

Ludwig-Maximilians-Universität München
Lehrstuhl für Datenbanksysteme und Data Mining
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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

5.6 Streams

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1. Introduction

2. Basics

3. Supervised Methods

4. Unsupervised Methods

5. Process Mining

5.1 Introduction

Motivation

Getting the Data

5.2 Process Models – An Overview

5.3 Process Discovery

5.4 Conformance Checking

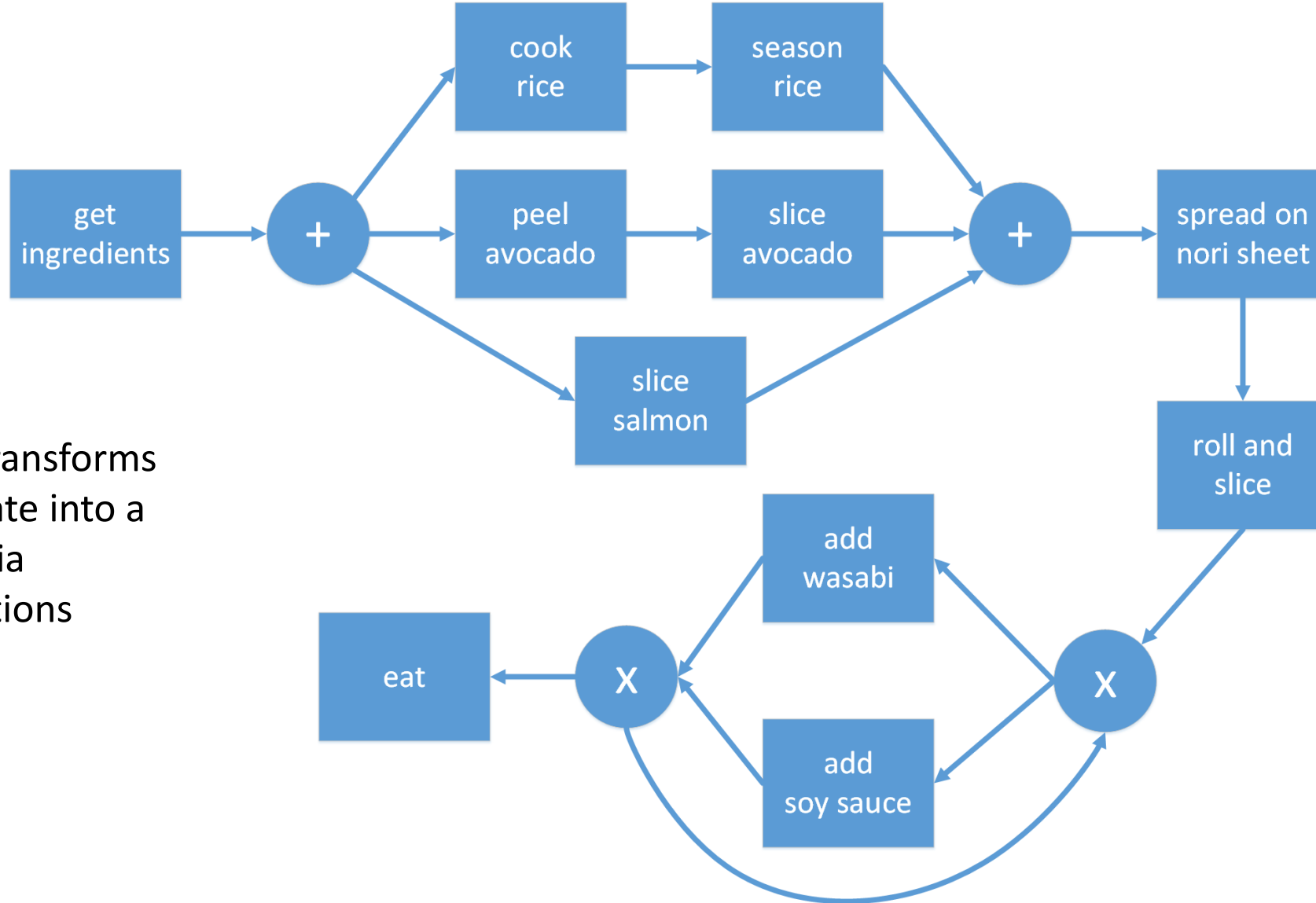
5.5 Additional Mining Tasks

5.6 Streams

