

Concurrent Plan Recognition & Execution for Human-Robot Teams

Cognitive Robotics 2016 Lecture
Steven J. Levine

Wednesday, March 16th, 2016

Intent recognition & adaptation are siblings

- Intent recognition & robot adaptation are both necessary to build intelligent robots that work with people



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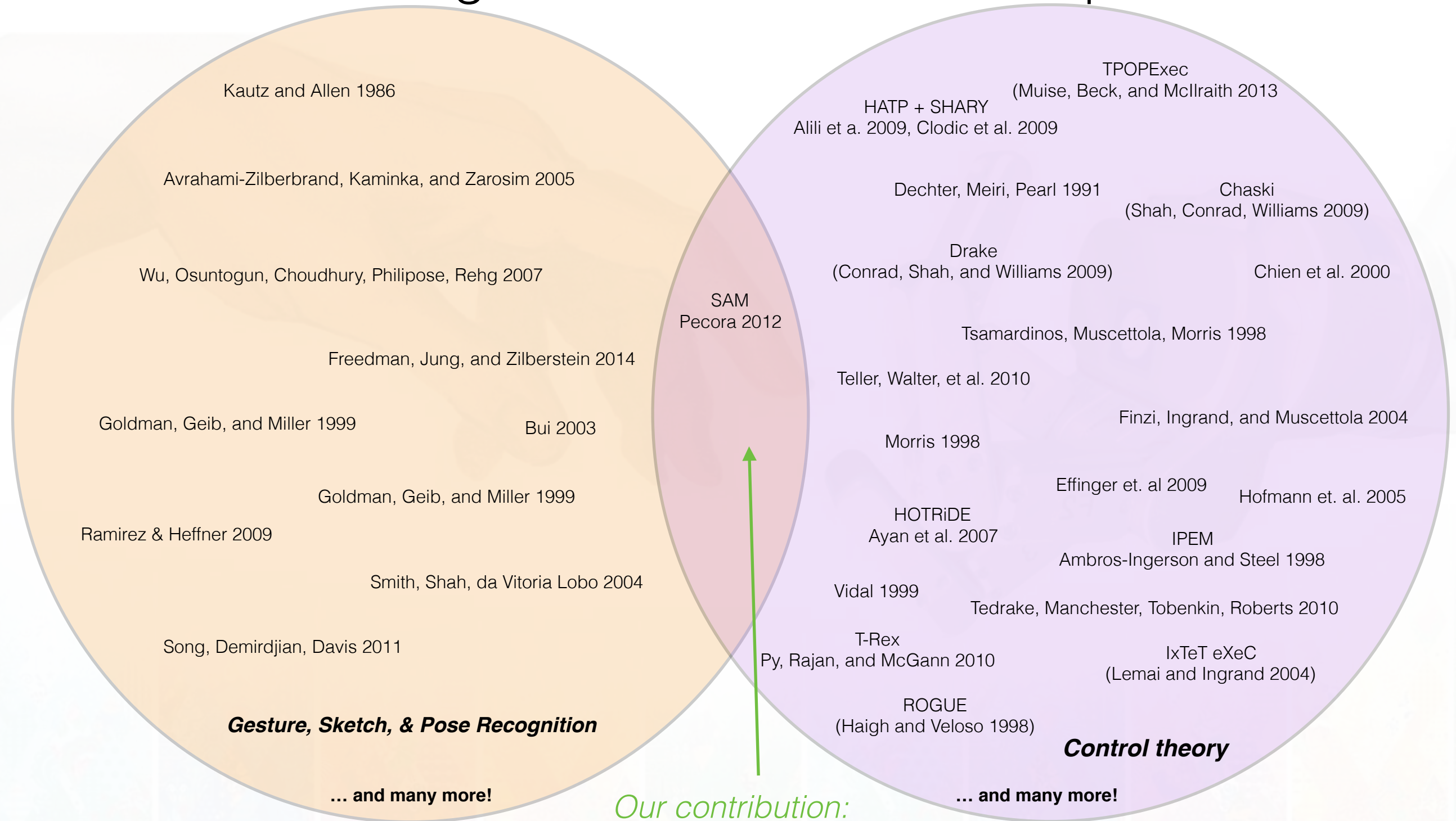


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Intent recognition & adaptation must be integrated

Intent Recognition

Robot Adaptation



Our contribution:
Pike

Intent recognition & adaptation must be integrated

- Much prior work on intent recognition, and on robotic adaptation, but largely as separate research
- We present a **unified approach** to plan recognition & robotic adaptation for plans with choice
 - Single algorithm concurrently achieves both
 - **Result:** mixed-initiative execution where robots & humans work together as team

Pike: an executive for human-robot teams

- Given a plan with choice (contingent, temporally flexible):
 - **Make decisions** online (consistent with human's intent)
 - **Dispatch** activities at proper times
 - **Monitor** execution for problems

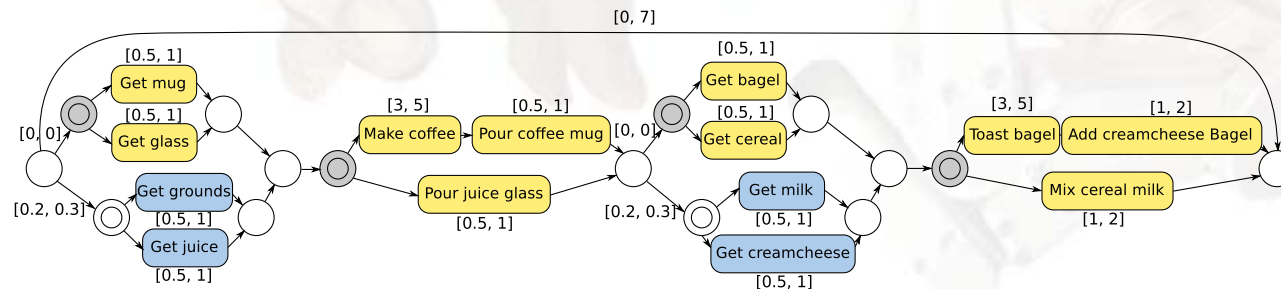
How to recognize intent & adapt?

$\left\{ \begin{array}{l} \text{Intent recognition} \\ \text{Robot adaptation} \end{array} \right\}$ is $\left\{ \begin{array}{l} \text{recognizing} \\ \text{making} \end{array} \right\}$ decisions consistent with team's task goals

- Assume rational, cooperative agents
- Prune any (irrational) decisions resulting in plan failure:
 - Unmet action preconditions: \Rightarrow Causal link reasoning
 - Missed deadlines: \Rightarrow Temporal conflicts
 - Unanticipated failures: \Rightarrow Online execution monitoring

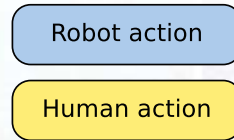
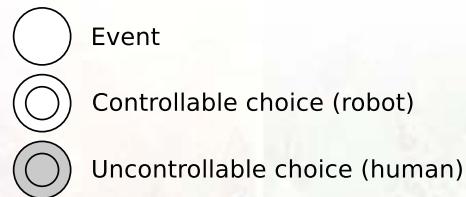
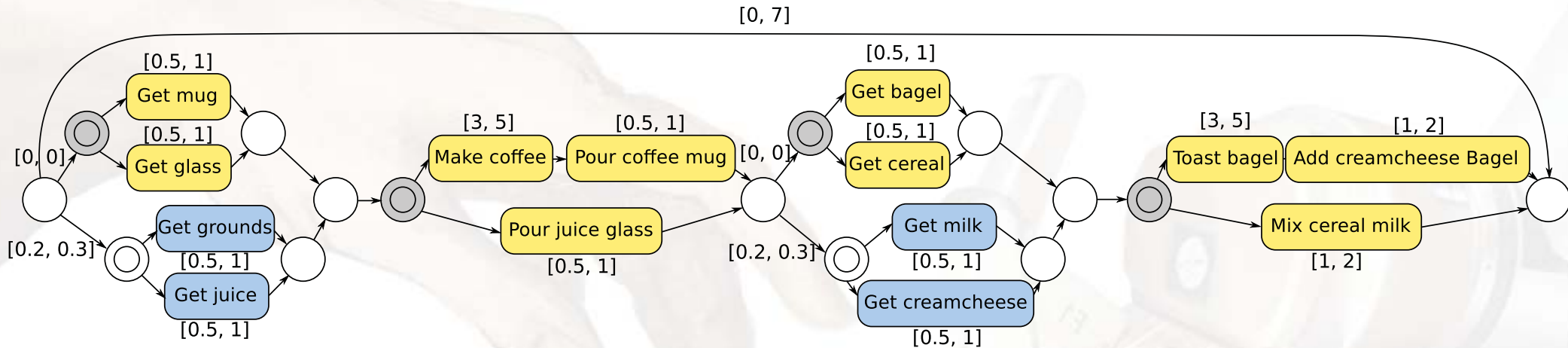
Approach in a nutshell

- Key to our approach:
 - Plan representation with choices & actions for human, robot



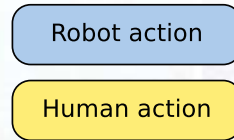
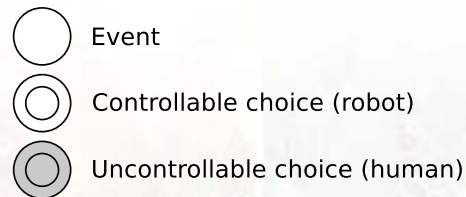
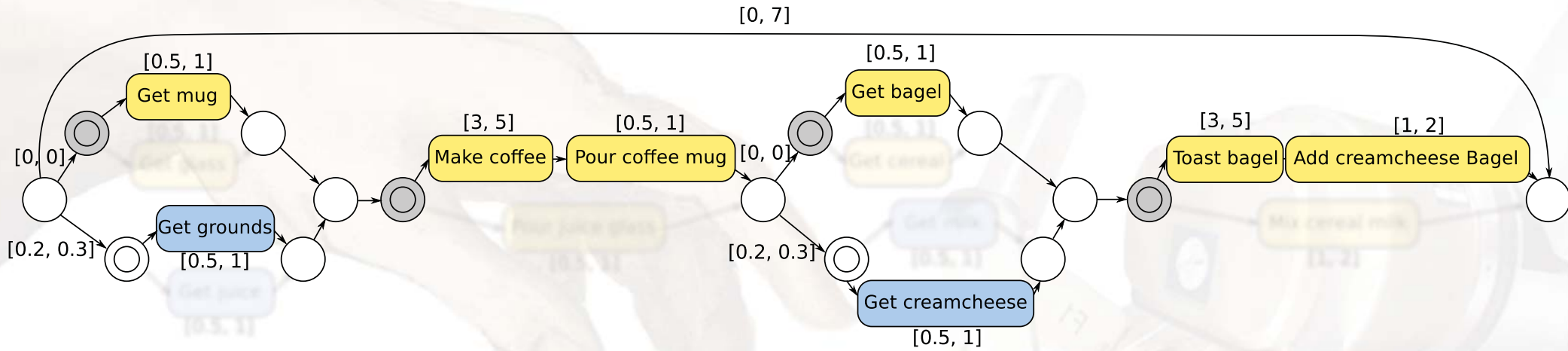
Contingent, temporally-flexible plans

Temporal Planning Network with Uncertainty (TPNU)



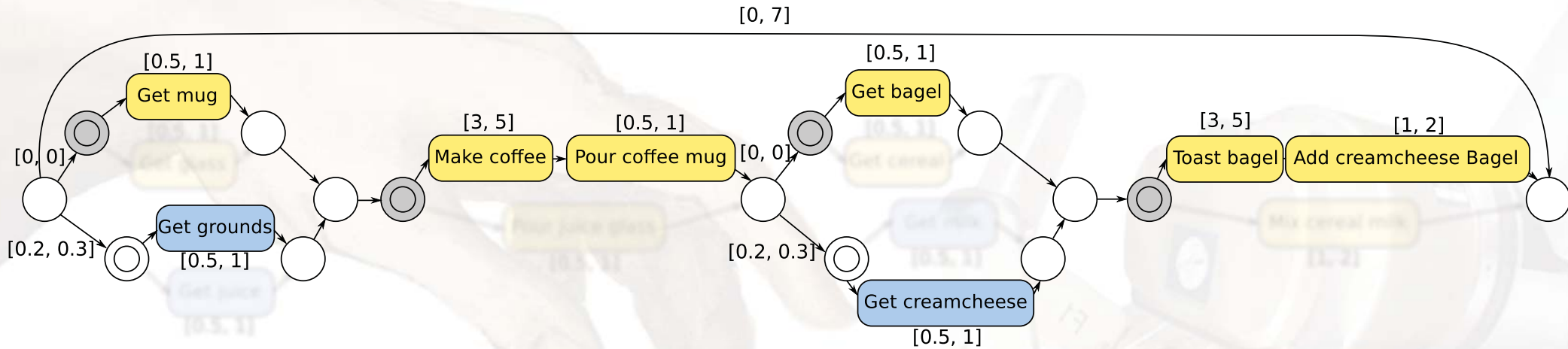
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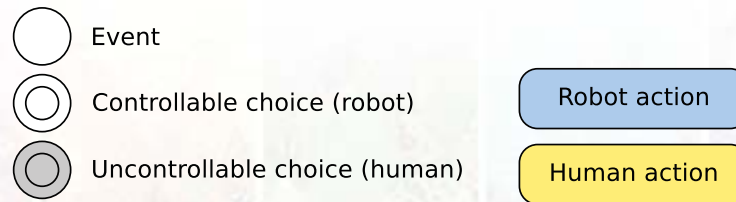
Contingent, temporally-flexible plans

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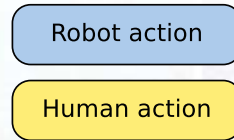
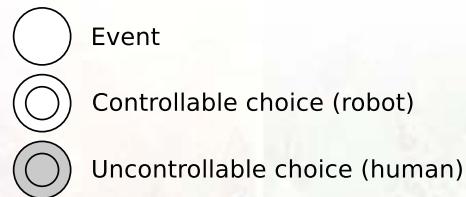
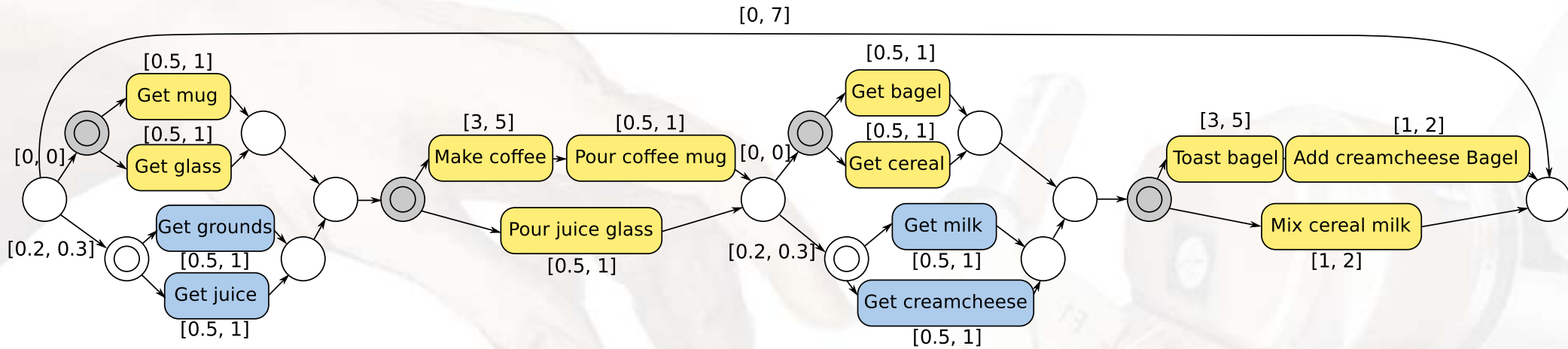
This candidate subplan is temporally inconsistent.

Conflict: $\neg(x_{A_2} = coffee \wedge x_{A_4} = bagel)$
 (Conrad 2009)

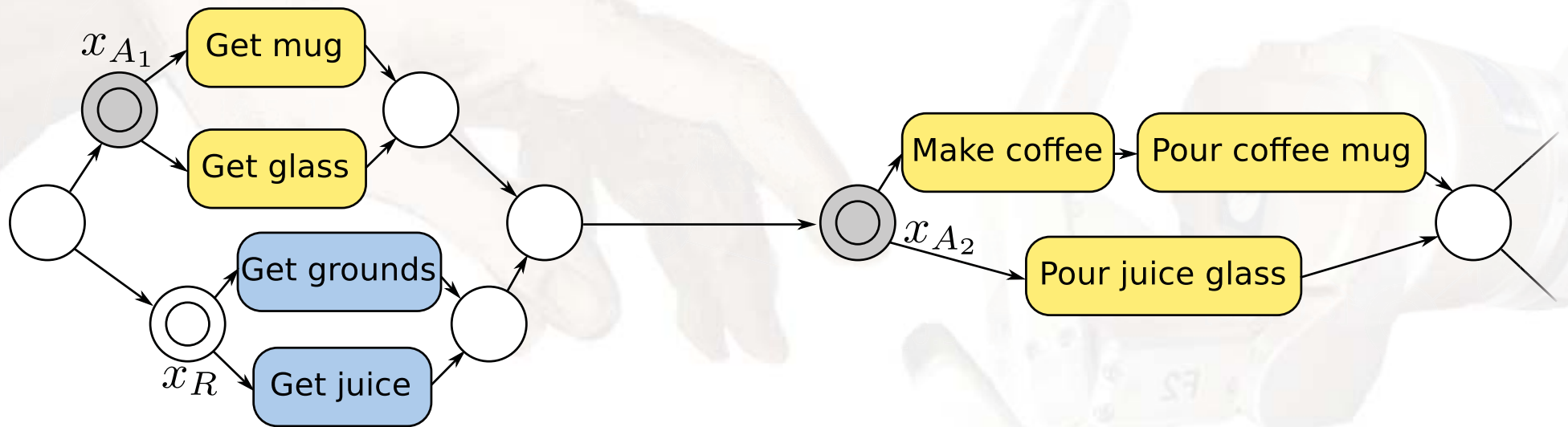


Contingent, temporally-flexible plans

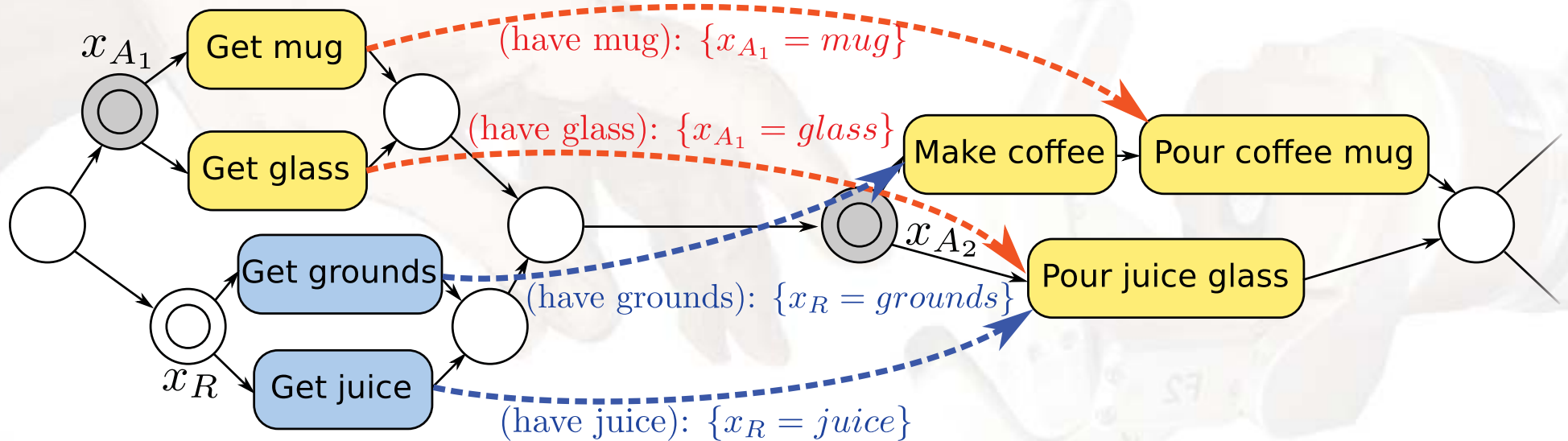
Temporal Planning Network with Uncertainty (TPNU)



