.23"/>
    <trace>
        <string key="concept:name" value="Trace number one"/>
        <event>
            <string key="concept:name" value="Register client"/>
            <string key="system" value="alpha"/>
            <date key="time:timestamp" value="2009-11-25T14:12:45:000+02:00"/>
            <int key="attempt" value="23">
                <boolean key="tried hard" value="false"/>
            </int>
        </event>
        <event>
            <string key="concept:name" value="Mail rejection"/>
            <string key="system" value="beta"/>
            <date key="time:timestamp" value="2009-11-28T11:18:45:000+02:00"/>
        </event>
    </trace>
</log>
```

Event Logs Formally

An **event $\boldsymbol{e}$** is a tuple $e = (c, a, t, \dots)$ containing
a case identifier c,
an activity label a and
a timestamp t.

An event can contain additional attributes.

case id	activity	timestamp	resource 1	resource 2	execution quality
		...			
Sushi 113	get ingredients	09:31	Andreas	bag	good
Sushi 239	slice salmon	09:35	Bianca	knife 1	medium
Sushi 239	spread on nori sheet	09:42	Bianca		very good
Sushi 248	eat	09:43	Charlie		-
Sushi 249	get ingredients	09:47	Andreas	bag	good
Sushi 113	cook rice	09:51	Bianca	rice cooker 3	poor
Sushi 239	roll and slice	09:51	Charlie	knife 1	good
Sushi 113	peel avocado	09:53	Andreas	knife 2	poor
Sushi 239	add soy sauce	09:54	Bianca		good
Sushi 239	add soy sauce	09:55	Bianca		poor
Sushi 239	eat	09:57	Andreas		-
		...			

For an event $e = (c, a, t)$, we define the projections
$\#_{case}(e) = c$, $\#_{activity}(e) = a$, and $\#_{time}(e) = t$.

An **event log $\boldsymbol{L}$** is a multiset of events.

Event Logs Formally

A **case $\boldsymbol{C}$**, identified by c in the log,
is the set of events

$$C = \{e \in L \mid \#_{case}(e) = c\}$$

case id	activity	timestamp	resource 1	resource 2	execution quality
		…			
Sushi 113	get ingredients	09:31	Andreas	bag	good
Sushi 239	slice salmon	09:35	Bianca	knife 1	medium
Sushi 239	spread on nori sheet	09:42	Bianca		very good
Sushi 248	eat	09:43	Charlie		-
Sushi 249	get ingredients	09:47	Andreas	bag	good
Sushi 113	cook rice	09:51	Bianca	rice cooker 3	poor
Sushi 239	roll and slice	09:51	Charlie	knife 1	good
Sushi 113	peel avocado	09:53	Andreas	knife 2	poor
Sushi 239	add soy sauce	09:54	Bianca		good
Sushi 239	add soy sauce	09:55	Bianca		poor
Sushi 239	eat	09:57	Andreas		-
		…			

A **trace $\boldsymbol{\sigma_c}$** is the sequence of activities for a case $C = \{e_1, \dots, e_n\}$ with

$$\sigma_c = \#_{activity}(e_{\pi(1)}), \dots, \#_{activity}(e_{\pi(n)})$$

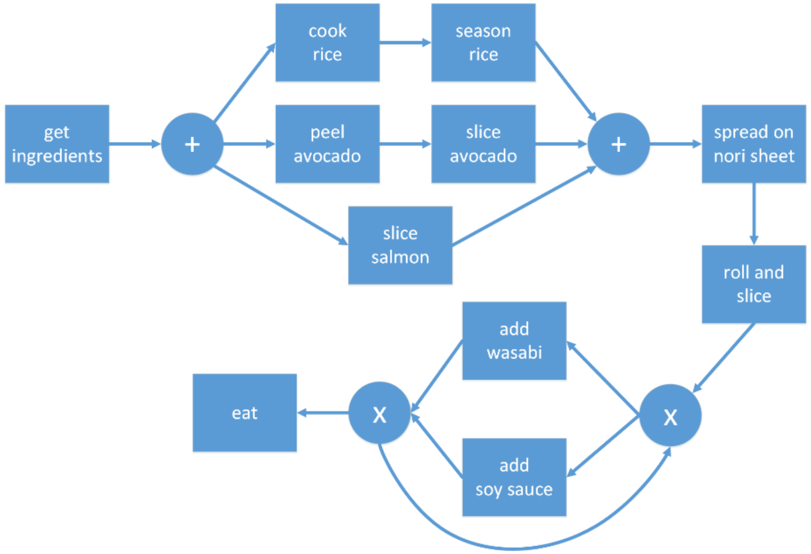
such that $\#_{timestamp}(e_{\pi(i)}) < \#_{timestamp}(e_{\pi(j)})$ for $\pi(i) < \pi(j)$.

Integration into the Data Mining World

Itemsets
(e.g. frequent itemset mining)

$\{rice, avocado, salmon\}$

Processes



Sequences
(e.g. sequential pattern mining)

$get\ ingredients$
$\rightarrow prepare\ ingredients$
$\rightarrow spread\ on\ nori\ sheet$
$\rightarrow roll\ and\ slice$
$\rightarrow season\ with\ wasabi$
$\rightarrow season\ with\ soy\ sauce$
$\rightarrow eat$

no order ⟷ total order

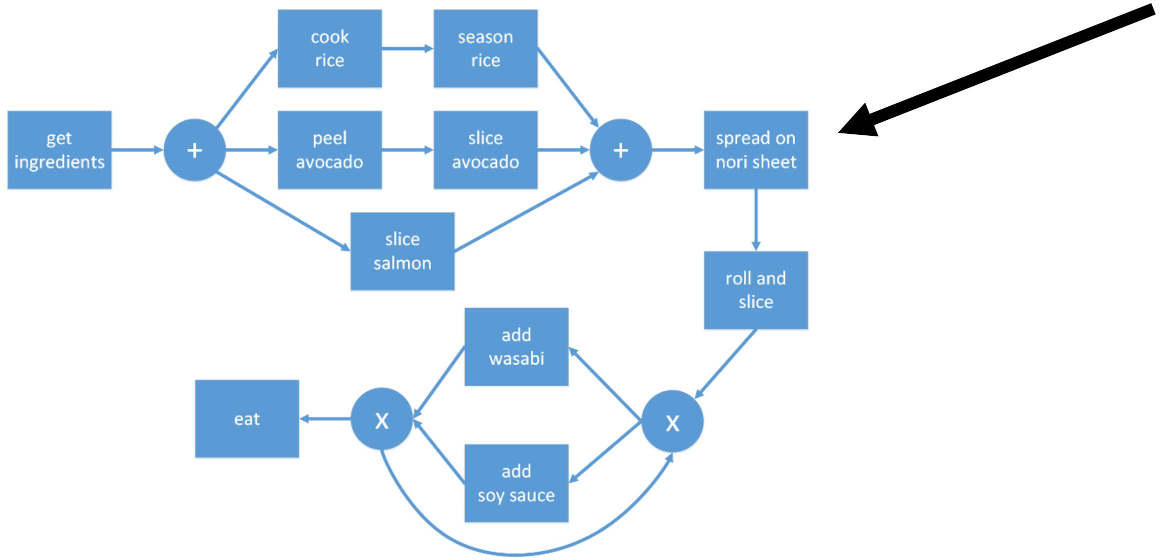
- unordered
- set-based

- partially ordered
- sequences can occur, models are directed graphs
- branches break order (concurrency)

- strictly totally ordered
- sequence-based

Process Mining Task: Discovery

- Given an event log, find a process model which
  - must be able to replay the log ⇒ *Fitness*
  - simplifies as far as possible ⇒ *Simplicity*
  - does not overfit the log ⇒ *Generalization*
  - does not underfit the log ⇒ *Precision*

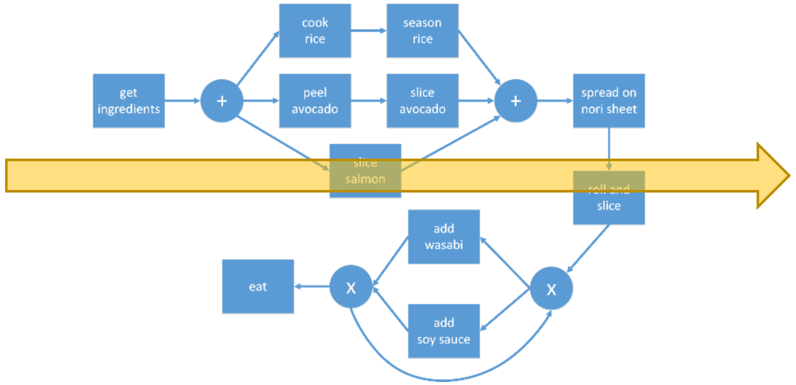


case id	activity	timestamp
	…	
Sushi 113	get ingredients	09:31
Sushi 239	slice salmon	09:35
Sushi 239	spread on nori sheet	09:42
Sushi 248	eat	09:43
Sushi 249	get ingredients	09:47
Sushi 113	cook rice	09:51
Sushi 239	roll and slice	09:51
Sushi 113	peel avocado	09:53
Sushi 239	add soy sauce	09:54
Sushi 239	add soy sauce	09:55
Sushi 239	eat	09:57
	…	

Process Mining Task: Conformance Checking

- Given an event log and a process model, decide for each case whether it conforms to the model or not. If not, give the issues.

cook rice, add wasabi,
roll and slice, eat

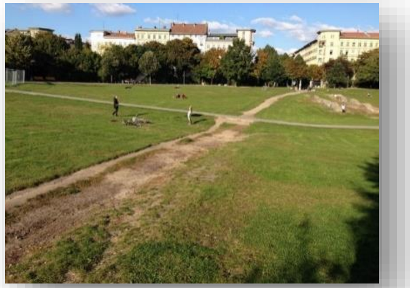


conform

non-conform

- A case instance can perform better than others. Then reveal the beneficial deviations to improve the general workflow.
- If the case performs worse, identify the root cause to avoid misbehavior.

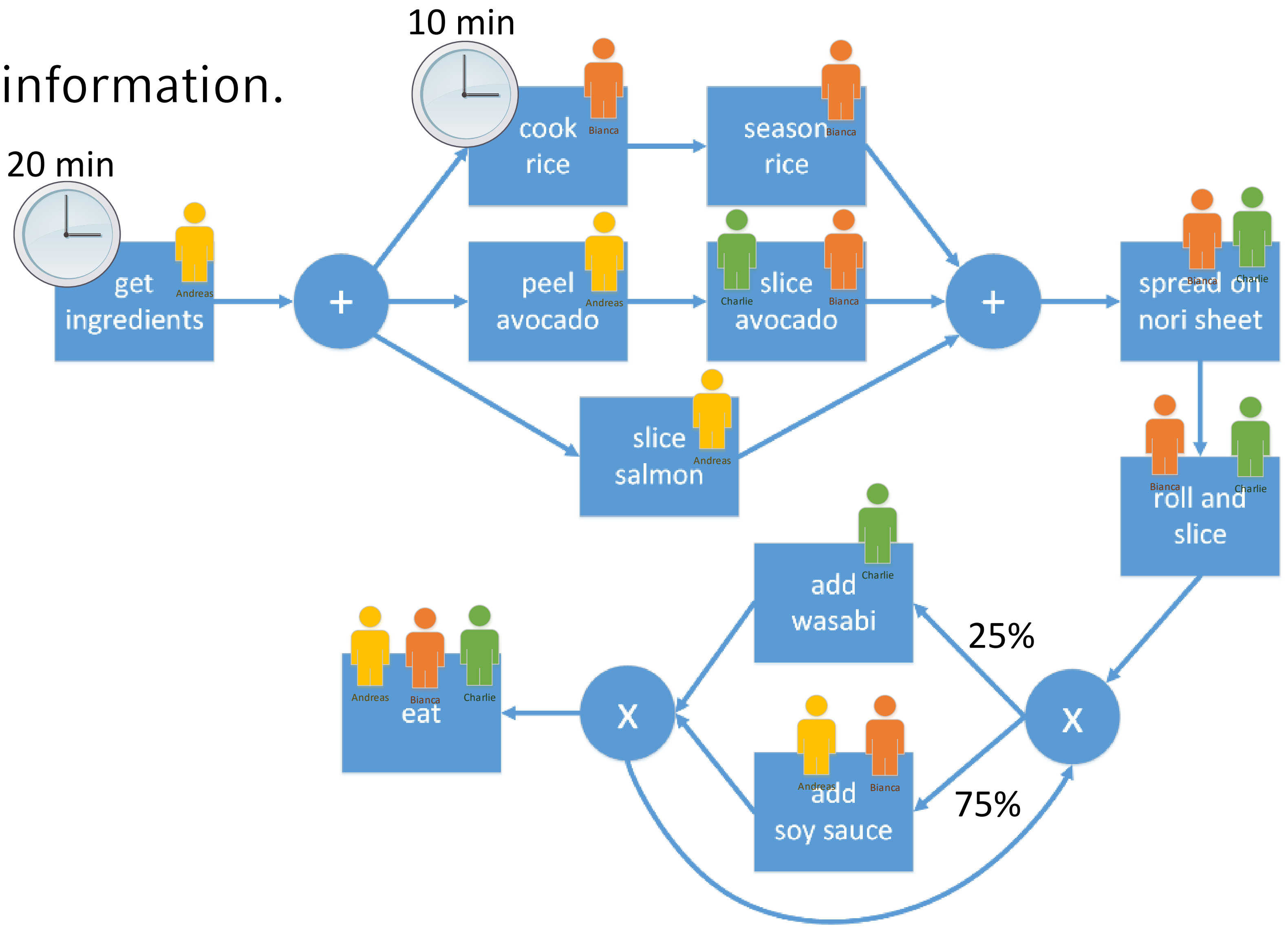

Housebreaking

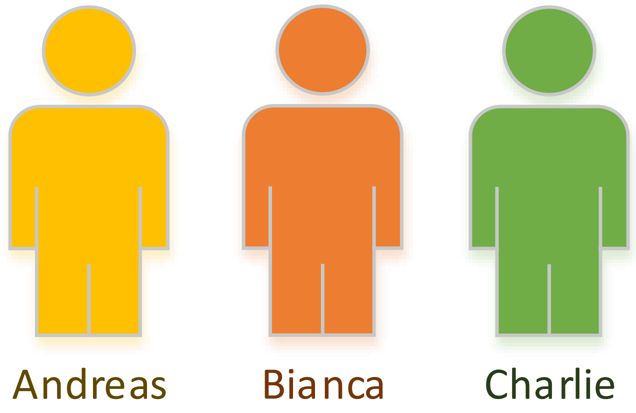

Trails


Tool choice

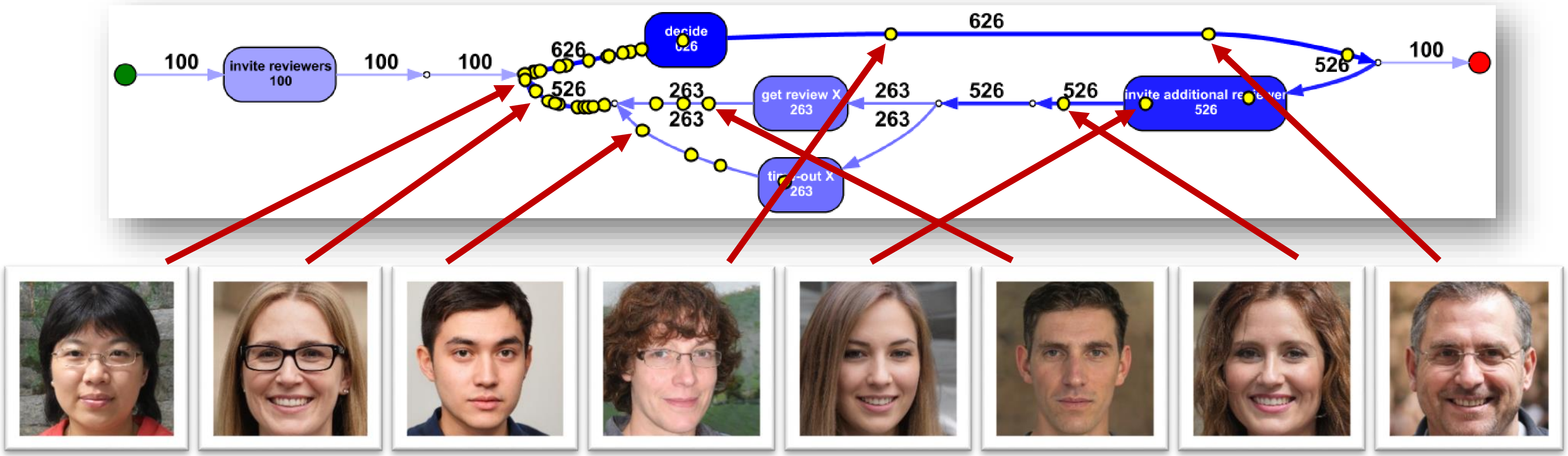
Process Mining Task: Enhancement

- Given a process model, augment with additional information.
  - Temporal information
  - Social networks
  - Organisational roles
  - Decision rules





Process Mining Risks and Green Data Science

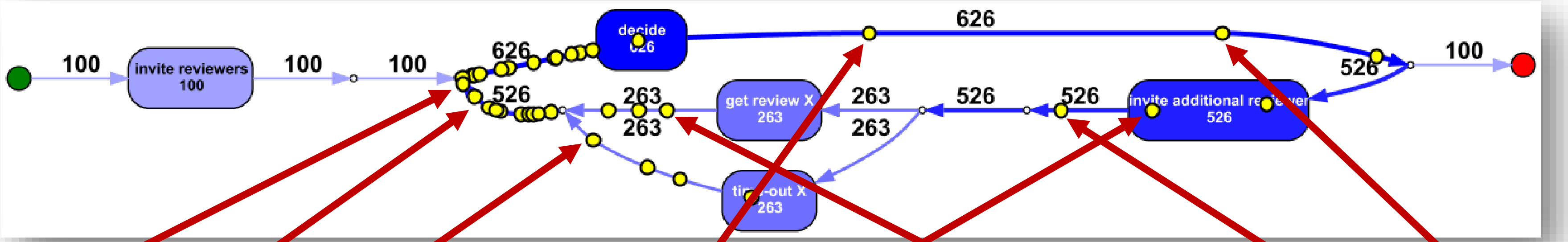


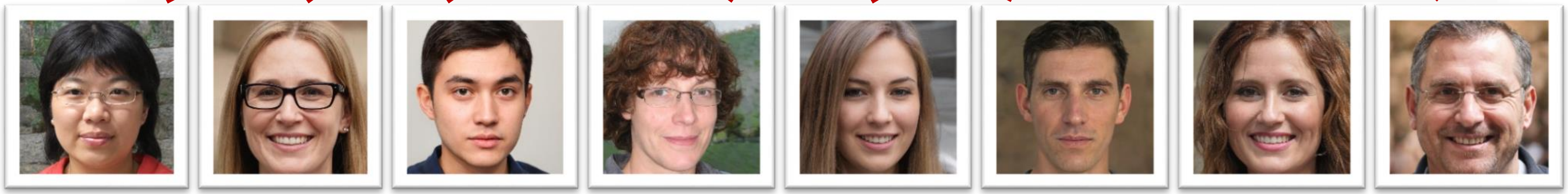
Made with StyleGAN
arXiv:1912.04958

- Mostly: Cases related to people. But what is in the data?
  - Students *Who asks the most questions?*
  - Employees *Who is associated with long execution terms?*
  - Tenants *Who needs maintenance often?*
  - Clients *Who calls most for service?*

neutral,
objective,
data-oriented

Process Mining Risks and Green Data Science



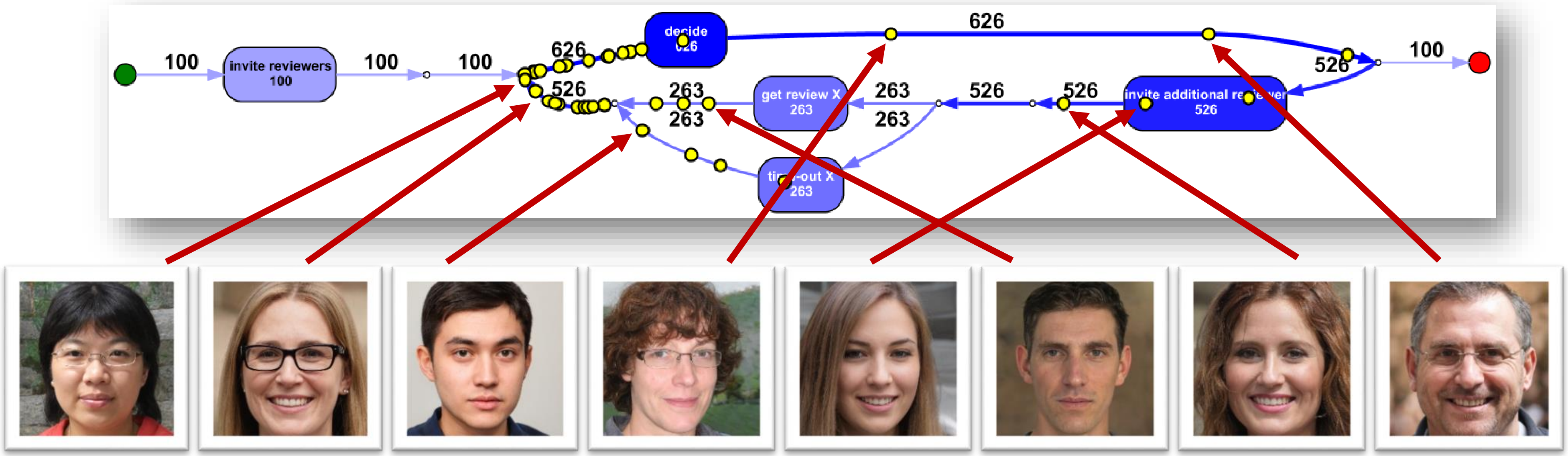


Made with StyleGAN
arXiv:1912.04958

- Same results, but with intentional mindset:
  - Students *Who is the least intelligent student?*
  - Employees *Who is the slowest worker?*
  - Tenants *Who caused the most repairs?*
  - Clients *Who complains the most?*

bad intention, negative-subjective, pessimistic

Process Mining Risks and Green Data Science

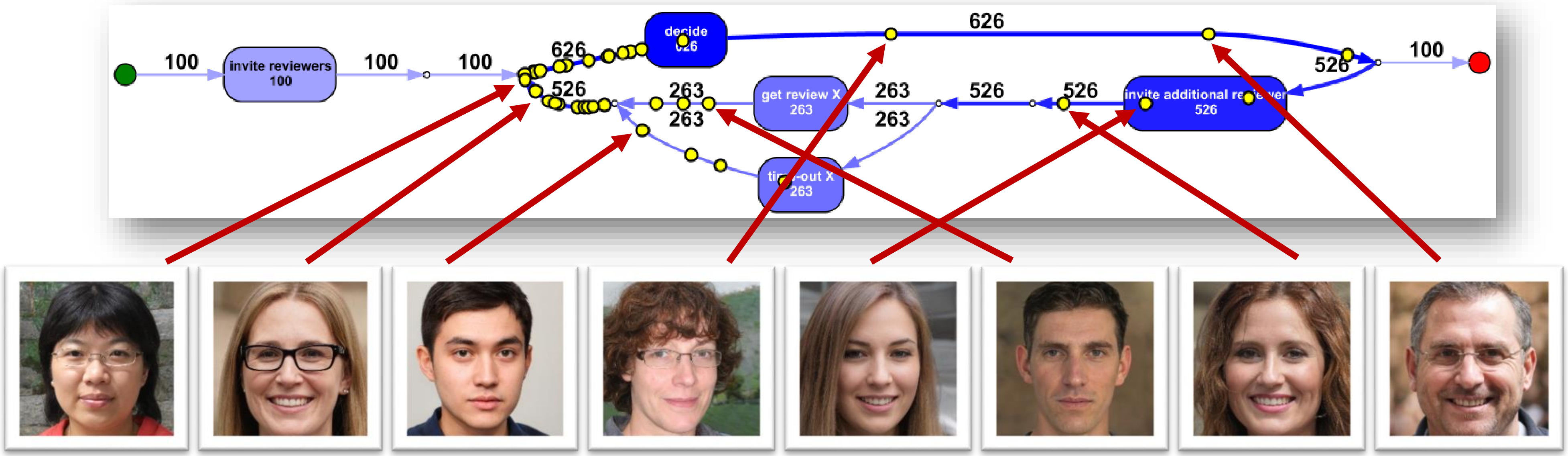


Made with StyleGAN
arXiv:1912.04958

- And the other extreme, changed mindset:
  - Students *Who is the most interested student?*
  - Employees *Who handles the most difficult tasks?*
  - Tenants *Who takes care of the rental property?*
  - Clients *Who gives a lot of constructive feedback?*

good intention, positive-subjective, optimistic

Process Mining Risks and Green Data Science



Made with StyleGAN
arXiv:1912.04958

- Be careful with interpretations.