Processes in Applications



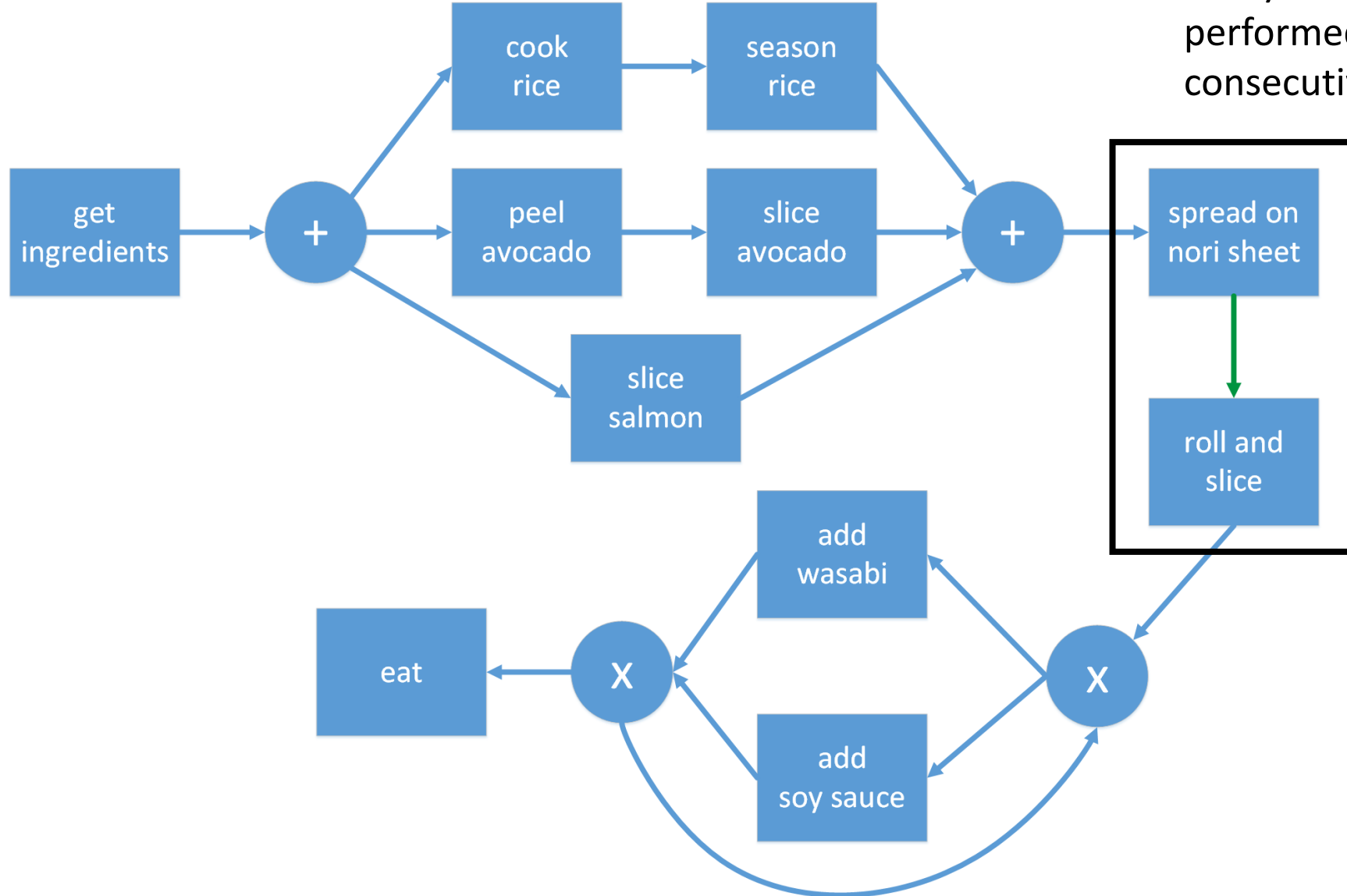
Example: The Sushi Process



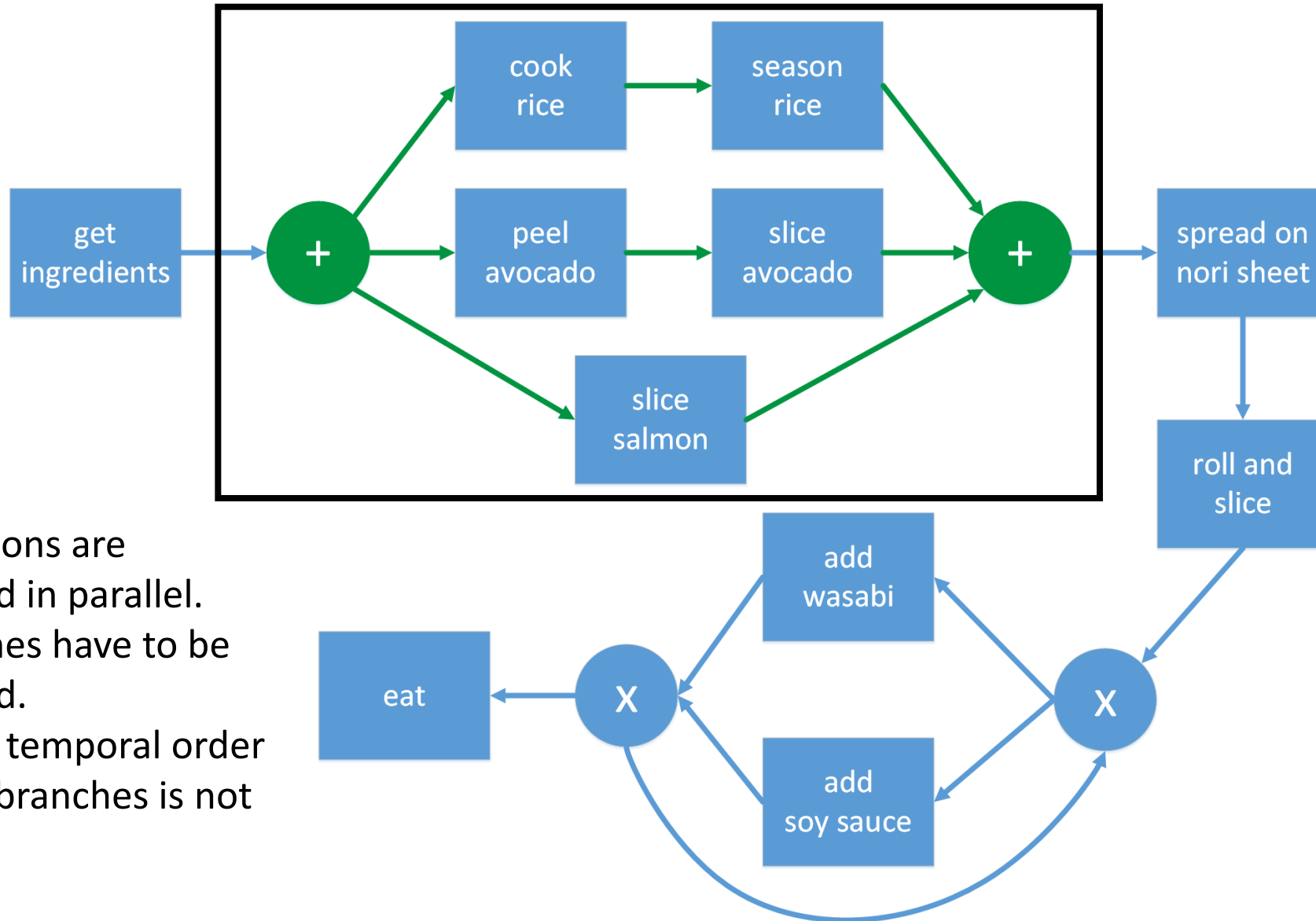
A process transforms an initial state into a final state via multiple actions

Process Properties: Sequence

- Many actions are performed in consecutive order

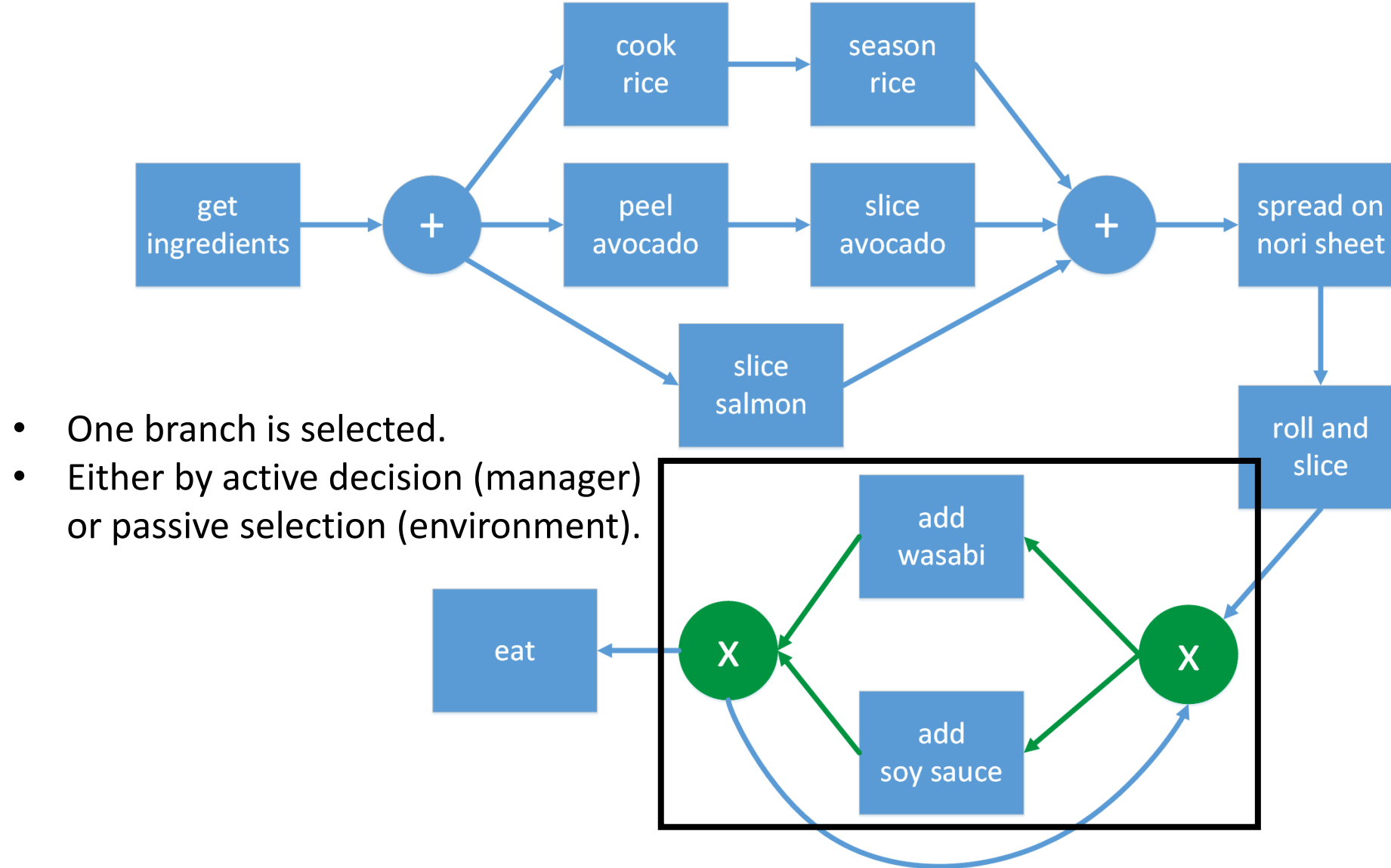


Process Properties: Concurrency

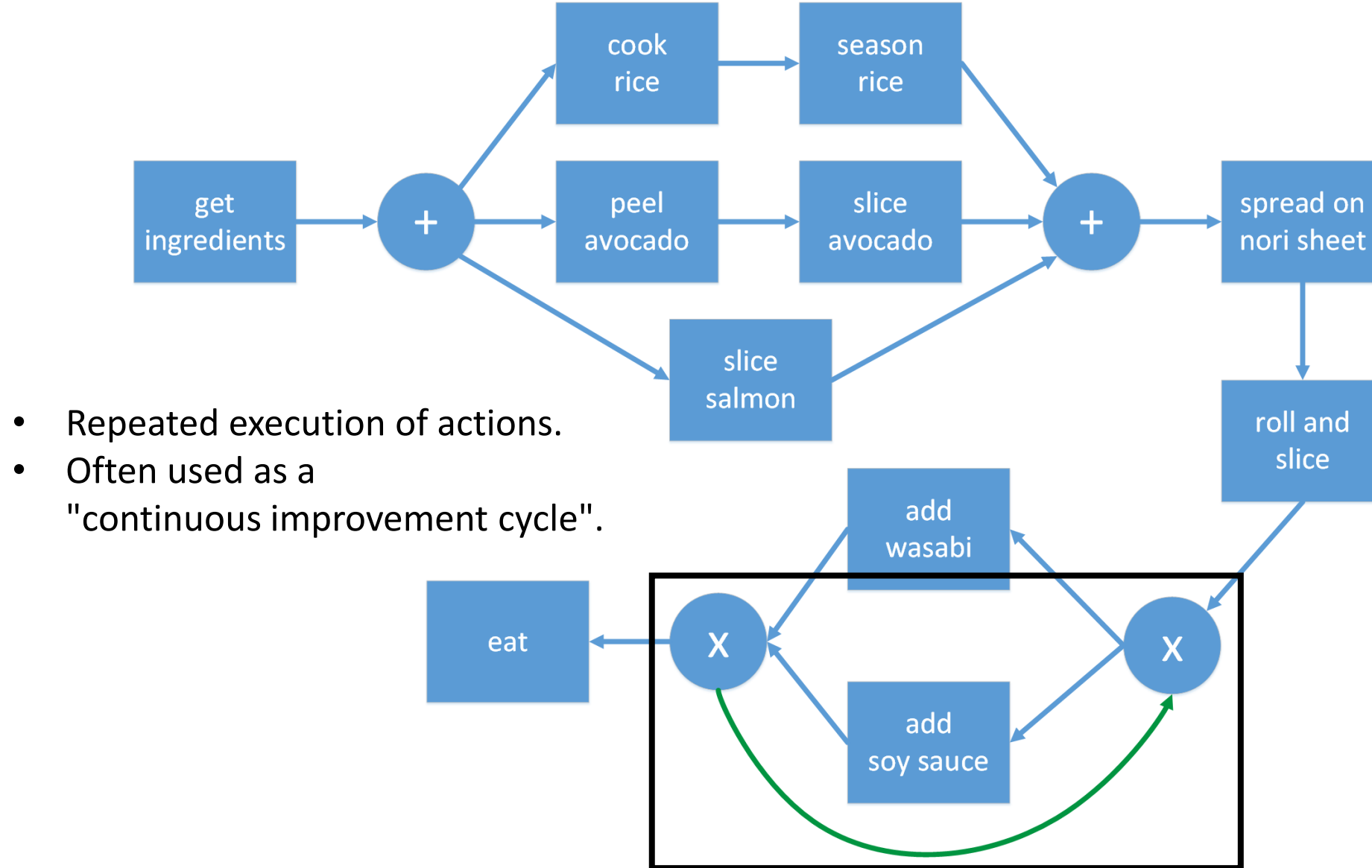


- Some actions are performed in parallel.
- All branches have to be performed.
- The exact temporal order between branches is not strict.