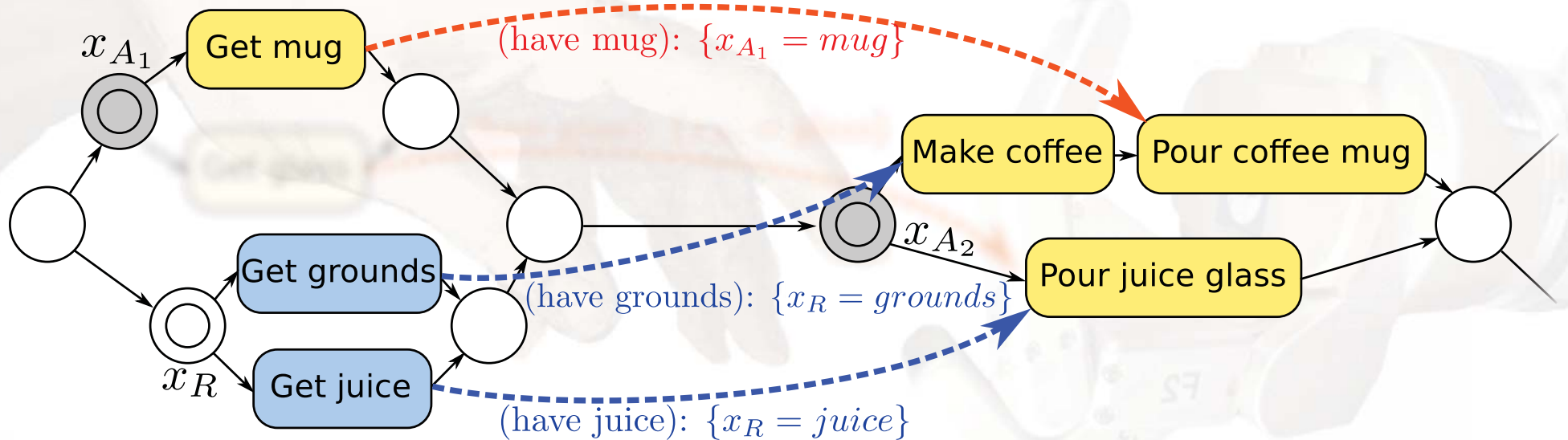
First part: making a drink



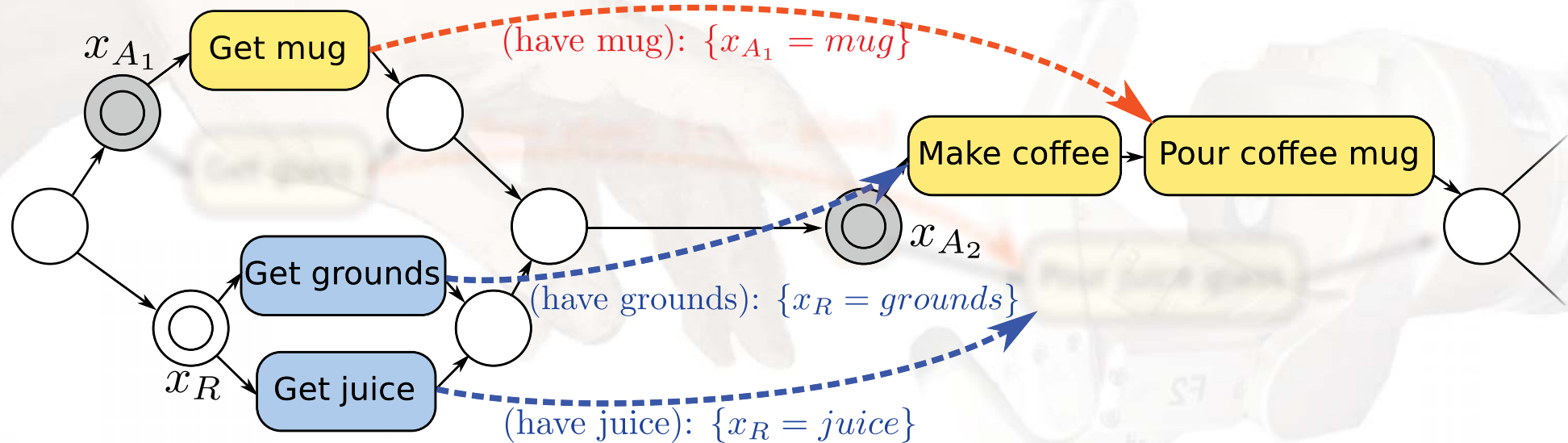
Extracting labeled causal links



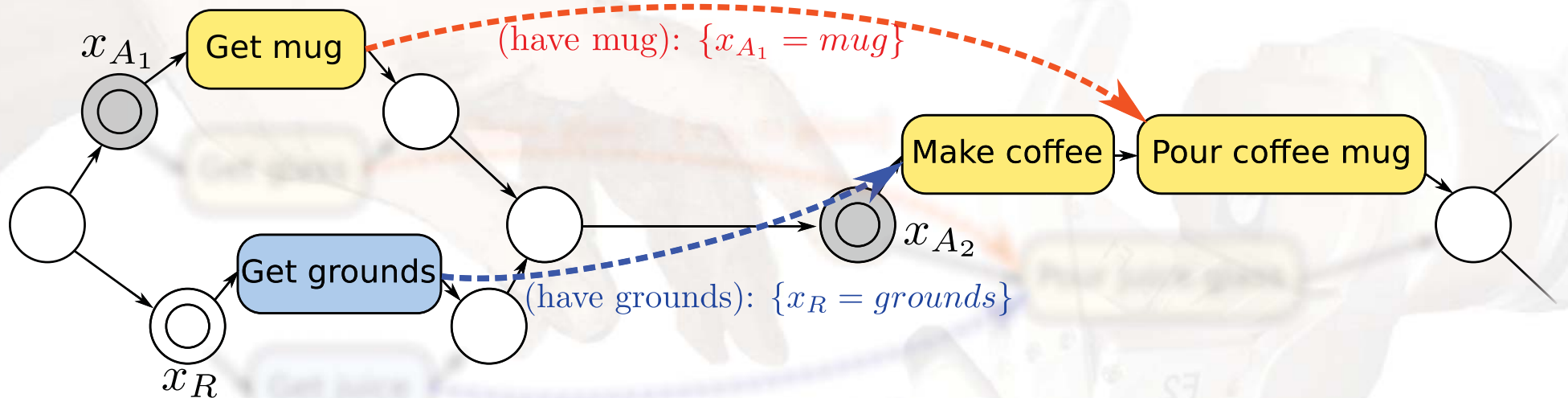
Suppose person picks up mug...



...so can't pour juice later...



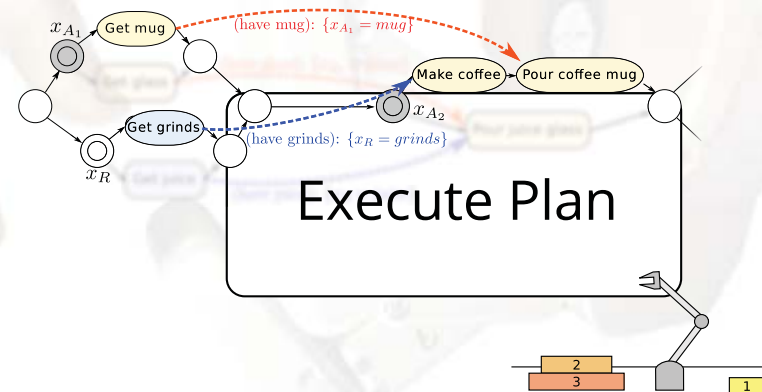
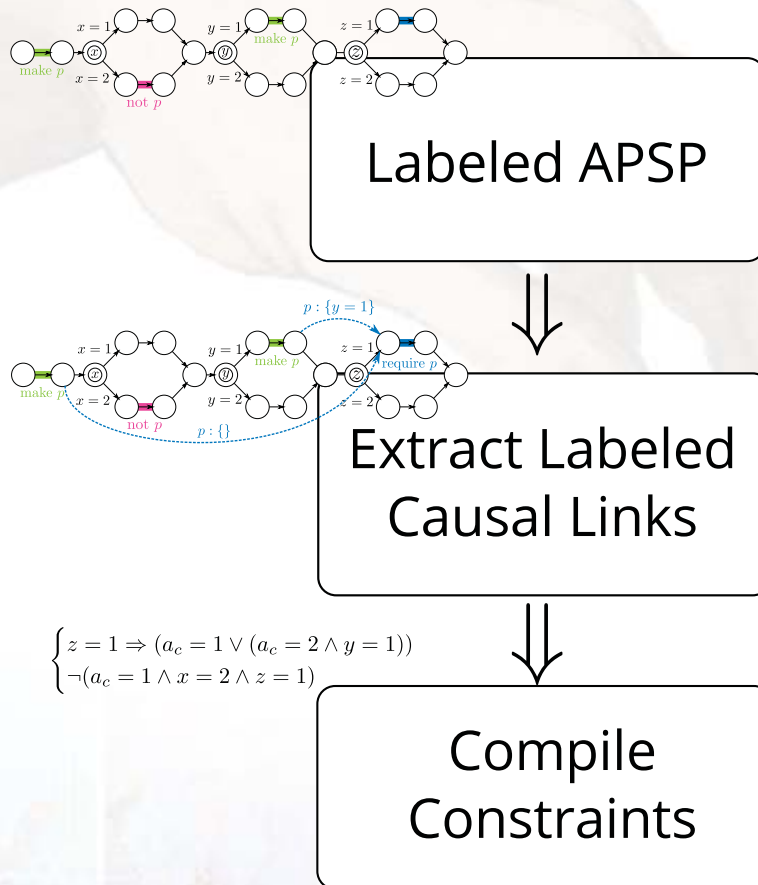
...so robot should get coffee now.



- 
- **Intent Recognition:** recognizing human's choices consistent with *at least one* team subplan
 - **Robot adaptation:** making robot's choices consistent with *at least one* remaining team subplan

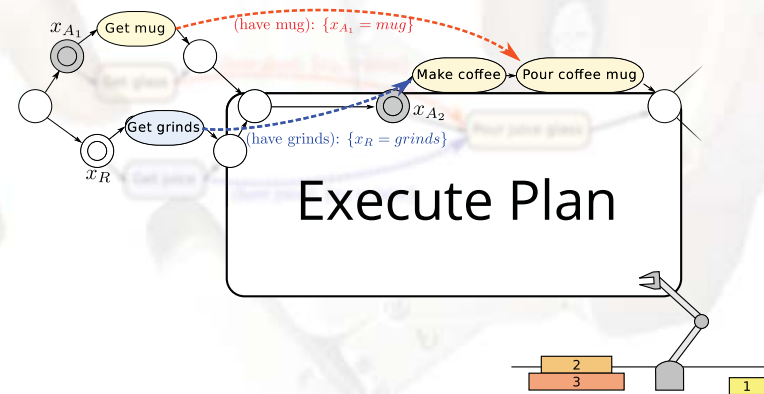
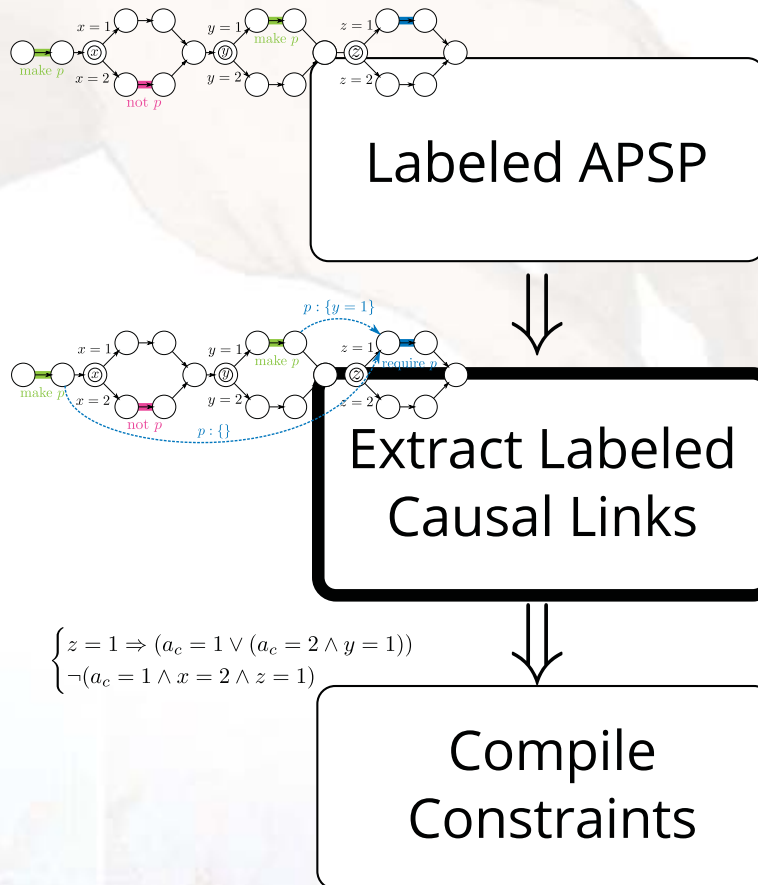
Offline

Online

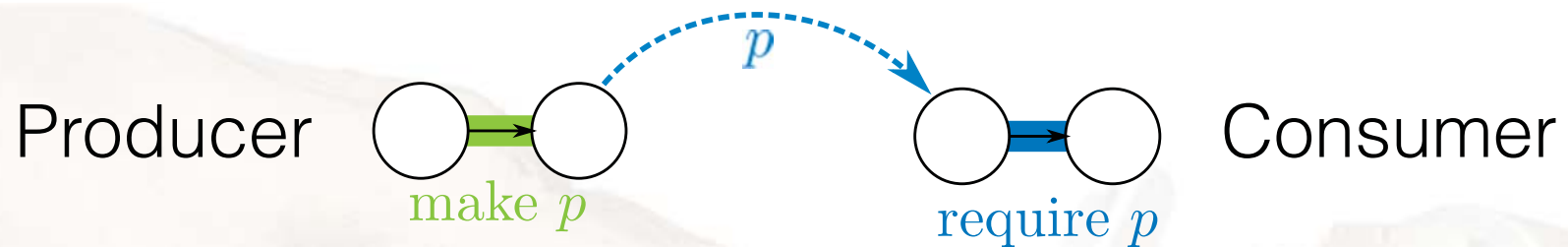


Offline

Online

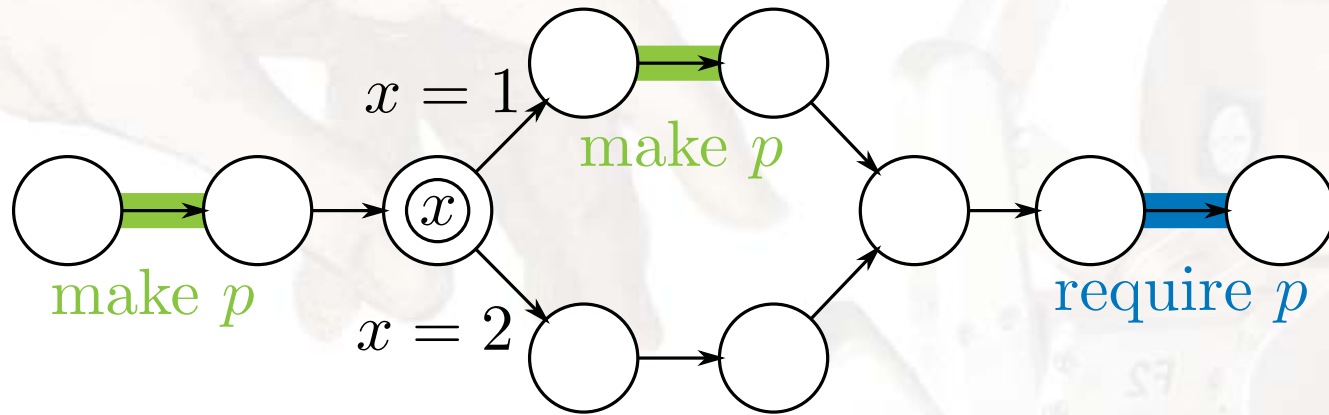


Causal links justify action preconditions

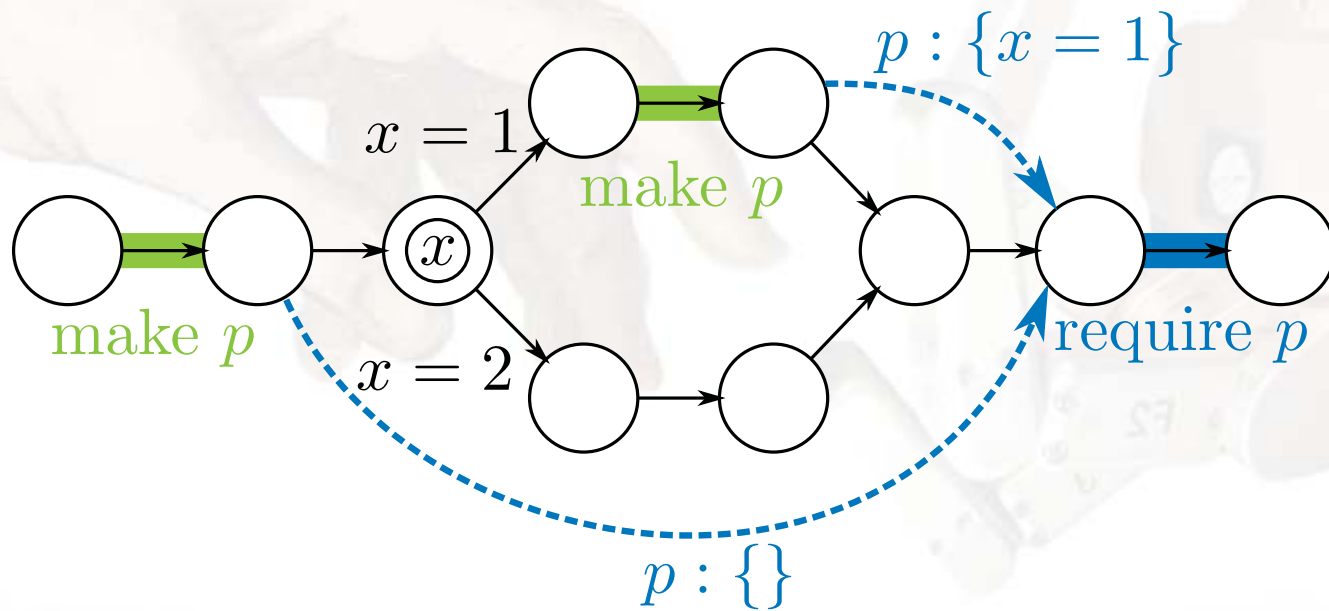


- Insufficient for contingent, temporally-flexible plans:
 - What if producer doesn't execute?
 - What if consumer doesn't execute?
 - Determining ordering is non-trivial
- We generalize to ***labeled causal links***
 - Encode requisite choices for causal link to hold

Labeled causal links

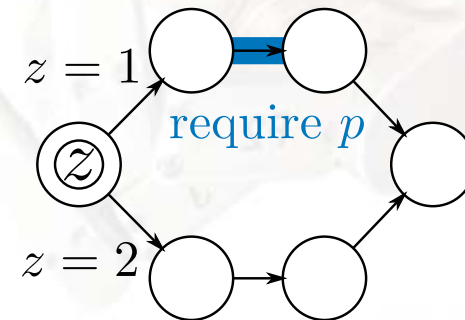


Labeled causal links



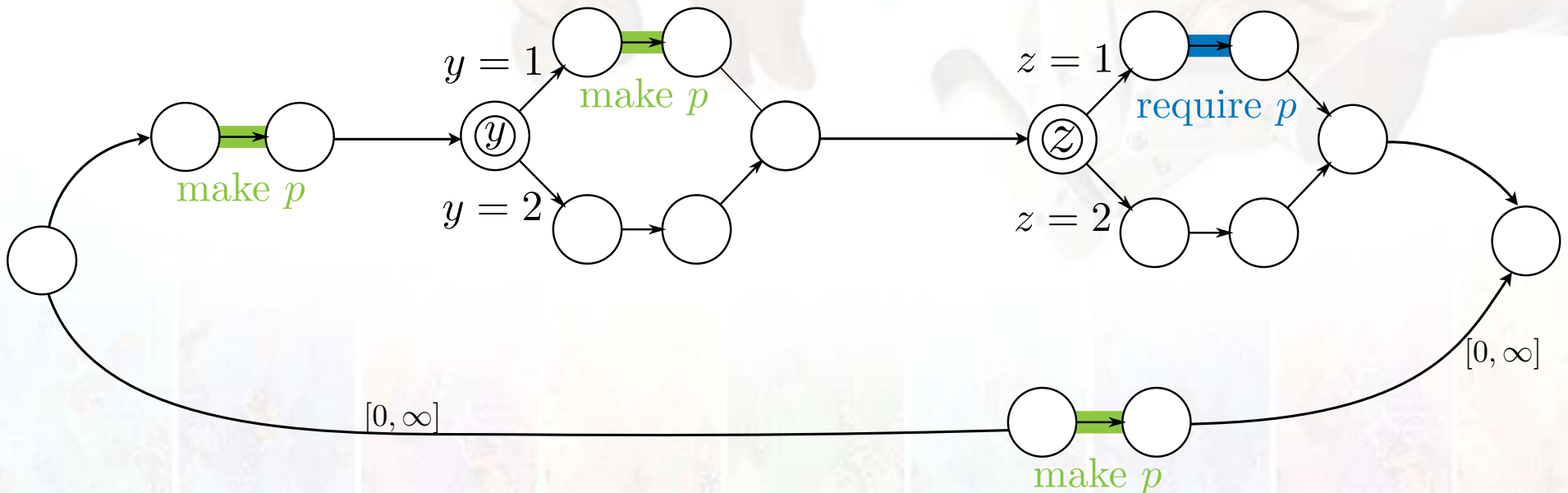
Causal link extraction in a nutshell*

- For each precondition of each **consumer** event:



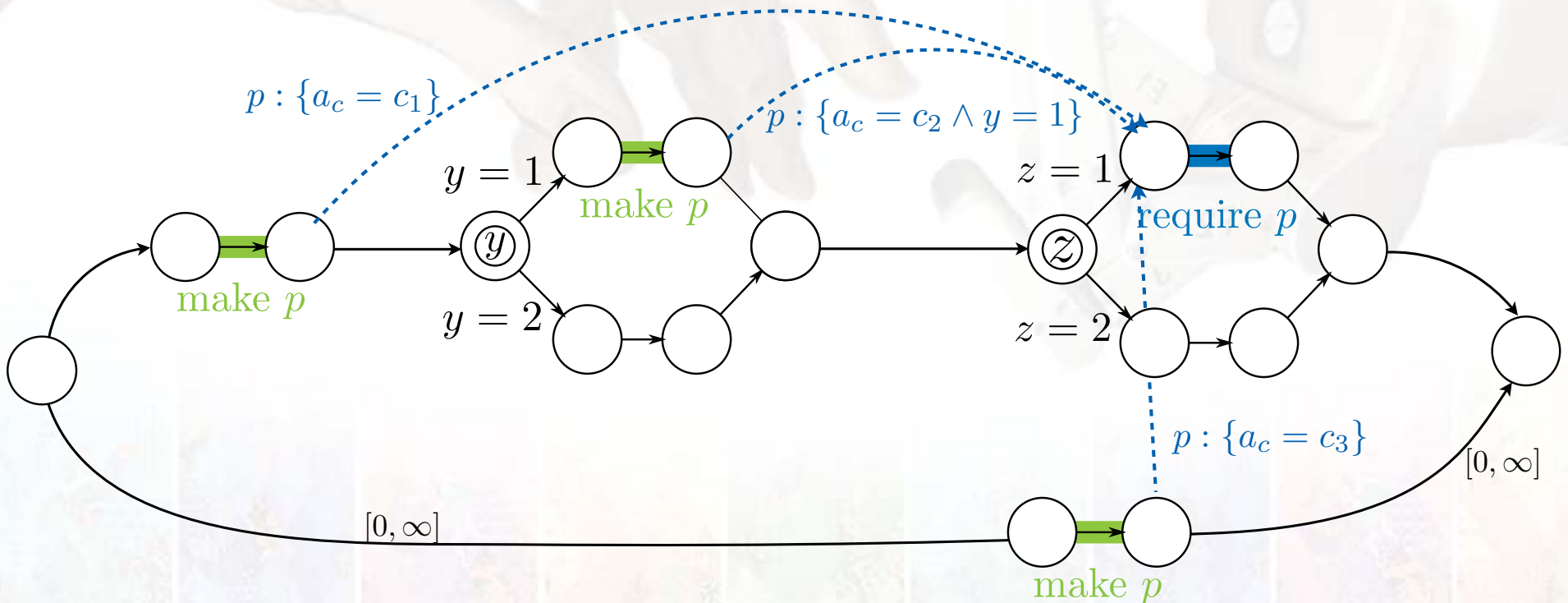
Causal link extraction in a nutshell*

- For each precondition of each **consumer** event:
 - Find all **producers** provably before or during consumer



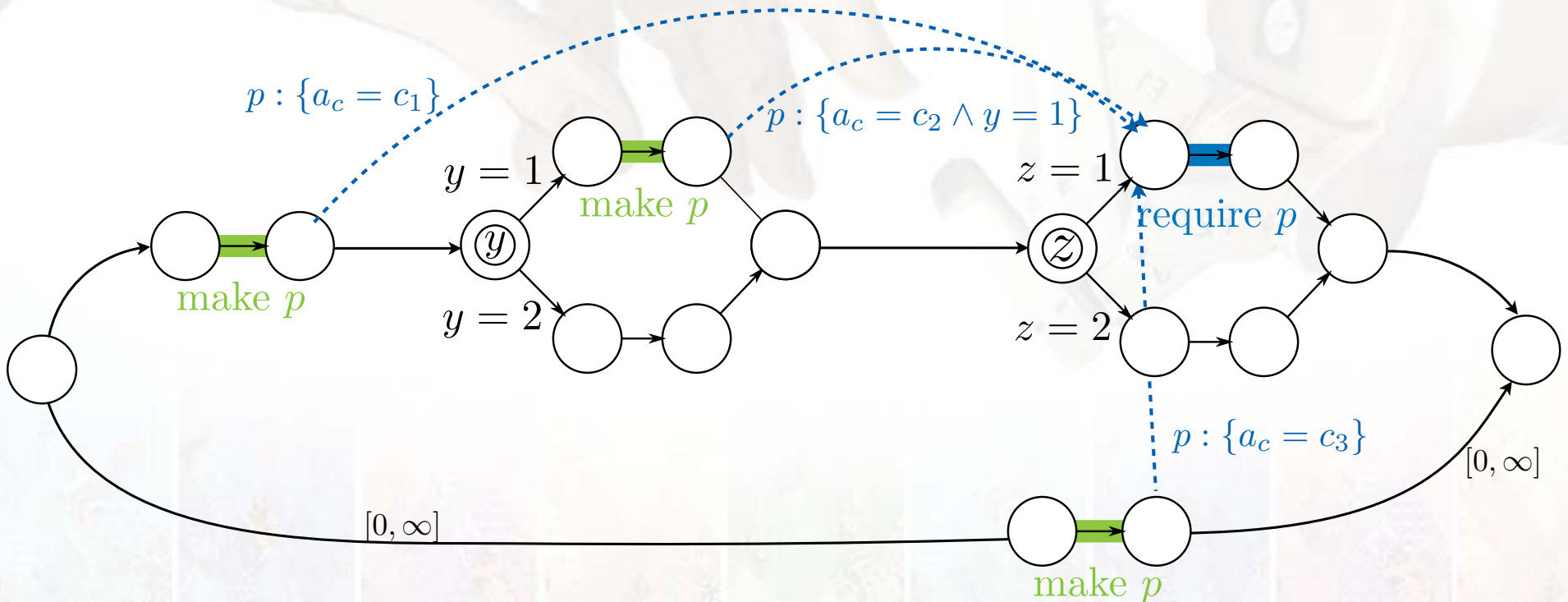
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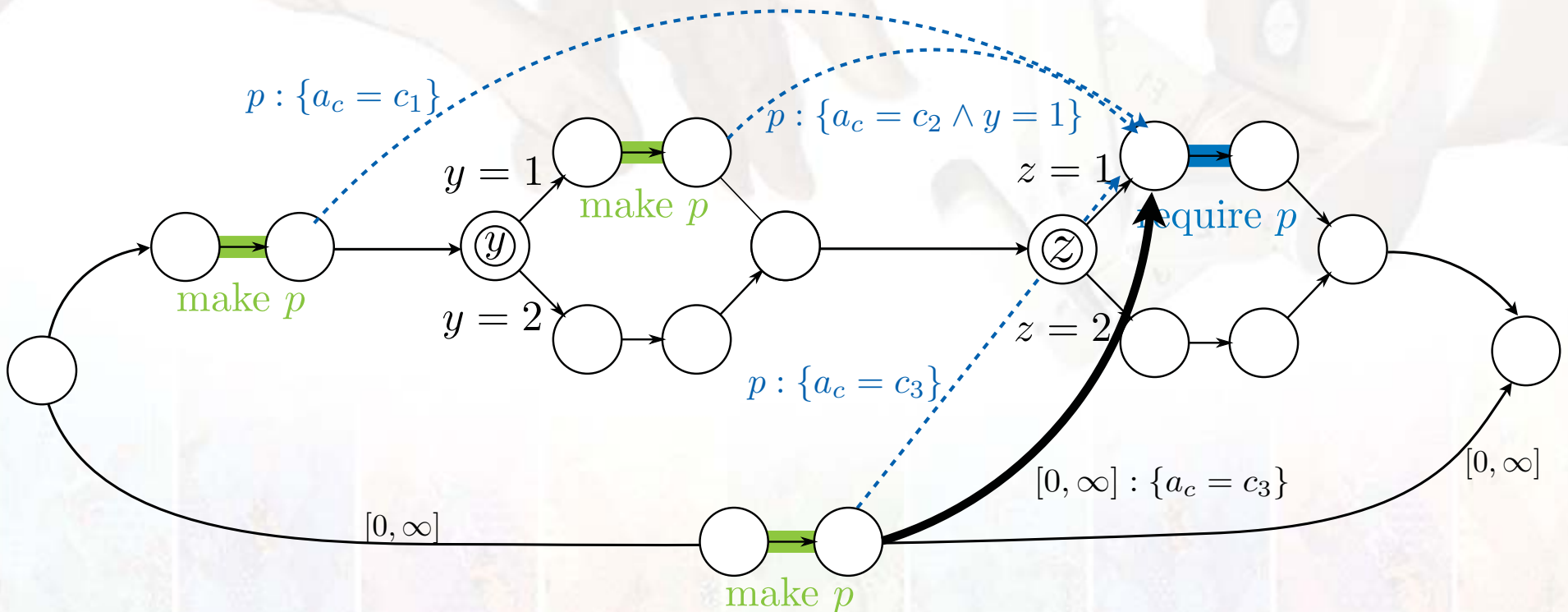
Causal link extraction in a nutshell*

- For each precondition of each **consumer** event:
 - Find all **producers** provably before or during consumer
 - Add propositional & temporal constraints for each producer



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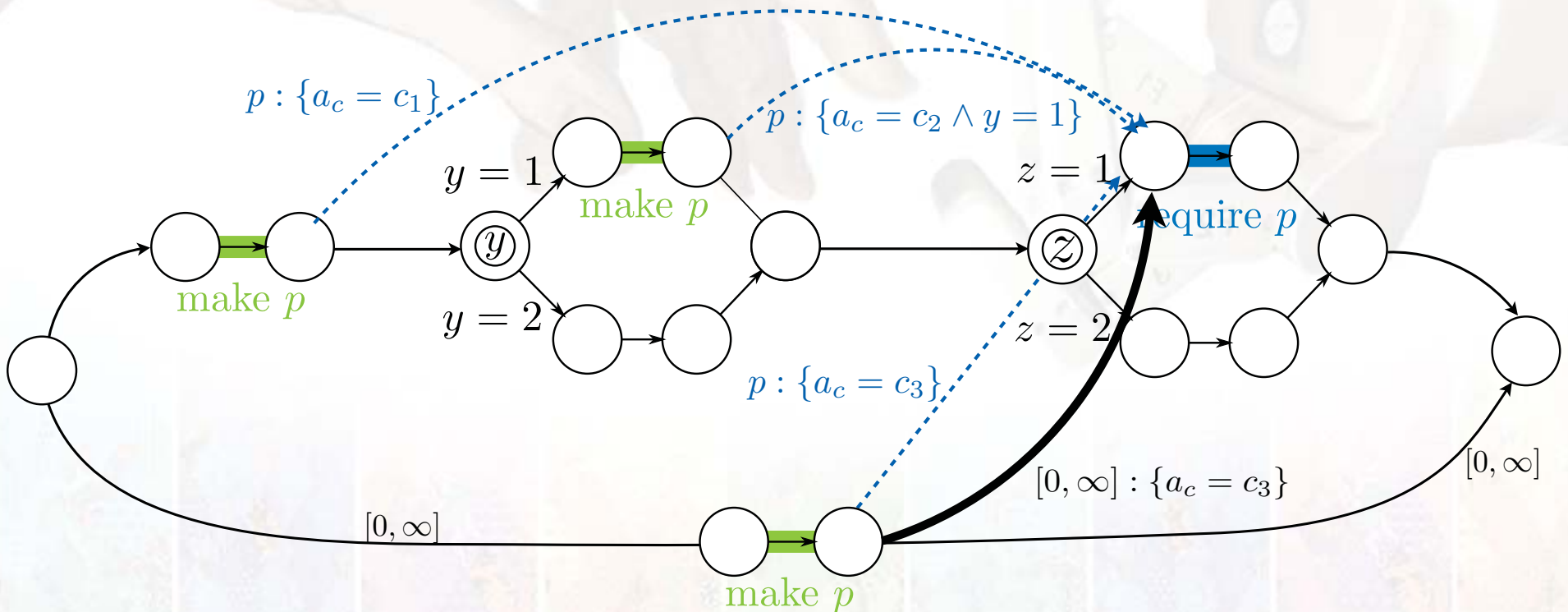
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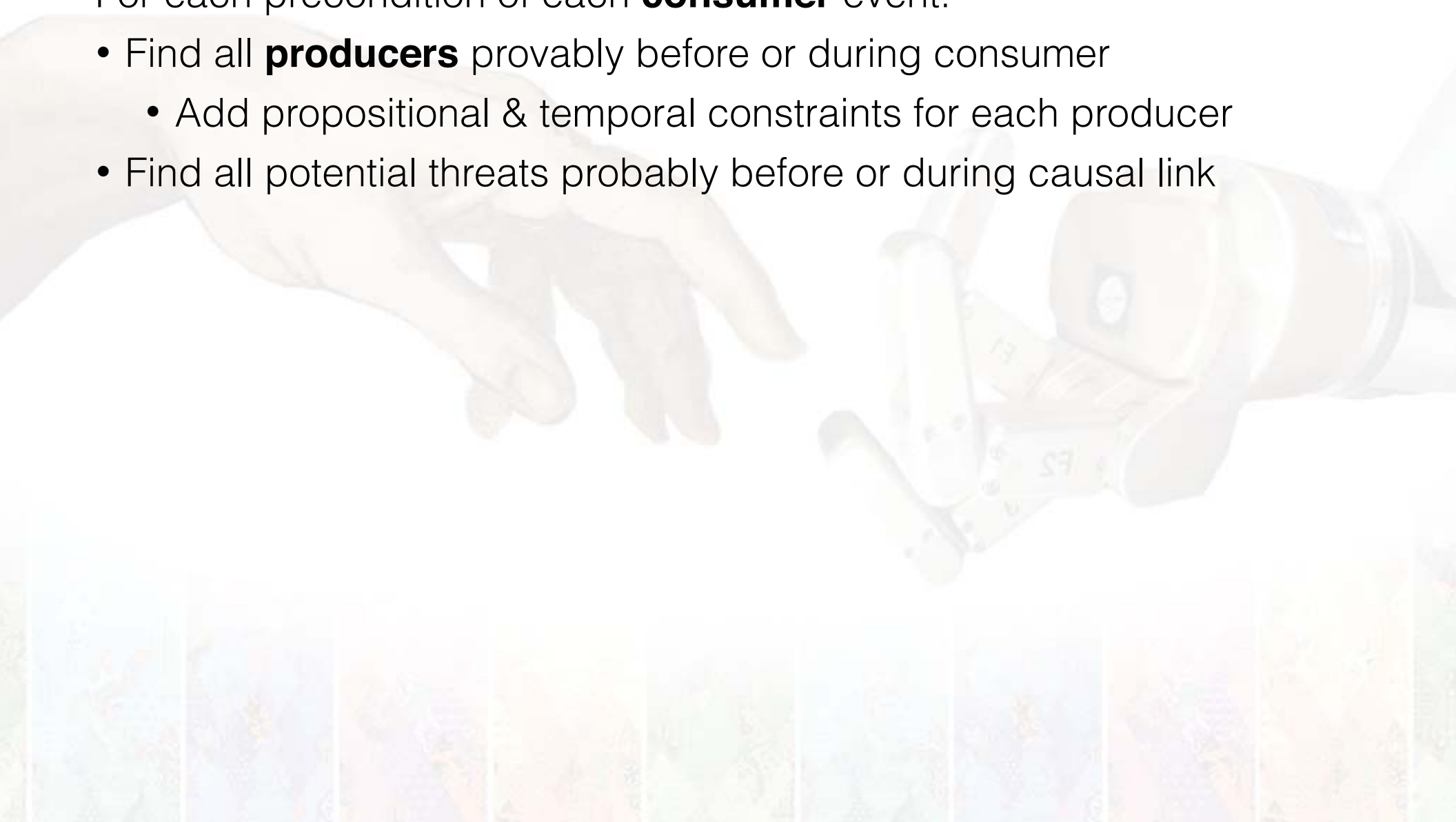
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Constraint: $(z = 1) \Rightarrow [(a_c = c_1) \vee (a_c = c_2 \wedge y = 1) \vee (a_c = c_3)]$



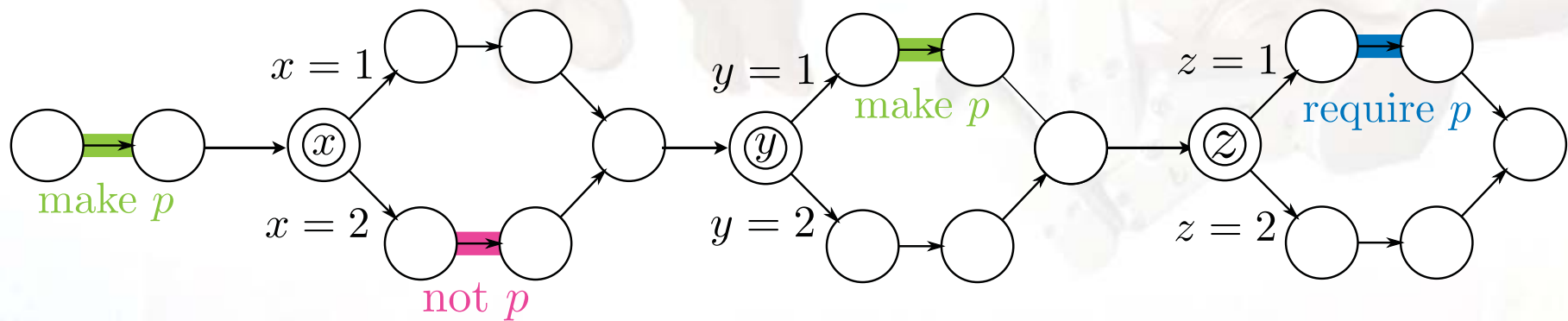
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- For each precondition of each **consumer** event:
 - Find all **producers** provably before or during consumer
 - Add propositional & temporal constraints for each producer
 - Find all potential threats probably before or during causal link