- Even if you are objective, can your results be interpreted otherwise?
- Can you obscure the results so they stay meaningful, but protect individuals?
  e.g. cluster individuals, top-k-rankings, k-anonymity, hashing, noise addition,…

Scientific Process Mining Tools

- PROM:
  - First version in 2010.
  - Java-based.
  - Provides many algorithms in a GUI.

- pm4py:
  - First version in 2019
  - Python-based
  - Documentation: https://pm4py.fit.fraunhofer.de/
  - Several algorithms available

Agenda

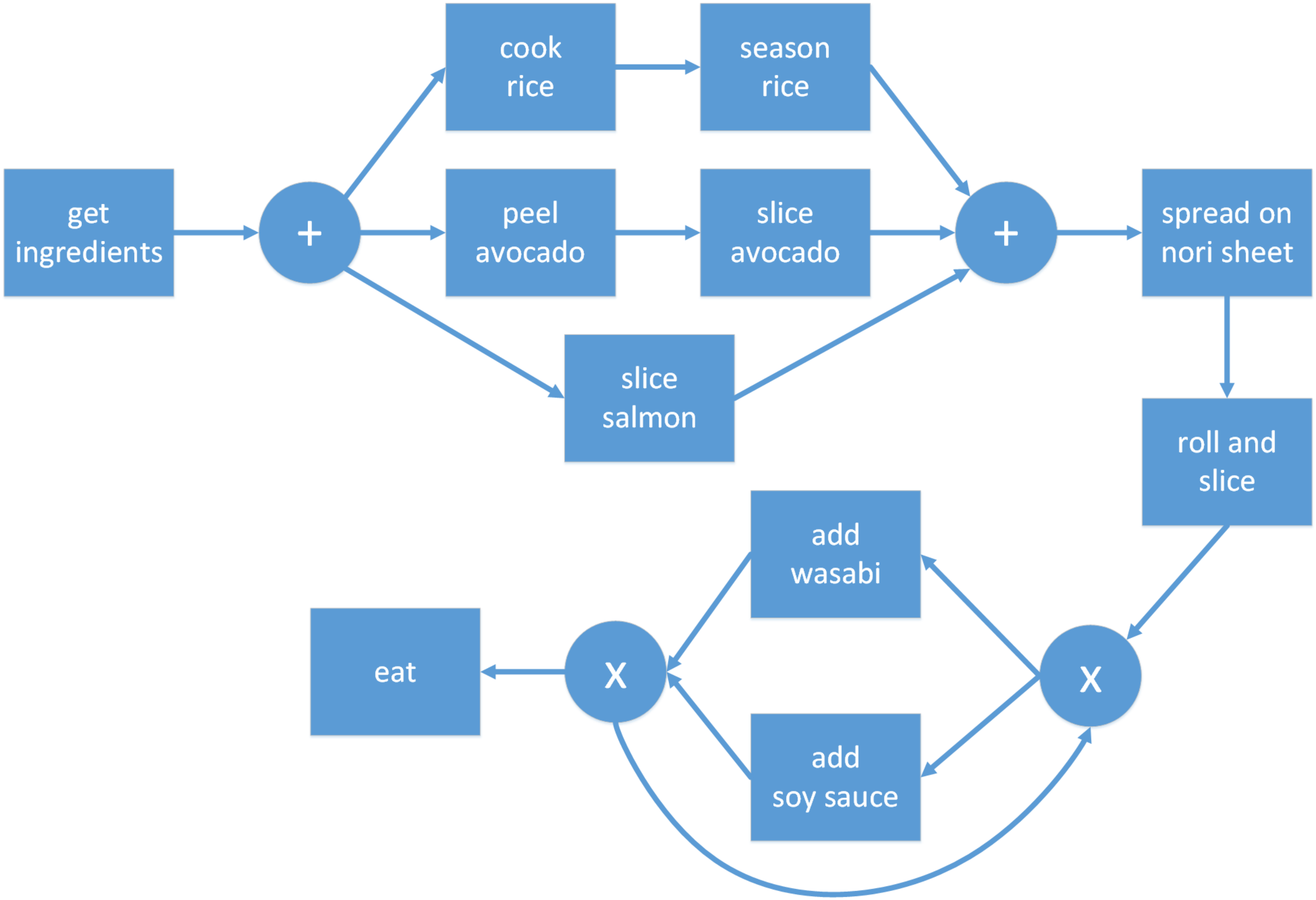
Motivation

Why do we need Process Models?

- Predetermine operational processes in the form of guidelines
  - Descriptive vs. Normative model
- Visualization of processes
- Process reasoning
- Analysis of given processes
  - Starting point for initial implementation and re-design
  - Distribution of responsibilities
  - Planning and controlling
  - Compliance checking
  - Performance prediction via simulation
  - …

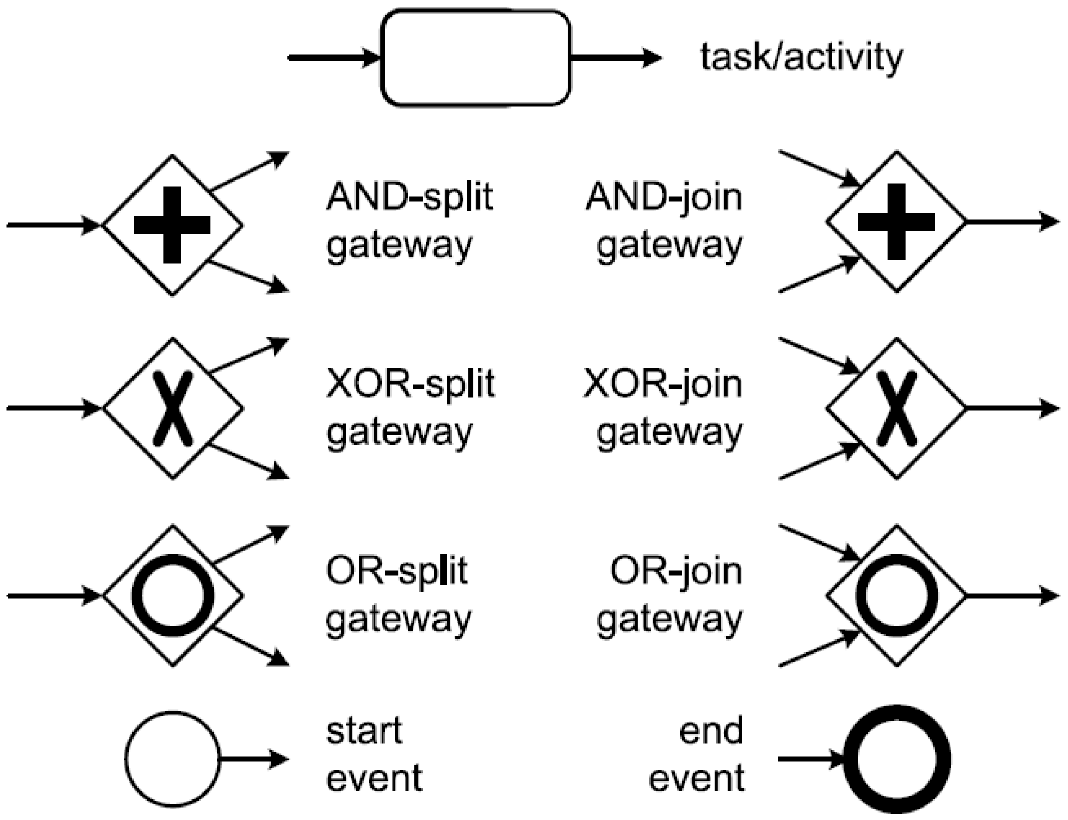
Process Model – BPMN (Business Process Modeling Notation)

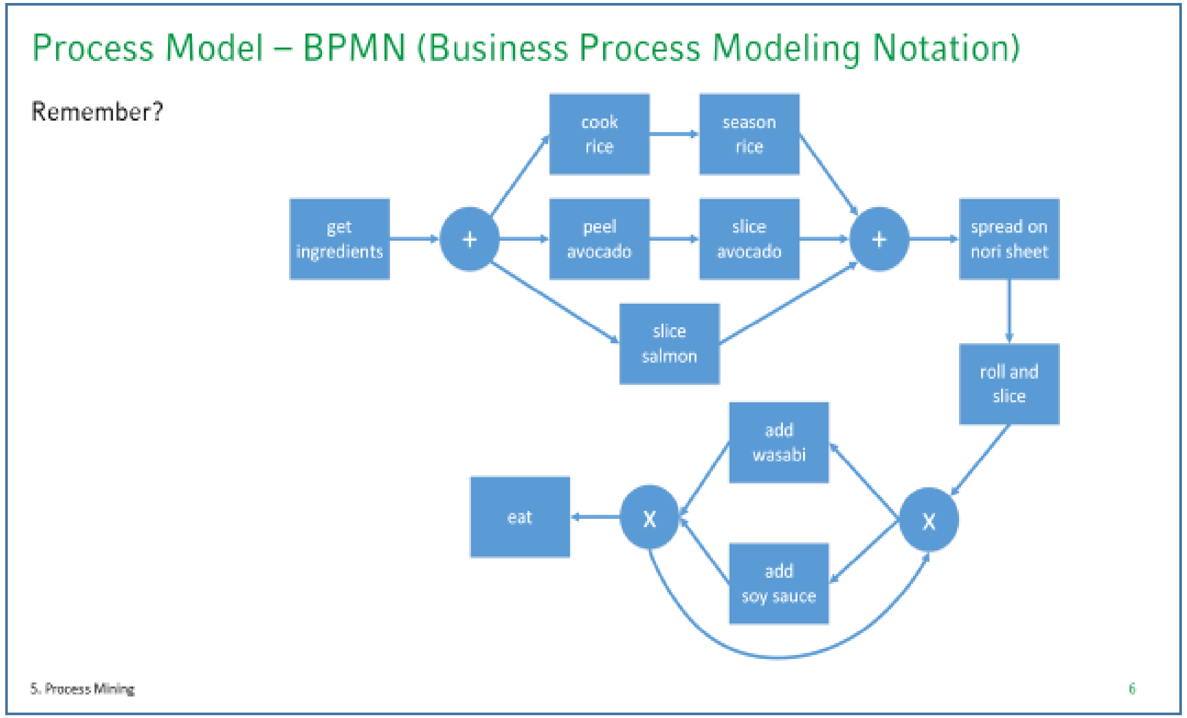
Remember?



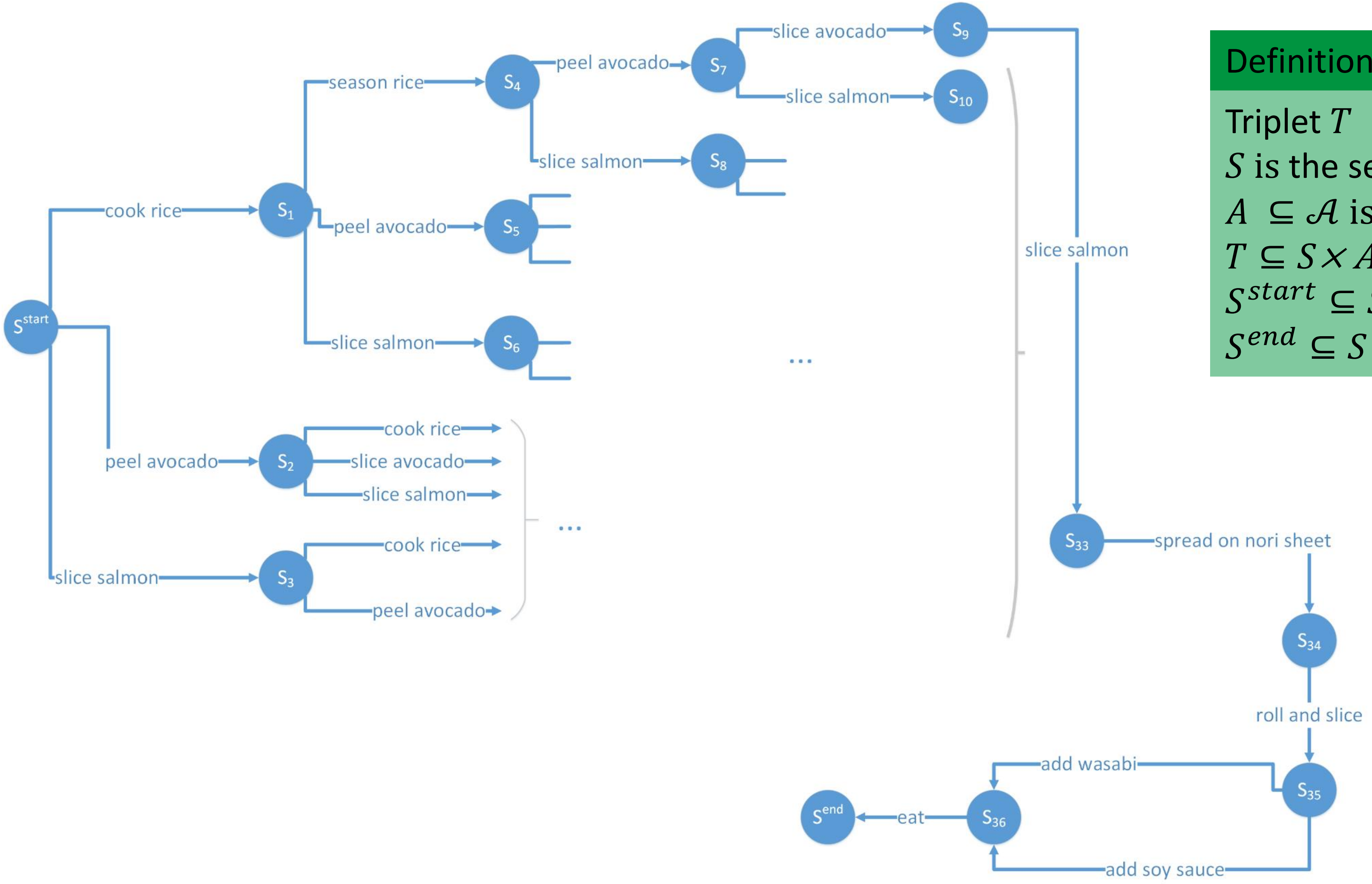
Process Model – BPMN (Business Process Modeling Notation)

Exemplary subset of elements contained in BPMN





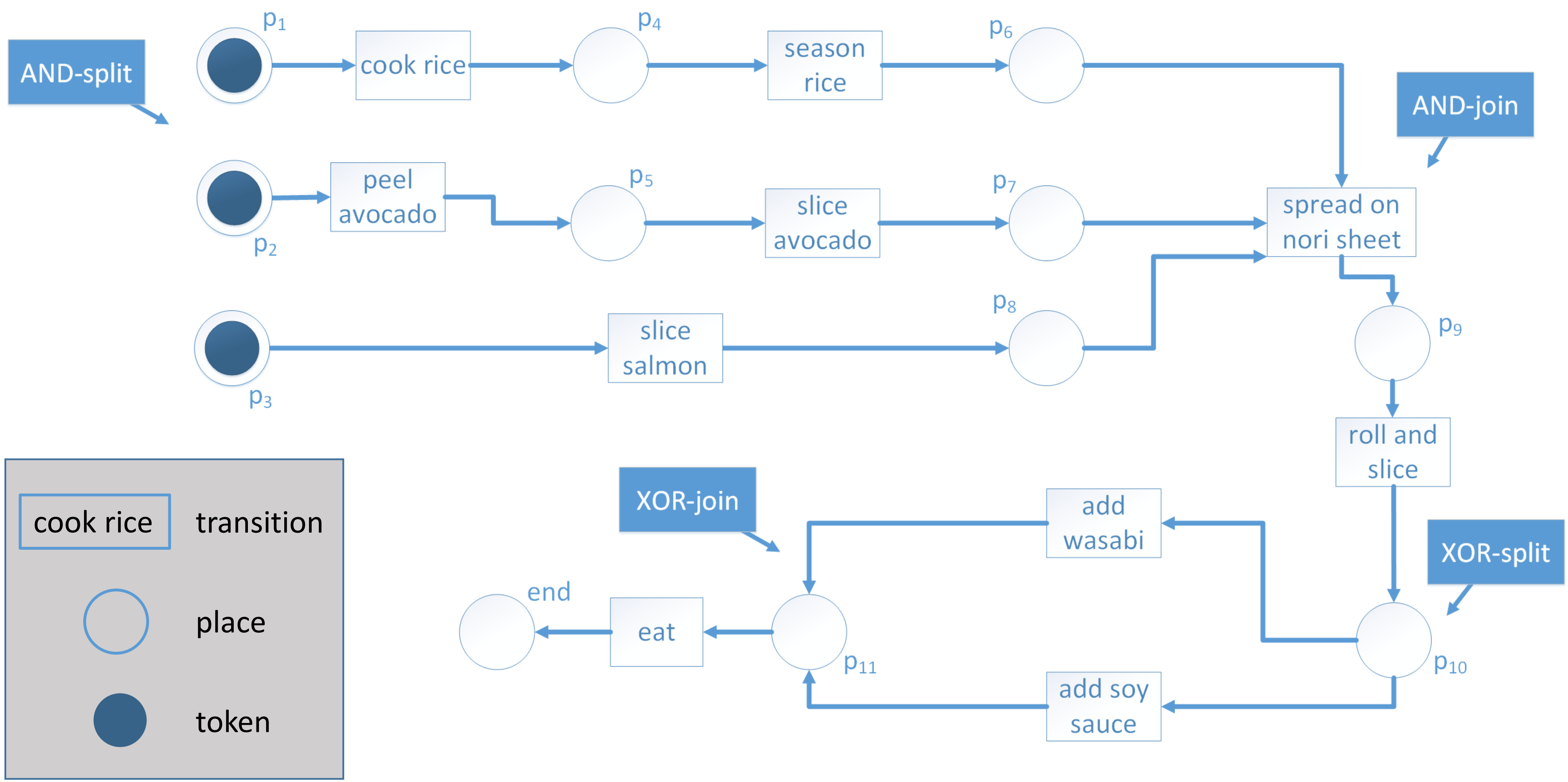
Process Model – Transition System



Definition (Transition system)

Triplet $T = (S, A, T)$, where
S is the set of *states*
$A \subseteq \mathcal{A}$ is the set of *activities*
$T \subseteq S \times A \times S$ is the set of *transitions*
$S^{start} \subseteq S$ is the set of *inital states*
$S^{end} \subseteq S$ is the set of *final states*

Process Model – Petri Nets



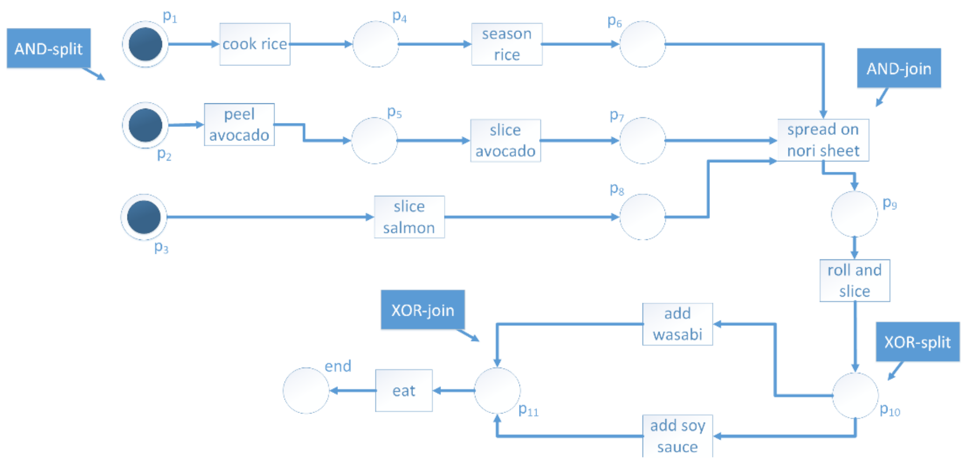
Process Model – Petri Nets

As already seen the Petri net is a bipartite graph.