Process Properties: Choice



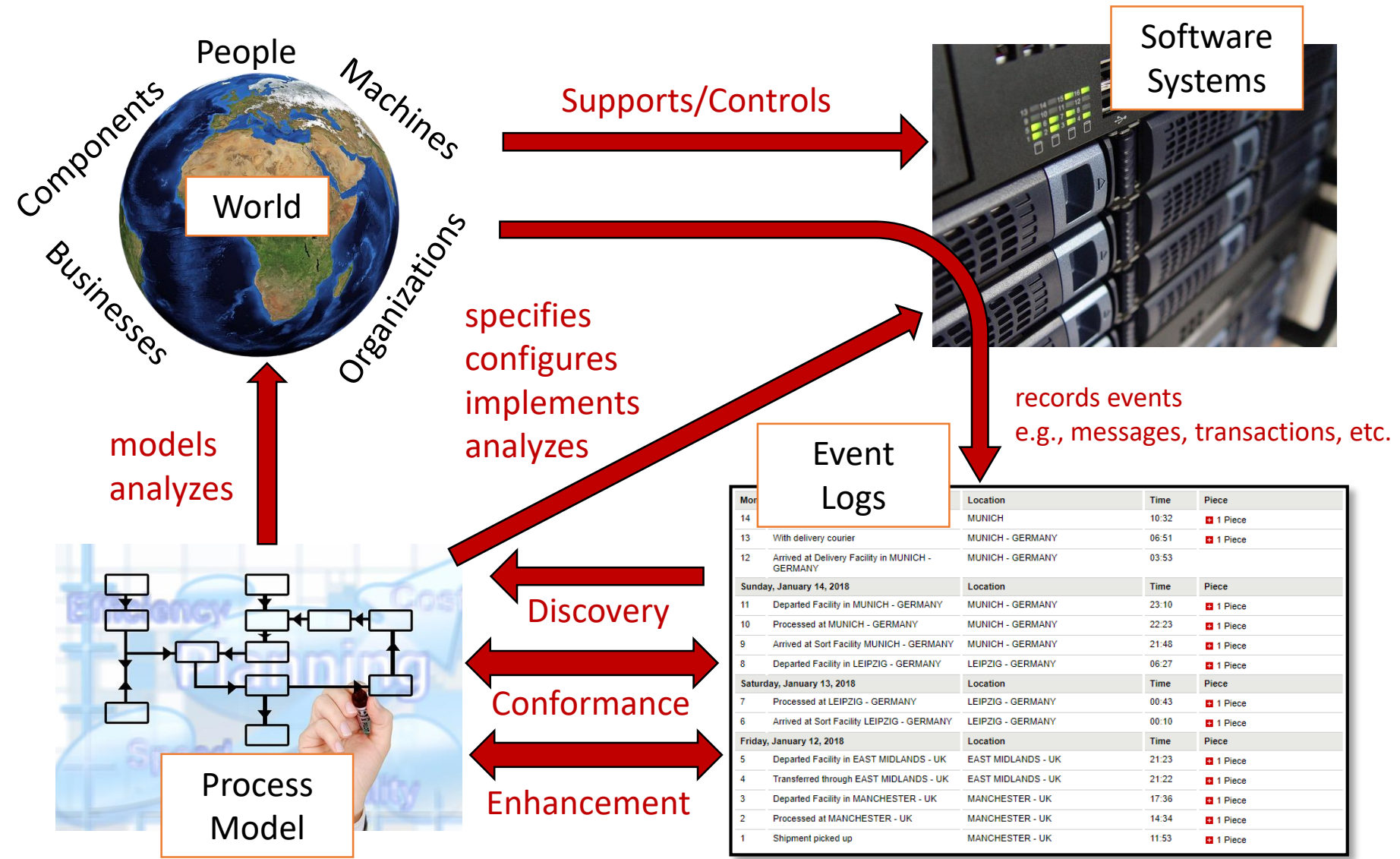
Process Properties: Loop



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 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** 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
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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** L is a multiset of events.

Event Logs Formally

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

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

case id	activity	timestamp	resource 1	resource 2	execution quality
...					
Sushi 113	get ingredients	09:31	Andreas	bag	good
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Sushi 239	eat	09:57	Andreas		-
...					

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

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

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

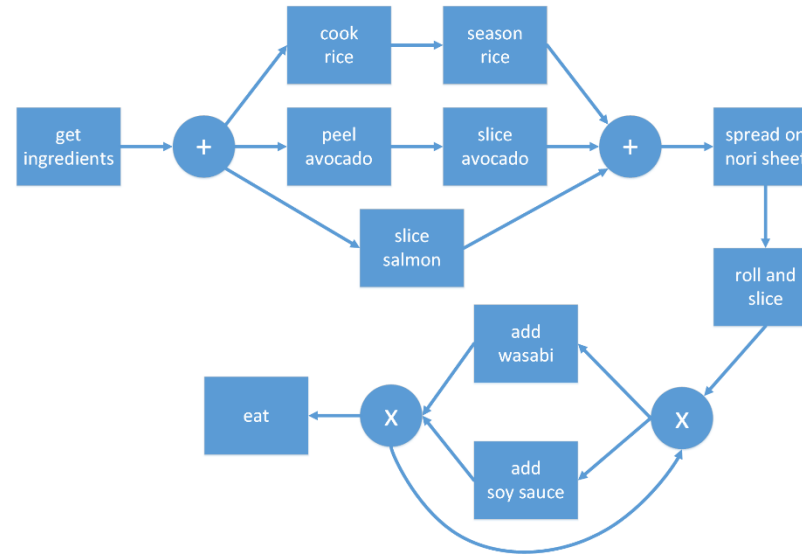
Integration into the Data Mining World

Itemsets

(e.g. frequent itemset mining)

 $\{rice, avocado, salmon\}$

Processes



Sequences

(e.g. sequential pattern mining)

- get ingredients*
- prepare ingredients*
- spread on nori sheet*
- roll and slice*
- season with wasabi*
- season with soy sauce*
- eat*

no order

total order.

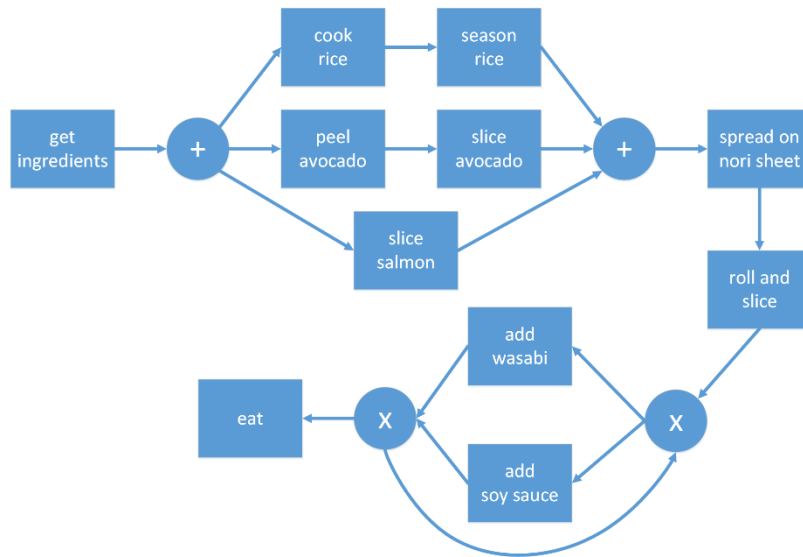
- unordered
- set-based

- 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 \Rightarrow *Fitness*
 - simplifies as far as possible \Rightarrow *Simplicity*
 - does not overfit the log \Rightarrow *Generalization*
 - does not underfit the log \Rightarrow *Precision*

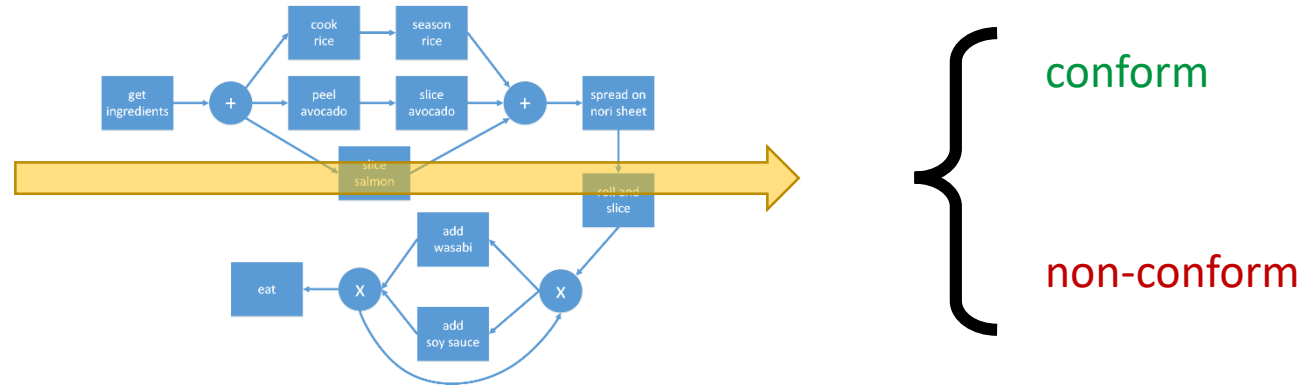


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Sushi 239	eat	09:57
...		