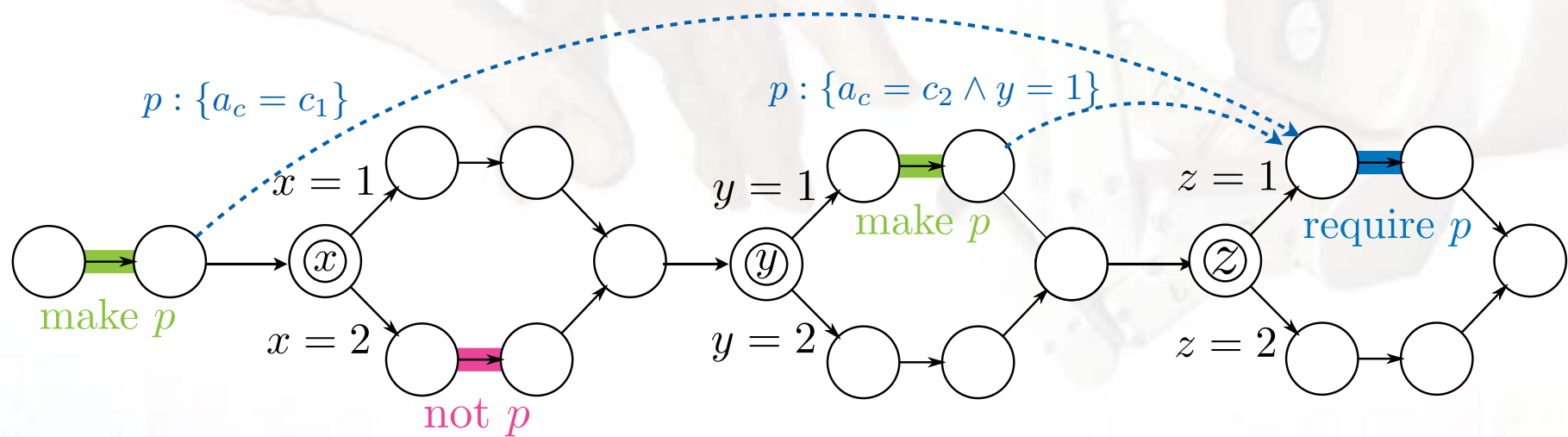
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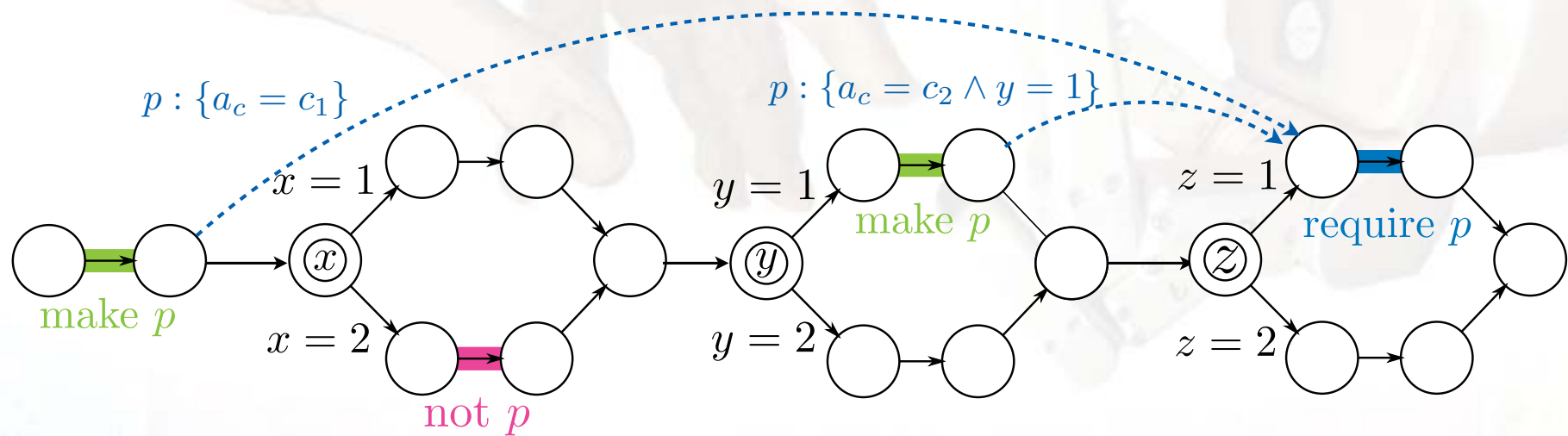
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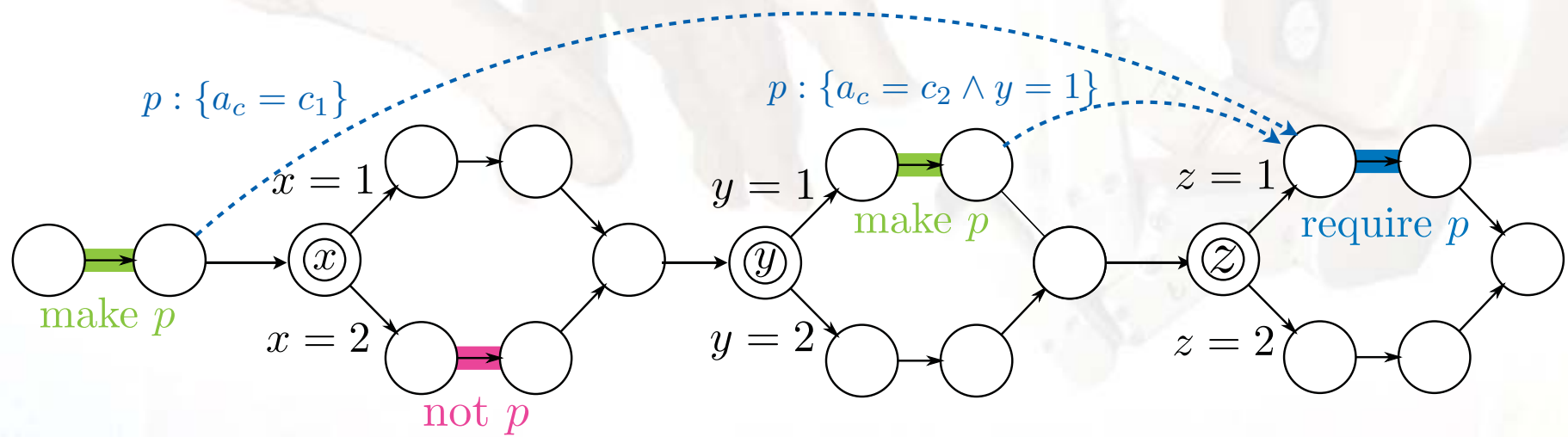
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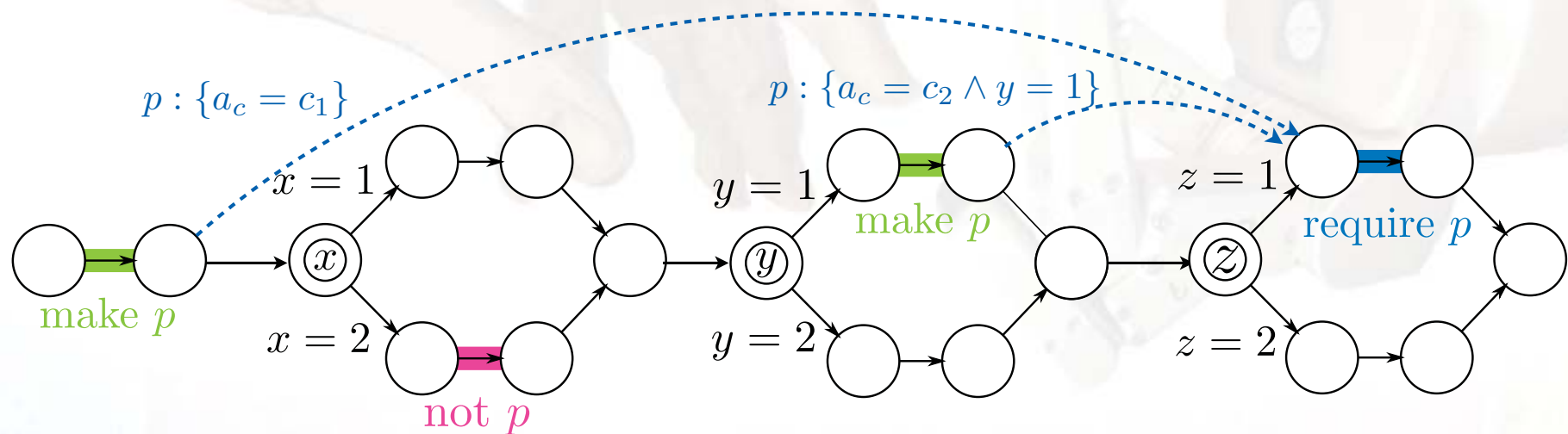
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 - Resolve via additional propositional & temporal constraints



Causal link extraction in a nutshell*

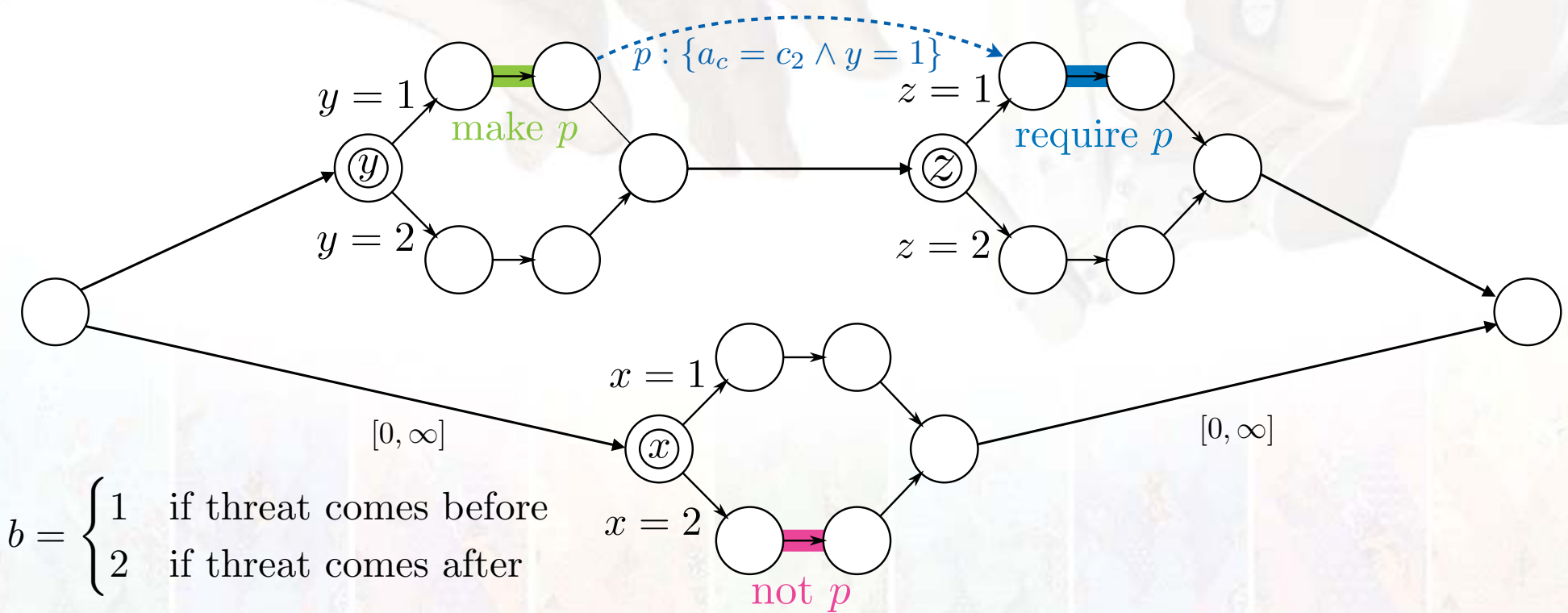
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Constraint: $\neg(z = 1 \wedge a_c = c_1 \wedge x = 2)$

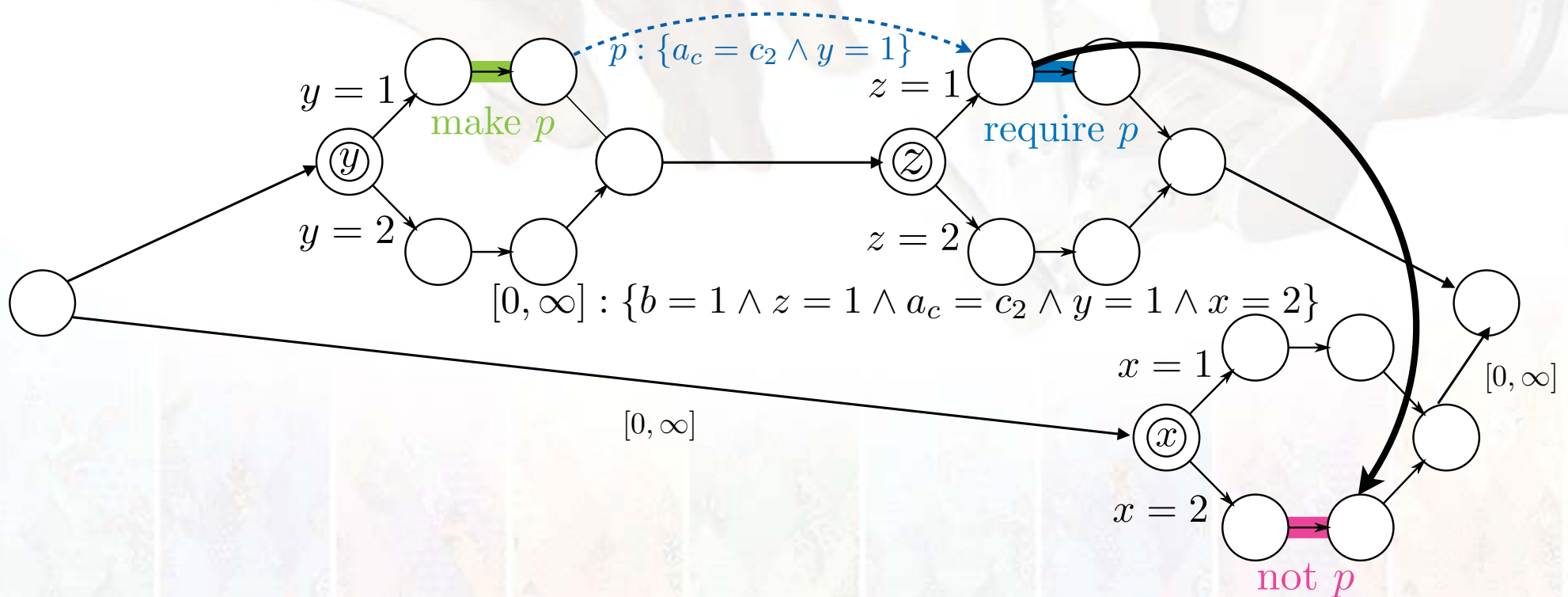
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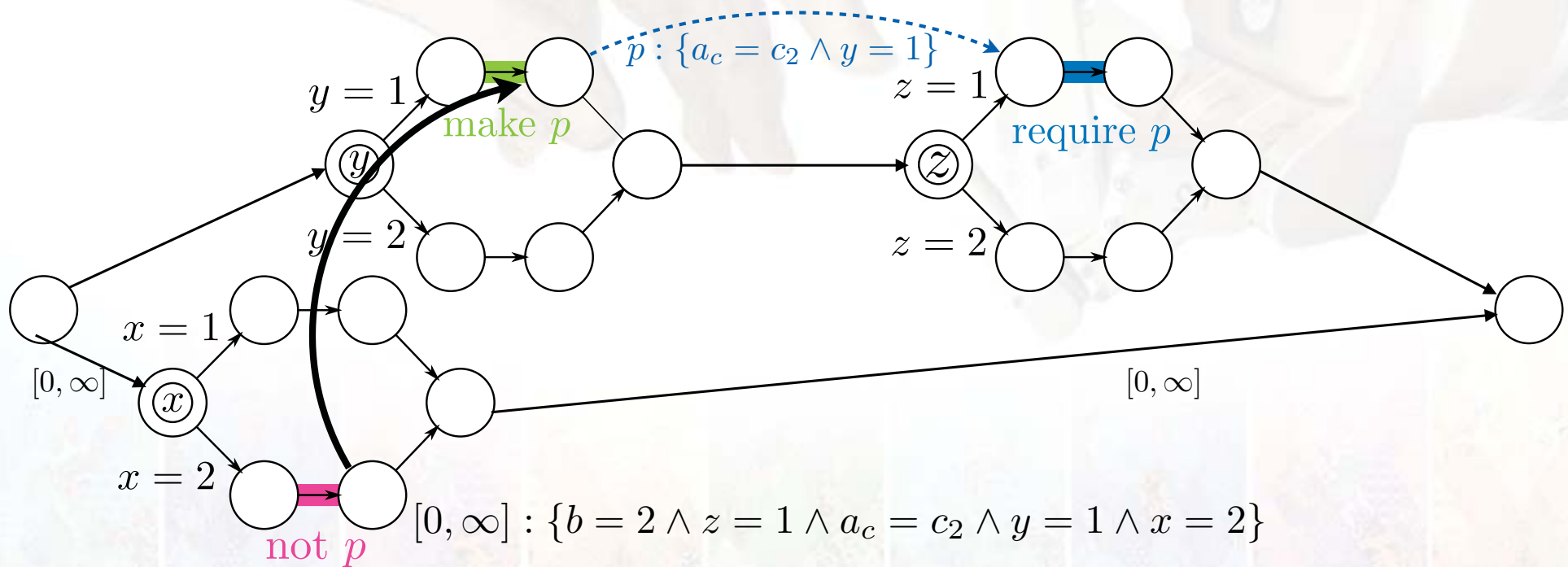
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Constraints

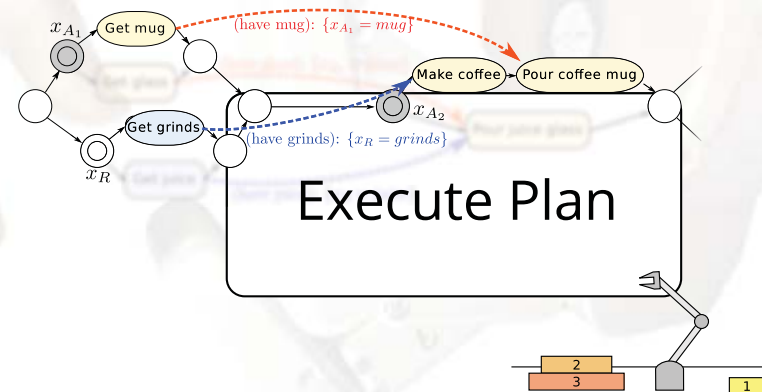
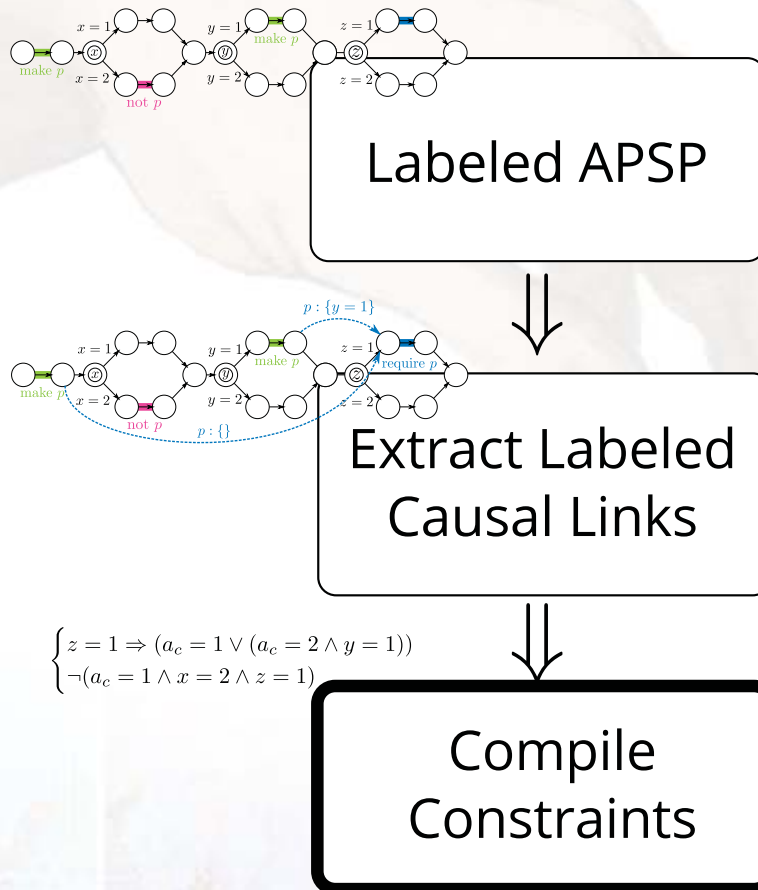
$\phi_{e_c} \Rightarrow \bigvee_i (a_i = e_{p_i} \wedge \phi_{e_{p_i}})$	One candidate causal link must hold
$[\epsilon, \infty] : \{a_{e_c, p} = e_{p_i}\} \wedge \phi_{e_{p_i}} \wedge \phi_{e_c}$ from e_{p_i} to e_c	Producers precede consumers
$\neg\phi_C$	Temporal conflicts (Conrad 2009)
$\neg\phi_C$	Threat resolutions
$[\epsilon, \infty] : \phi_C$ from e_c to e_{t_i}	Threat resolutions
$[\epsilon, \infty] : \phi_C$ from e_{p_i} to e_{t_i}	Threat resolutions
$[\epsilon, \infty] : \{b_{e_c, p, e_{p_i}, e_{t_i}} = 1\} \wedge \phi_C$ from e_{t_i} to e_{p_i}	Threat resolutions
$[\epsilon, \infty] : \{b_{e_c, p, e_{p_i}, e_{t_i}} = 2\} \wedge \phi_C$ from e_c to e_{t_i}	Threat resolutions



- Constraints satisfied: team success!
 - Preconditions of all executed actions met
 - No missed deadlines