Definition (Petri Net)

Triplet N $= (P, T, F)$, where
P is a finite set of *places*
T is a finite set of *transitions*, $P \cap T = \emptyset$
$F \subseteq (T \times P) \cup (P \times T)$ is a set of *directed arcs* (called *flow relation*)

Exemplary formalization of given Petri Net:



P = {p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8, p_9, p_{10}, p_{11}, end}

T = {cook rice, season rice, peel avocado, slice avocado, slice salmon,
spread on nori sheet, roll and slice, add wasabi, add soy sauce, eat}

F = {(p_1, cook rice), (p_2, peel avocado), (p3, slice salmon), (cook rice, p4), (peel avocado, p5), …}

Process Models – Workflow-Nets (WF-Nets)

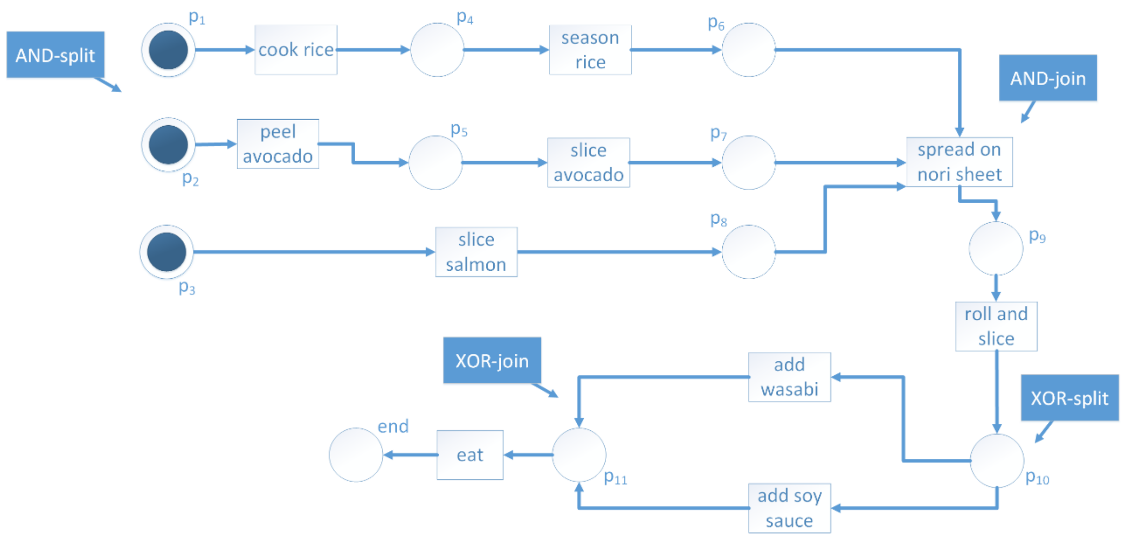
Subclass of Petri Nets

Definition (Workflow Net)

$N = (P, T, F)$, where
(P, T, F) is a Petri net as already defined
N is a *workflow net* iff.
a) P contains a source place i s. t. $\bullet\, i = \emptyset$
b) P contains a sink place o s. t. $o \bullet = \emptyset$
c) If we add a transition t^* to N which connects o with i
i. e. $\bullet t^* = \{o\}$ and $t^* \bullet = \{i\}$, then
the resulting Petri net is strongly connected.

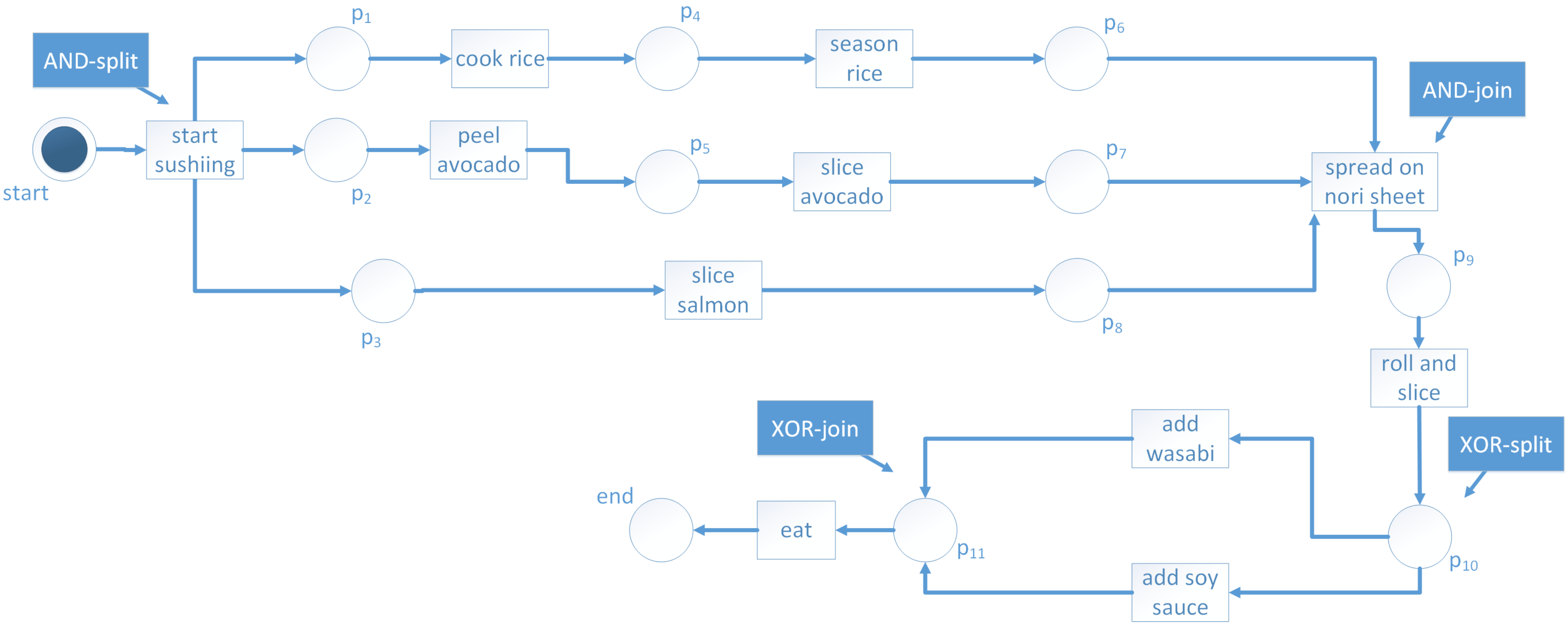
Definition (Strongly connected)

A Petri net is strongly connected iff for every pair of nodes (i.e. places and transitions) x and y, there is a path leading from x to y



Can the Petri Net shown be considered a Workflow Net?

Process Models – Workflow-Nets (WF-Nets)



Process Models – Additional Criterion (Soundness)

A WF-net does not necessarily represent a correct process

→ Deadlocks, livelocks, not activatable activities etc. are possible

Definition (Soundness)

Let $N = (P, T, F)$ be a $workflow\ net$ with i and o as input and output places.
N is *sound* iff.

- *(safeness)* Places do not hold multiple tokens at the same time
- *(proper completion)* The moment the procedure terminates there is a token in place *o* and all the other places are empty
- *(option to complete)* For any case the procedure will terminate eventually
- *(absence of dead parts)* For any $t \in T$ there is a firing sequence enabling t

Process Models – Methods (Verification)

Verification is a method to analyze process models against specific properties (*Model checking*).

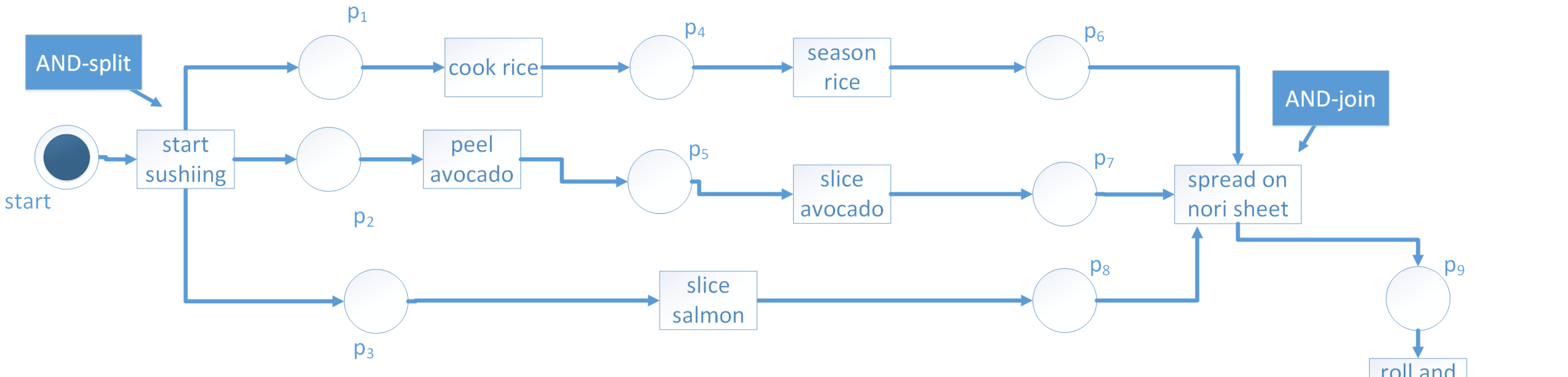
- Those properties can be expressed in temporal logic.
- Specifically in LTL (Linear Temporal Logic) which is an significant example in relation to process models.

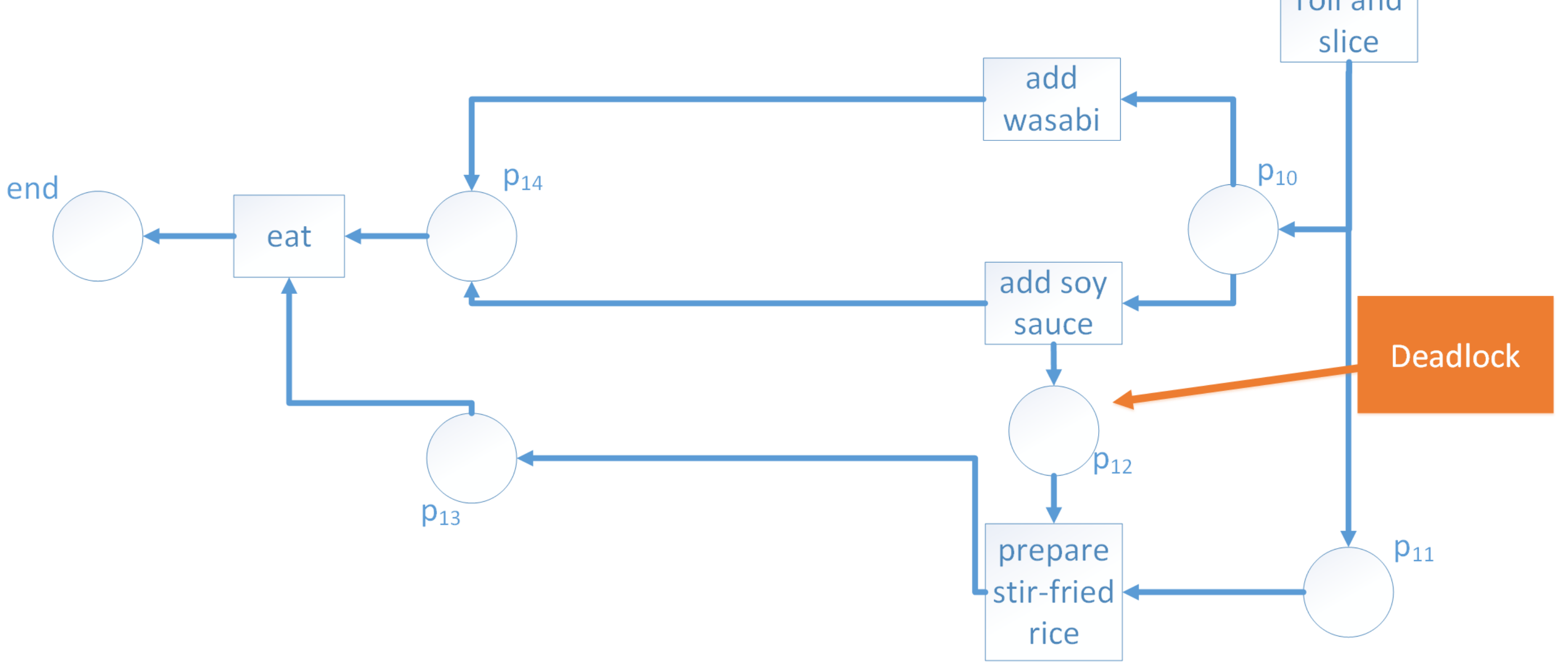
<u>Two further exemplary verification tasks in the following:</u>

1. Two process models can be checked against each other using ***Verification***.

E.g. Trying to match a descriptive and a normative model to see where reality differs from guidelines

Process Models – Methods (Verification)





2. Soundness as a correctness criterion can be checked using ***Verification.***

<…, roll and slice, add wasabi> leads to a dead marking [p_{11}, p_{14}] (*Deadlock*)

Process Models – Roundup

Known process model types so far:

- Transitions systems
- BPMN
- Petri Nets
- Workflow Nets

There are still others like

- Reachability graphs
- Causal nets
- …

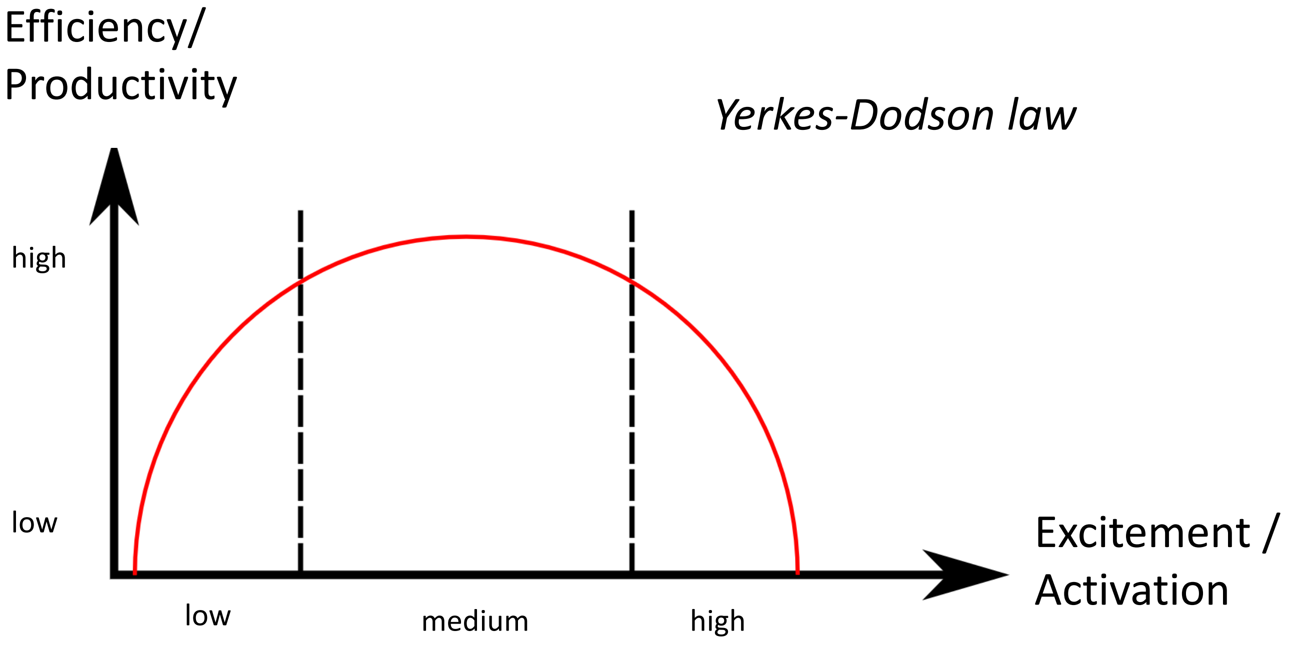
Benefit:

- Process analysis gets simplified
- Predict performance via simulation
- Predetermine guidelines
- Purpose determines outcome
- …

Process Models – Discussion

Creating a model is not an easy task

- **Capturing human behavior**
  - Human covers multiple processes with different priorities → dependencies evolve
    → Difficult to model one process in isolation
  - Productivity of a human is varying over time.
    It also depends on other factors e.g. Yerkes-Dodson law



Process Models – Discussion (cont.)

- **Idealization of reality**
  - Hand-made models tend to be
    - subjective
    - oversimplified

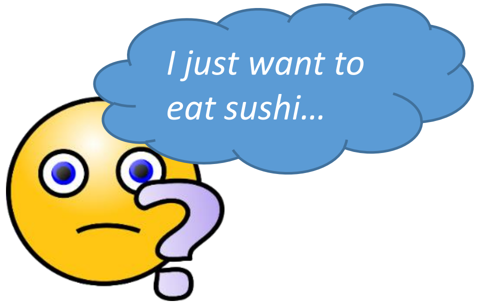
  - The choice of a representative sample of cases is crucial
    → Biased focus on *normal / desirable* behavior

Actually it only covers 80% of cases but is seen as a representative

Remaining 20% could possibly cover high amount of problems

Process Models – Discussion (cont.)

- **Granularity**
  E.g. there are many types of sushi: Nigiri, Sashimi, Maki, Uramaki…



E.g. **discrete** vs. **continuous**

cook rice vs. get pot → get rice → fill rice into pot → add water → …

⇒ A suitable granularity for the process model depends on

- **the input data**
- **the model‘s purpose**

References

Yerkes, R.M., & Dodson, J.D. (1908). The Relation of Strength of Stimulus to Rapidity of Habit Formation. *Journal of Comparative Neurology & Psychology, 18,* 459–482. https://doi.org/10.1002/cne.920180503

Wil van der Aalst. 2016. *Process Mining: Data Science in Action* (2nd. ed.). Springer Publishing Company, Incorporated

Wil van der Aalst. *(1998). "The application of Petri nets to workflow management" (PDF). Journal of Circuits, Systems and Computers.* ***8*** *(1): 21–66.*

Agenda

Motivation

- Process models are generated eigther normative or descriptive
  - **Normative**: - invented by human

    - represent how a certain process is supposed to work
  - **Descriptive**: - created by process discovery algorithms based on log files

    - represent how a certain process is actually running

Process Discovery Algorithm „α-Miner“[1]

Idea: A simple algorithm to visualize processes

Input: Event log L over activities A

Output: marked petri net / Workflow net

1. Detect log-based ordering relations from event Log L
2. Create Footprint Table
3. Execute the algorithm of the α-Miner
4. Derive the WF-net

[1] van der Aalst, W M P and Weijters, A J M M and Maruster, L (2004). "Workflow Mining: Discovering process models from event logs", *IEEE Transactions on Knowledge and Data Engineering*, vol 16

Process Discovery Algorithm „α-Miner“

Let L be an event log over activities A, and let $a, b \in A$.

1. *Detect log-based ordering relations from event Log L*

   i. „(direct) following“-relation $\boldsymbol{a >_L b}$
   $\Leftrightarrow \exists\ trace\ \ \sigma = \langle t_1, t_2, t_3, \ldots, t_{n-1} \rangle\ and\ i \in \{1,2, \ldots, n-2\}$
   $\text{s. t. } \sigma \in L$ and $t_i = a$ and $t_{i+1} = b$ and $t_{i+1} = b$.

   ii. „potential parallelism“ $\boldsymbol{a \parallel_L b}$
   $\Leftrightarrow a >_L b\ and\ b >_L a$

   iii. „sequential task“-relation $\boldsymbol{a \rightarrow_L b}$
   $\Leftrightarrow a >_L b\ and\ b \not>_L a$

   iv. „not followed“-relation $\boldsymbol{a \#_L b}$
   $\Leftrightarrow a \not>_L b\ and\ b \not>_L a$

$L = [\langle a,c,d \rangle^3, \langle a,d,c \rangle^2, \langle b,c,d \rangle^2, \langle b,d,c \rangle^4]$

2. Create Footprint Table:
 i) Find the directly followed tupels

	a	b	c	d
a				
b				
c				
d				

$>_L: \{(a,c), (a,d), (b,c), (b,d), (c,d), (d,c)\}$

Process Discovery Algorithm „α-Miner“

Let L be an event log over activities A, and let $a, b \in A$.

1. *Detect log-based ordering relations from event Log L*

   i. „(direct) following“-relation $\boldsymbol{a >_L b}$
   $\Leftrightarrow \exists\ trace\ \ \sigma = \langle t_1, t_2, t_3, \dots, t_{n-1}\rangle\ and\ i \in \{1,2,\dots,n-2\}$
   s. t. $\sigma \in L$ and $t_i = a$ and $t_{i+1} = b$ and $t_{i+1} = b$.

   ii. „potential parallelism“ $\boldsymbol{a\ \|_L\ b}$
   $\Leftrightarrow a >_L b\ and\ b >_L a$

   iii. „ sequential task“-relation $\boldsymbol{a \rightarrow_L b}$
   $\Leftrightarrow a >_L b\ and\ b \ngtr_L a$

   iv. „not followed“-relation $\boldsymbol{a \#_L b}$
   $\Leftrightarrow a \ngtr_L b\ and\ b \ngtr_L a$

$L\ =\ [\langle a,c,d\rangle^3, \langle a,d,c\rangle^2, \langle b,c,d\rangle^2, \langle b,d,c\rangle^4]$

2. Create Footprint Table:
ii) Find the potential parallel tupels and mark them in the table

	a	b	c	d
a				
b				
c				$\|_L$
d			$\|_L$	

$>_L: \{(a,c), (a,d), (b,c), (b,d), (c,d), (d,c)\}$
$\|_L$: {(c,d), (d,c)}

Process Discovery Algorithm „α-Miner“

Let L be an event log over activities A, and let $a, b \in A$.

1. *Detect log-based ordering relations from event Log L*

   i. „(direct) following“-relation $\boldsymbol{a >_L b}$
   $\Leftrightarrow \exists\ trace\ \ \sigma = \langle t_1, t_2, t_3, \dots, t_{n-1}\rangle\ and\ i \in \{1,2,\dots,n-2\}$
   s. t. $\sigma \in L$ and $t_i = a$ and $t_{i+1} = b$ and $t_{i+1} = b$.

   ii. „potential parallelism“ $\boldsymbol{a \parallel_L b}$
   $\Leftrightarrow a >_L b\ and\ b >_L a$

   iii. „sequential task“-relation $\boldsymbol{a \rightarrow_L b}$
   $\Leftrightarrow a >_L b\ and\ b \not>_L a$

   iv. „not followed“-relation $\boldsymbol{a \#_L b}$
   $\Leftrightarrow a \not>_L b\ and\ b \not>_L a$

$L = [\langle a,c,d\rangle^3, \langle a,d,c\rangle^2, \langle b,c,d\rangle^2, \langle b,d,c\rangle^4]$

2. Create Footprint Table:
iii) Find the sequential task tupels
and mark them in the table

	a	b	c	d
a			$\rightarrow_L$	$\rightarrow_L$
b			$\rightarrow_L$	$\rightarrow_L$
c				$\parallel_L$
d			$\parallel_L$	

$>_L: \{(a,c), (a,d), (b,c), (b,d), (c,d), (d,c)\}$
$\parallel_L$: {(c,d), (d,c)}
$\rightarrow_L: \{(a,c), (a,d), (b,c), (b,d)\}$

Process Discovery Algorithm „α-Miner“

Let L be an event log over activities A, and let $a, b \in A$.