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



- 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



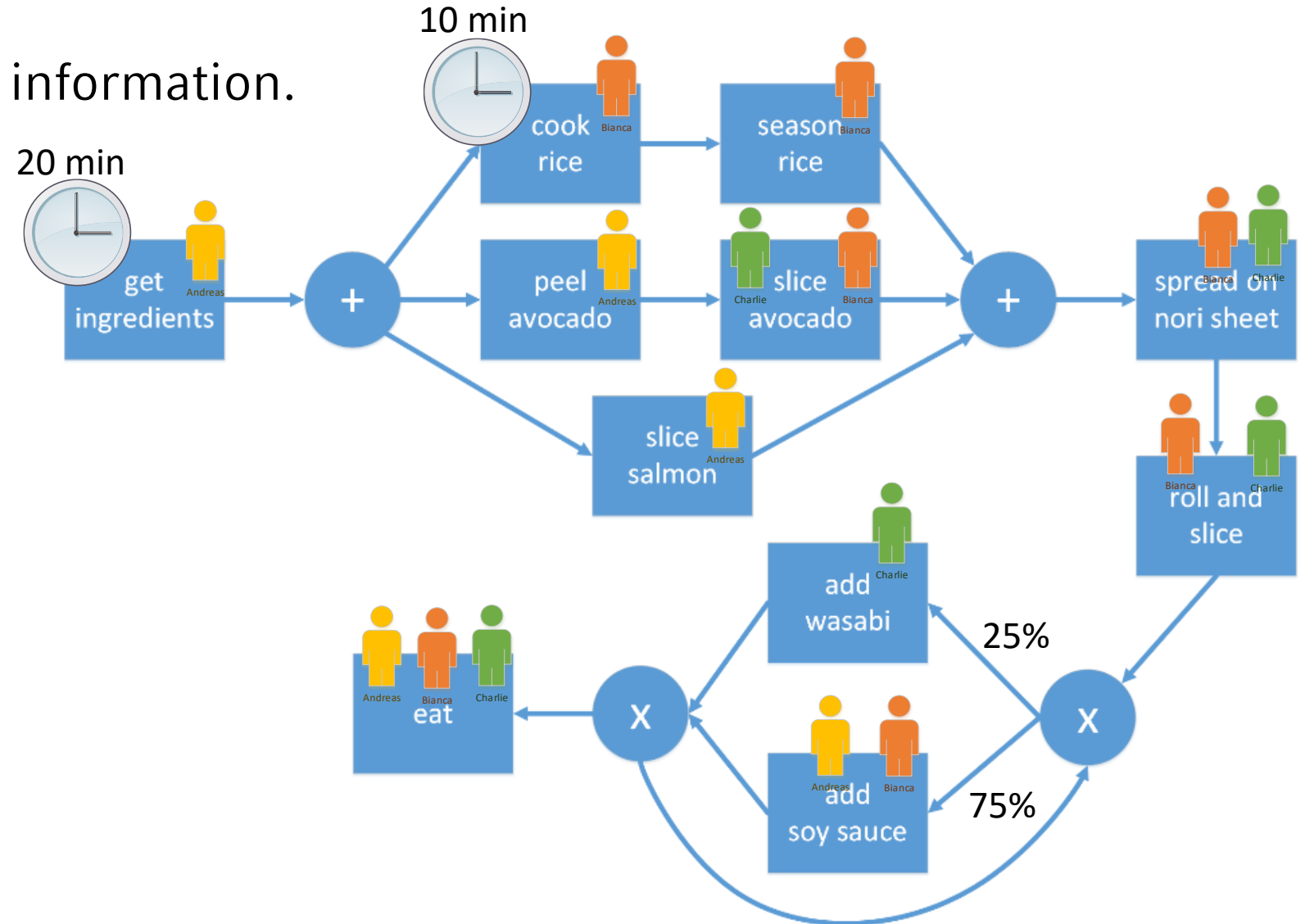
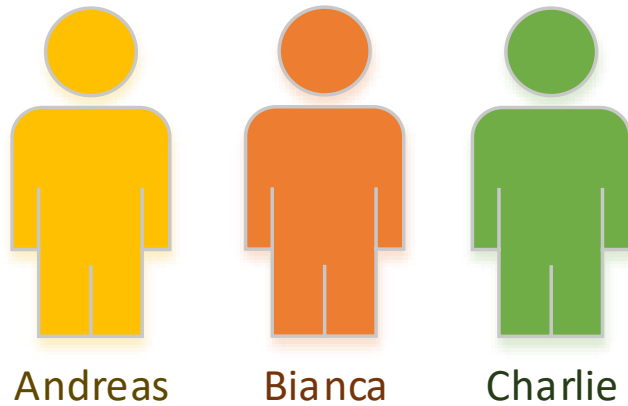
Trails



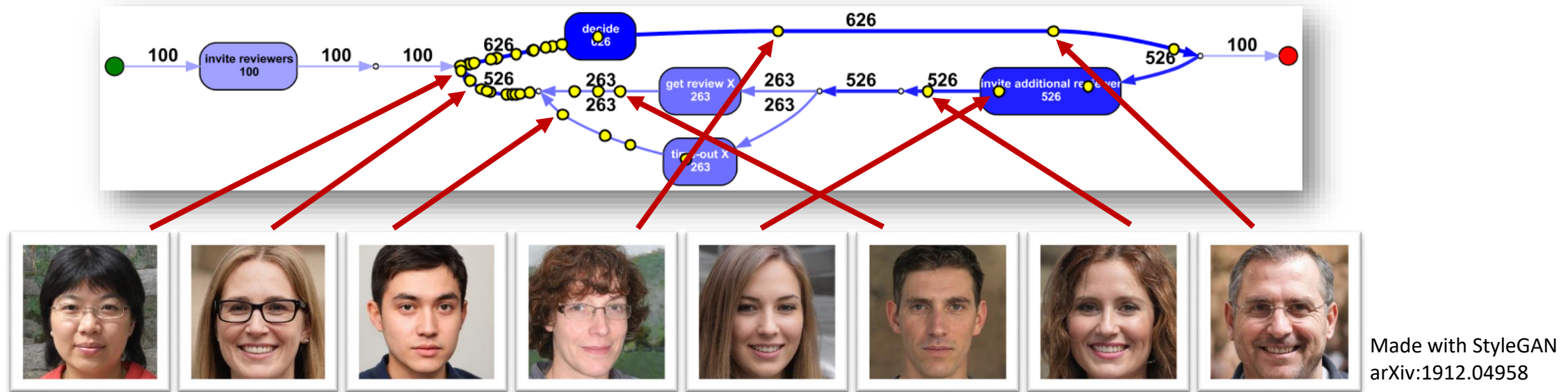
Tool choice

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



- Mostly: Cases related to people. But what is in the data?

- Students
- Employees
- Tenants
- Clients

Who asks the most questions?

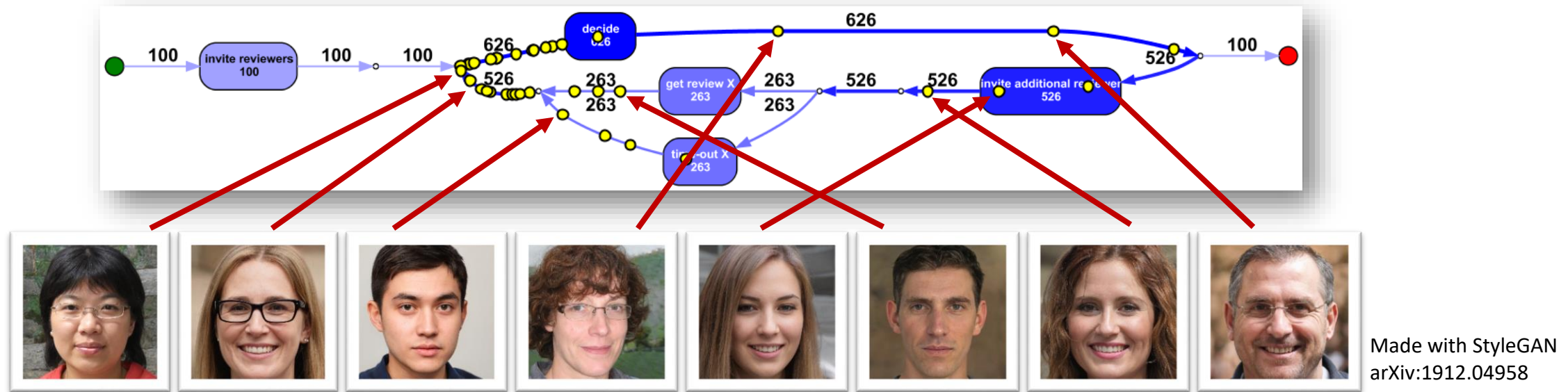
Who is associated with long execution terms?

Who needs maintenance often?