Offline

Online

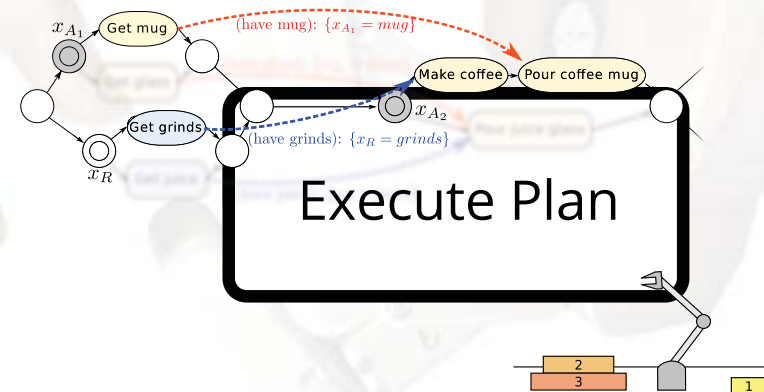
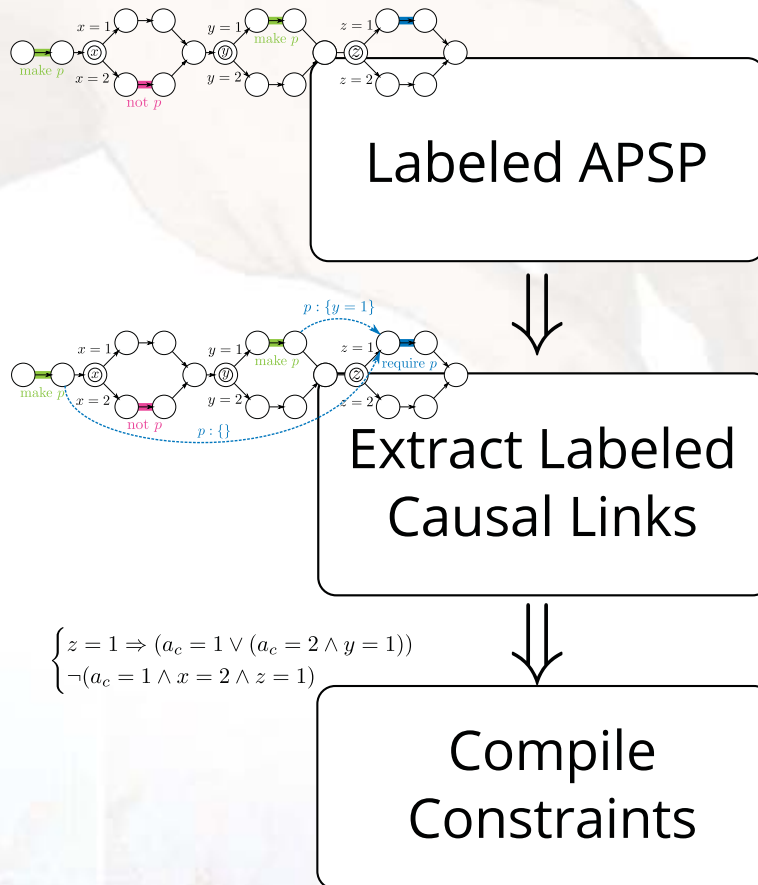


Compile constraints with ATMS

- Compile constraints for fast, online reactivity.
- Assumption-based Truth Maintenance System (ATMS): knowledge base permitting fast querying of assumptions
- Fast online queries without re-solving CSP:
 - “Can robot pick up coffee grounds now?”
 - “Is plan still feasible?”
- Internally, employs label propagation to pre-compute sets of consistent solutions

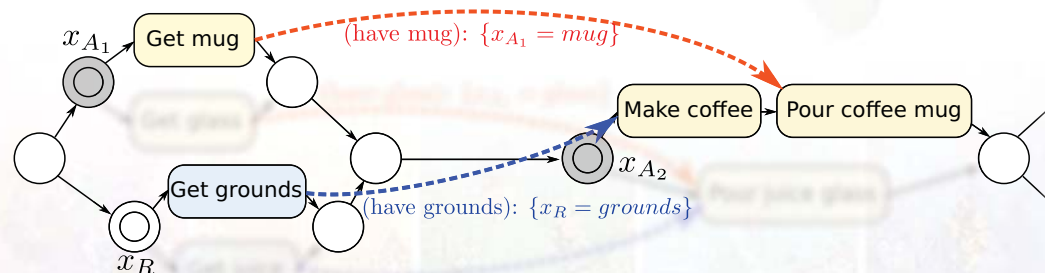
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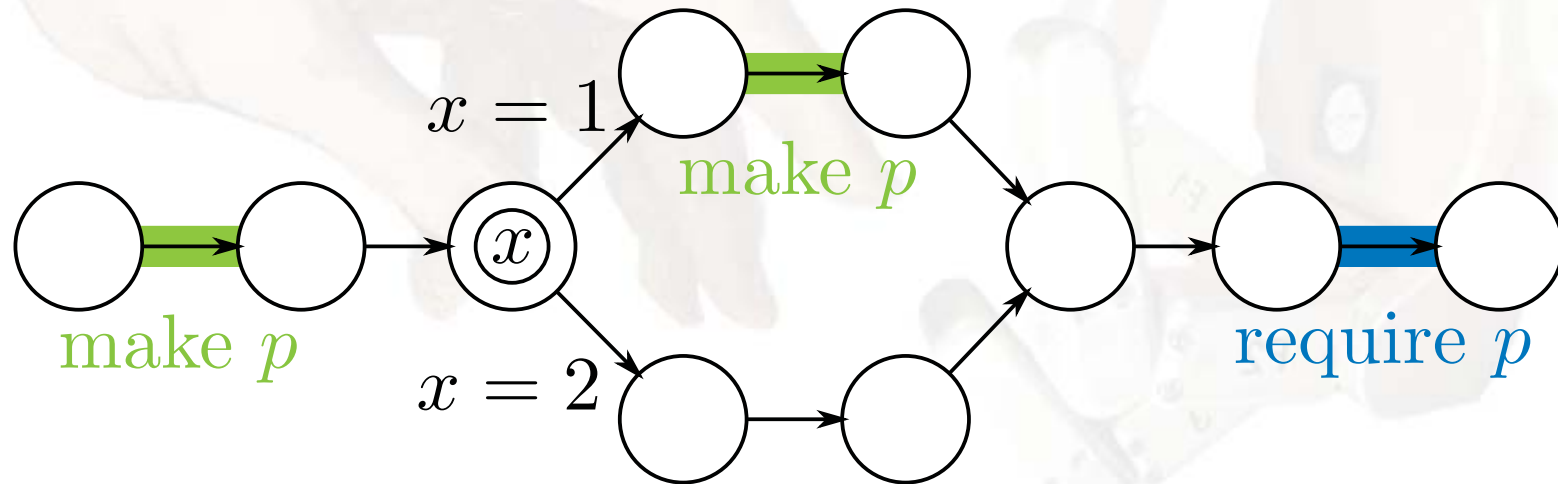
Online execution

- Similar architecture to (Conrad 2009)
- Continually iterates over all events:
 - Gathers constraints necessary to execute event *now*
 - Queries ATMS: can commit to constraints?
 - If yes: execute event & dispatch appropriate activities
- Receives human's choice outcomes (from activity recognizer)
- Monitors active causal links
 - Upon violation: add appropriate constraints to ATMS
 - Execution infeasible? Signal execution error.



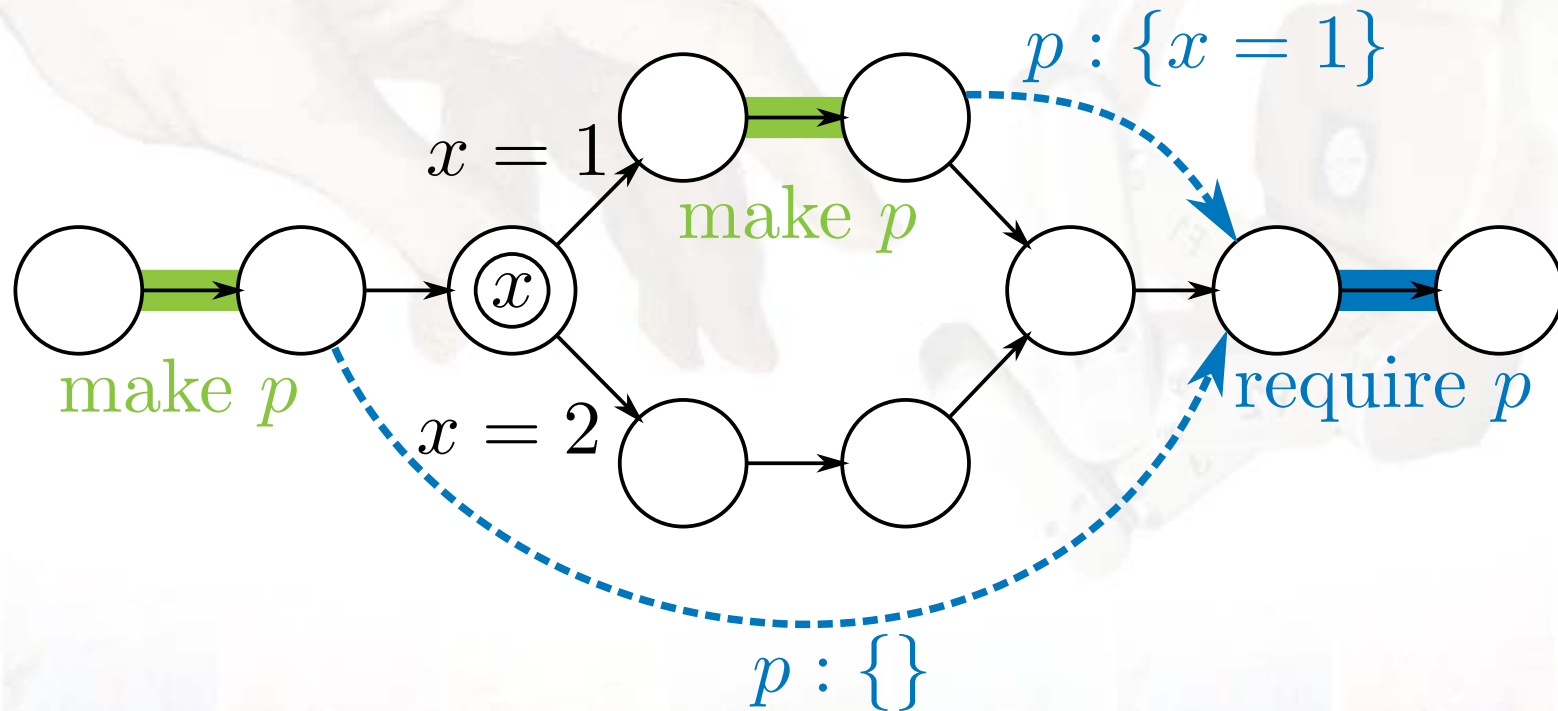
Online causal link execution monitoring

- Detects potential problems immediately
- Allows recovery actions (if modeled in plan)



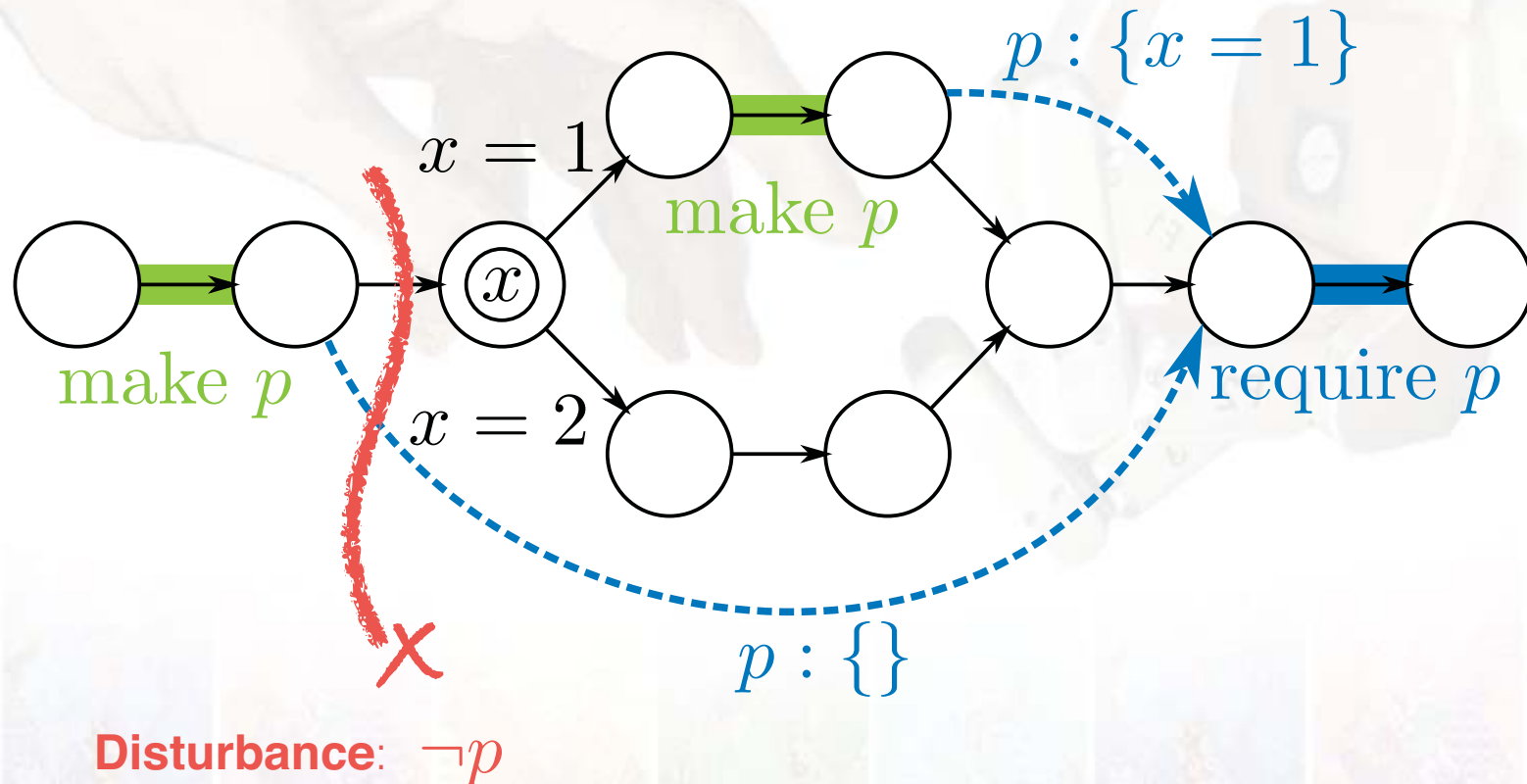
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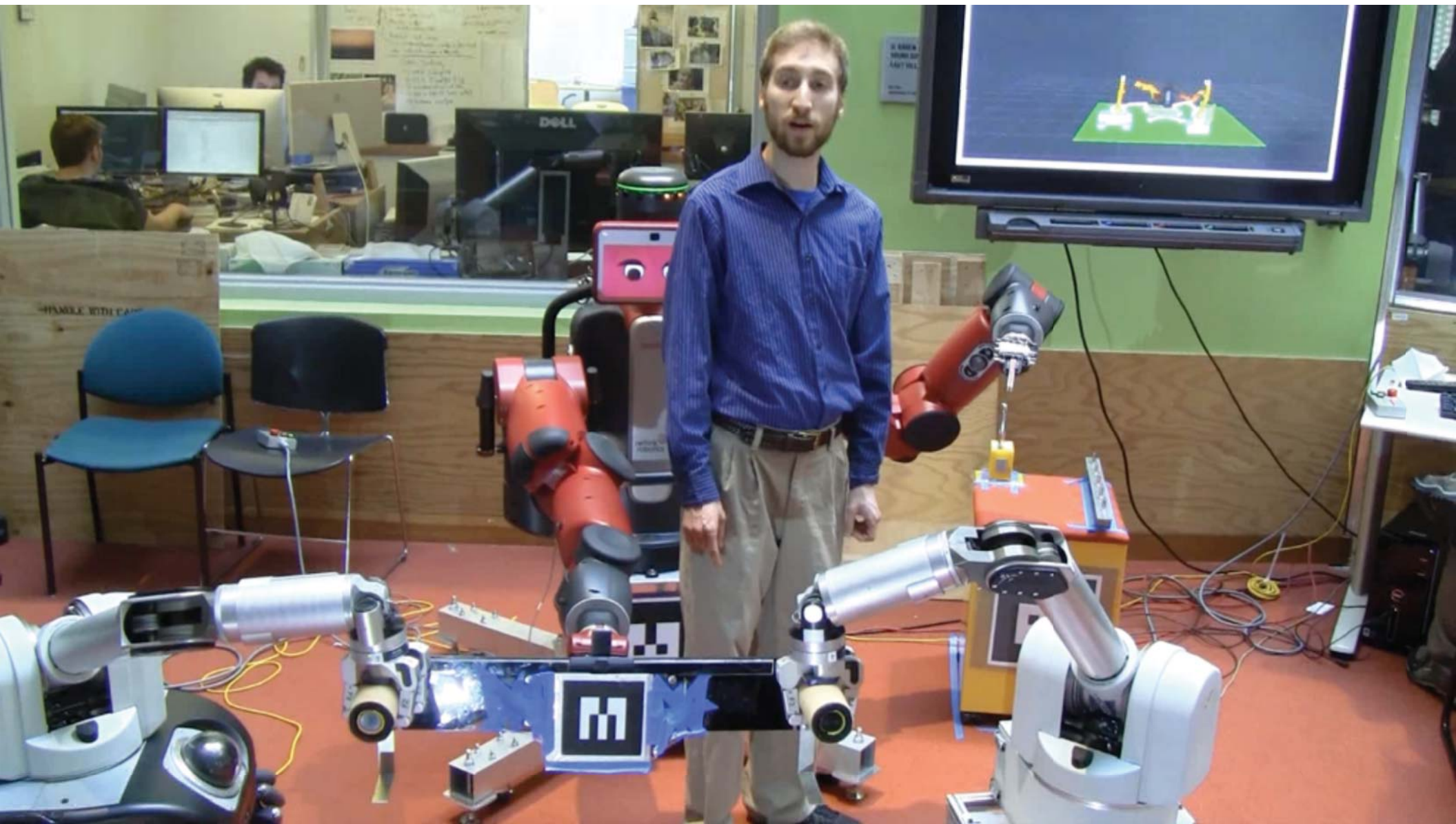
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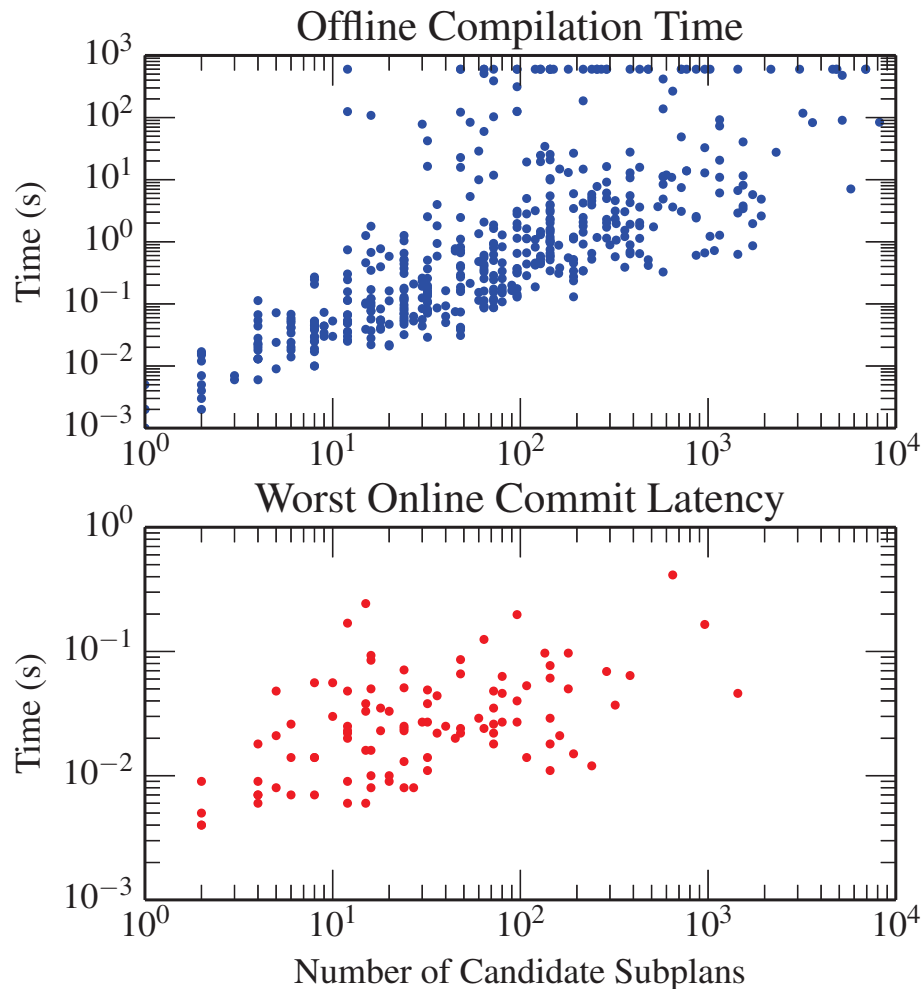
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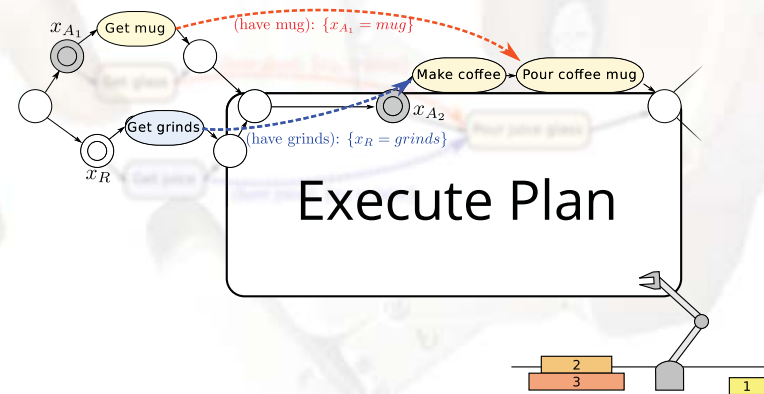
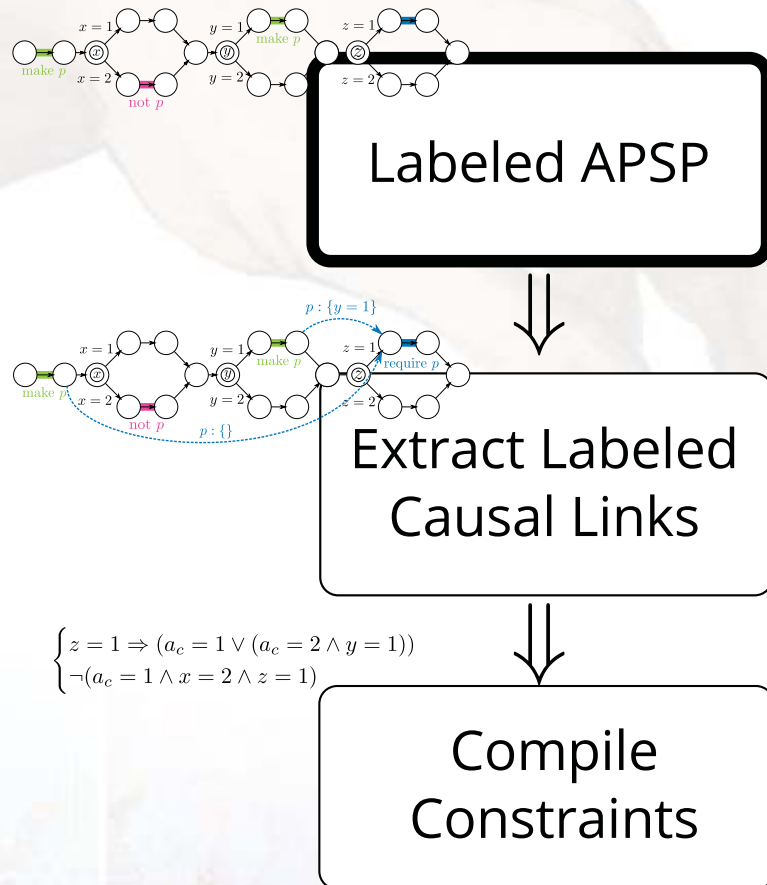
Experimental results