1. *Detect log-based ordering relations from event Log L*

   i. „(direct) following“-relation $\boldsymbol{a >_L b}$
   $\Leftrightarrow \exists\ trace\ \ \sigma = \langle t_1, t_2, t_3, \dots, t_{n-1}\rangle\ and\ i \in \{1,2,\dots,n-2\}$
   $\text{s. t. } \sigma \in L \text{ and } t_i = a \text{ and } t_{i+1} = b \text{ and } t_{i+1} = b.$

   ii. „potential parallelism“ $\boldsymbol{a \parallel_L b}$
   $\Leftrightarrow a >_L b\ and\ b >_L a$

   iii. „ sequential task“-relation $\boldsymbol{a \rightarrow_L b}$
   $\Leftrightarrow a >_L b\ and\ b \not>_L a$

   iv. „not followed“-relation $\boldsymbol{a \#_L b}$
   $\Leftrightarrow a \not>_L b\ and\ b \not>_L a$

$L = [\langle a,c,d\rangle^3, \langle a,d,c\rangle^2, \langle b,c,d\rangle^2, \langle b,d,c\rangle^4]$

2. Create Footprint Table:
iv) Find the not followed tupels
and mark them in the table

	a	b	c	d
a	$\#_L$	$\#_L$	$\rightarrow_L$	$\rightarrow_L$
b	$\#_L$	$\#_L$	$\rightarrow_L$	$\rightarrow_L$
c			$\#_L$	$\parallel_L$
d			$\parallel_L$	$\#_L$

$>_L: \{(a,c),(a,d),(b,c),(b,d),(c,d),(d,c)\}$
$\parallel_L$: {(c,d), (d,c)}
$\rightarrow_L: \{(a,c),(a,d),(b,c),(b,d)\}$
$\#_L$: {(a,a),(a,b),(b,a),(b,b),(c,c),(d,d)}

Process Discovery Algorithm „α-Miner“

Let L be an event log over activities A, and let $a, b \in A$.

1. *Detect log-based ordering relations from event Log L*

   i. „(direct) following“-relation $\boldsymbol{a >_L b}$
   $\Leftrightarrow \exists\ trace\ \ \sigma = \langle t_1, t_2, t_3, \dots, t_{n-1} \rangle\ and\ i \in \{1,2,\dots,n-2\}$
   s. t. $\sigma \in L$ and $t_i = a$ and $t_{i+1} = b$ and $t_{i+1} = b$.

   ii. „potential parallelism“ $\boldsymbol{a \parallel_L b}$
   $\Leftrightarrow a >_L b\ and\ b >_L a$

   iii. „ sequential task“-relation $\boldsymbol{a \rightarrow_L b}$
   $\Leftrightarrow a >_L b\ and\ b \ngtr_L a$

   iv. „not followed“-relation $\boldsymbol{a \#_L b}$
   $\Leftrightarrow a \ngtr_L b\ and\ b \ngtr_L a$

$L = [\langle a,c,d\rangle^3, \langle a,d,c\rangle^2, \langle b,c,d\rangle^2, \langle b,d,c\rangle^4]$

2. Create Footprint Table:
(v) The remaining tupels represent a „directly before“ relation, marked as $\leftarrow_L$ and mark them in the table

	a	b	c	d
a	$\#_L$	$\#_L$	$\rightarrow_L$	$\rightarrow_L$
b	$\#_L$	$\#_L$	$\rightarrow_L$	$\rightarrow_L$
c	$\leftarrow_L$	$\leftarrow_L$	$\#_L$	$\parallel_L$
d	$\leftarrow_L$	$\leftarrow_L$	$\parallel_L$	$\#_L$

$>_L$: $\{(a,c),(a,d),(b,c),(b,d),(c,d),(d,c)\}$
$\parallel_L$: {(c,d), (d,c)}
$\rightarrow_L$: $\{(a,c),(a,d),(b,c),(b,d)\}$
$\#_L$: {(a,a),(a,b),(b,a),(b,b),(c,c),(d,d)}

Process Discovery Algorithm „α-Miner“

3. Execute the algorithm of the α-Miner

   i) All activities that start any trace yield the set of **starting activities,** collected in $\boldsymbol{T_{in}}$.

   ii) All activities that end any trace yield the set of **output activities,** $\boldsymbol{T_{out}}$.

   …

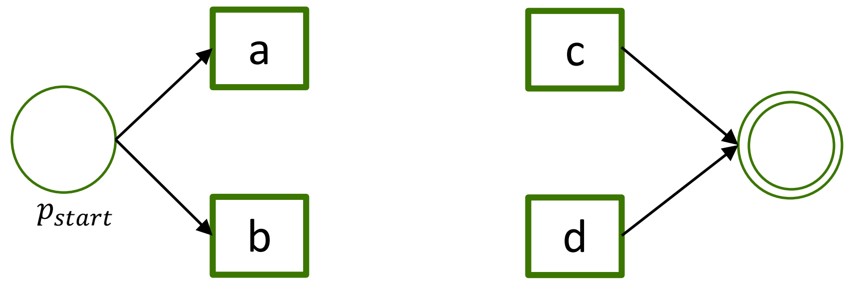
4. Derive the WF-net:

- The set of **transitions** is equal to A, so each activity represents a transition
- A starting place is created and connected to each node in $\boldsymbol{T_{in}}$.
- Also, a final place is created and each node in $\boldsymbol{T_{out}}$ is connected to it.

$$L = [\langle a,c,d\rangle^3, \langle a,d,c\rangle^2, \langle b,c,d\rangle^2, \langle b,d,c\rangle^4]$$

$$T_{in} = \{a, b\}$$

$$T_{out} = \{c, d\}$$



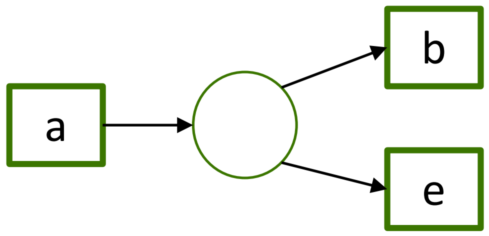
Process Discovery Algorithm „α-Miner“

3. Execute the algorithm of the α-Miner …

   iii) Determine all pairs of sets A and B, such that
   - $\forall a_1, a_2 \in A: a_1 \# a_2$
   - $\forall b_1, b_2 \in B: b_1 \# b_2$
   - $\forall a_1 \in A, \forall b_1 \in B: a_1 \rightarrow b_1$
   - Select only the "maximal pairs":
     e.g. $(\{a\},\{c\}), (\{a\},\{d\}), (\{a\},\{c,d\}) \Longrightarrow (\{a\},\{c,d\})$

4. A place is added in between A and B and connected accordingly

e.g.$A = \{a\}, B = \{b, e\}$

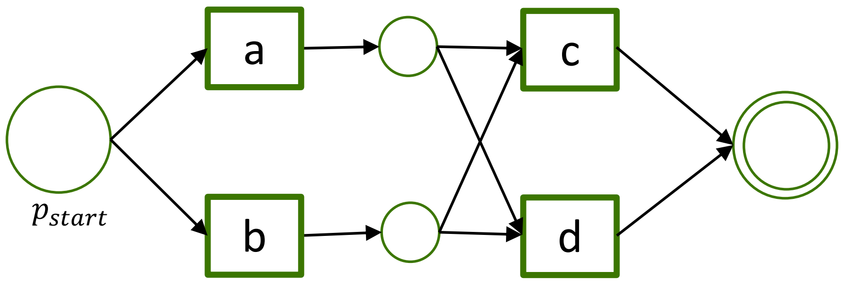


Heuristics-Miner is our first algorithm to capture concurrent process behavior.

	a	b	c	d
a	$\#_L$	$\#_L$	$\rightarrow_L$	$\rightarrow_L$
b	$\#_L$	$\#_L$	$\rightarrow_L$	$\rightarrow_L$
c	$\leftarrow_L$	$\leftarrow_L$	$\#_L$	$\parallel_L$
d	$\leftarrow_L$	$\leftarrow_L$	$\parallel_L$	$\#_L$

valid set of „maximal pairs“:

$(\{a\},\{c,d\}), (\{b\},\{c,d\})$



Process Discovery Algorithm „Heuristics-Miner" [2]

Idea: α-Miner has several flaws (1-loops, 2-loops, no weighting).

Heuristics-Miner uses dependency as the condition to connect activities.

Input: Event log L

Output: Causal net, *here we stop at the dependency graph*

[2] Weijters, A. J. M. M., Wil MP van Der Aalst, and AK Alves De Medeiros. "Process mining with the heuristics miner-algorithm." *Technische Universiteit Eindhoven, Tech. Rep. WP* 166 (2006): 1-34.

Process Discovery Algorithm „Heuristics-Miner“

Let L be an event log over activities A, and let $a, b \in A$.

1. Create table displaying frequency of „directly follows“ relation $>_L$

$$L = [\langle a,e\rangle^5, \langle a,b,c,e\rangle^{10}, \langle a,c,b,e\rangle^{10}, \langle a,b,e\rangle^{10}, \langle a,d,d,e\rangle^2, \langle a,d,d,d,e\rangle^1]$$

$>_L$	a	b	c	d	e
a	0	11	11	13	5
b	0	0	10	0	11
c	0	10	0	0	11
d	0	0	0	4	13
e	0	0	0	0	0

Process Discovery Algorithm „Heuristics-Miner“

2. Create a table showing the value of „dependency measures“ of all pairs of activities over L

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

$$|a \Rightarrow_L b| \in]-1,1[$$

$|a \Rightarrow_L b| = 0$, if $|a >_L b| = |b >_L a|$

$|a \Rightarrow_L b| \rightarrow 1$, if a follows almost always after b

$>_L$	a	b	c	d	e
a	0	11	11	13	5
b	0	0	10	0	11
c	0	10	0	0	11
d	0	0	0	4	13
e	0	0	0	0	0

$\vert\Rightarrow_L\vert$	a	b	c	d	e
a					
b					
c					
d					
e					

Process Discovery Algorithm „Heuristics-Miner“

2. Create a table showing the value of „dependency measures“ of all pairs of activities over L

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

$|a \Rightarrow_L b| \in]-1,1[$

$|a \Rightarrow_L b| = 0$, if $|a >_L b| = |b >_L a|$

$|a \Rightarrow_L b| \rightarrow 1$, if a follows almost always after b

Lower triangular matrix is the negative and transposed of the upper triangular matrix.

$>_L$	a	b	c	d	e
a	0	11	11	13	5
b	0	0	10	0	11
c	0	10	0	0	11
d	0	0	0	4	13
e	0	0	0	0	0

$\vert\Rightarrow_L\vert$	a	b	c	d	e
a	0	0.92	0.92	0.93	0.83
b	-0.92	0	0	0	0.92
c	-0.92	0	0	0	0.92
d	-0.93	0	0	0.80	0.93
e	-0.83	-0.92	-0.92	-0.93	0

$$|a \Rightarrow_L b| = \frac{11 - 0}{11 + 0 + 1} = 0.92$$

$$|b \Rightarrow_L c| = \frac{10-10}{10+10+1} = 0$$

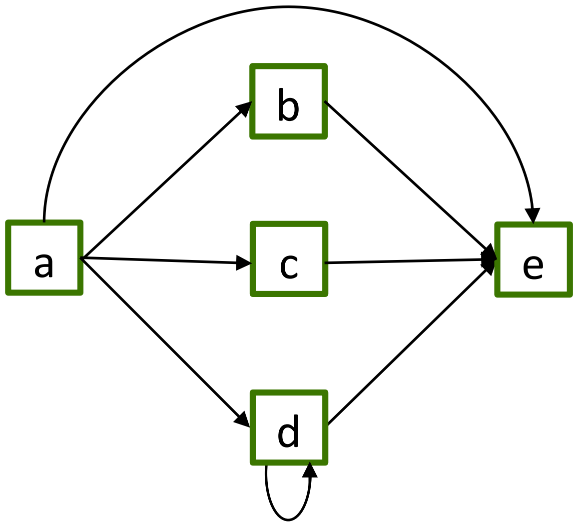
Process Discovery Algorithm „Heuristics-Miner“

3. i) Select **two thresholds** to reduce noise ($\tau_{>_L}$) and infrequent traces ($\tau_{\Rightarrow_L}$)
   ii) Create the dependency graph DG: an arc between x and y is only included if $|x <_L y| \geq \tau_{>_L} \ \wedge \ |x \Rightarrow_L y| \geq \tau_{\Rightarrow_L}$

$>_L$	a	b	c	d	e
a	0	11	11	13	5
b	0	0	10	0	11
c	0	10	0	0	11
d	0	0	0	4	13
e	0	0	0	0	0

$\lvert\Rightarrow_L\rvert$	a	b	c	d	e
a	0	0.92	0.92	0.93	0.83
b	~~-0.92~~ 0	0	0	0	0.92
c	~~-0.92~~ 0	0	0	0	0.92
d	~~-0.93~~ 0	0	0	0.80	0.93
e	~~-0.83~~ 0	~~-0.92~~ 0	~~-0.92~~ 0	~~-0.93~~ 0	0

Ex. 1:
Setting $\tau_{>_L} = 2$ and $\tau_{\Rightarrow_L} = 0.7$ yields to the following dependency graph:



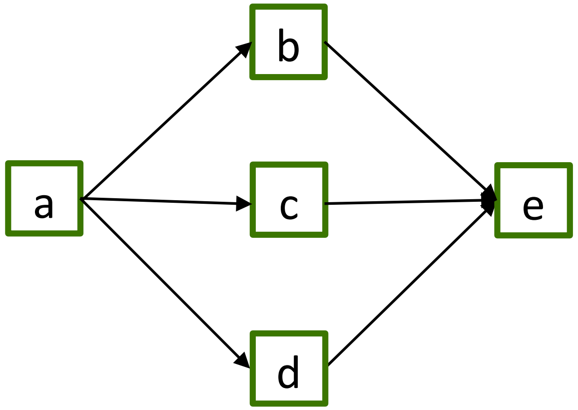
Process Discovery Algorithm „Heuristics-Miner“

3. i) Select **two thresholds** to reduce noise ($\tau_{>_L}$) and infrequent traces ($\tau_{\Rightarrow_L}$)
ii) Create the dependency graph DG: an arc between x and y is only included if
$|x <_L y| \geq \tau_{>_L} \ \wedge \ |x \Rightarrow_L y| \geq \tau_{\Rightarrow_L}$

$>_L$	a	b	c	d	e
a	0	11	11	13	5
b	0	0	10	0	11
c	0	10	0	0	11
d	0	0	0	40	13
e	0	0	0	0	0

$\lvert\Rightarrow_L\rvert$	a	b	c	d	e
a	0	0.92	0.92	0.93	~~0.83~~ 0
b	~~-0.92~~ 0	0	0	0	0.92
c	~~-0.92~~ 0	0	0	0	0.92
d	~~-0.93~~ 0	0	0	~~0.80~~ 0	0.93
e	~~-0.83~~ 0	~~-0.92~~ 0	~~-0.92~~ 0	~~-0.93~~ 0	0

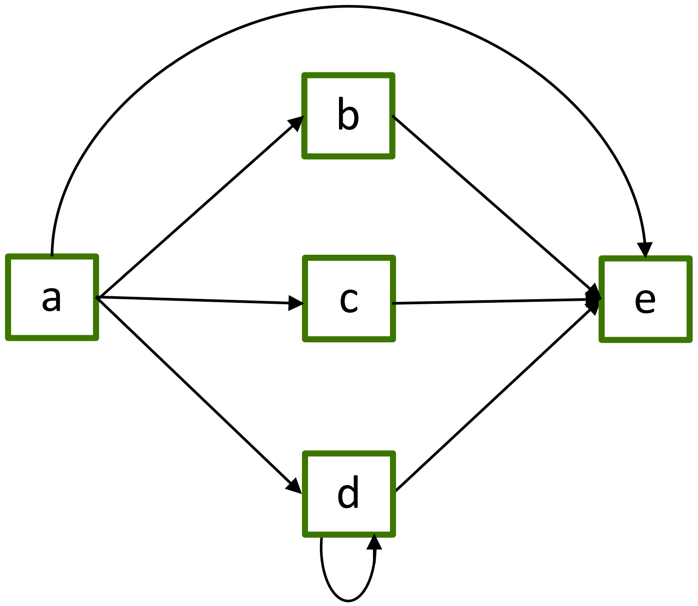
Ex. 2:
Setting $\tau_{>_L} = 5$ and $\tau_{\Rightarrow_L} = 0.9$ yields to the following dependency graph:



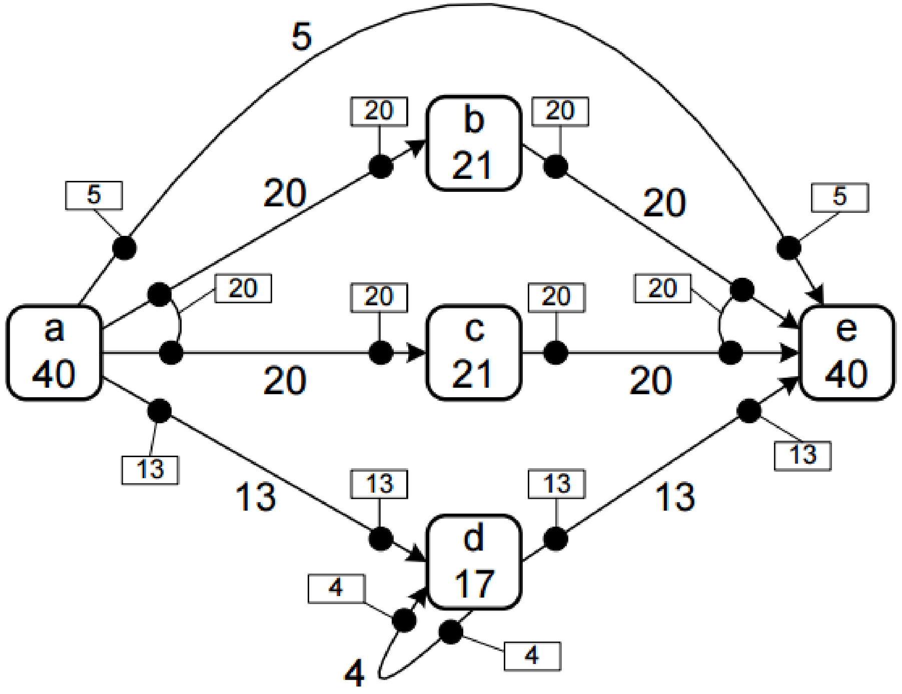
Process Discovery Algorithm „Heuristics-Miner“

4. Last step – *not in this lecture*:

   dependency graph → causal net



→



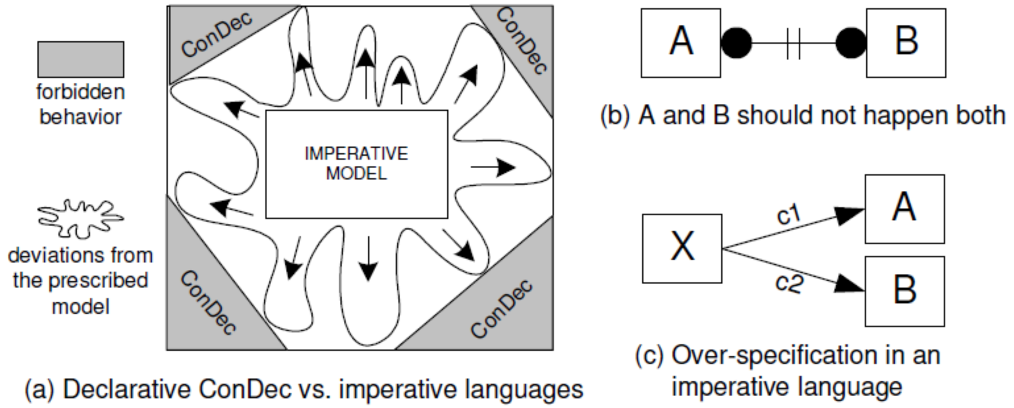
Process Discovery Algorithm – Some Others

- **„Inductive-Miner (IM)“** [3]:

  It uses the directly-follows graph that corresponds to the „direct follows“ relation ($>_L$) used by the α-Miner and creates a Process Tree Q.

- **„Declare“** [4]**:**

  It is a constrained based declarative approach.



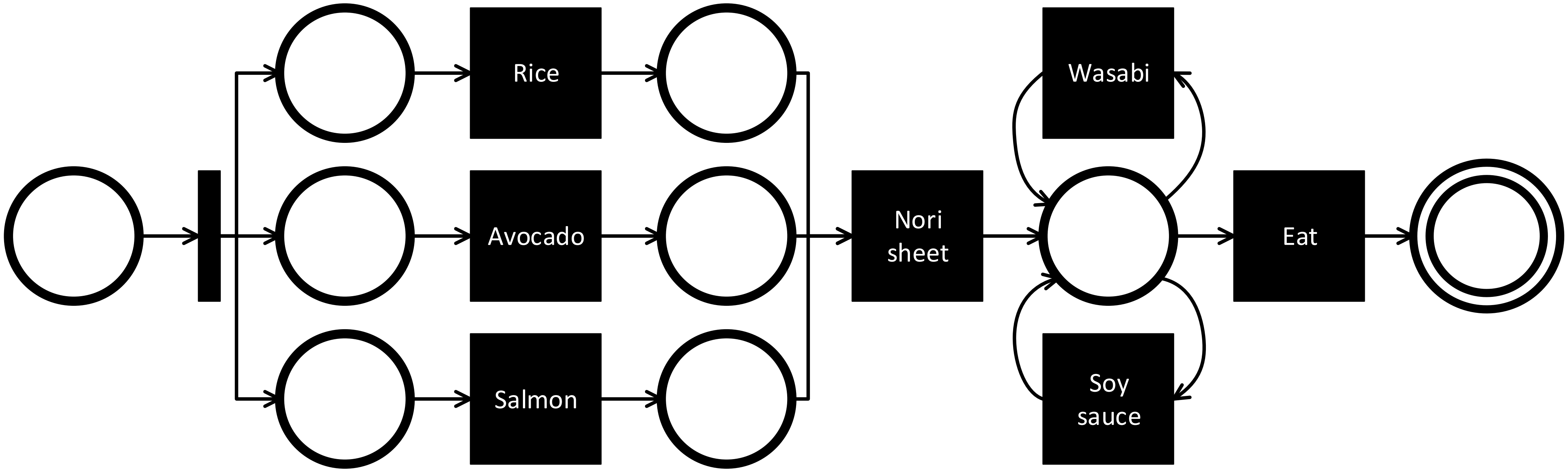
Imperative vs. Declarative approaches

[3] S.J.J. Leemans, D. Fahland, andW.M.P. van der Aalst. Discovering Block-structured Process Models from Event Logs: A Constructive Approach. In J.M. Colom and J. Desel, editors, *Applications and Theory of Petri Nets 2013*, volume 7927 of *Lecture Notes in Computer Science*, pages 311–329. Springer, Berlin, 2013.