Who calls most for service?

neutral,
objective,
data-oriented

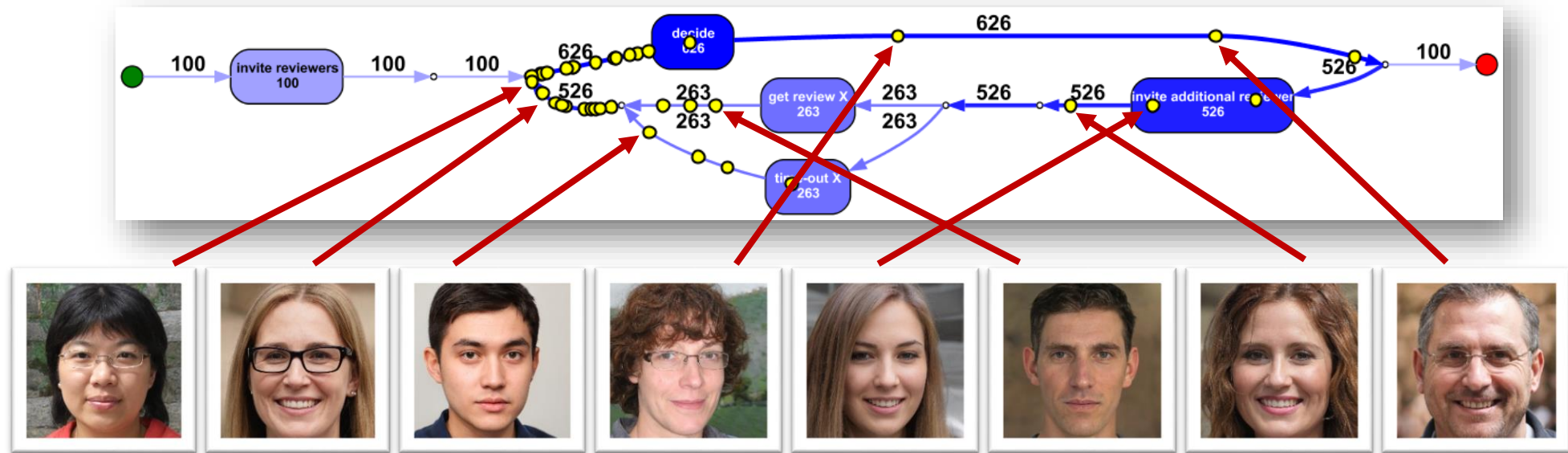
Process Mining Risks and Green Data Science



- 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

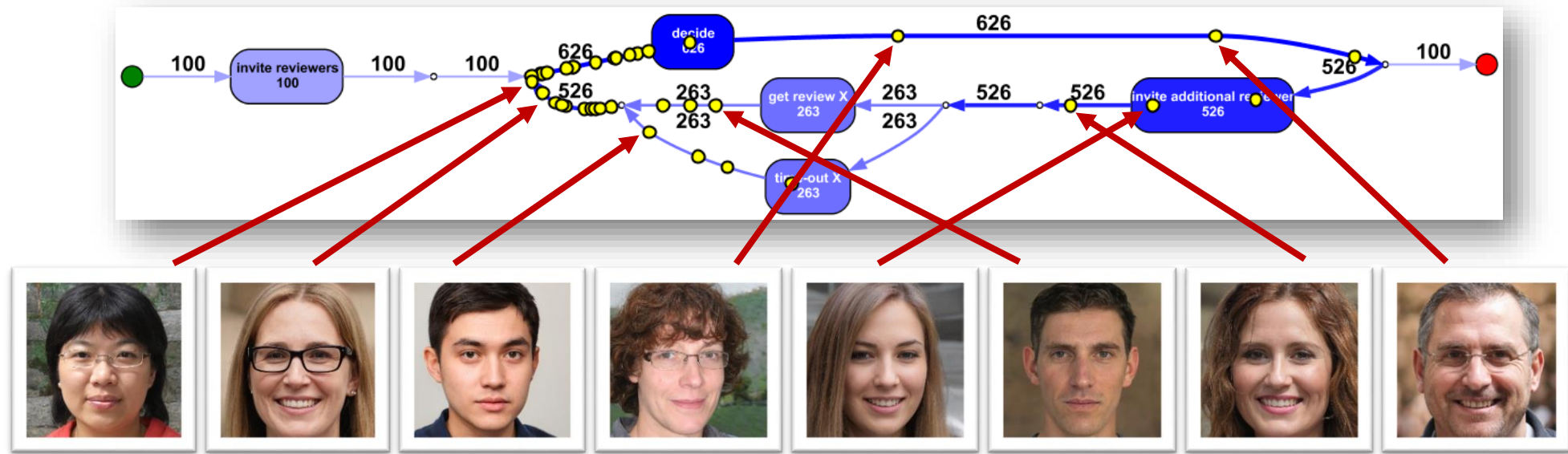


Made with StyleGAN
arXiv:1912.04958

- 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



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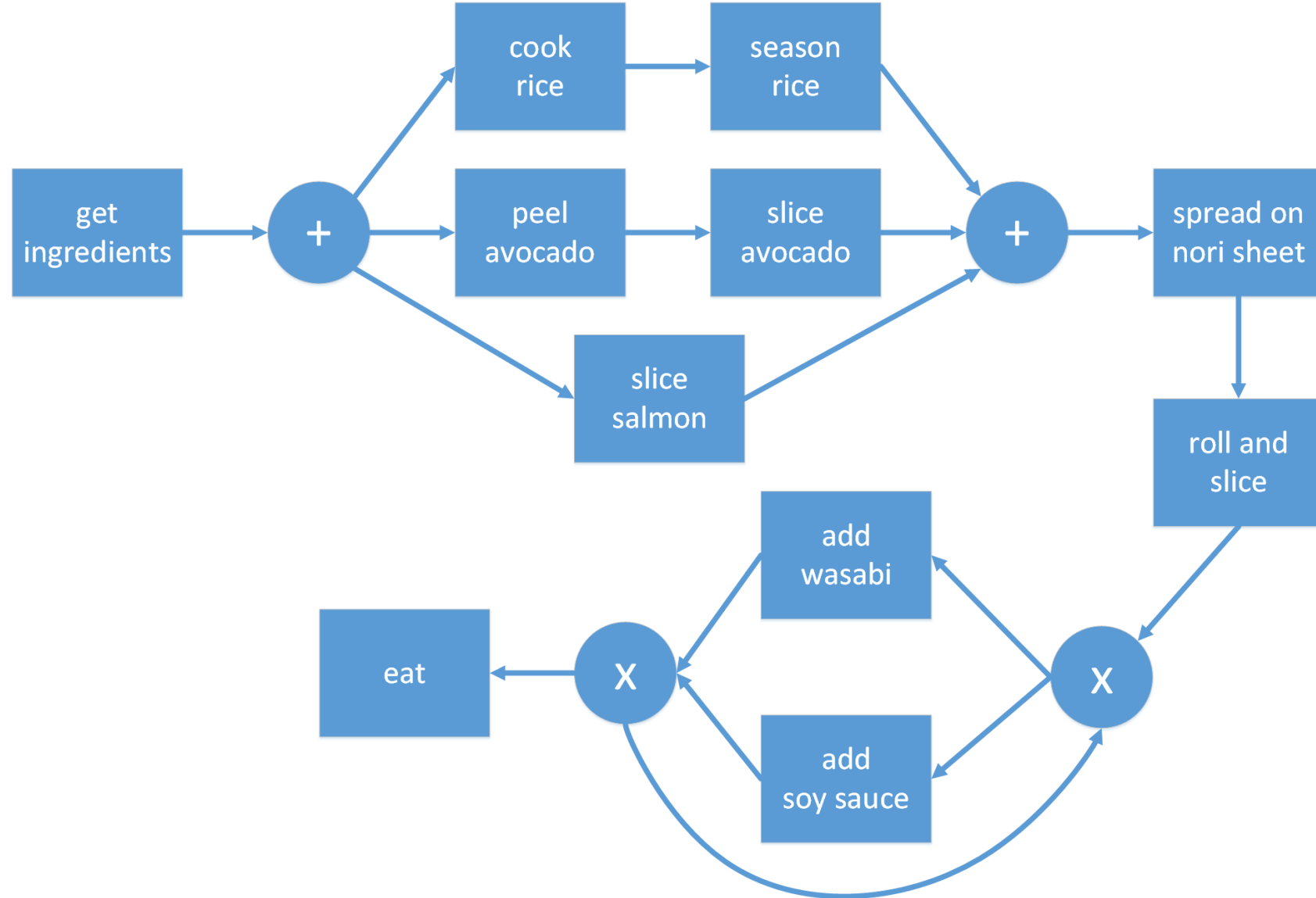
Motivation