- Randomly-generated TPNU's with randomly-generated causal link structure (probably harder)
- Compilation time roughly proportional to candidate subplans, (large variance)
- Reactive online performance

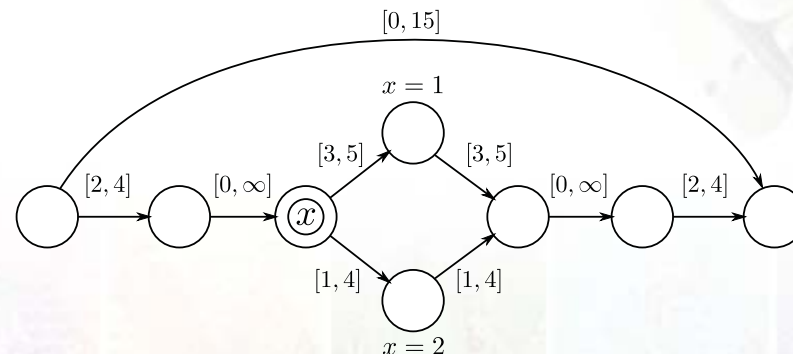
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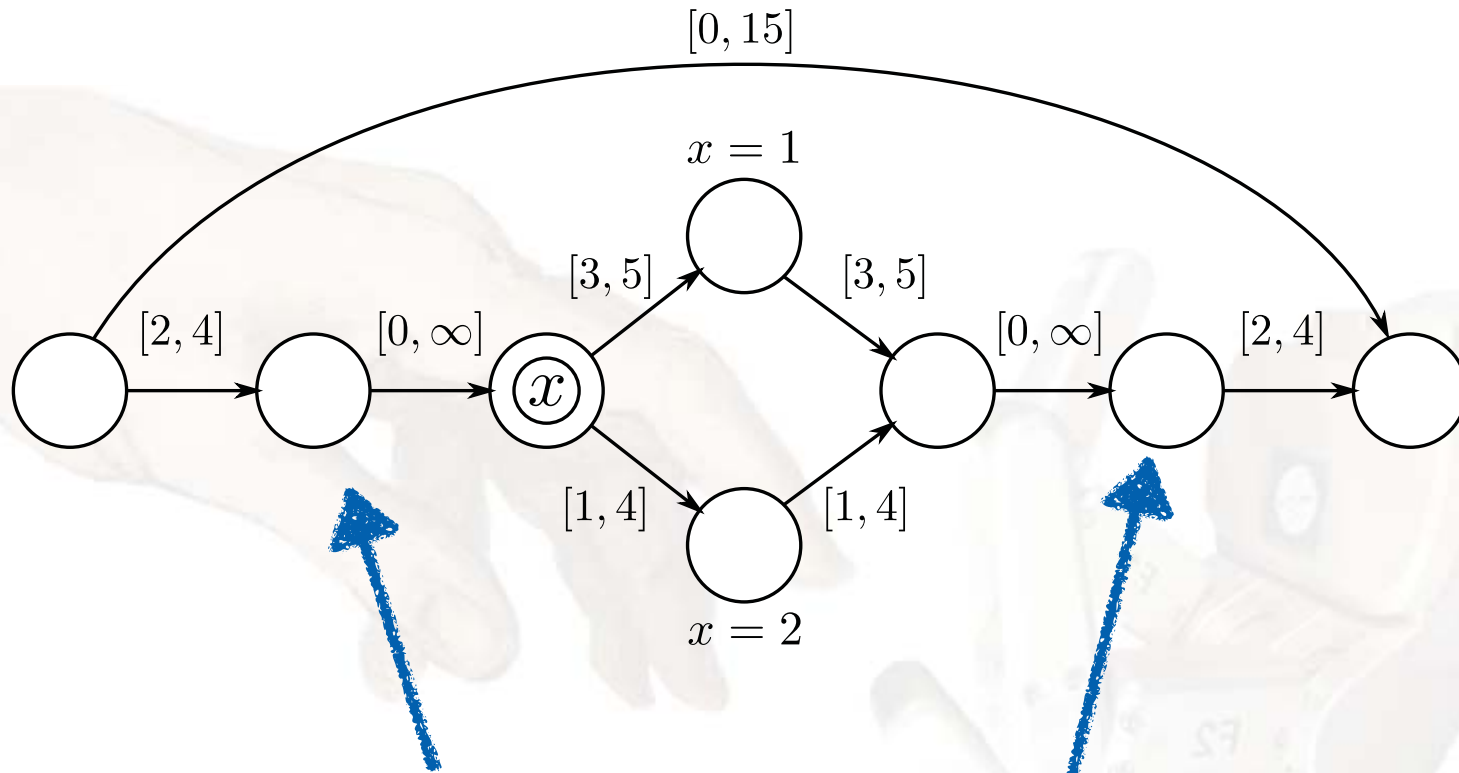


Labeled all-pairs shortest path (APSP)

- Developed in (Conrad 2009)
- Three purposes:
 1. Dispatchable form for online execution
 2. Ordering over events for causal link extraction
 3. Temporal conflict extraction

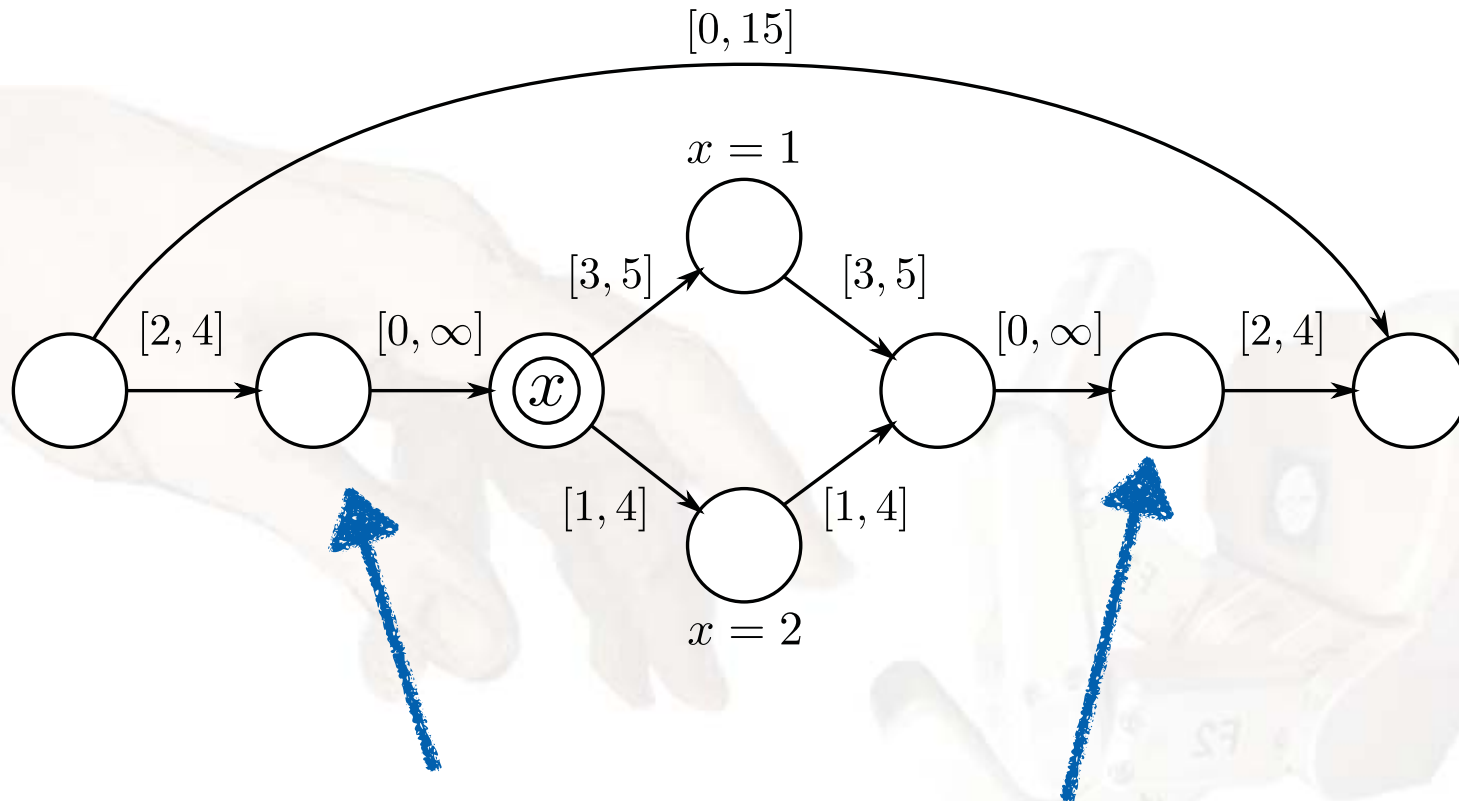


Labeled all-pairs shortest path (APSP)



- What is temporal distance between these events?

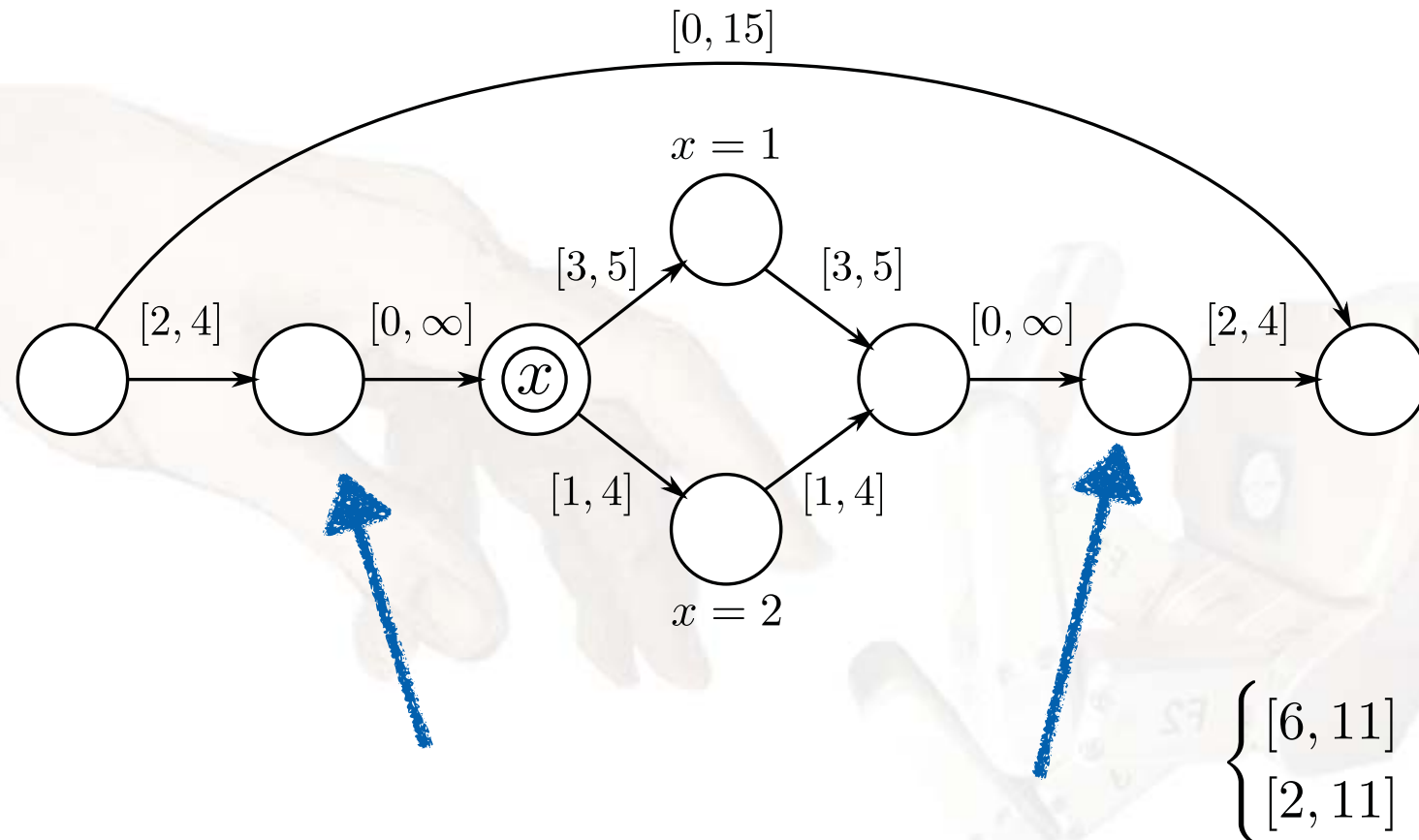
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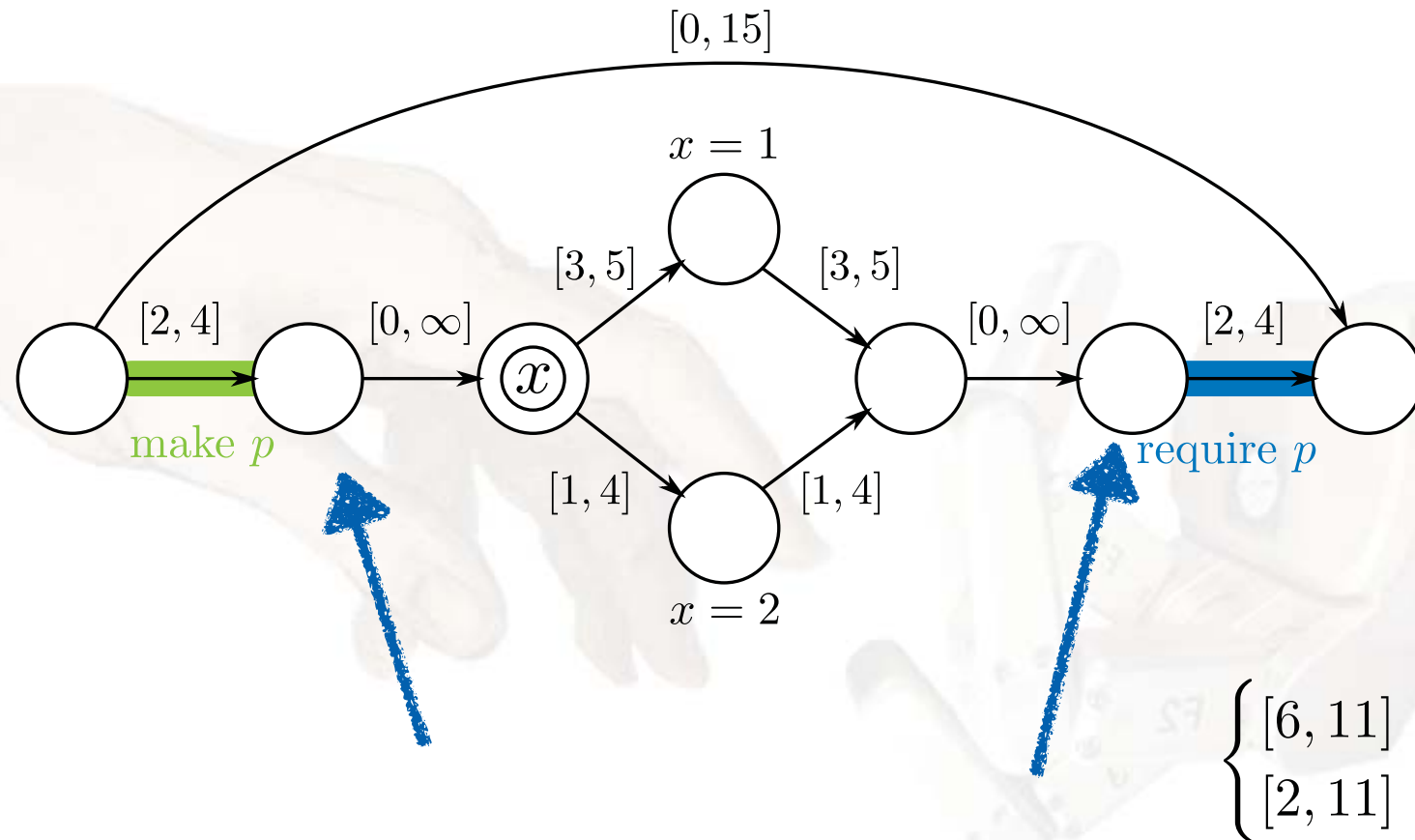
• Event dependent:
$$\begin{cases} [6, 11] & \text{if } x = 1 \\ [2, 11] & \text{if } x = 2 \end{cases}$$

Labeled all-pairs shortest path (APSP)



- Labeled all pairs shortest path computes these temporal distances, as a function of environment
- Compact encoding using Labeled Value Set (LVS)

Labeled all-pairs shortest path (APSP)



- Causal link extraction: provides ordering
 - In this case, producer *guaranteed* to precede consumer
 - Labeled causal link extracted

Labeled Value Set (LVS)

- LVS encodes tightest known value for some condition, as a function of environment
 - Ex. Suppose $t < a$ where a depends on environment
 - LVS: $t < \{(2, \{x = 1, y = 2\}), (3, \{x = 1\}), (6, \{\})\}$
- **Query** an LVS with Q operator: “what is tightest value over all environments where $x = 1, y = 2$ ”?
 - $Q(\{x = 1, y = 2\}) = 2$
 - $Q(\{y = 2\}) = 6$
- **Dominance**: labeled pair (a_i, ϕ_i) dominates (a_j, ϕ_j) iff $a_i < a_j$ and ϕ_i subsumes ϕ_j

LVS introduced in (Conrad 2009)

Operations on LVS's

- We use $<$ to compare numbers, but generalizes to other partial order relation R
- Operations on LVS's:
 - Adding new labeled pairs
 - Query
 - Binary operations, like $+$
- See (Conrad 2009) for full details