[4]Pesic, Maja, Helen Schonenberg, and Wil MP Van der Aalst. "Declare: Full support for loosely-structured processes." *11th IEEE International Enterprise Distributed Object Computing Conference (EDOC 2007)*. IEEE, 2007.

Agenda

Motivation

- Given an event log and a process model, decide for each case wether it conforms to the model or not. If not, give the issues.



<Salmon, Rice, Avocado, Nori, Eat>
<Rice, Salmon, Wasabi>
<Avocado, Rice, Soy sauce, Nori, Eat>

conform?

non-conform?

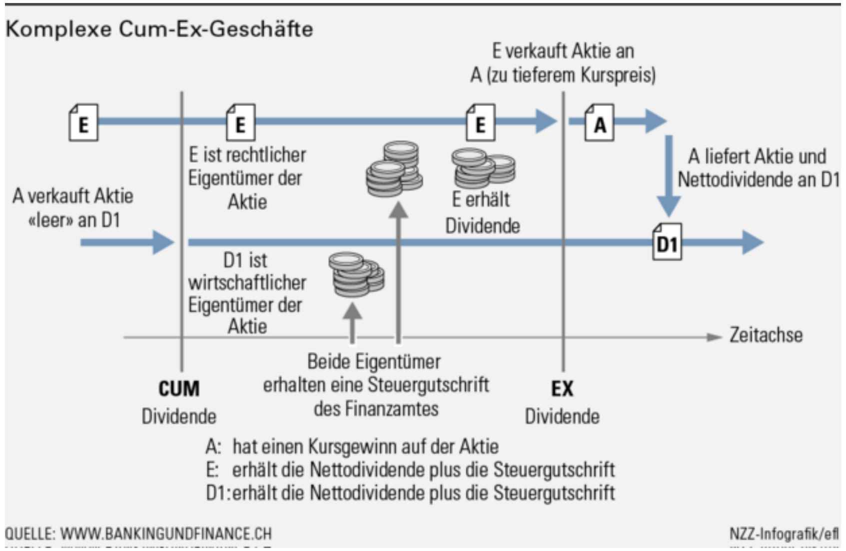
Goal: Fraud detection

- Alteration of medical treatment, usually for higher compensations ("upcoding"). Cheap medication billed as costly medication. Medication is non-conform to the treatment plan, e.g. flu vaccination after broken leg.

- Duplicate execution of actions.
  Billing twice for same service or good

		Key Figures	SalesOdrAmt_D
Sales Organization	**Sales Order**	**Billing Document**	
Dom. Sales Org US	388	90000324	78 EUR
		90000339	78 EUR
	389	#	19 EUR
	390	90000336	233 EUR

- Embezzlement, theft or misuse of company assets.
  Usage of company truck at suspicious times for private actions (evenings, vacation,…),
  or faked payments using complex and unusual cashflows.

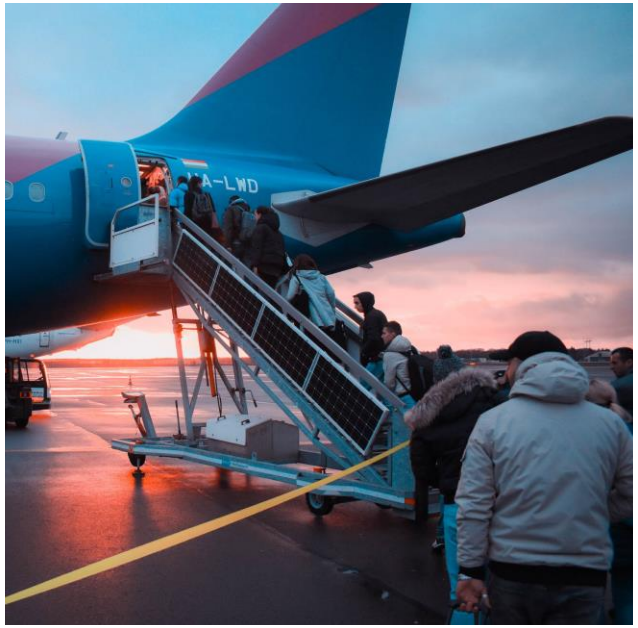


Goal: Workflow improvements

- Root-cause detection
  Quality check failed for some products. Search for shared historic activities (e.g. same supplier, preprocessed by same employee or machine, similar environmental conditions).

- Standardization of deviations
  Customers are processed faster at a certain counter. How has the employee deviated the process? E.g. Families with children board first at the airport.

- Customer aggregation
  Some customers look for furniture in a popular shop. The order of furniture presentation influences their habbits. Where to offer the small items like tealights? Which customer types map to which market traversal paths?



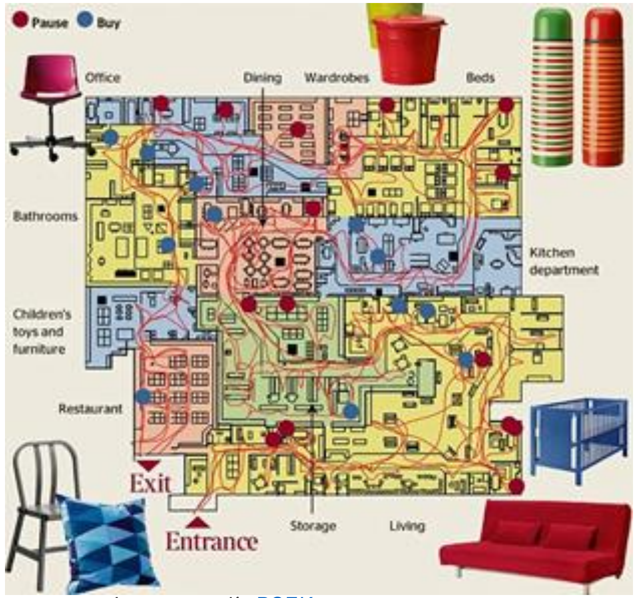


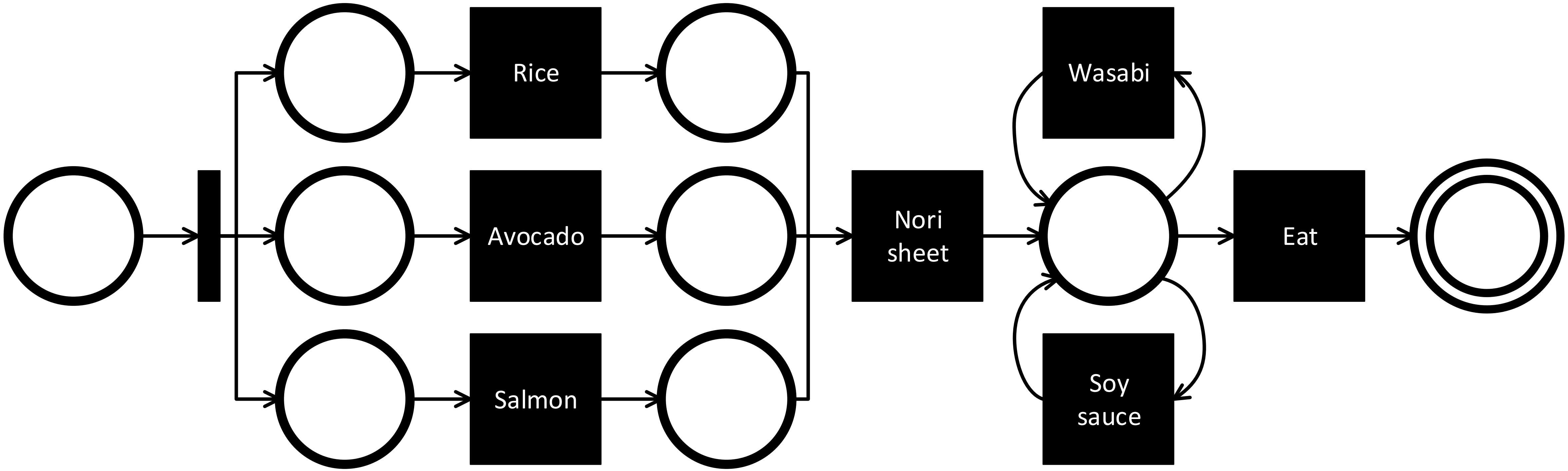
Image credit [PSFK]

Automata Theory: Decide Language Membership

- Idea:
  - Put a token into the start position.
  - For each event, fire the transition with the same label in the Petri net.
  - If the Petri net accepts the sequence, the trace passed the conformance checking.
  - Otherwise, a rejected trace has zero fitness.

[1] A.K. Alves de Medeiros,W.M.P. van der Aalst, and A.J.M.M.Weijters. Quantifying Process Equivalence Based on Observed Behavior. *Data and Knowledge Engineering*, **64**(1):55–74, 2008.

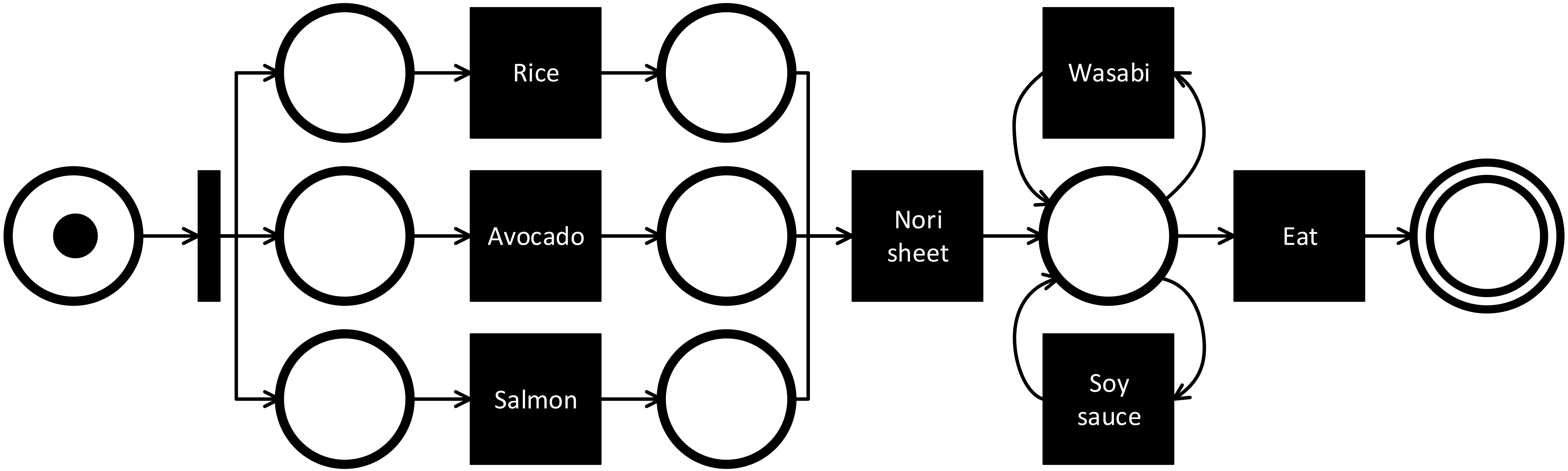
Petri Net Membership Test



Checking: <Avocado, Rice, Salmon, Nori, Eat>

(p)roduced : 0 (c)onsumed : 0

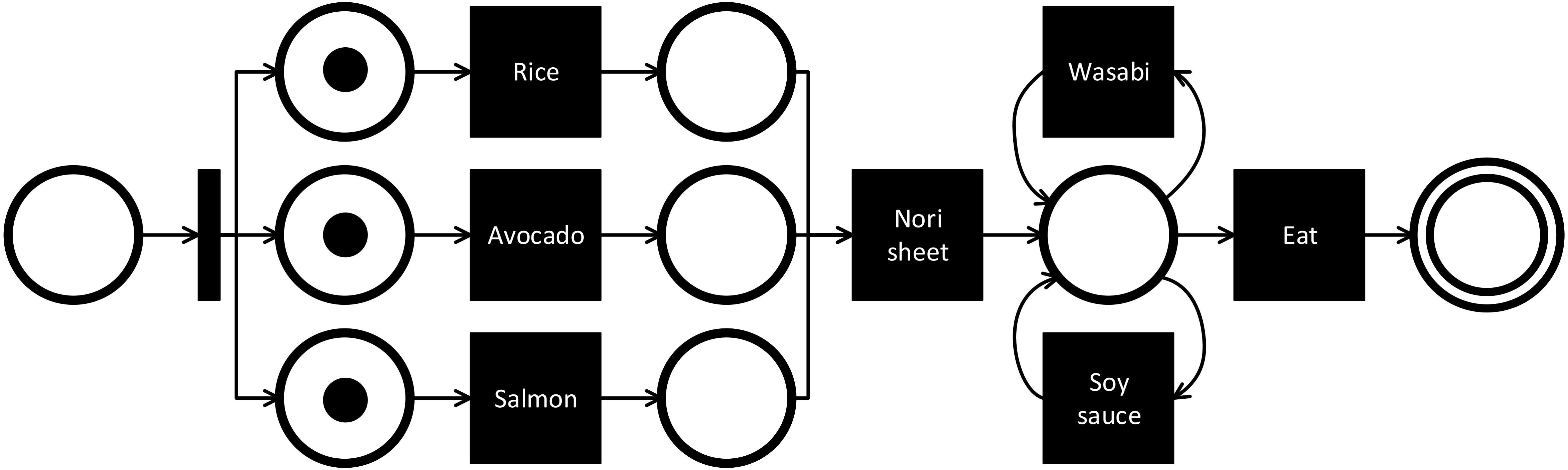
Petri Net Membership Test



Checking: <Avocado, Rice, Salmon, Nori, Eat>

(p)roduced : 1 (c)onsumed : 0

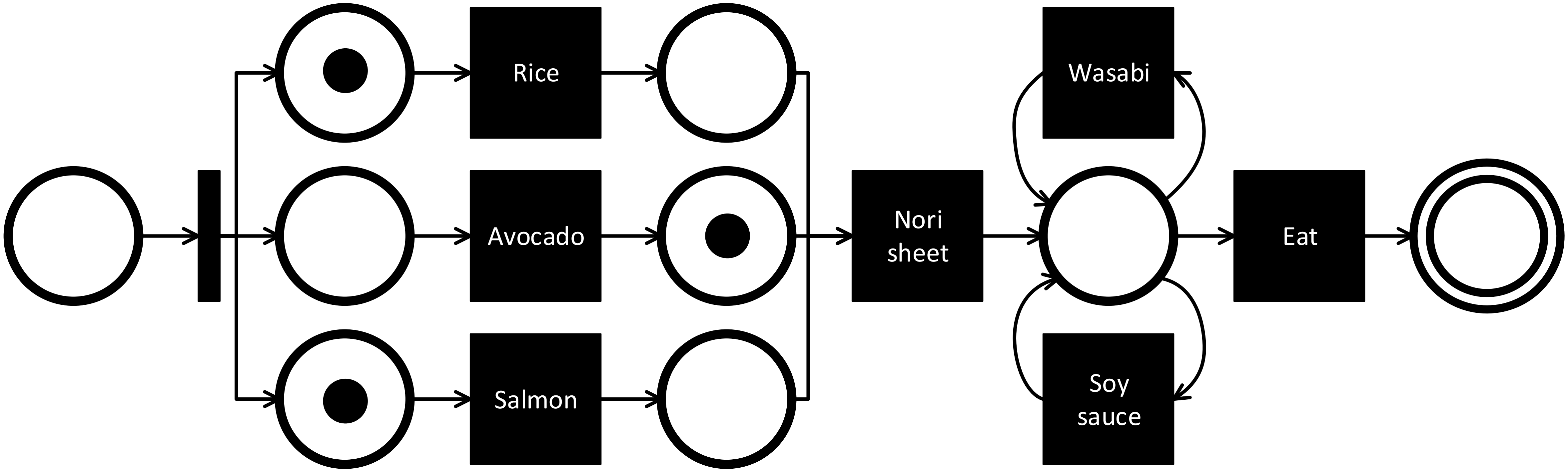
Petri Net Membership Test



Checking: <Avocado, Rice, Salmon, Nori, Eat>

(p)roduced : 4 (c)onsumed : 1

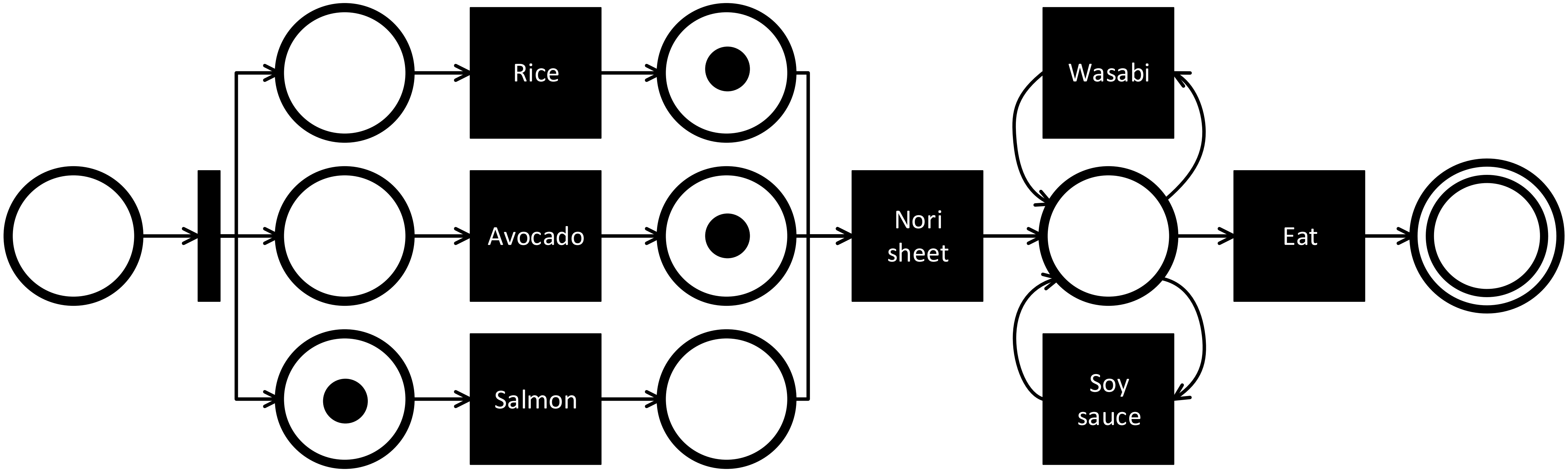
Petri Net Membership Test



Checking: <Avocado, Rice, Salmon, Nori, Eat>

(p)roduced : 5 (c)onsumed : 2

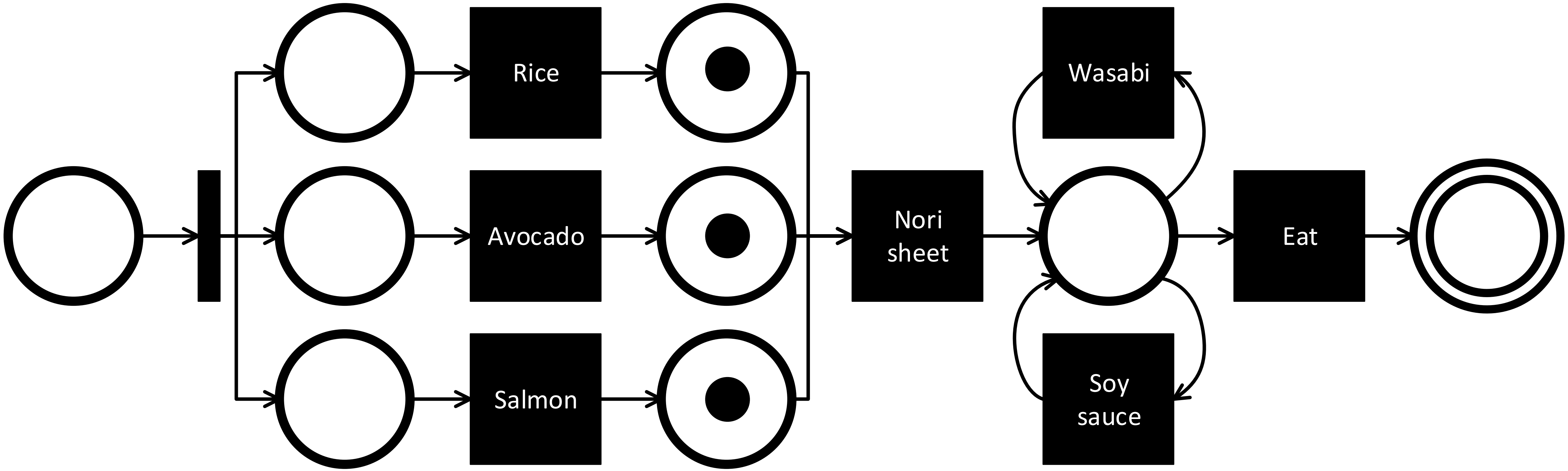
Petri Net Membership Test



Checking: <Avocado, Rice, Salmon, Nori, Eat>