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
 - ...
- 

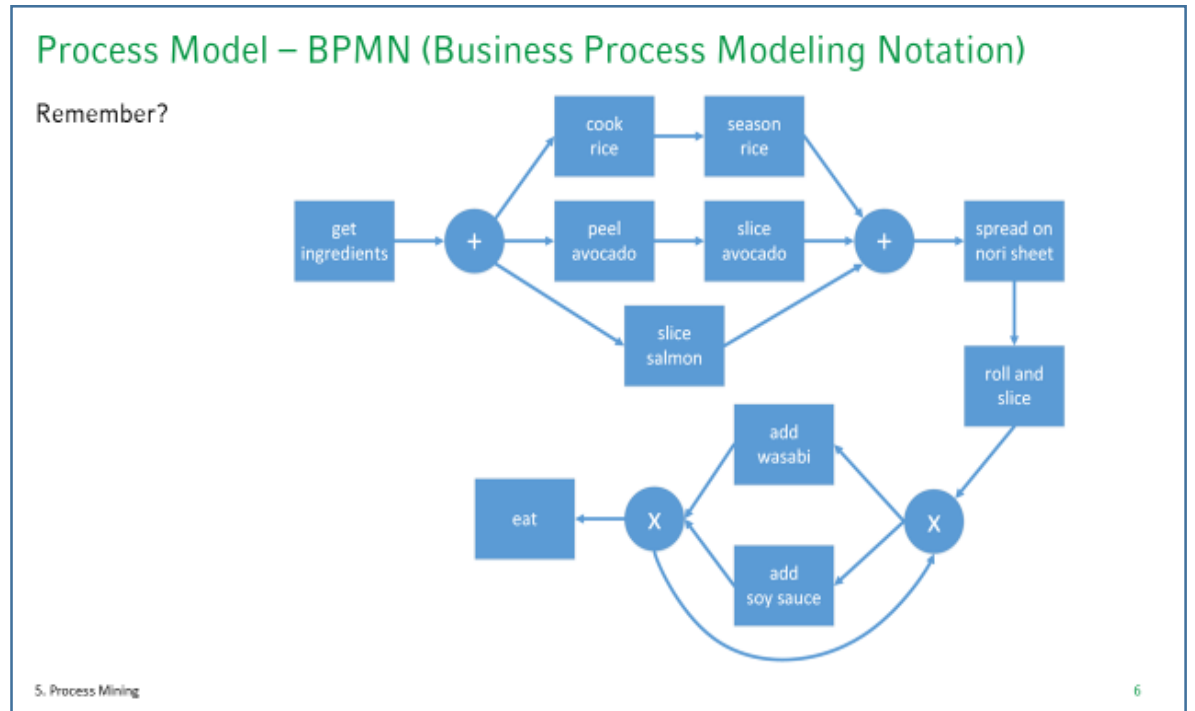
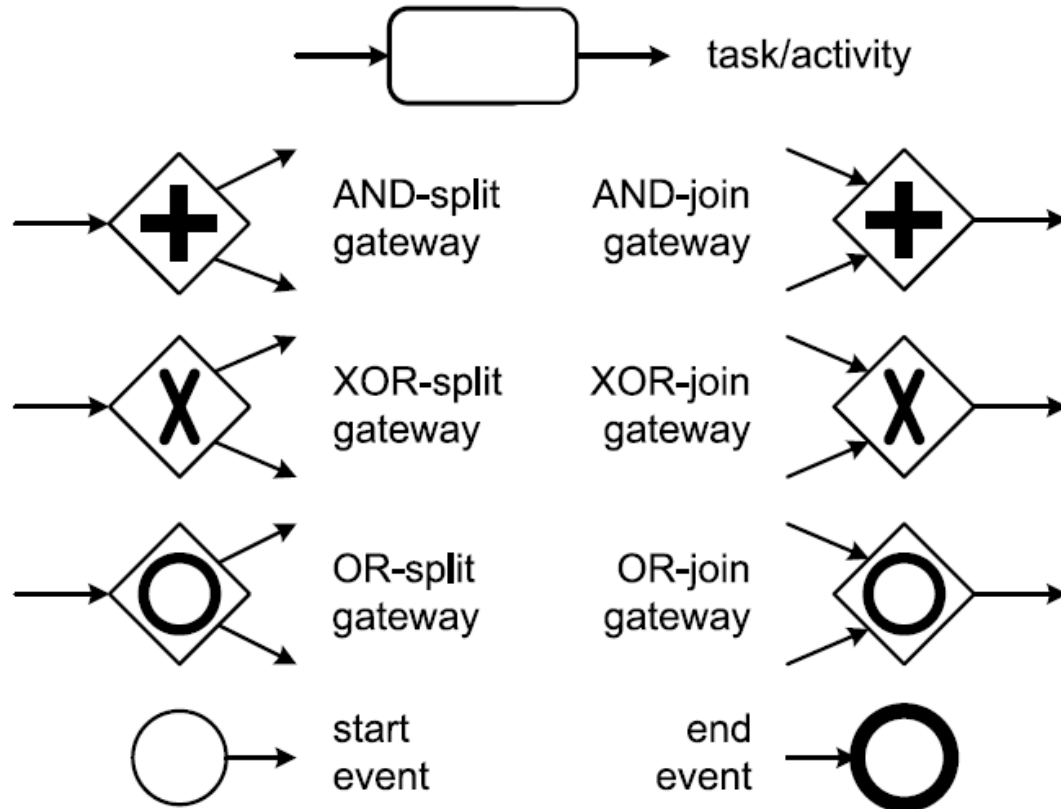
Process Model – BPMN (Business Process Modeling Notation)

Remember?

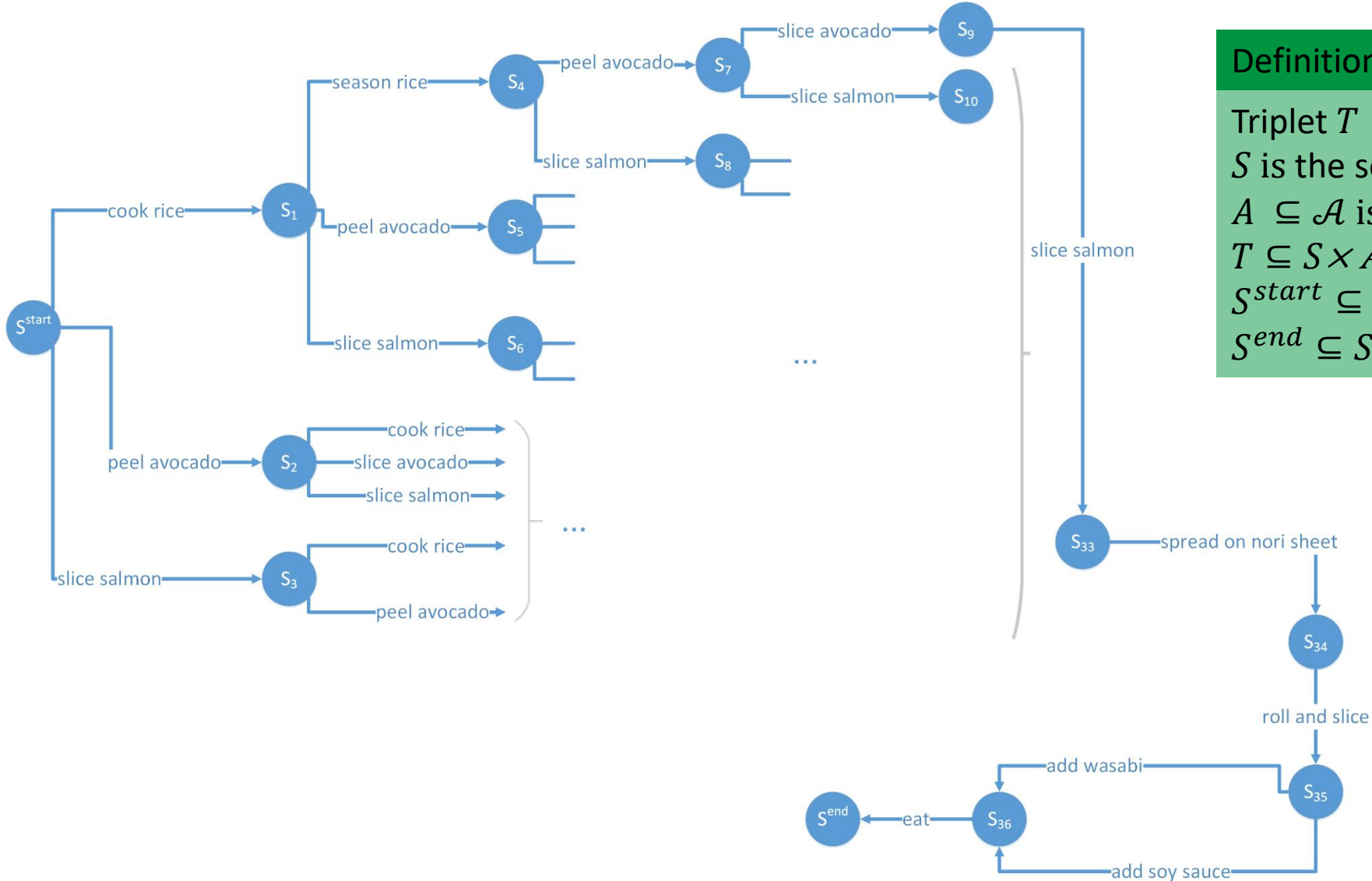


Process Model – BPMN (Business Process Modeling Notation)