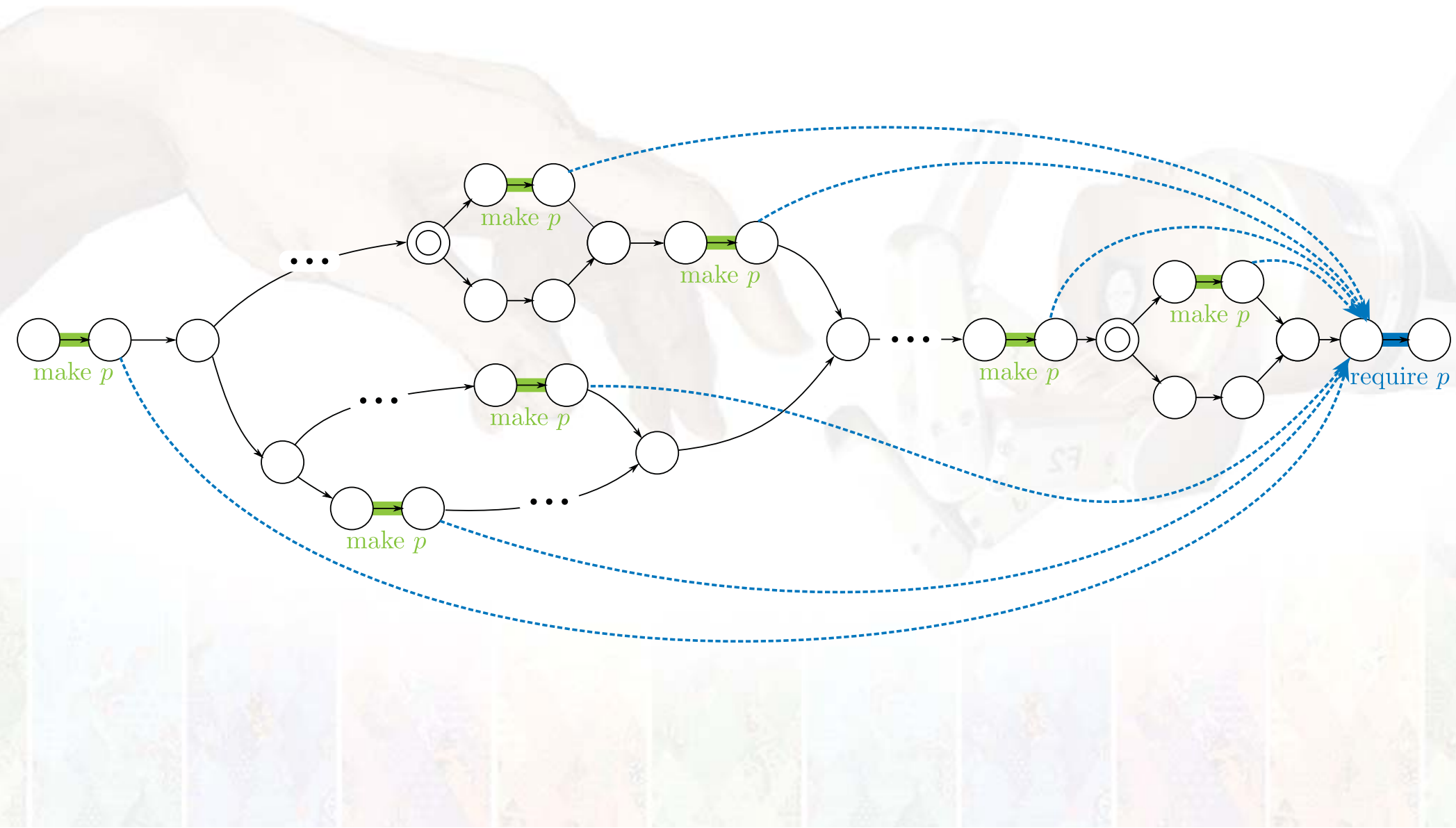
Labeled all-pairs shortest path (APSP)

- Labeled APSP:
 - Dispatchable form suitable for online execution
 - Allows precedence inference for causal link extraction
 - Detects temporal conflicts
- Computes an LVS for each pair of graph, representing shortest distance as function of environment
- Generalization of Floyd Warshall algorithm that uses LVS operations instead of standard + and <
- See (Conrad 2010) for details

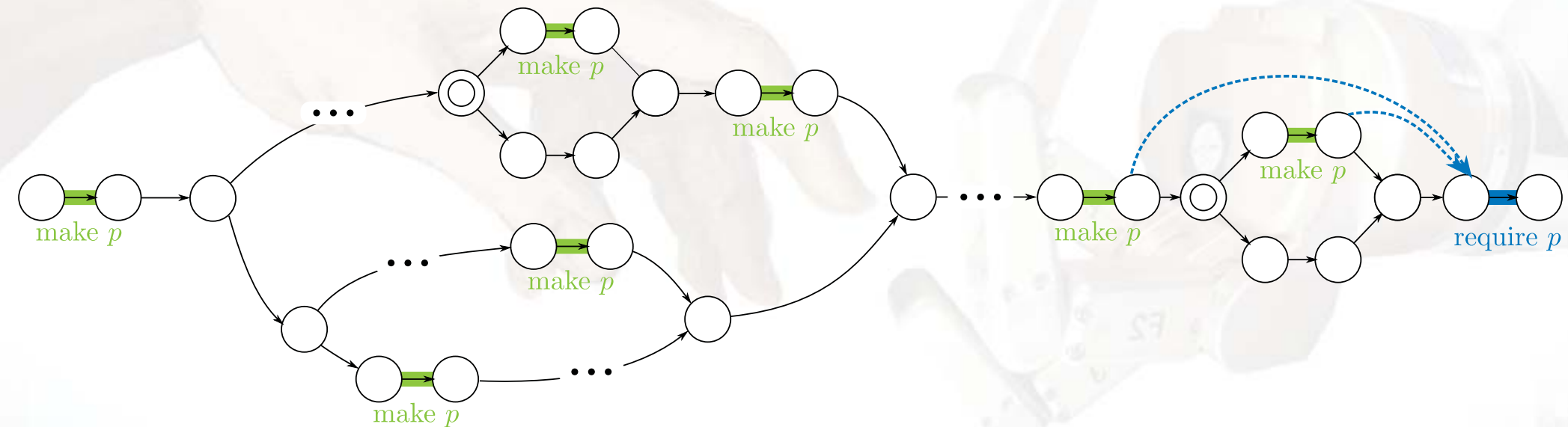
Optimization: Causal link dominance



Optimization: Causal link dominance



Optimization: Causal link dominance



- **Dominance:** Later-occurring producers that are active whenever earlier ones are dominant.
- Reduce number of constraints & solutions

Future Work

- Rank intent/adaptation hypotheses.
 - Probability: consider only likely human intents first
- Richer model for state & human
 - Hybrid state with continuous, spatial variables
 - Hybrid causal links via flow tubes / funnels
- Robot to actively influence human
 - Actively ask clarification questions
 - Informing human of increasingly likely failures (deadlines getting close, likely violated causal link, etc.)

Questions

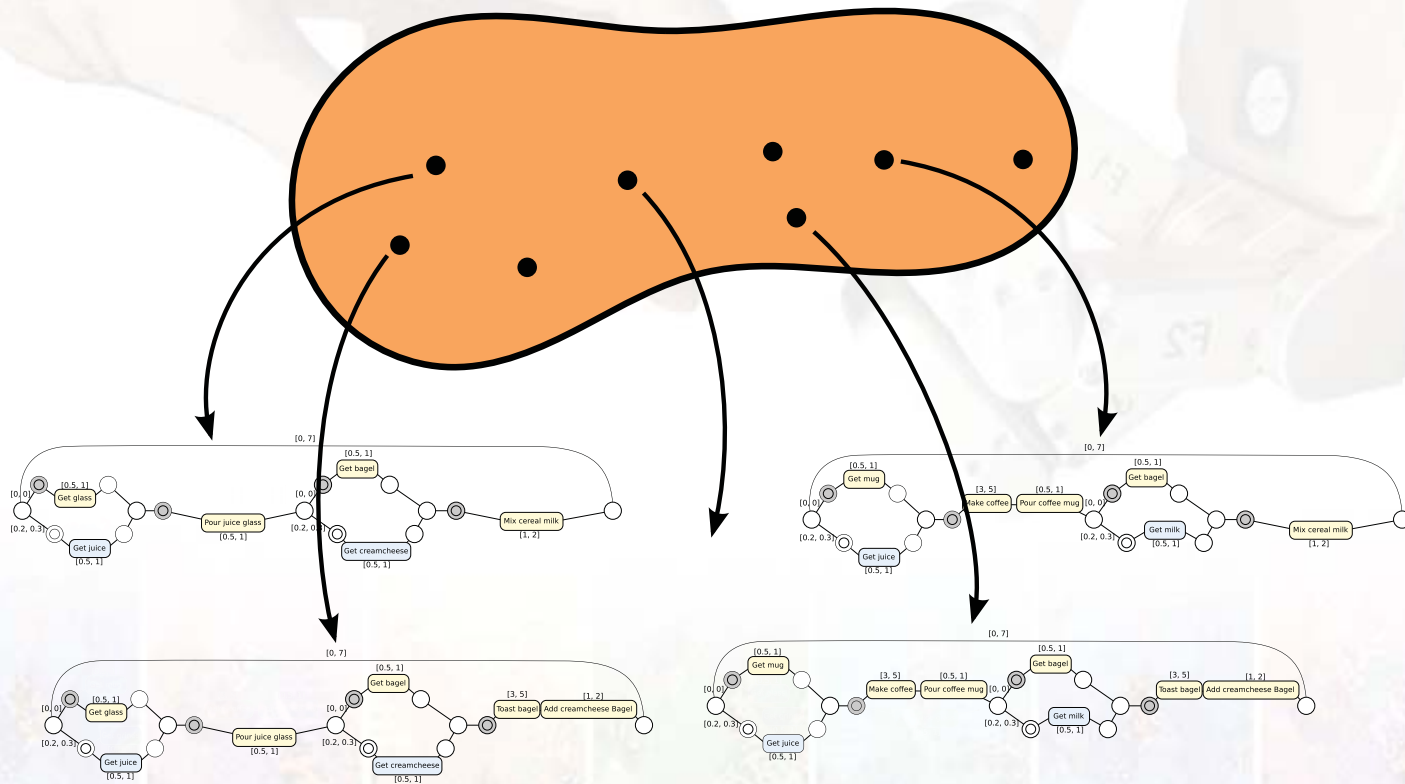


Backup slides



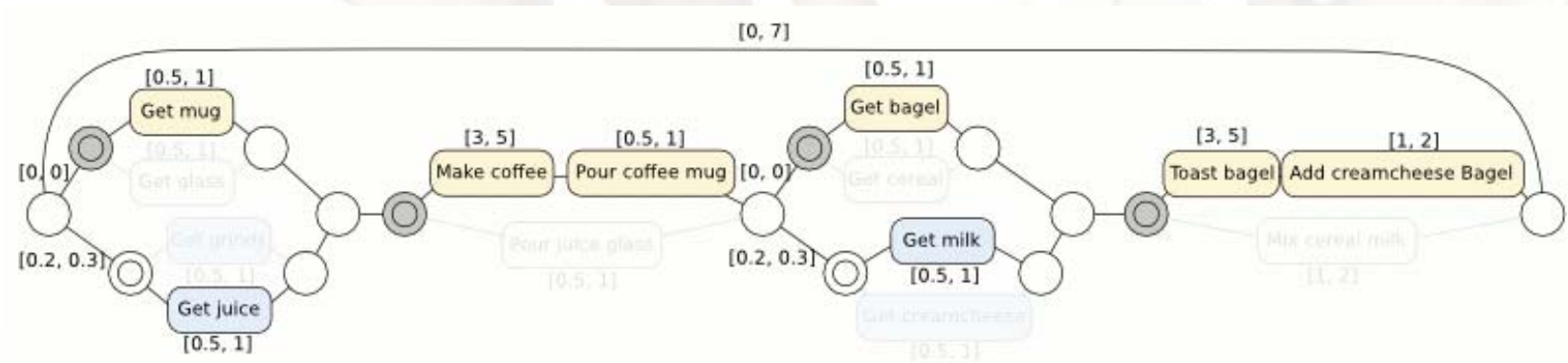
Environments represent sets of subplans

- **Environment:** partial assignment to choice variables
- Represents a *set* of possible subplans



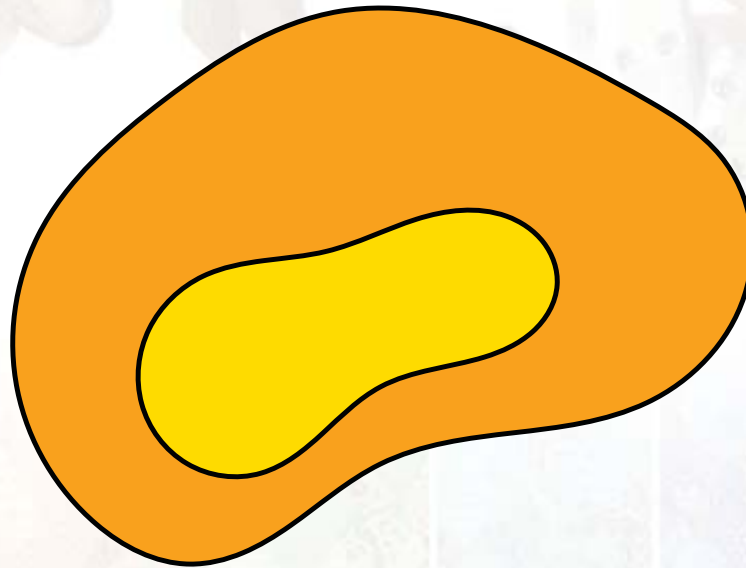
Environments represent sets of subplans

- Ex., $\{x_{R1} = juice, x_{A3} = bagel\}$ represents:

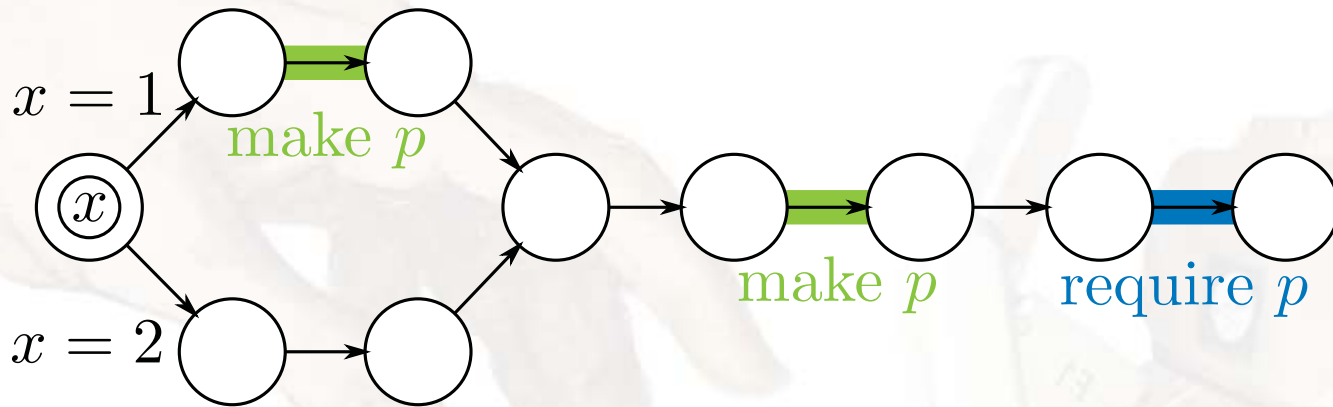


Environments and subsumption

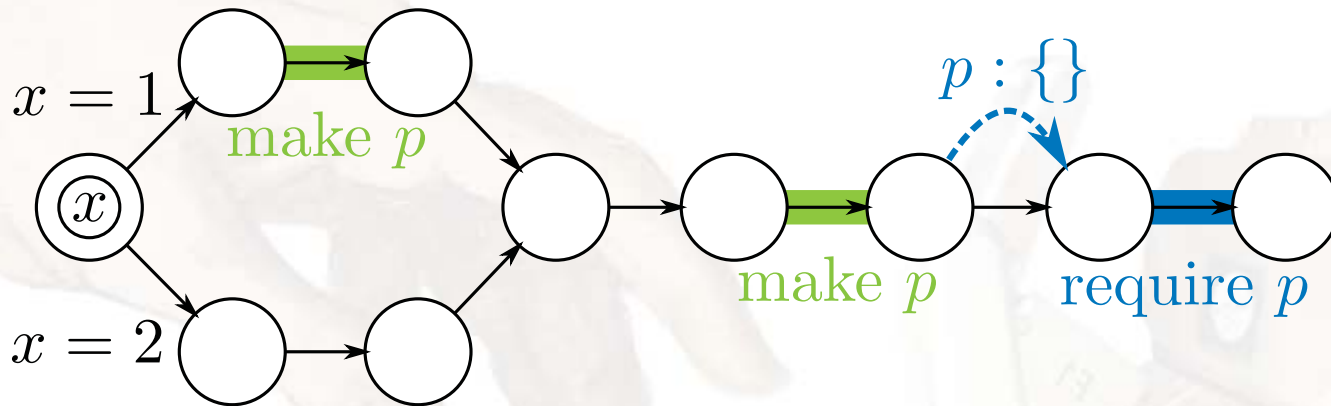
- Environment e_1 **subsumes** e_2 iff e_2 contains all assignments in e_1
 - ex., $\{x_{R1} = juice\}$ subsumes $\{x_{R1} = juice, x_{A3} = bagel\}$
- Intuitively, all subplans represented by e_2 also represented by e_1 (subset)



Labeled causal links

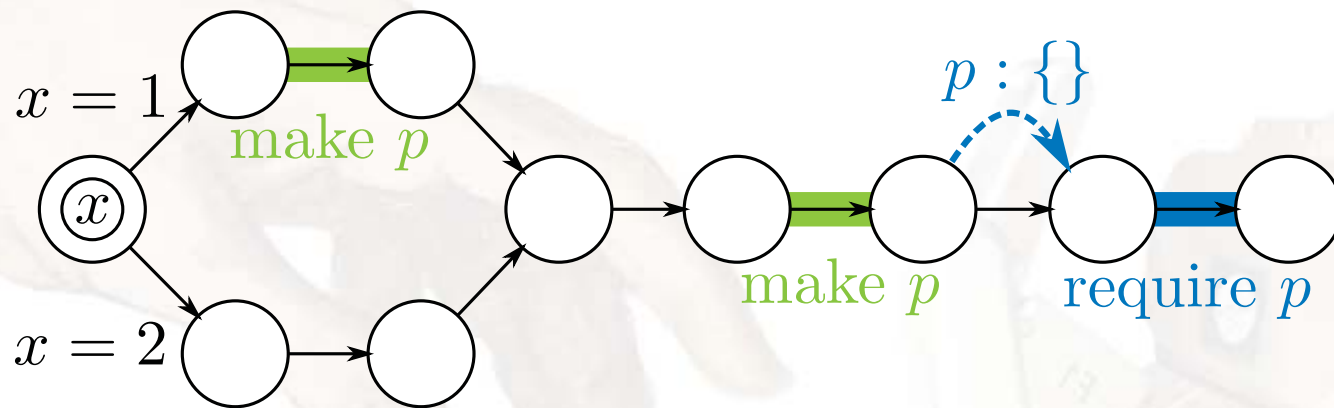


Labeled causal links



- Label causal links with producer's execution environment
- Ordering determined via labeled APSP

Labeled causal link *dominance*



- **Dominance:** Later-occurring producers with subsuming environments *dominate* others
- Above, later occurring producer dominates earlier one.