(p)roduced : 6 (c)onsumed : 3

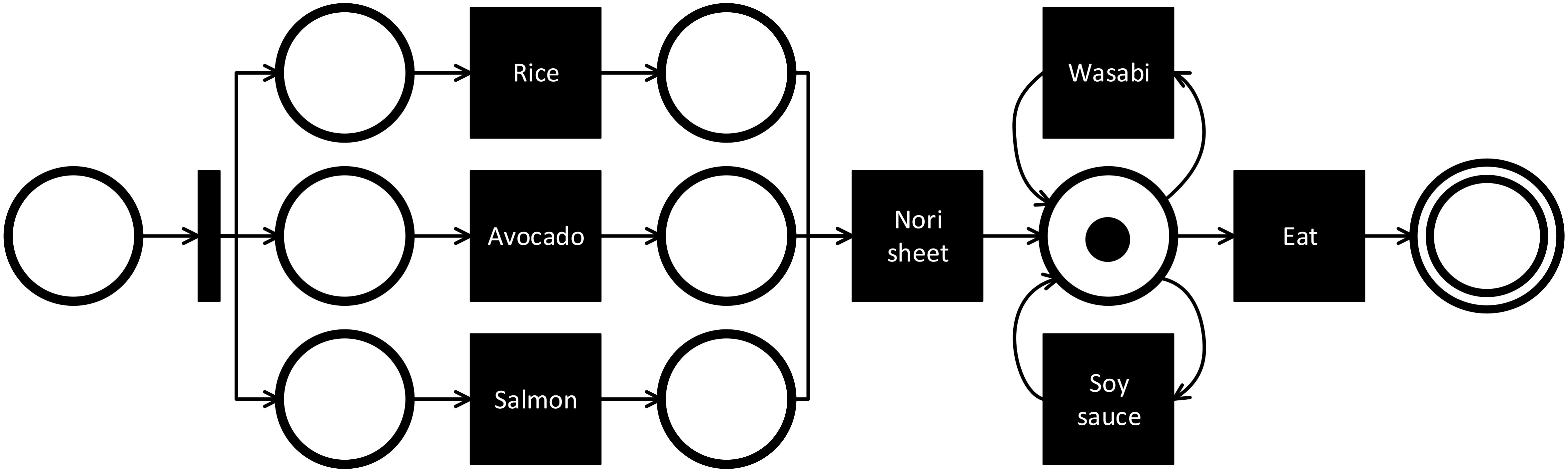
Petri Net Membership Test



Checking: <Avocado, Rice, Salmon, Nori, Eat>

(p)roduced : 7 (c)onsumed : 4

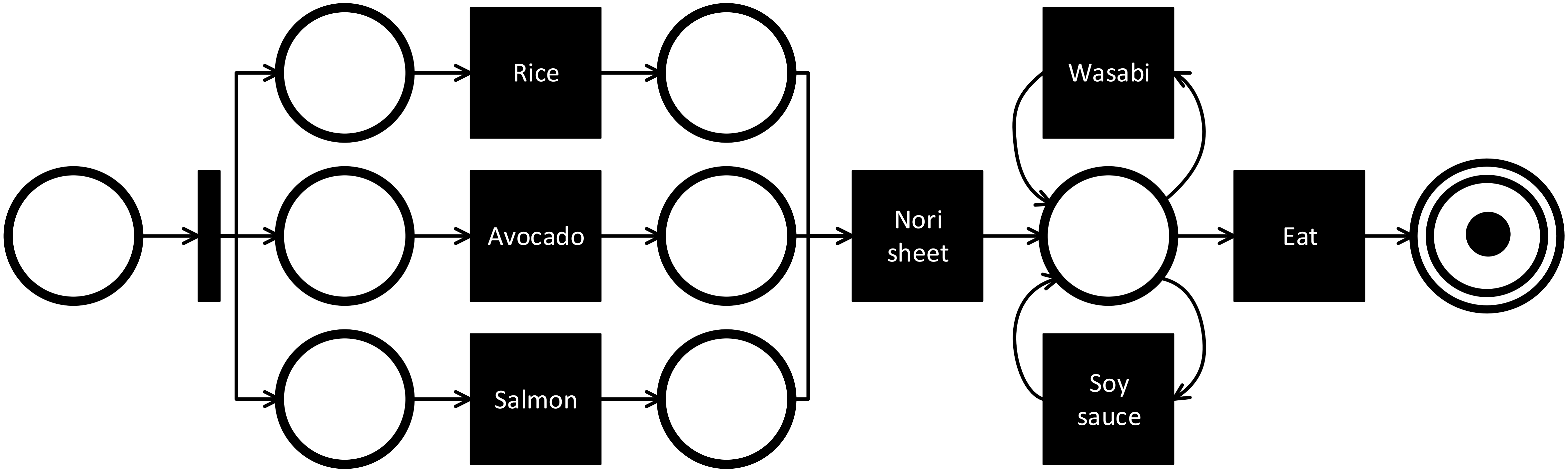
Petri Net Membership Test



Checking: <Avocado, Rice, Salmon, Nori, <u>Eat</u>>

(p)roduced : 8 (c)onsumed : 7

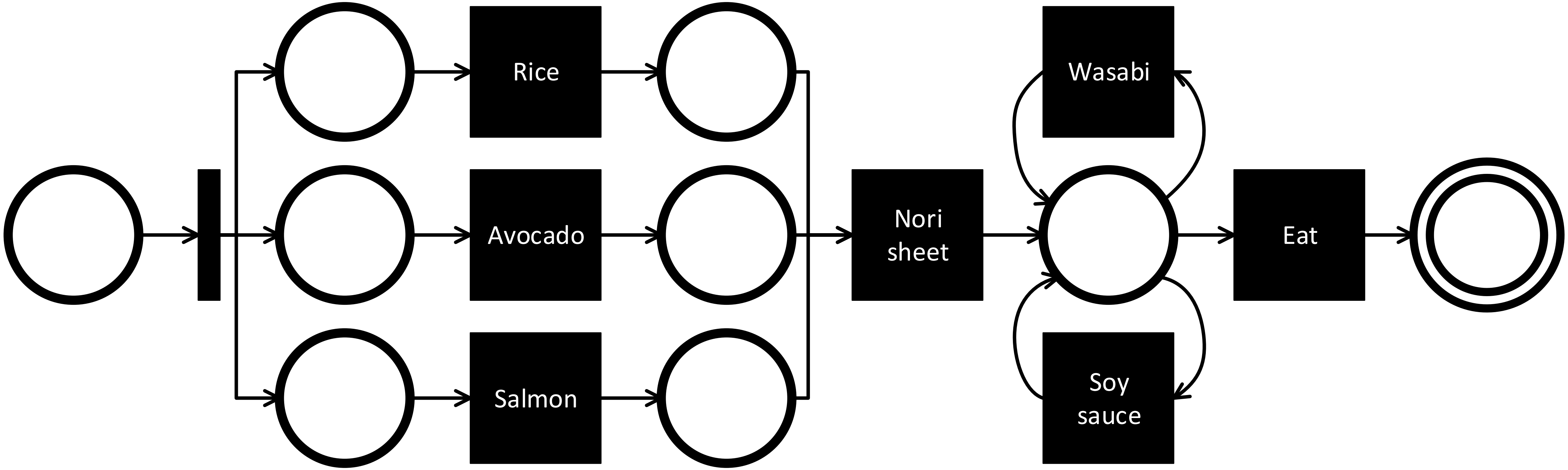
Petri Net Membership Test



Checking: <Avocado, Rice, Salmon, Nori, Eat>

(p)roduced : 9 (c)onsumed : 8

Petri Net Membership Test



Checking: <Avocado, Rice, Salmon, Nori, Eat>

(p)roduced : 9 (c)onsumed : 9

Petri Net Membership Test

The fitness of a case with trace σ on WF-net M is defined as:

$$fitness(\sigma, M) = \frac{1}{2}\left(1 - \frac{m}{c}\right) + \frac{1}{2}\left(1 - \frac{r}{p}\right)$$

Considering the example:

Checking: $\sigma =$ <Avocado, Rice, Salmon, Nori, Eat>

(p)roduced : 9 (c)onsumed : 9

$$fitness(\sigma, M) = \frac{1}{2}\left(1 - \frac{0}{9}\right) + \frac{1}{2}\left(1 - \frac{0}{9}\right) = 1$$

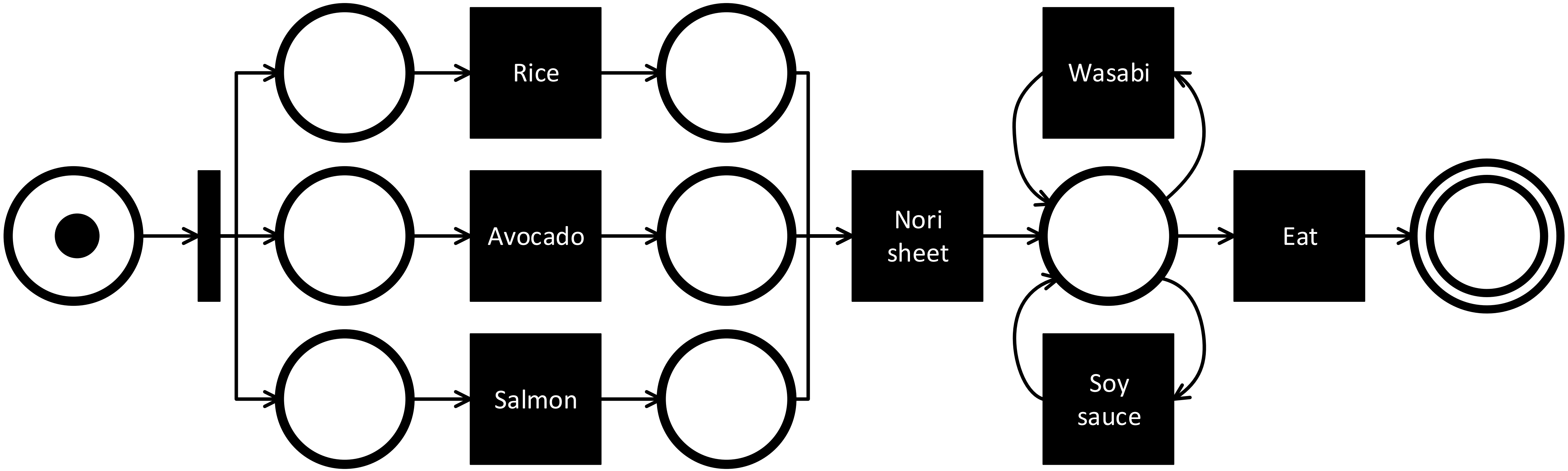
Token Replay[1]

- Problem with pure Automata approach:
  - We cannot decide between almost fit and critically deviating traces (binary classifier).
  - In practical applications we often need some flexibility to execute the processes.

- Modified Idea:
  - Put a token into the start position.
  - For each event, try to fire the corresponding transition in the net.
  - If not possible, create a virtual new token after the transition.
  - In the end, determine the fitness based on the tokens left in the model and the virtually added ones.

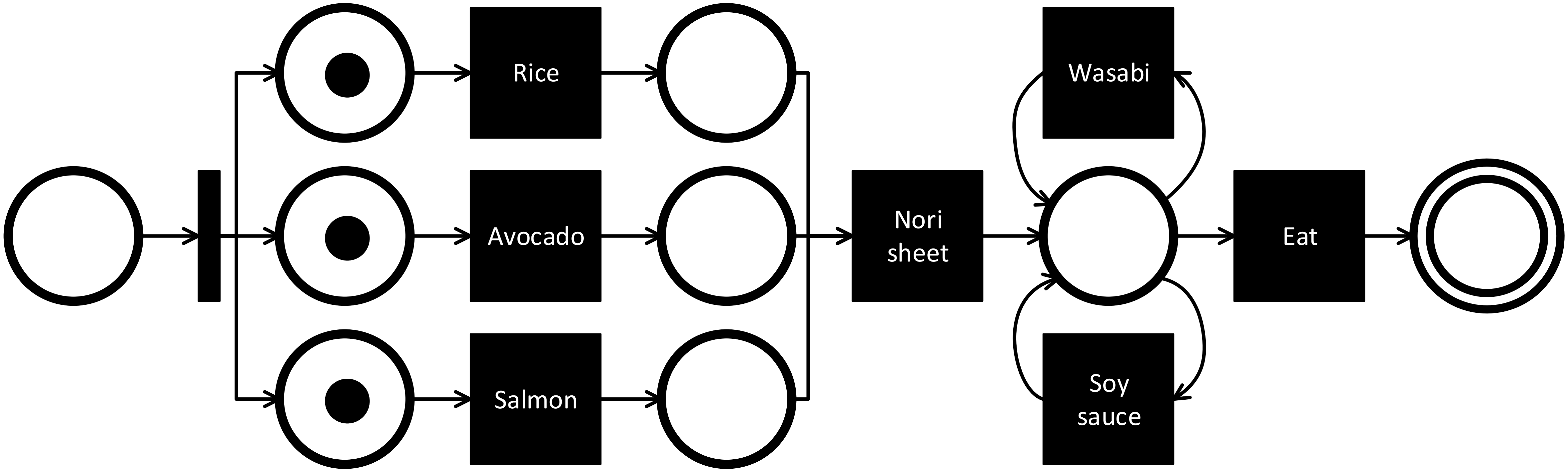
[1] A.K. Alves de Medeiros,W.M.P. van der Aalst, and A.J.M.M.Weijters. Quantifying Process Equivalence Based on Observed Behavior. *Data and Knowledge Engineering*, **64**(1):55–74, 2008.

Token Replay Example



Checking:	<Rice, Salmon, Wasabi>		
(p)roduced :	1	(c)onsumed :	0
(m)issing :	0	(r)emaining :	0

Token Replay Example

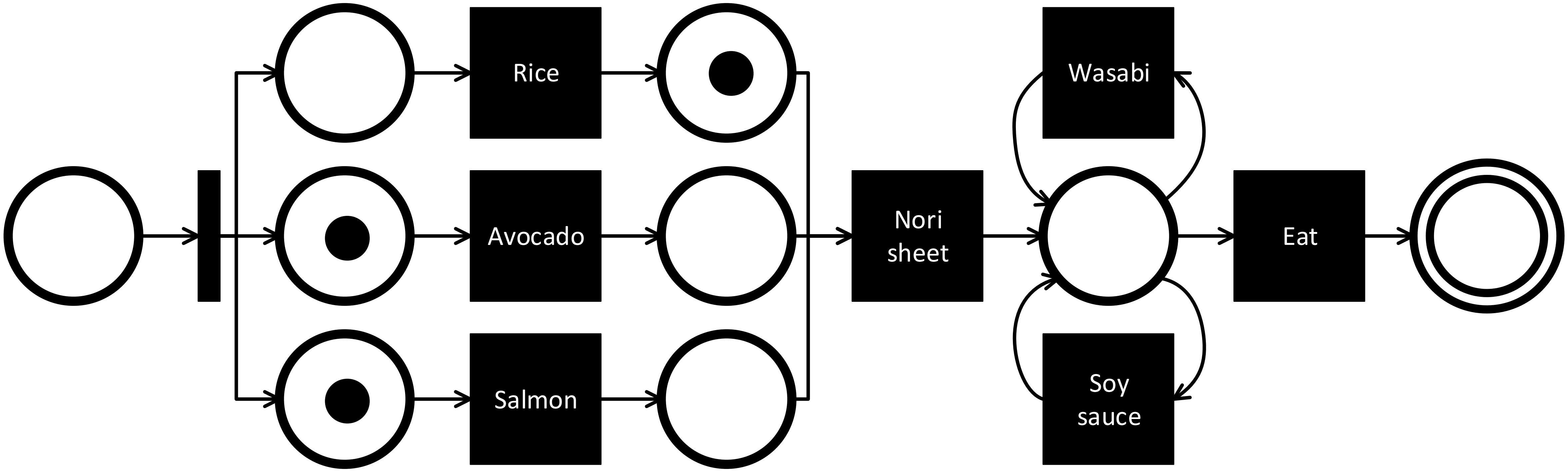


Checking: <Rice, Salmon, Wasabi>

(p)roduced : 4 (c)onsumed : 1

(m)issing : 0 (r)emaining : 0

Token Replay Example

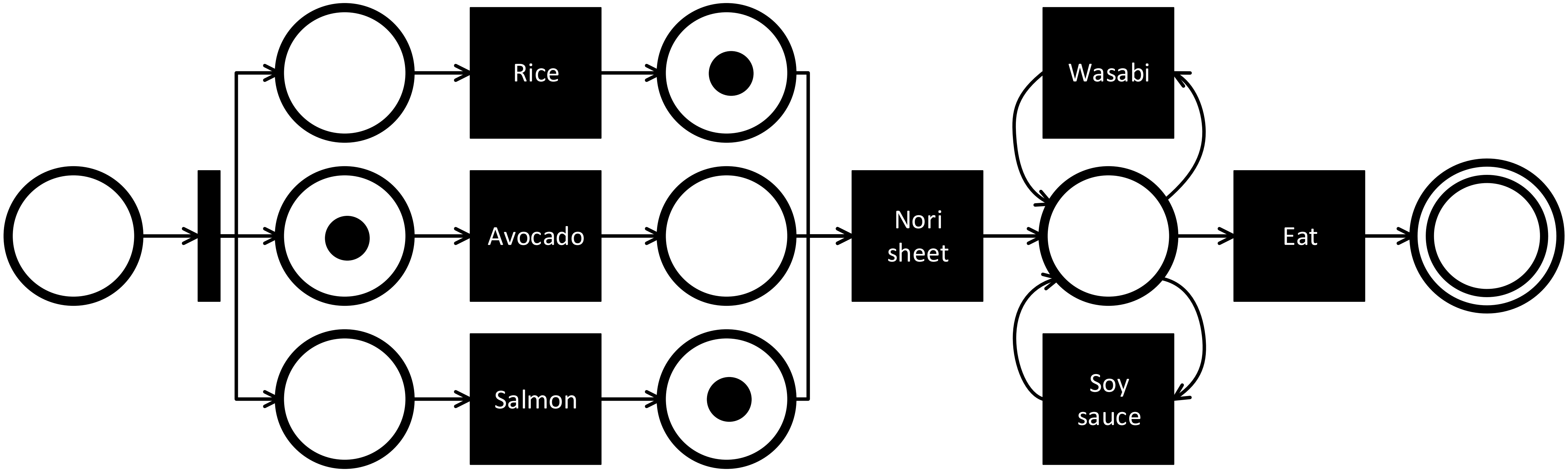


Checking: <Rice, Salmon, Wasabi>

(p)roduced : 5 (c)onsumed : 2

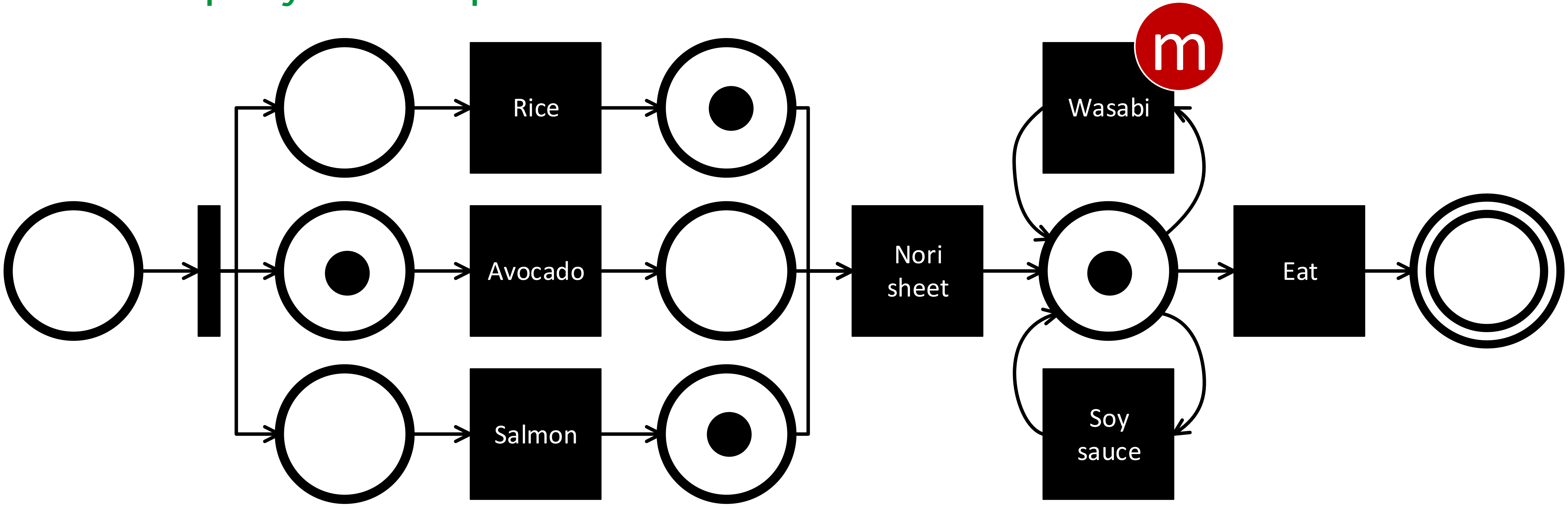
(m)issing : 0 (r)emaining : 0

Token Replay Example



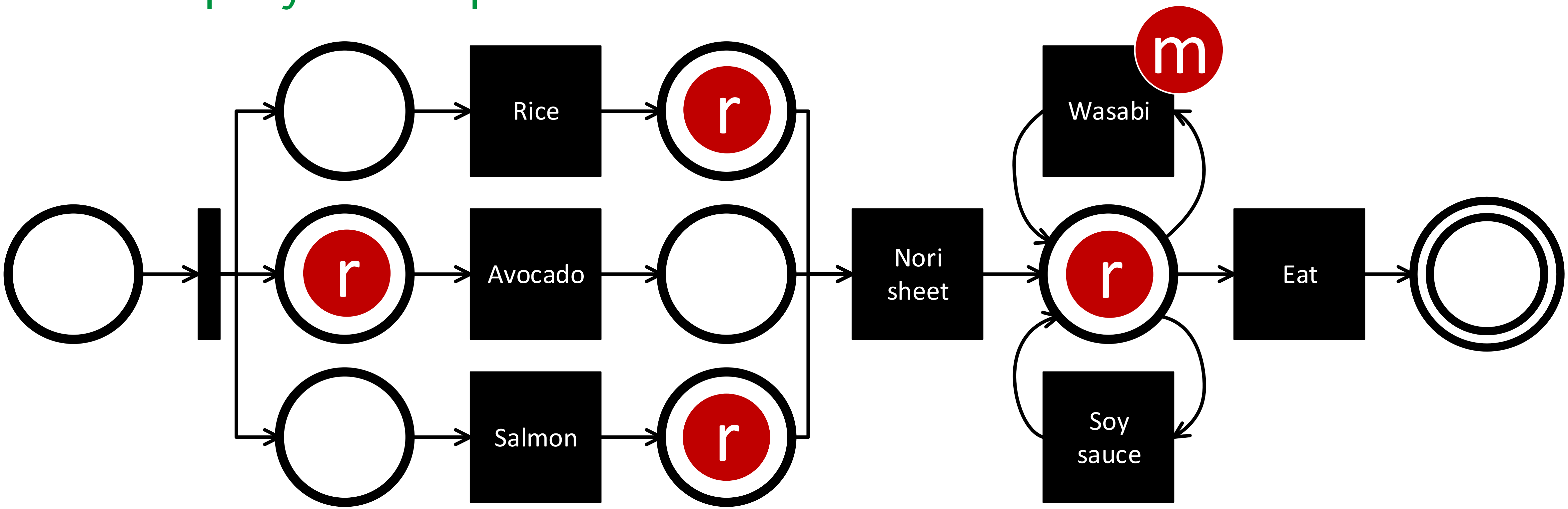
Checking:	<Rice, Salmon, Wasabi>		
(p)roduced :	6	(c)onsumed :	3
(m)issing :	0	(r)emaining :	0

Token Replay Example



Checking:	<Rice, Salmon, Wasabi>		
(p)roduced :	7	(c)onsumed :	4
(m)issing :	1	(r)emaining :	0

Token Replay Example



Checking: <Rice, Salmon, Wasabi>

(p)roduced : 7 (c)onsumed : 4

(m)issing : 1 (r)emaining : 4

Token Replay Example

The fitness of a case with trace σ on WF-net M is defined as:

$$fitness(\sigma, M) = \frac{1}{2}\left(1 - \frac{m}{c}\right) + \frac{1}{2}\left(1 - \frac{r}{p}\right)$$

Considering the example:

Checking: $\sigma =$ <Rice, Salmon, Wasabi>

(p)roduced : 7 (c)onsumed : 4

(m)issing : 1 (r)emaining : 4

$$fitness(\sigma, M) = \frac{1}{2}\left(1 - \frac{1}{4}\right) + \frac{1}{2}\left(1 - \frac{4}{7}\right) = 0{,}375$$

Token Replay: Discussion

- Allows a continuous fitness score in the interval $[0,1]$.