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*

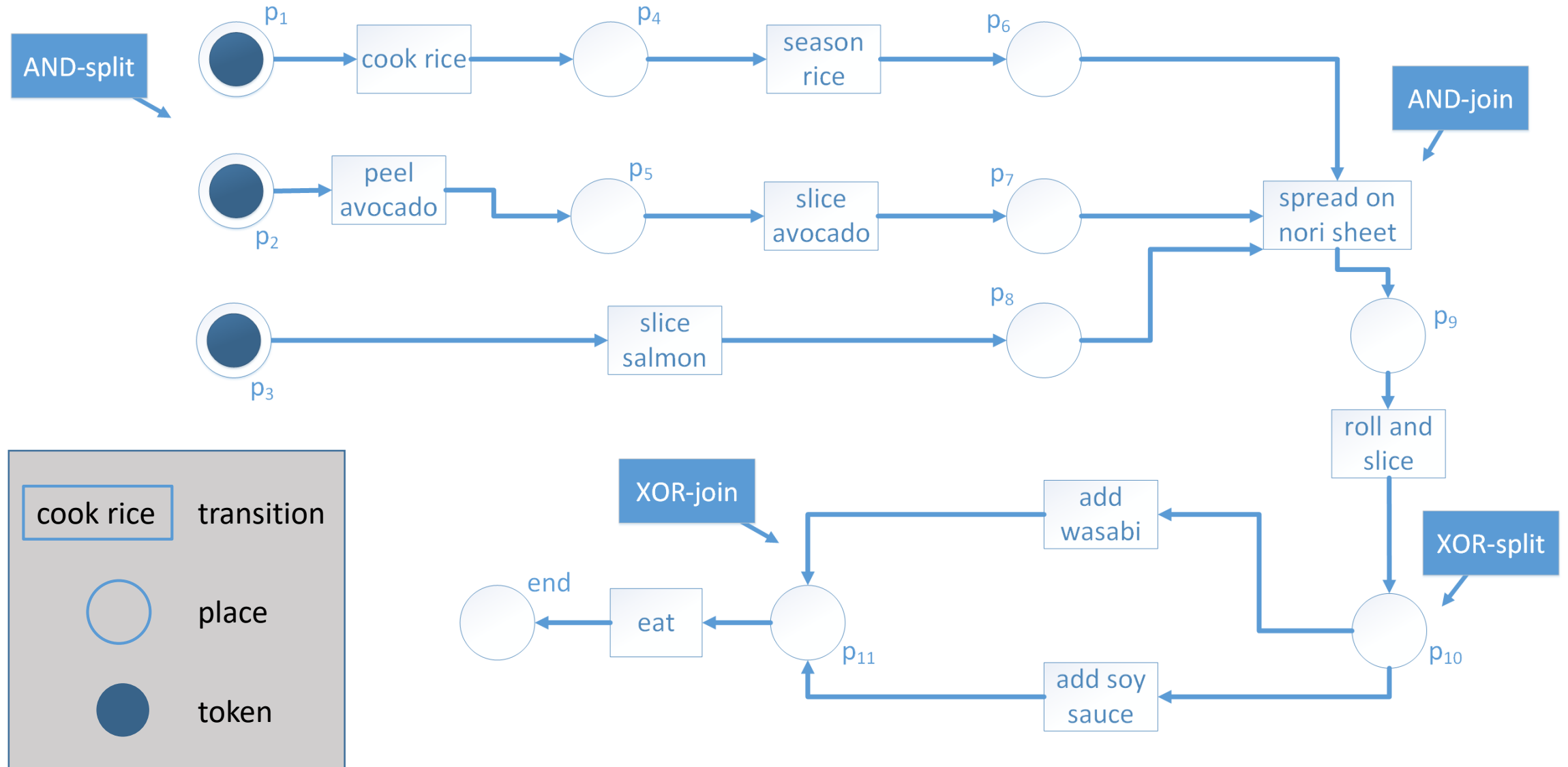
$A \subseteq \mathcal{A}$ is the set of *activities*

$T \subseteq S \times A \times S$ is the set of *transitions*

$S^{start} \subseteq S$ is the set of *initial 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*, $P \cap T = \emptyset$

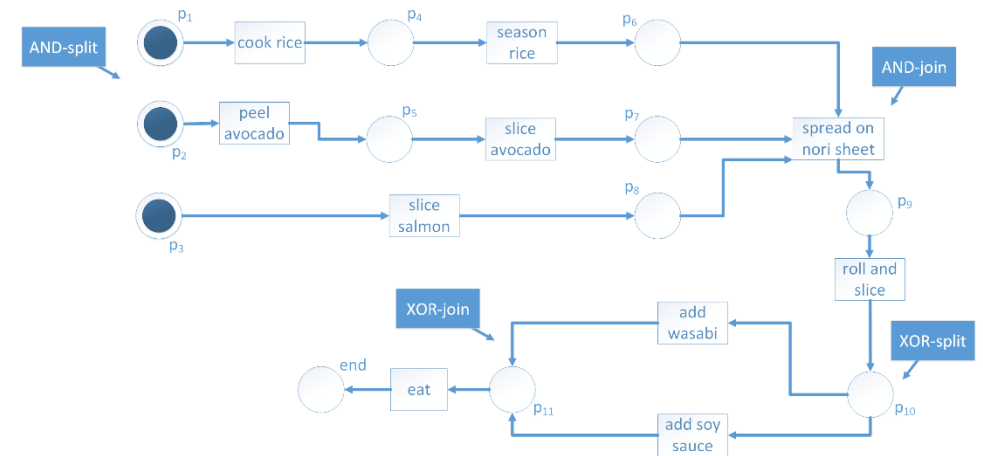
$F \subseteq (T \times P) \cup (P \times T)$ is a set of *directed arcs* (called *flow relation*)

Exemplary formalization of given Petri Net:

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

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

$F = \{(p_1, \text{cook rice}), (p_2, \text{peel avocado}), (p_3, \text{slice salmon}), (\text{cook rice}, p_4), (\text{peel avocado}, p_5), \dots\}$



Process Models – Workflow-Nets (WF-Nets)

Subclass of Petri Nets

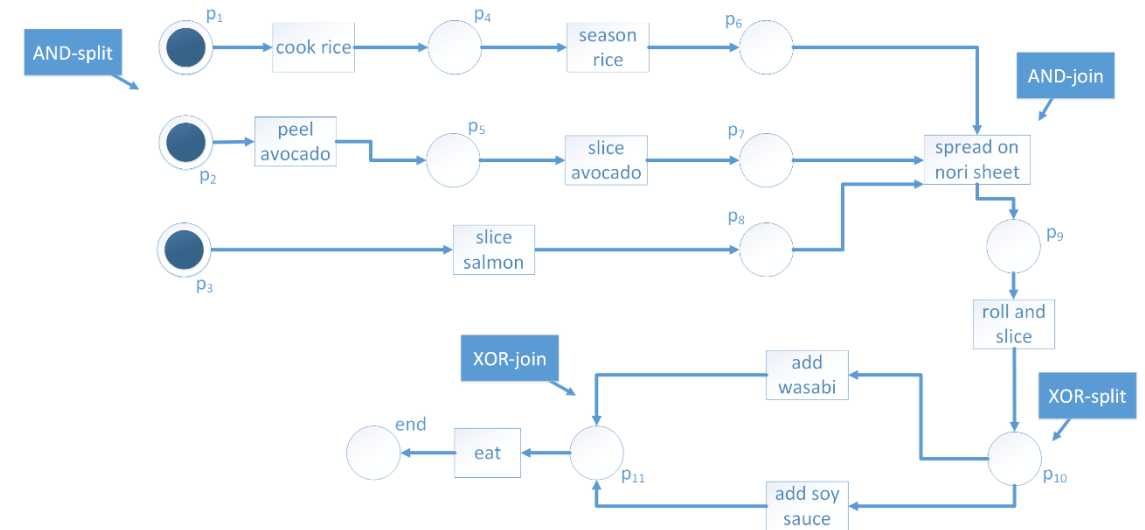
Definition (Workflow Net)

$N = (P, T, F)$, 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.

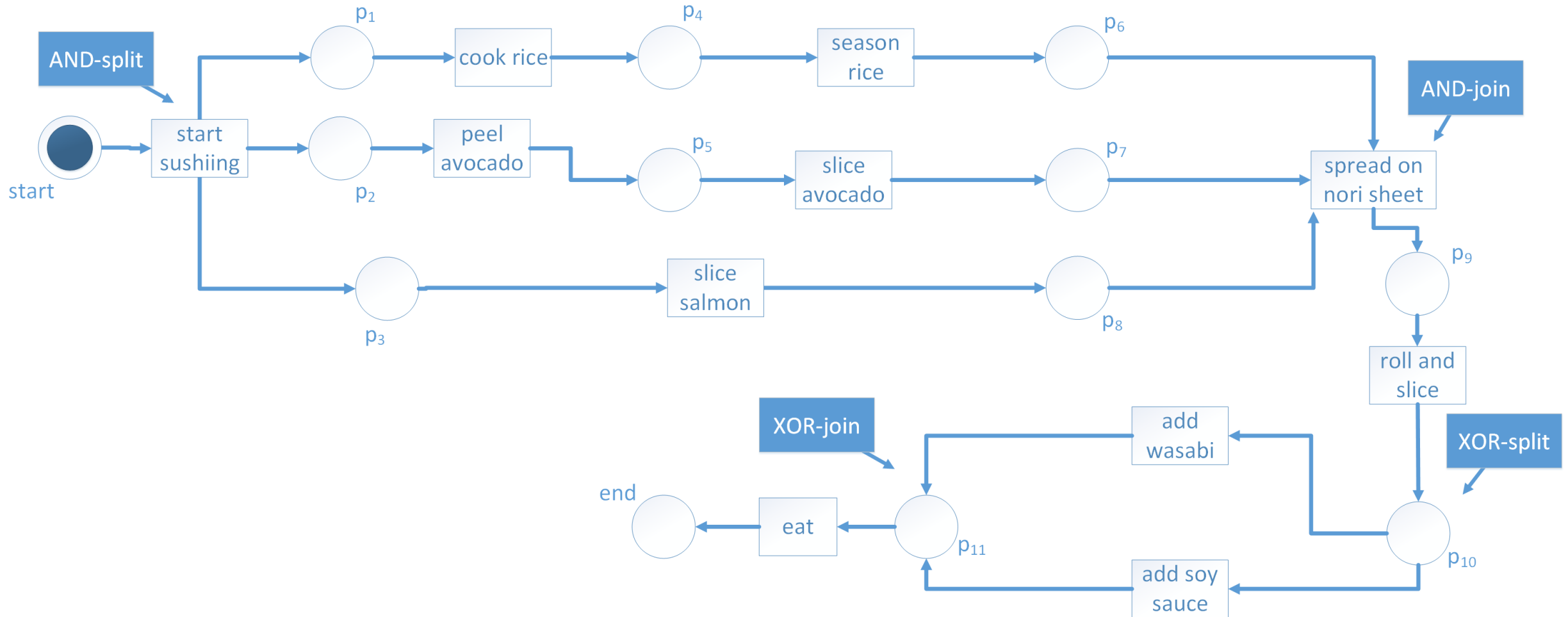
Definition (Strongly connected)

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*).