Extraction algorithm

Algorithm 8: EXTRACTCAUSALLINKCONSTRAINTS()

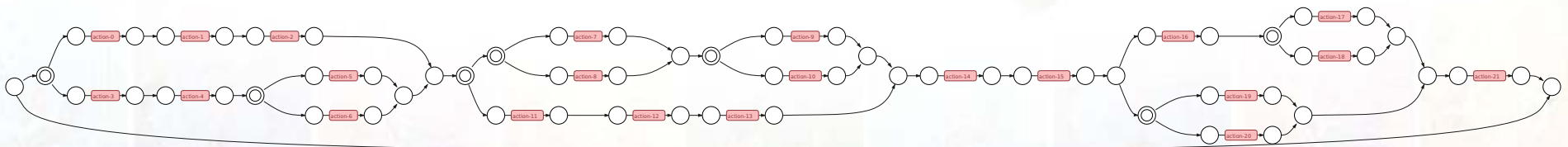
```
Input:
Output:
1 foreach  $e_c \in \mathcal{E}$  do
2   foreach  $p \in \text{PRECONDITIONS}(e_c)$  do
3      $\xi \leftarrow$  new LVS  $\{\}$  with relation  $\prec$ 
4     foreach  $e \neq e_c \in \mathcal{E}$  with  $p$  or  $\neg p$  in  $\text{EFFECTS}(e)$  do
5       if not  $e_c \prec e$  and  $\phi_e \wedge \phi_{e_c}$  is feasible(!) then
6         | ADDLVS( $(e, \phi_e), \xi$ )
7       end
8     end
9     Separate  $\xi$  into  $P$  and  $T$ 
10    Create decision variable  $a_{e_c, p}$  with domain  $P$ 
11    ADDCONSTRAINT( $\phi_{e_c} \Rightarrow \bigvee_i (a_i = e_{p_i} \wedge \phi_{e_{p_i}})$ )
12    foreach  $e_{p_i} \in P$  where not  $e_{p_i} \prec e_c$  do
13      | Add  $[\epsilon, \infty] : \{a_{e_c, p} = e_{p_i}\} \wedge \phi_{e_{p_i}} \wedge \phi_{e_c}$  from  $e_{p_i}$  to  $e_c$ 
14    end
15    foreach  $e_{p_i} \in P$  do
16      foreach  $e_{t_i} \in T$  do
17         $\phi_C \leftarrow \{a_{e_c, p} = e_{p_i}\} \wedge \phi_{e_{p_i}} \wedge \phi_{e_{t_i}} \wedge \phi_{e_c}$ 
18        if  $e_{p_i} \prec e_{t_i} |_{\phi_C}$  and  $e_{t_i} \prec e_c |_{\phi_C}$  then
19          | ADDCONSTRAINT( $\neg \phi_C$ )
20        else if  $e_{p_i} \prec e_{t_i} |_{\phi_C}$  and  $e_{t_i} \parallel e_c |_{\phi_C}$  then
21          | Add  $[\epsilon, \infty] : \phi_C$  from  $e_c$  to  $e_{t_i}$ 
22        else if  $e_{p_i} \parallel e_{t_i} |_{\phi_C}$  and  $e_{t_i} \prec e_c |_{\phi_C}$  then
23          | Add  $[\epsilon, \infty] : \phi_C$  from  $e_{p_i}$  to  $e_{t_i}$ 
24        else if  $e_{p_i} \parallel e_{t_i} |_{\phi_C}$  and  $e_c \parallel e_{t_i} |_{\phi_C}$  then
25          | Create decision variable  $b_{e_c, p, e_{p_i}, e_{t_i}}$  with domain  $\{1, 2\}$ 
26          | Add  $[\epsilon, \infty] : \{b_{e_c, p, e_{p_i}, e_{t_i}} = 1\} \wedge \phi_C$  from  $e_{t_i}$  to  $e_{p_i}$ 
27          | Add  $[\epsilon, \infty] : \{b_{e_c, p, e_{p_i}, e_{t_i}} = 2\} \wedge \phi_C$  from  $e_c$  to  $e_{t_i}$ 
28        end
29      end
30    end
31  end
32 end
```

TPN Encodings

- What useful things can be encoded by TPN's?
 - Resource / agent allocation
 - Recovery actions
 - Flexibility to execute different tasks (HTN-like)

Random TPNU generation

- Random sequential, parallel, and choice structure
- Randomly-generated causal link structure (encoded through plant domain) with potential threats
- Temporal “squeezing”
- Wide range of problem sizes



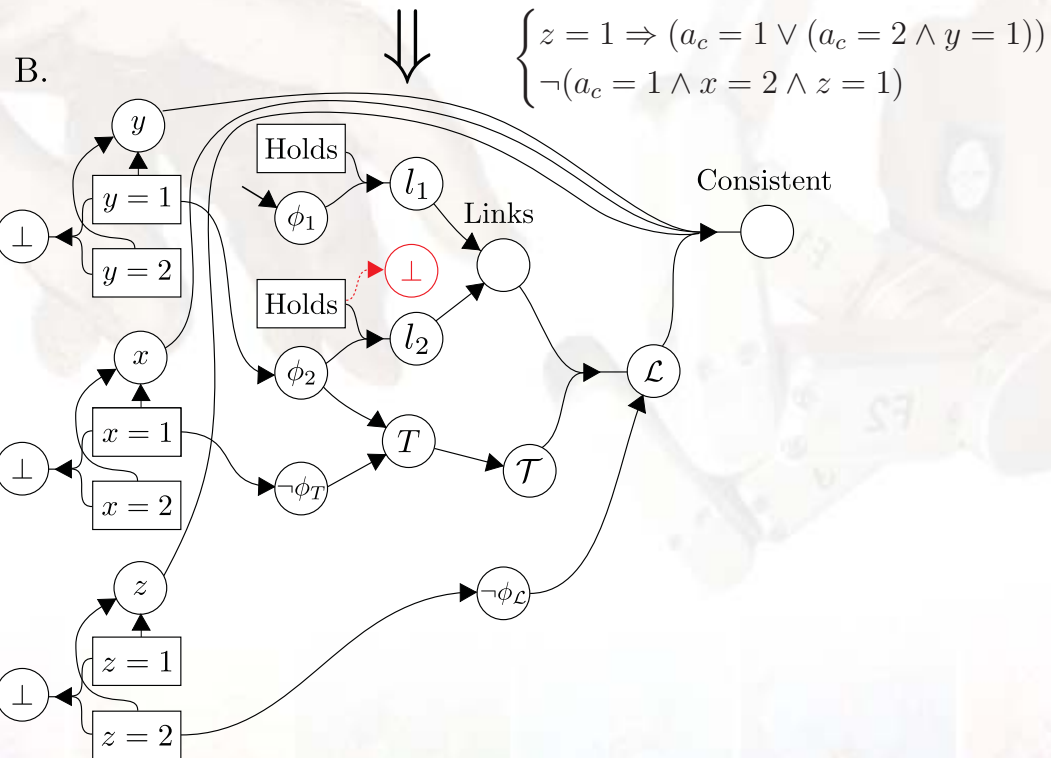
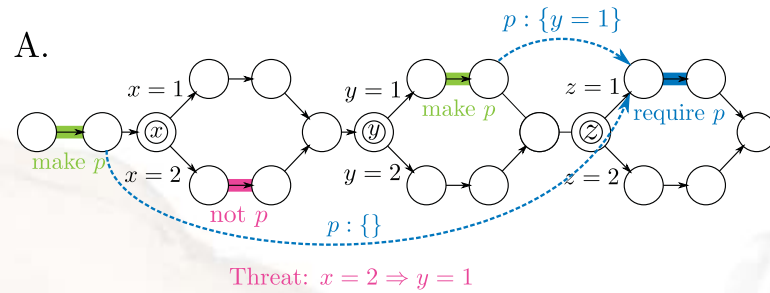
Labeled causal link extraction

- Uses an LVS, except:
 - Values are TPNU *events*, rather than *numbers*
 - Relation R is not $<$ but rather succession (via labeled APSP):

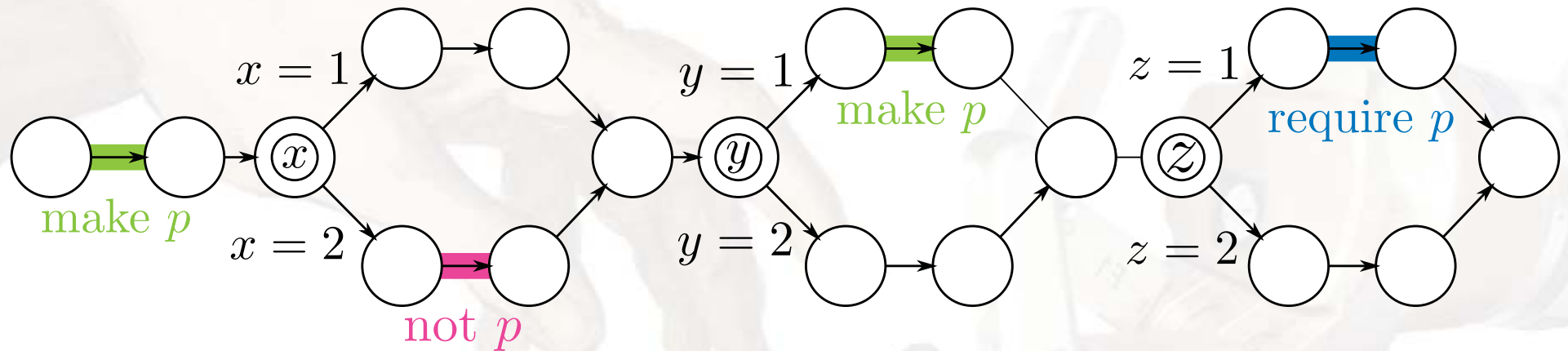
$$e_a R e_b = \begin{cases} \text{TRUE} & \text{if } Q_{d_{e_a \rightarrow e_b}}(\phi_a \cup \phi_b) \leq 0 \\ \text{FALSE} & \text{otherwise} \end{cases}$$

- To find producers for consumer ec requiring p :
 - Insert all e_p that produce p or $\neg p$ into LVS
 - Extract threat resolution constraints from those producing $\neg p$
 - Extract labeled causal links from those producing p
 - (See paper for full details)

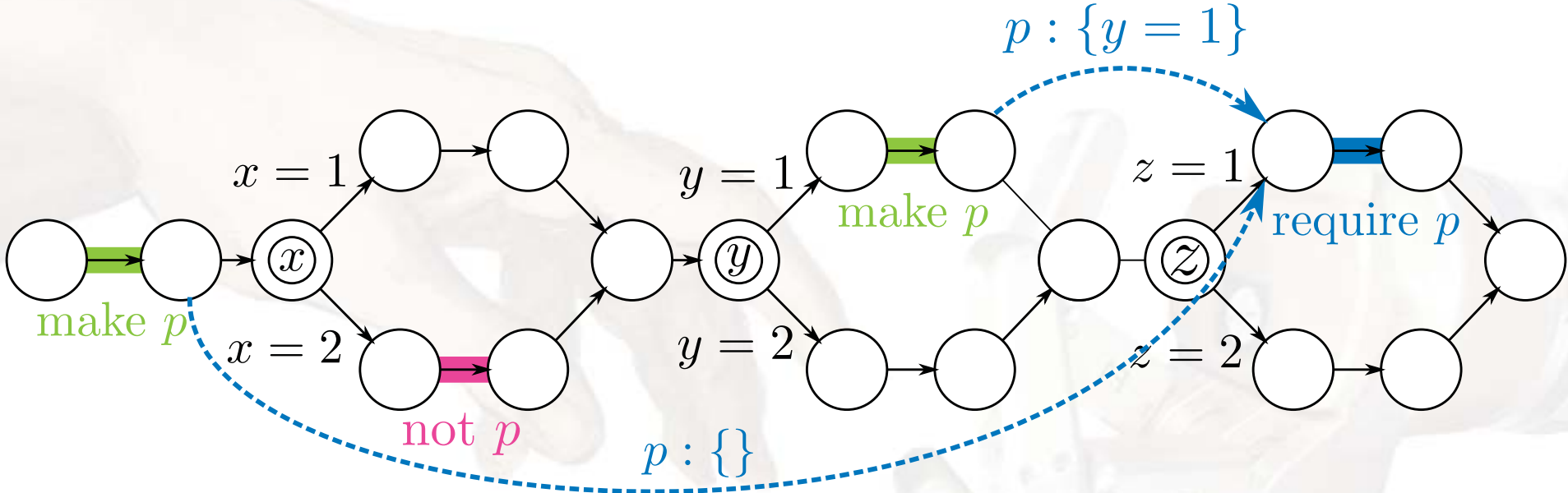
Encoding in an ATMS



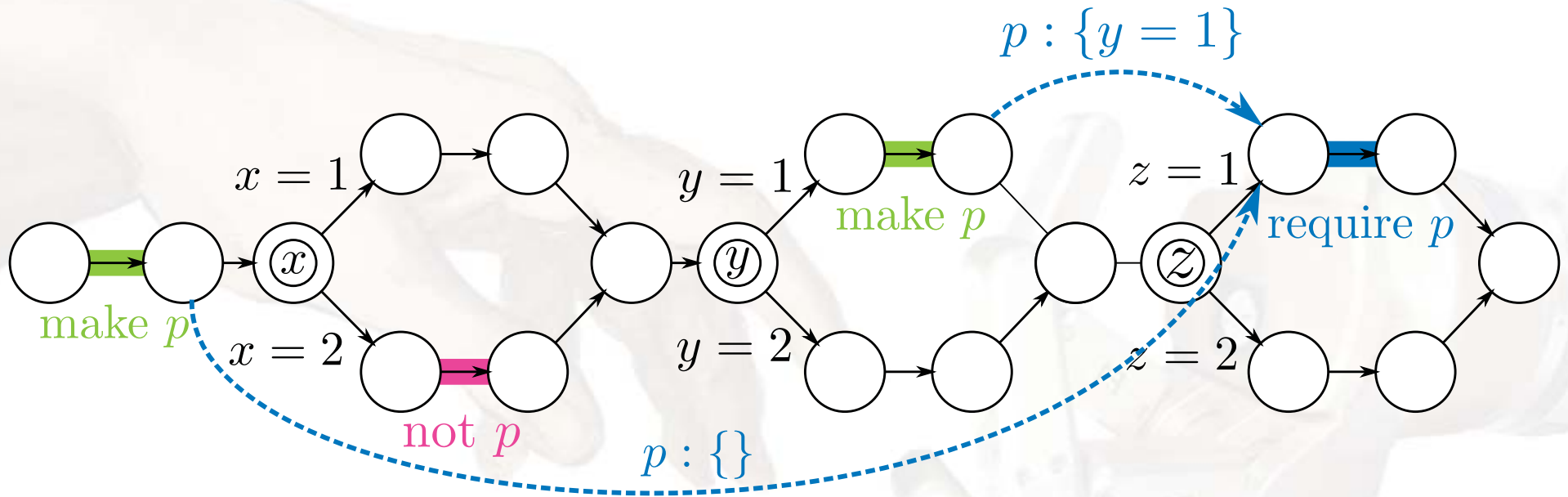
A basic threat



A basic threat

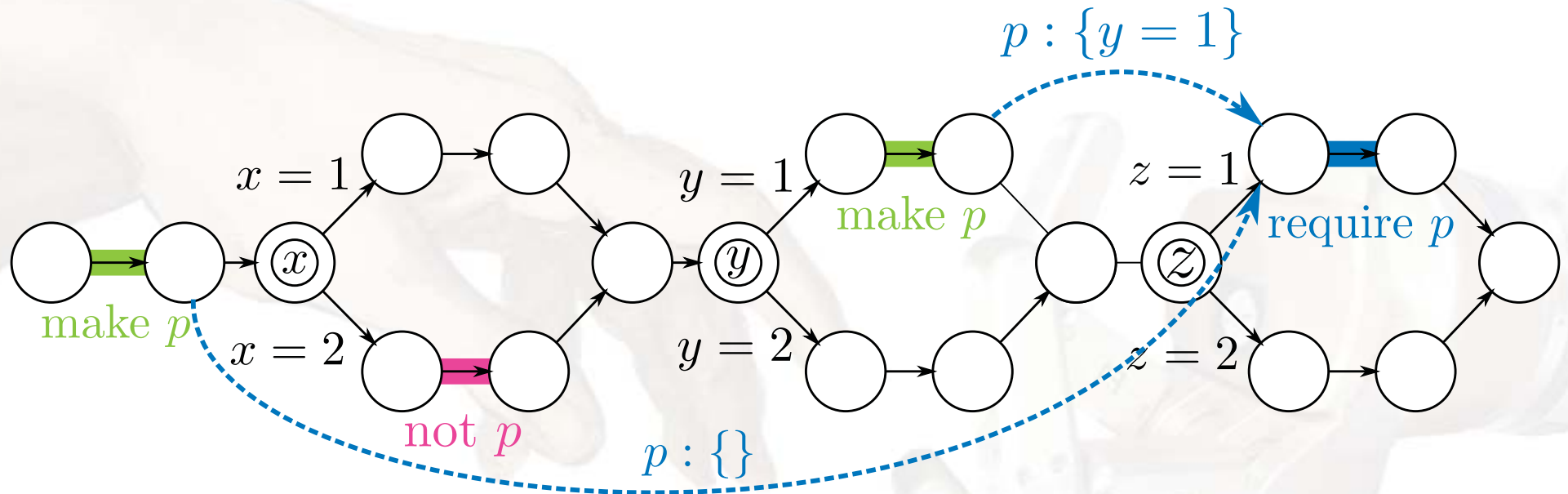


A basic threat



$$a_c = \begin{cases} 1 & \text{if first causal link enforced} \\ 2 & \text{if second causal link enforced} \end{cases}$$

Extracting propositional constraints

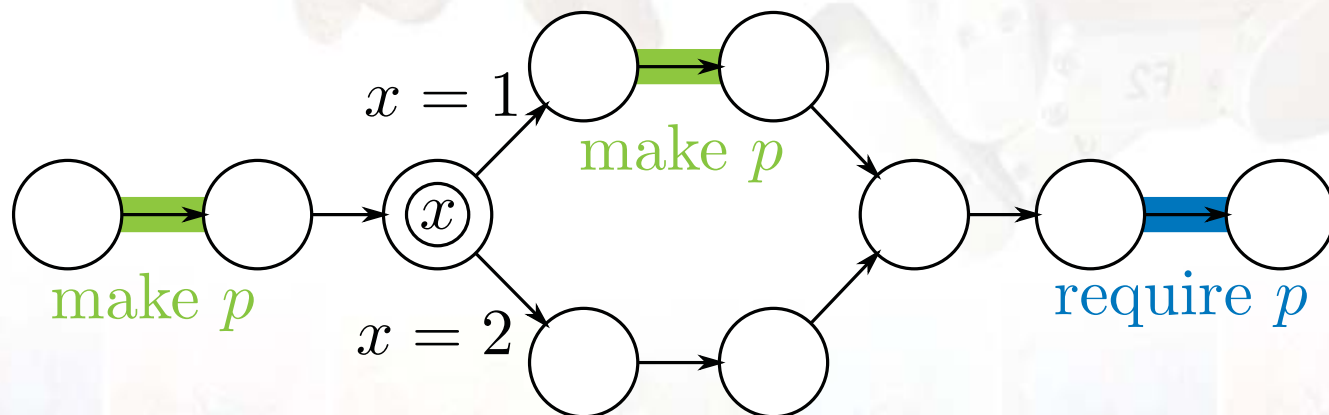


$$a_c = \begin{cases} 1 & \text{if first causal link enforced} \\ 2 & \text{if second causal link enforced} \end{cases}$$

$$\begin{cases} z = 1 \Rightarrow (a_c = 1 \vee (a_c = 2 \wedge y = 1)) & \text{At least 1 causal link holds} \\ \neg(a_c = 1 \wedge x = 2 \wedge z = 1) & \text{Threat resolved} \end{cases}$$

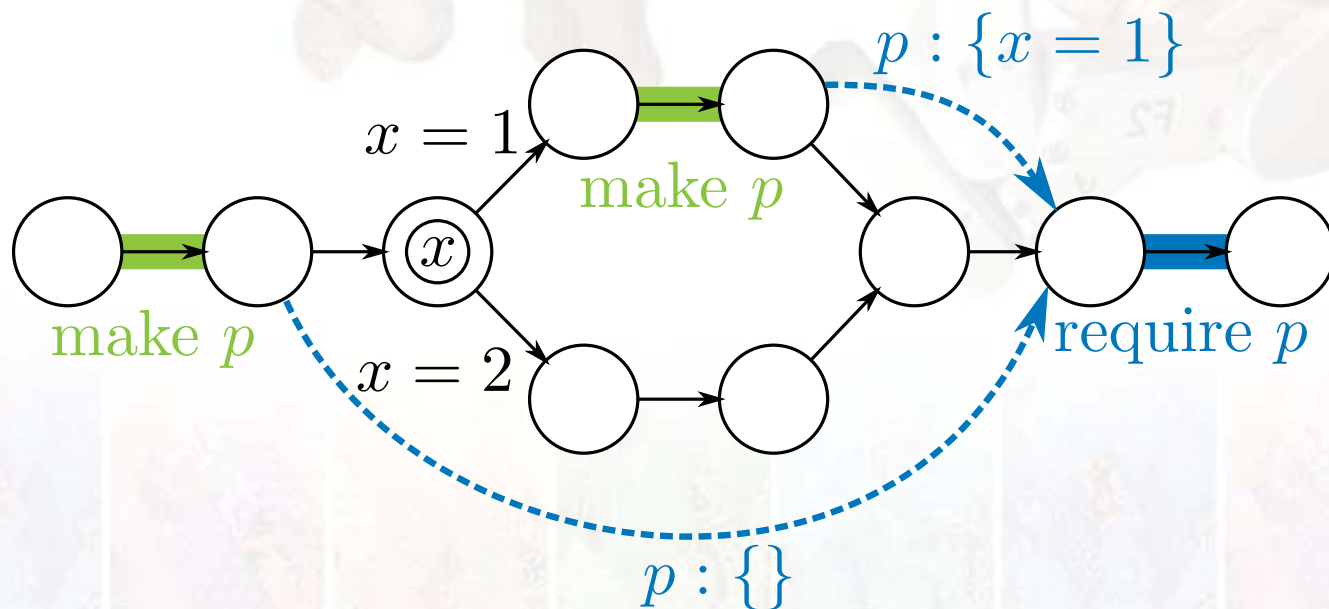
Causal link extraction in a nutshell*

- For each precondition of each **consumer** event:
 - Find all **producer** provably before or during consumer



Causal link extraction in a nutshell*

- For each precondition of each **consumer** event:
 - Find all **producer** provably before or during consumer
 - Add propositional & temporal constraints for each producer



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