- Intuitive and easy to implement.
- For critical deviating behavior, model gets flooded with tokens. Earlier deviations mask later deviations.
  → all behavior afterwards gets accepted, fitness values too low
- Depending on a Petri net representation of the process.

Alignments[2]

- To overcome drawbacks of Token Replay, it might be better to map observed behavior on modelled behavior.

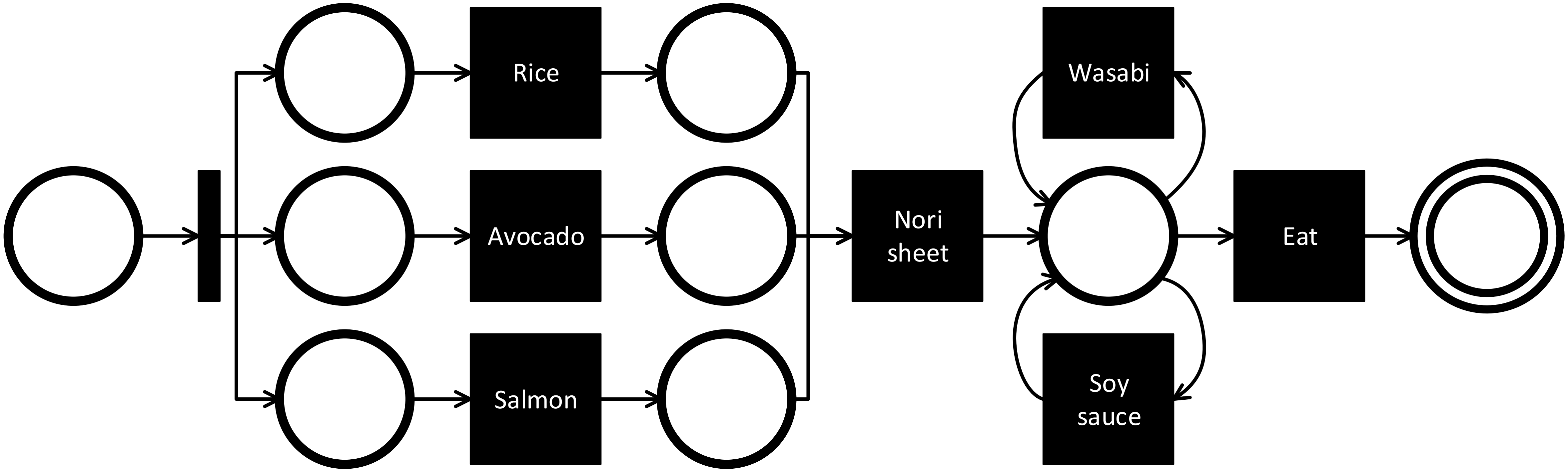
- Idea:
  - Consider all mappings between a model and a trace.
  - Simulate moves in the model and in the trace.
  - Optimize for most synchronuous moves
    (fire transition a and read a in the trace in parallel).
  - Finally, compare the optimal alignment with the worst alignment possible to determine the fitness.

moves in the log	a	b	c	d	>>	g	h
moves in the model	a	b	c	d	f	>>	h

>> is an asynchronous move

[2] W.M.P. van der Aalst, A. Adriansyah, and B. van Dongen. Replaying History on Process Models for Conformance Checking and Performance Analysis. *WIREs Data Mining and Knowledge Discovery*, **2**(2):182–192, 2012.

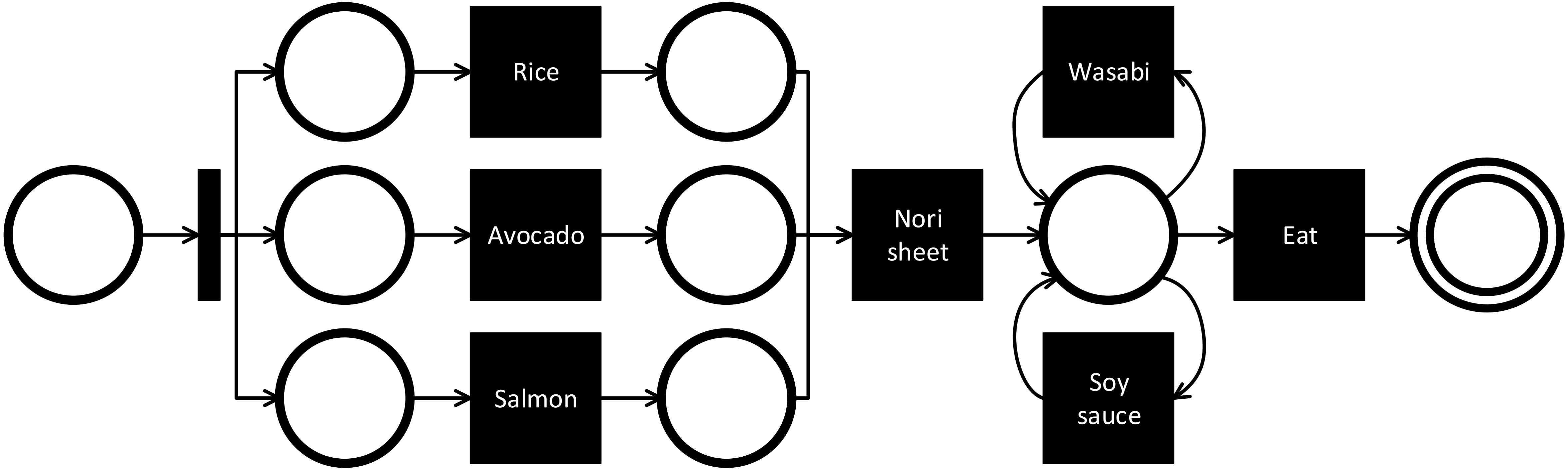
Alignments



- Worst possible alignment for <Rice, Salmon, Wasabi>:

Rice	Salmon	Eat	>>	>>	>>	>>	>>
>>	>>	>>	Rice	Avocado	Salmon	Nori sheet	Eat

Alignments



- Optimal alignment for <Rice, Salmon, Salmon, Wasabi>:

Rice	>>	Salmon	Salmon	Wasabi	>>
Rice	Avocado	Salmon	>>	Wasabi	Eat

Alignments

- Optimal alignment for <Rice, Salmon, Salmon, Wasabi>:

Rice	>>	Salmon	Salmon	Wasabi	>>
Rice	Avocado	Salmon	>>	Wasabi	Eat

- Optimal alignments do not require to be unique:

Rice	>>	Salmon	Salmon	Wasabi	>>
Rice	Avocado	>>	Salmon	Wasabi	Eat

Rice	Salmon	>>	Salmon	Wasabi	>>
Rice	Salmon	Avocado	>>	Wasabi	Eat

>>	Rice	Salmon	Salmon	Wasabi	>>
Avocado	Rice	>>	Salmon	Wasabi	Eat

>>	Rice	Salmon	Salmon	Wasabi	>>
Avocado	Rice	Salmon	>>	Wasabi	Eat

- However, the distance between log and model equal for all optimal alignments.

Alignments

- Optimal alignment for <Rice, Salmon, Salmon, Wasabi>:

$\lambda_{opt}^{M}(\sigma) =$

Rice	>>	Salmon	Salmon	Wasabi	>>
Rice	Avocado	Salmon	>>	Wasabi	Eat

$\delta\left(\lambda_{opt}^{M}(\sigma)\right) = 3$

- Worst alignment:

$\lambda_{worst}^{M}(\sigma) =$

Rice	Salmon	Eat	>>	>>	>>	>>	>>
>>	>>	>>	Rice	Avocado	Salmon	Nori sheet	Eat

$\delta\left(\lambda_{worst}^{M}(\sigma)\right) = 8$

- The fitness is defined as

$$fitness(\sigma, M) = 1 - \frac{\delta\left(\lambda_{opt}^{M}(\sigma)\right)}{\delta\left(\lambda_{worst}^{M}(\sigma)\right)} = 0.625$$

Alignments Discussion

- Alignments easier to understand: Instead of tokens in Petri-nets, we talk about skipped and inserted events.

- Higher accuracy, since Token Replay suffers from token flooding.

- Fitness values for Alignments tends to be to low, while Token Replay often yields higher values.

- More flexibility due to modifications of the costs δ. E.g. activity "avocado" might be cheaper to drop than dropping the activity "rice".

- Not depending on Petri-nets only.

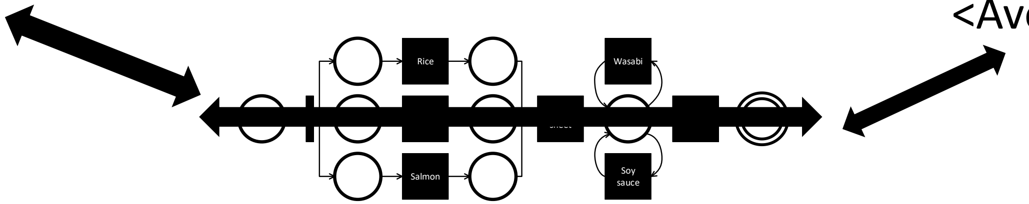
- However, very computational expensive.

Applications for Conformance Scores

- We only talked about conformance checking for fraud detection and workflow diagnostics.
- Fitness values determined by conformance checking provide us with a definition of distance between model and trace.
- The unstructured trace space, which is not a native vector space, becomes semi-metric.
  - The distance is not defined between traces, but uses models as reference points.
  - As the distance is not computed directly, but depends on a secondary structure, it is called geodetic.

<Rice, Salmon, Salmon, Wasabi>

<Avocado, Rice, Salmon, Nori, Eat>



  - Using this distance, clustering and outlier detection become possible:
    - Richter, F., Wahl, F., Sydorova, A., & Seidl, T. LWDA (2019). k-process: Model-Conformance-based Clustering of Process Instances.
    - Richter, F., Zellner, L., Sontheim, J., & Seidl, T. (2019, October). Model-Aware Clustering of Non-conforming Traces. In *OTM Confederated International Conferences" On the Move to Meaningful Internet Systems"* (pp. 193-200). Springer, Cham.
  - We can also lift this approach to a log-to-log level, defining distances between two process logs for clustering and outlier detection (k-means, DBSCAN,…):
    - Richter, F., Zellner, L., Azaiz, I., Winkel, D., & Seidl, T. (2019, September). LIProMa: Label-Independent Process Matching. In *International Conference on Business Process Management* (pp. 186-198). Springer, Cham.

Temporal Conformance Checking

- Until now: Does the order of events conform to a given model? Often it is interesting if events are also executed at the "right" time.
- Even for conform traces, an activity can be executed too early or too late.
- In the following, the execution order was correct and according to model, there is no problem:

$$\mathit{cook\ rice} \xrightarrow{6h13m12s} \mathit{prepare\ avocado} \xrightarrow{0h2m43s} \mathit{salmon} \xrightarrow{0h4m7s} \color{red}{\mathit{Combine\ and\ roll\ Nori\ sheet}}$$

The last event failed due to dry and hard rice.

- Recent research on this at DBS:
  - Richter, Florian, and Thomas Seidl. "TESSERACT: time-drifts in event streams using series of evolving rolling averages of completion times." *International Conference on Business Process Management*. Springer, Cham, 2017.
  - Richter, Florian, and Thomas Seidl. "Looking into the TESSERACT: Time-drifts in event streams using series of evolving rolling averages of completion times." *Information Systems* 84 (2019): 265-282.
  - Sontheim, J., Richter, F., & Seidl, T. LWDA (2019). Temporal Deviations on Event Sequences.

Agenda

Perspectives - Motivational Example

Average daily outside temperature in °C

	Log 1	Log 2	RLE-based (Log 1)
Day 1	**14.2**	**14.2**	**1*14.2**
Day 2	**14.4**	**14.4**	**4*14.4**
Day 3	**14.4**	**14.4**	**1*14.3**
Day 4	**14.4**	**-21.3**	**1*14.2**
Day 5	**14.4**	**14.4**	
Day 6	**14.3**	**14.3**	
Day 7	**14.2**	**14.2**	

Detecting
anomalous behavior in temperature data
by changing perspectives

Log 1:
E.g. Mean and standard deviation can be computed
$\Rightarrow$ still *seems* normal

Log 2:
Point anomaly is obvious

Log 3 (Saves entries of Log 1 in a **R**un-**L**ength **E**ncoding manner):
Exposes entries of Log 1 as a possible **collective anomaly**

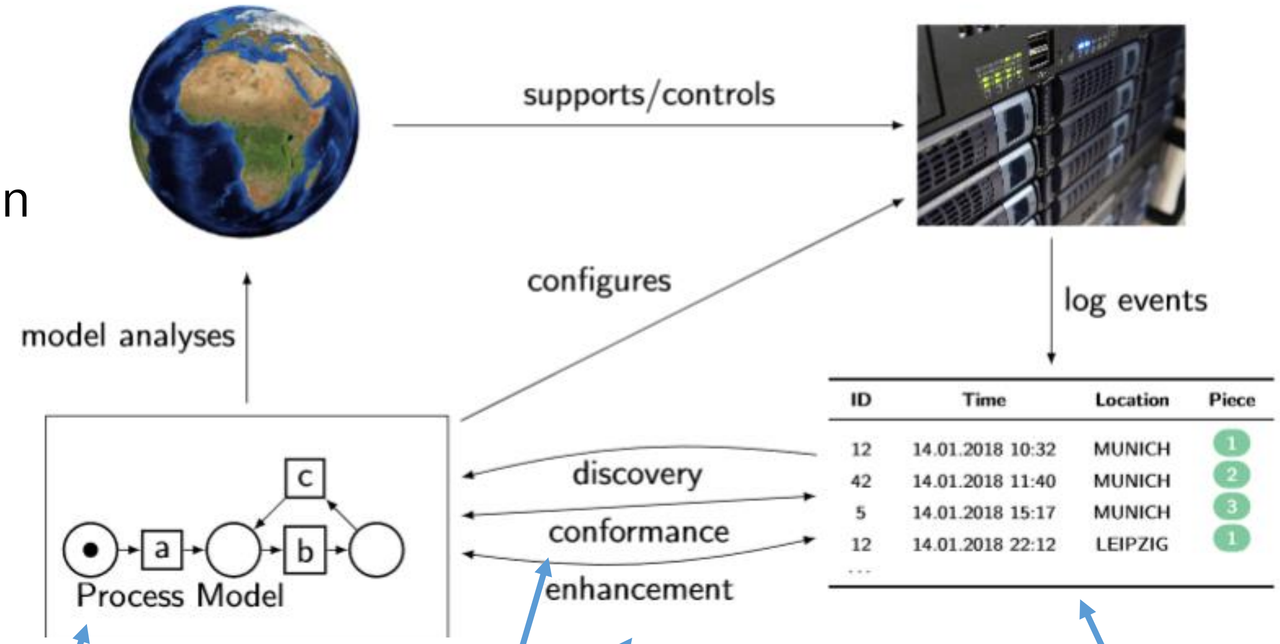
Motivation - Perspectives

- Analysis can be done by using different perspectives

=> Event logs provide much more information
E.g.: Timestamps, resources, transactions, costs etc.

- Thus far: **Control-flow perspective**

- Moreover:
  - **Time perspective**
  - **Case perspective**
  - **Organizational perspective**



Model can show multiple perspectives

Extension and conformance checks in every perspective possible

Events have attributes concerning various perspectives

Motivation - Perspectives

Time perspective

- Focus on timing and frequency of events
- Goals: Discover bottlenecks, monitor utilization of resources, remaining time prediction

Case perspective

- Focus on case properties
- Properties can be case attributes, event attributes, a path taken, performance information
- Goals: Mining decisions (e.g. a specific path) based on the characteristics of the case shows which data is relevant and should be included in the model

Organizational perspective

- Focus on information about resources
- Resources can be people, systems, roles, departments
- Goals: Classify actors in terms of roles, show social network

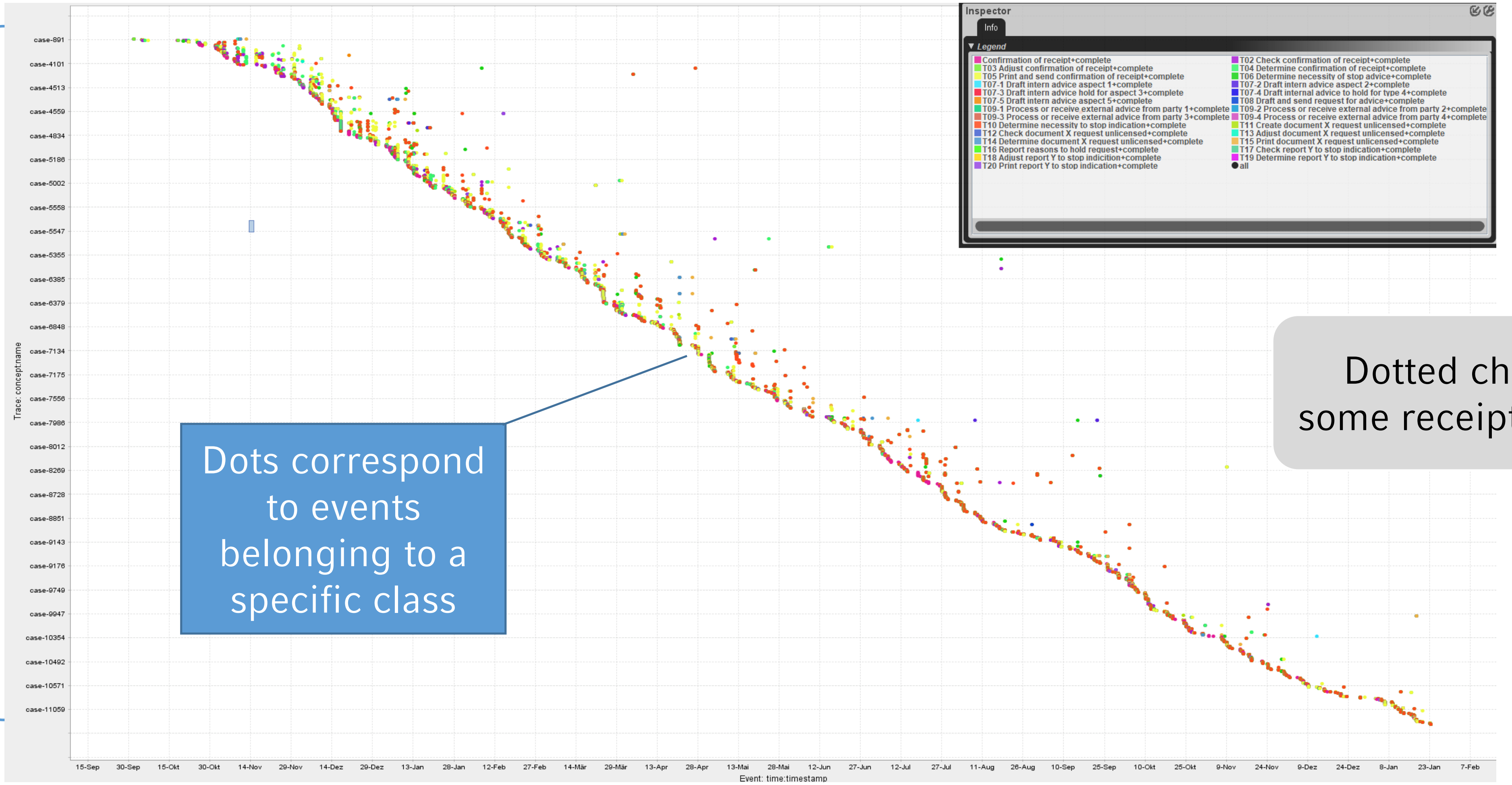
Exemplarily introducing temporal mining now

Temporal Visualization – Dotted Chart Analysis

- How to get a general overview: **Dotted Chart Analysis**

Legend mapping event colors to event descriptors

Classifier (here: *Case ID*) sorted by timestamp of first event

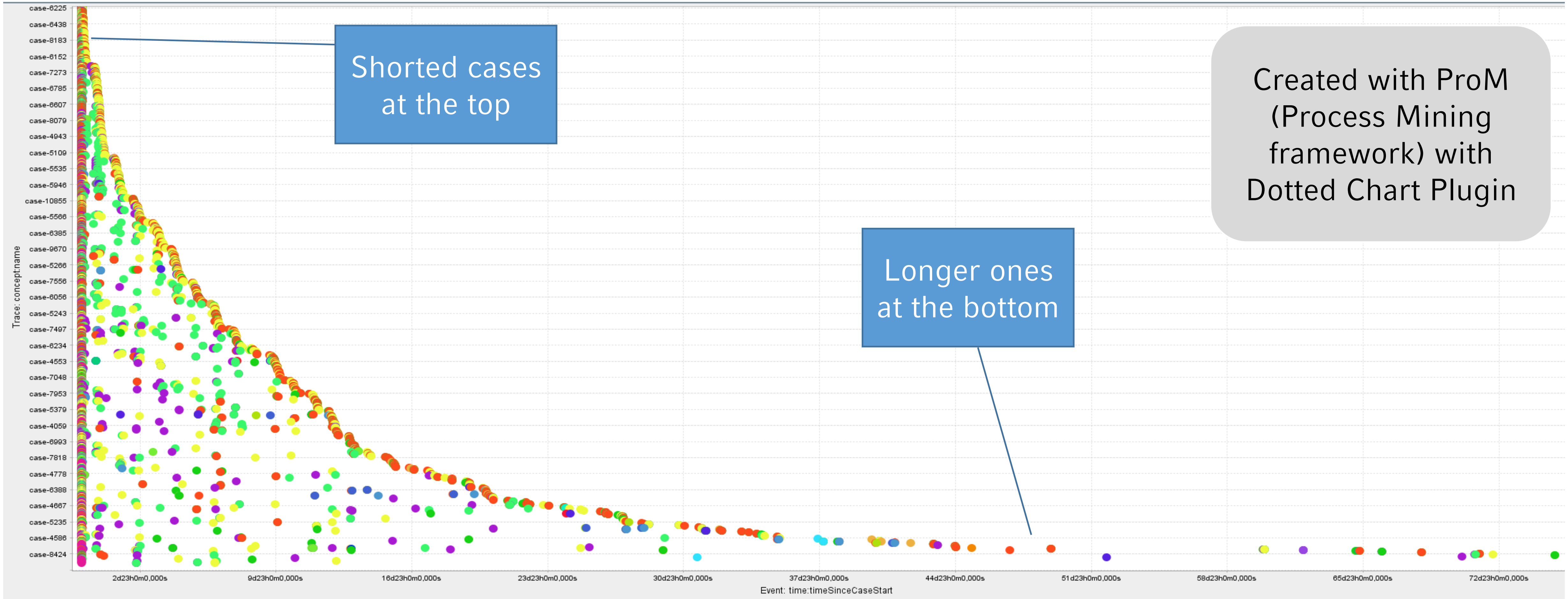


Dots correspond to events belonging to a specific class

Dotted chart for some receipt process

Time (absolute, relative or logical)

Temporal Visualization – Dotted Chart Analysis



Time since case started
sorted by duration of a case

Temporal Visualization – Dotted Chart Analysis

Time since week started.