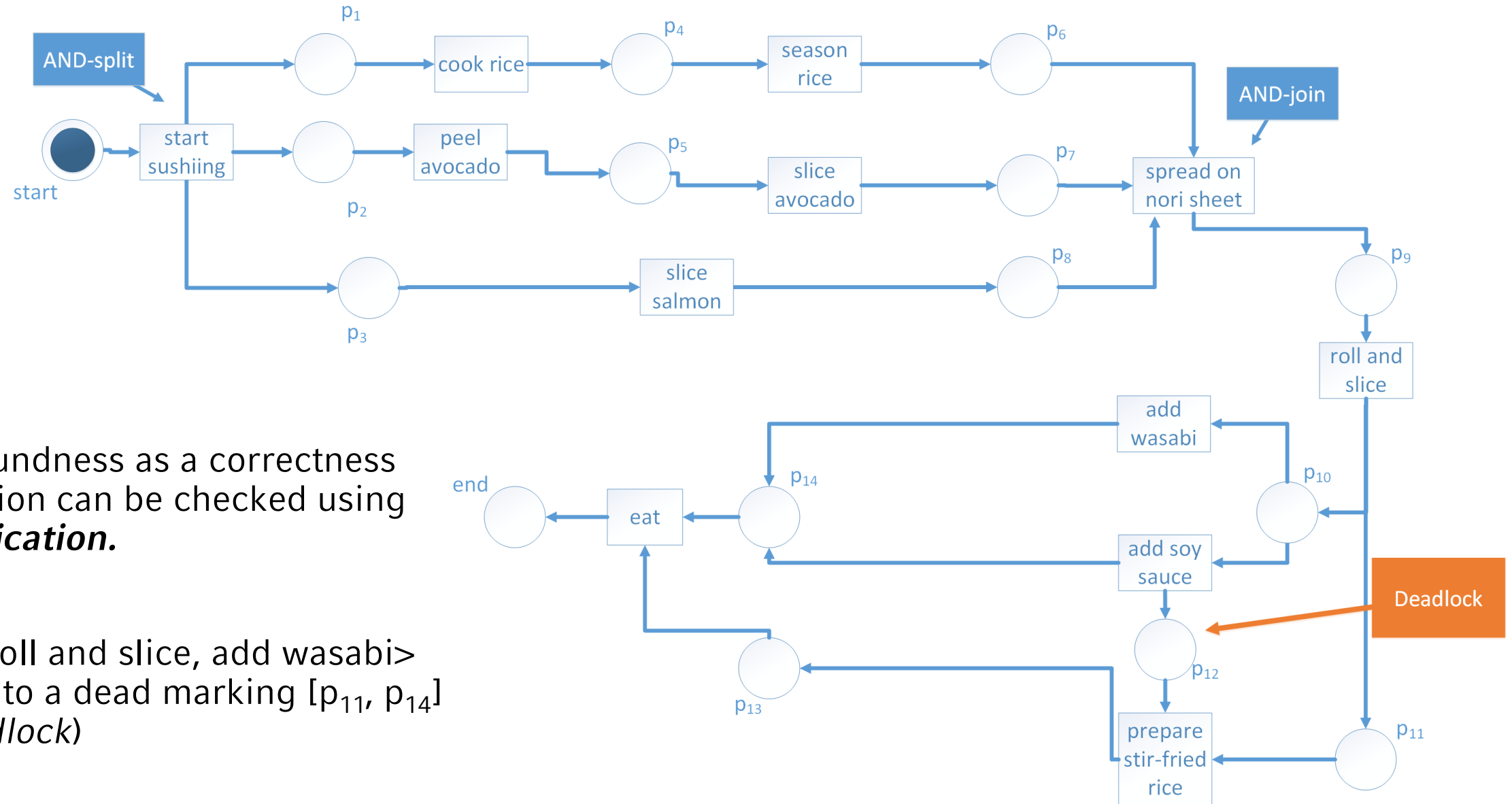
- Those properties can be expressed in temporal logic.
- Specifically in LTL (Linear Temporal Logic) which is an significant example in relation to process models.

Two further exemplary verification tasks in the following:

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 [p₁₁, p₁₄] (*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
- ...

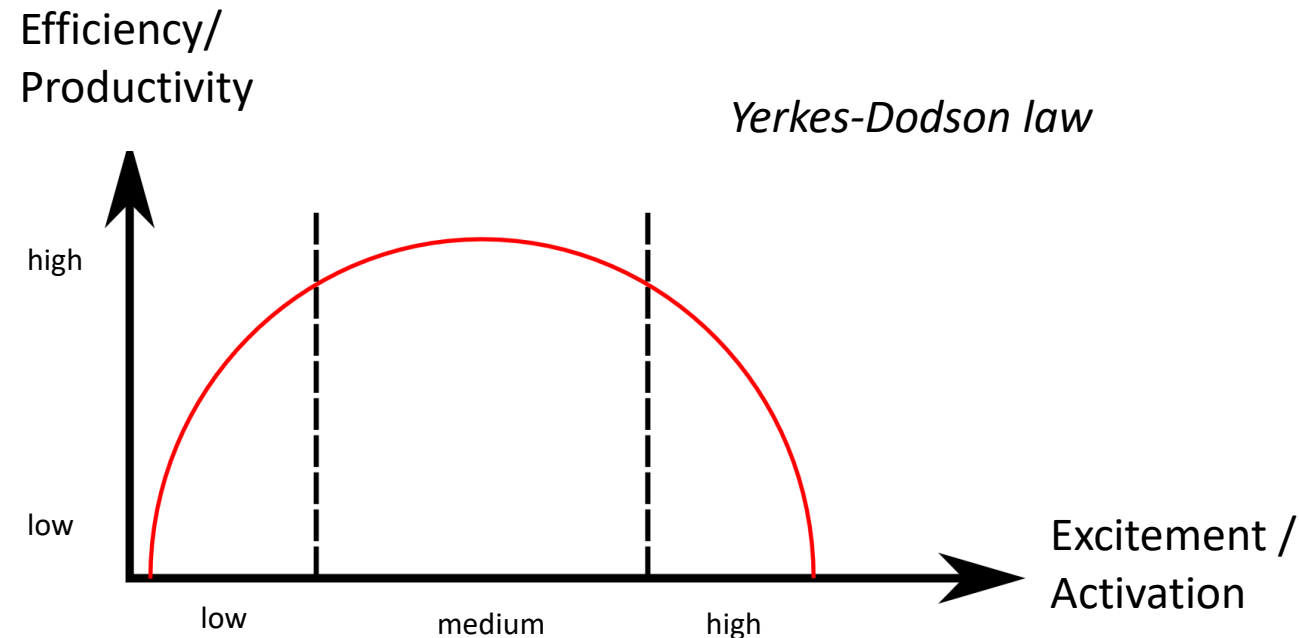
Benefit:

- 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

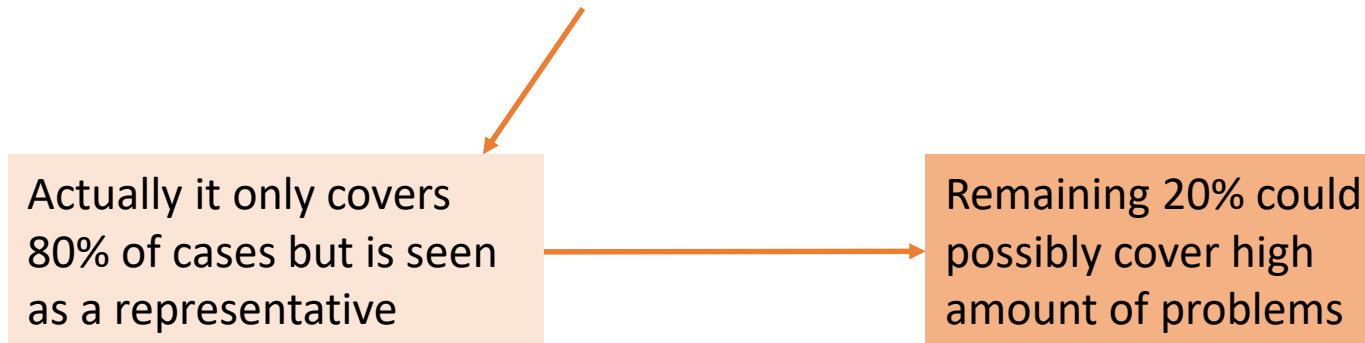


Process Models – Discussion (cont.)

- **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



Process Models – Discussion (cont.)

- **Granularity**

E.g. there are many types of sushi: Nigiri, Sashimi, Maki, Uramaki...



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



⇒ 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.
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