Indicates that only few events were executed by night and at weekends.

→ Most events on weekdays between 9am and 4pm

Temporal Mining

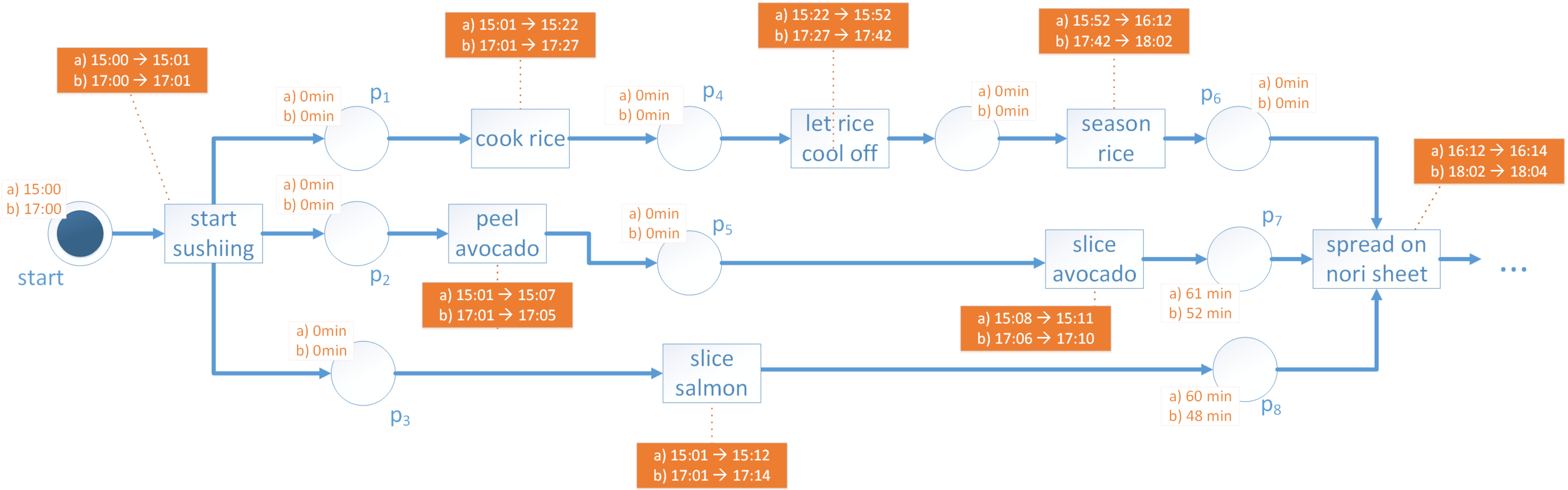
Presence of timestamps enables

- **discovery of bottlenecks**
  - Limitation of capacity of a specific resource
- **monitoring of resource utilization**
  - *Which resources are occupied by which activity the most?*
- **prediction of remaining processing times of running cases**
  - Based on computations made on discovered cases so far
- etc.

Token replay can be extended to replay event logs with timestamps included (*time-based replay*).

This can help to extract aforementioned information.

Temporal Mining – Time-based replay



Replay of first part of our sushi process
for two cases starting at 3pm i.e. 5pm

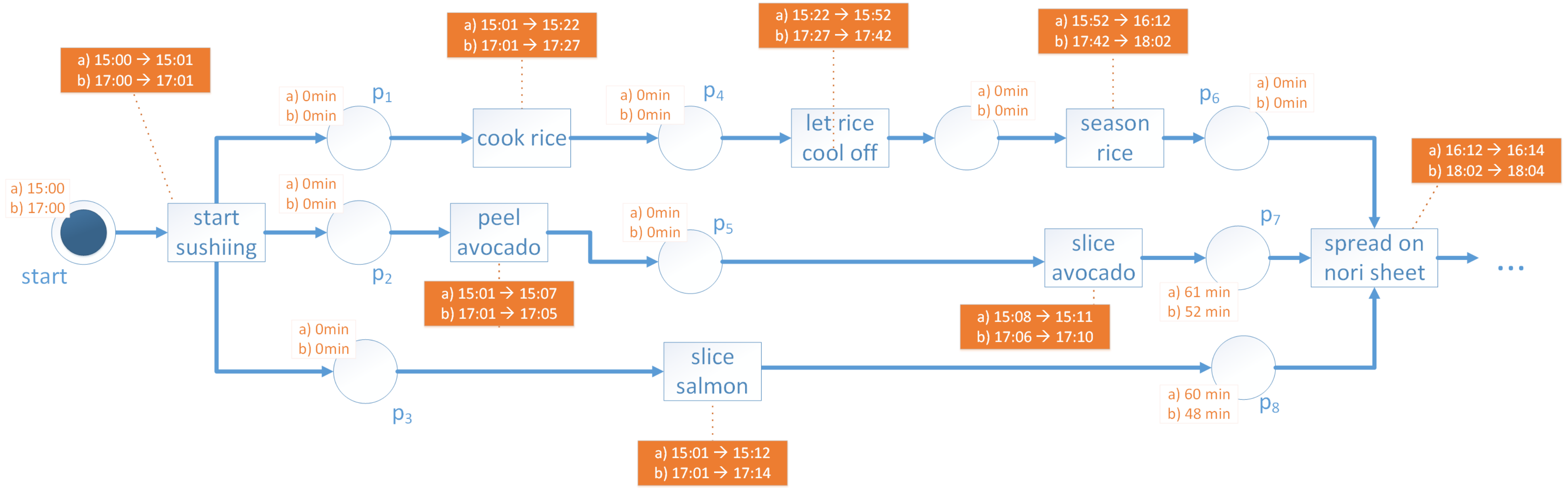
Timed replay for
2 cases showing
durations at transitions and
waiting times at places

Temporal Mining – Time-based replay

Replay of first part of our sushi process
for two cases starting at 3pm i.e. 5pm

Record collection of token visits
→ derive multi set of durations for each place

Partial sushiing process
seems to have a bottleneck at
$\langle cook\ rice,\ \ season\ rice \rangle$

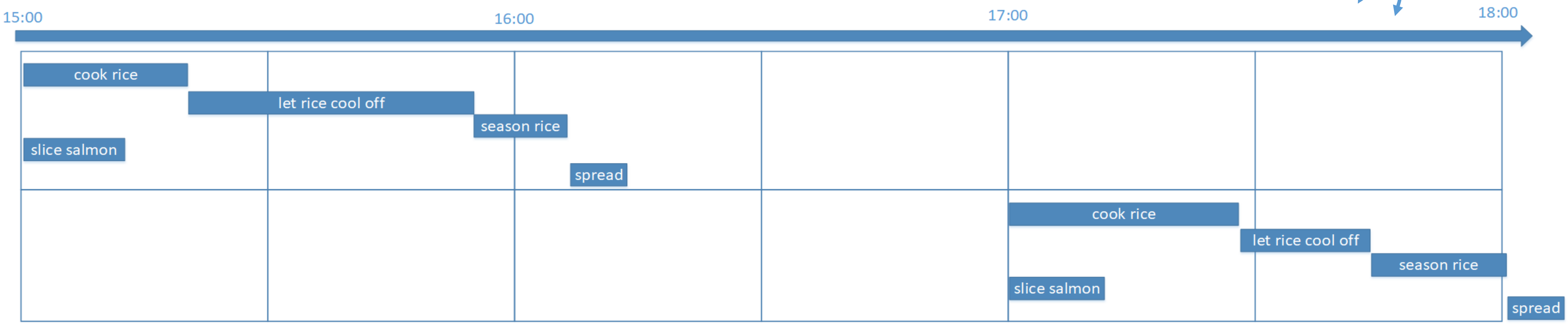


Temporal Mining – Time-based replay

Possibility to

- Fit distribution
- Compute statistics such as
  - mean,
  - standard deviation,
  - minimum,
  - maximum
  - etc.

⇒ Visualization of waiting times
⇒ Visualization of service times
⇒ Bottleneck detection and analysis



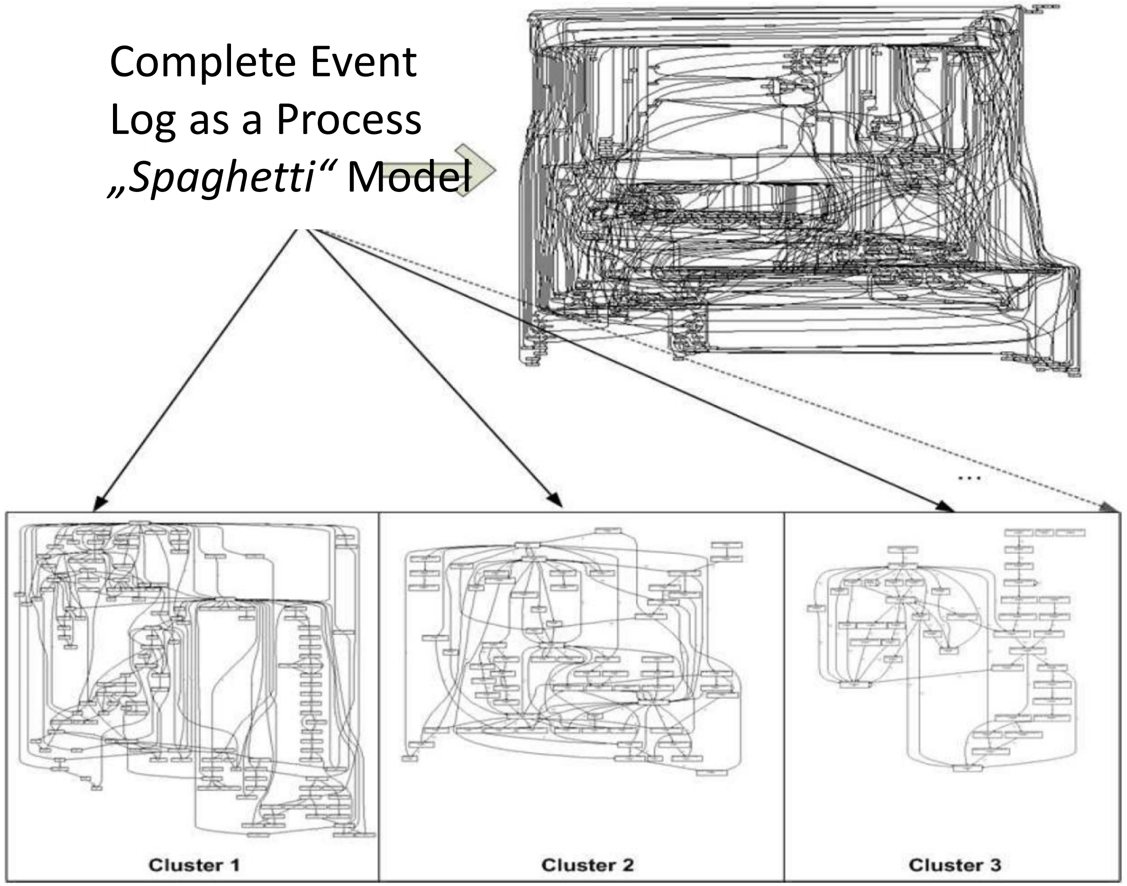
Timeline resembling a Gantt-Chart (excerpt of time-based replay)

Trace Clustering - Motivation

High *diversity:*

Single cases differ significantly from one another

→ possibly very complex models



Our sushiing process already can be very complex depending on the granularity of visualization

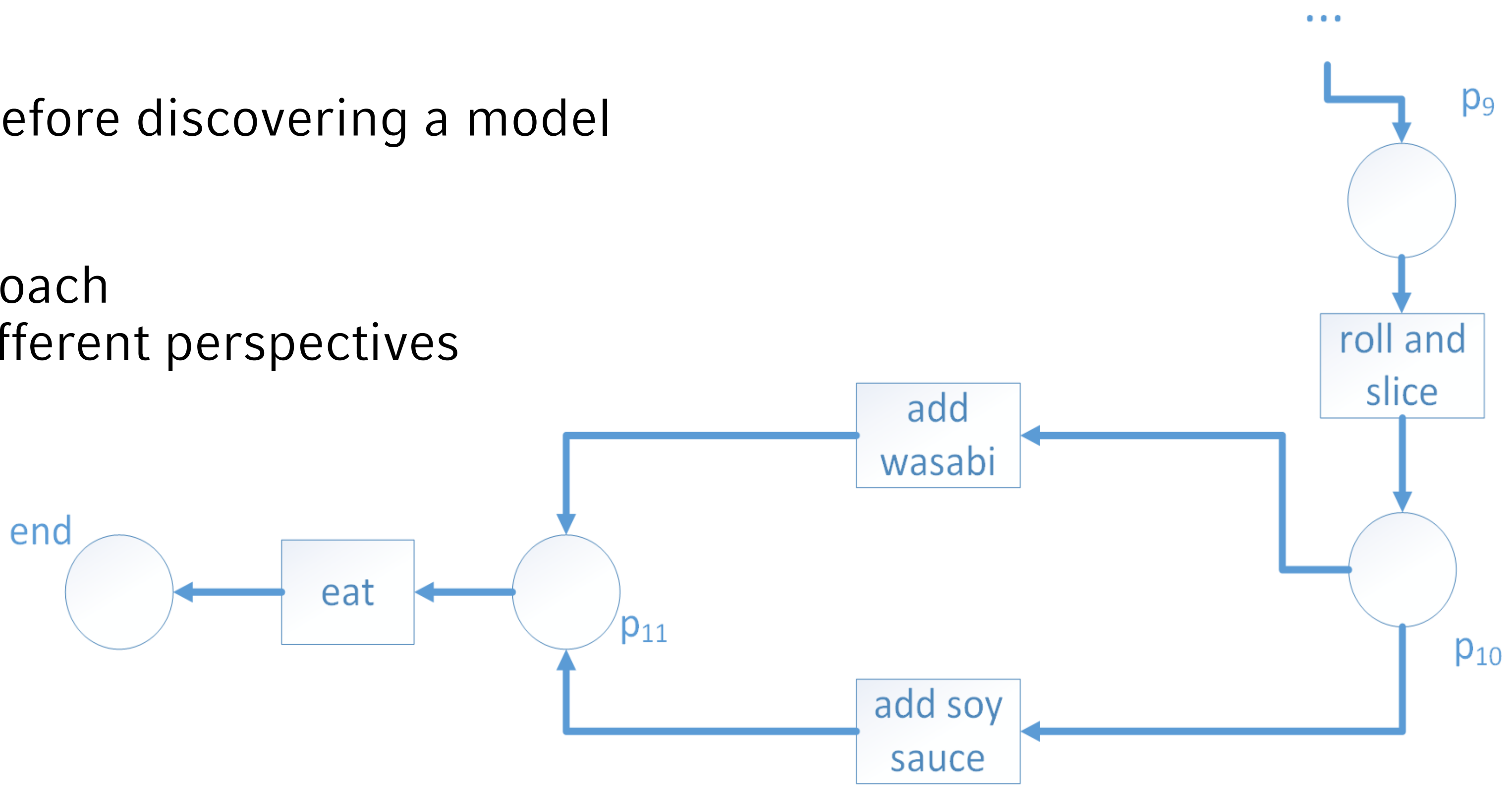
Trace Clustering - Motivation

Assumption:

Process variants hidden within the event log

⇒ Cluster traces before discovering a model

⇒ Clustering approach
also based on different perspectives



Example: Second part of our sushiing process

Trace Clustering - Example

- How to determine a similarity value between our data points (here: *cases*)?
- Clustering on points in vector space is well-known

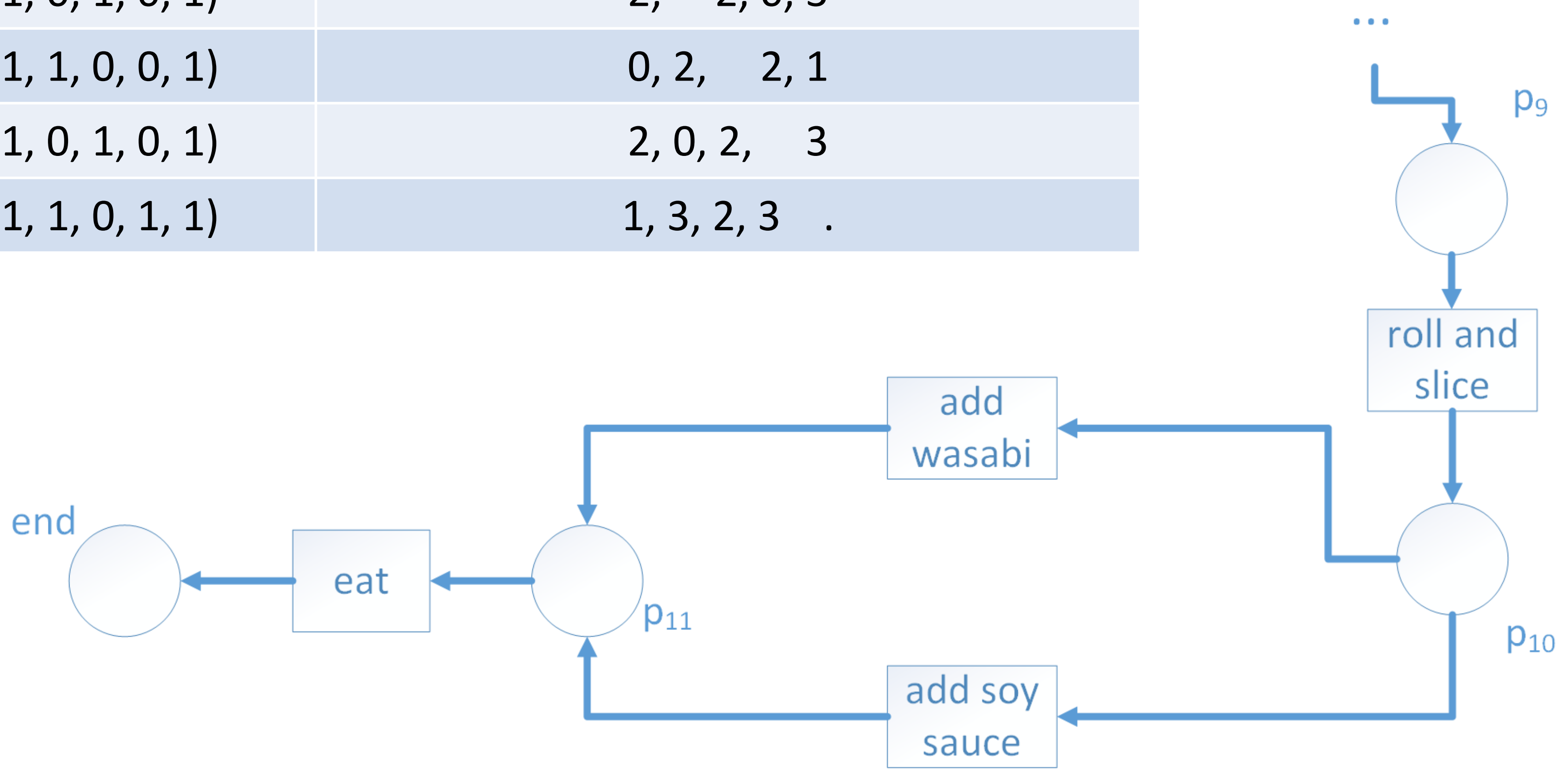
=> Embedding of *cases* into vector space necessary → **Profiles**

Case ID	Roll and slice	Add wasabi	Add soy sauce	Prepare stir-fried rice	Eat
1	1	1	0	0	1
2	1	0	1	0	1
3	1	1	0	0	1
4	1	0	1	0	1
5	1	1	0	1	1

Add up the number of activity execution for each case

Trace Clustering - Example

Case ID	Vector	Manhattan distance to other vectors
1	(1, 1, 0, 0, 1)	2, 0, 2, 1
2	(1, 0, 1, 0, 1)	2, 2, 0, 3
3	(1, 1, 0, 0, 1)	0, 2, 2, 1
4	(1, 0, 1, 0, 1)	2, 0, 2, 3
5	(1, 1, 0, 1, 1)	1, 3, 2, 3 .



⇒ **E.g. cluster with agglomerative approach**

Trace Clustering – Methods

Aforementioned profile is called *Activity Profile (Activity Histogram)*

- Defines one item (feature) per type of activity
- An activity item is measured by counting all events of a trace which have that activities name
- Of course, **various other profiles possible** as well

In General:

Profile: Set of items with measurements
Item: Assigns numeric value to each trace

$\Rightarrow$ A Profile can be considered a function f which maps a trace *t* to a vector $(i_1, i_2, \ldots, i_n)$ with *n* items:

$$f(t) \rightarrow (i_1, i_2, \ldots, i_n),$$

→ **✓ Embedding into vector space**

$\Rightarrow$ Various clustering methods can be applied now

Trace Clustering – Methods

More examples:

Transition profile:

Items: Direct following relations in a trace

Measure: How often an event A has been followed by an event B

Goal: Measure behavior of traces (capturing the context) cf. **n-grams**

Performance profile:

Items: Size of a trace
regarding timestamps: case duration, (min, max, mean) time difference between events etc.

Measure: Depends on predefined items e.g. size is measured by number of events

Goal: Measure performance of a trace (→ also part of Temporal Mining)

Additional Mining Tasks - Roundup

- Processes can be analyzed by using different **perspectives**
  - time
  - case
  - organizational

  perspective

- Get an overview by applying **Dotted Chart Analysis**

- **Temporal Mining** useful to
  - detect bottlenecks
  - monitor resource utilization
  - predict remaining processing time

- **Trace Clustering** helps to distinguish between process variants dependent on different perspectives (*profiles*)

Resources

- ProM Framework

- Wil van der Aalst. 2016. *Process Mining: Data Science in Action* (2nd. ed.). Springer Publishing Company, Incorporated

- Song, Minseok & Günther, Christian & Aalst, Wil. (2008). Trace Clustering in Process Mining. Lecture Notes in Business Information Processing. 17. 109-120. 10.1007/978-3-642-00328-8_11.

- R.P., Jagadeesh Chandra Bose & Aalst, Wil. (2009). Context Aware Trace Clustering: Towards Improving Process Mining Results. SDM. 10.1137/1.9781611972795.35.