Lecture *Hierarchical Planning*

Chapter:
Planning Capabilities Motivated by Real World Applications

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Overview:

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- Autonomous systems, like intelligent factories, robotics.

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  - The environment unexpectedly changed without the agent causing it.

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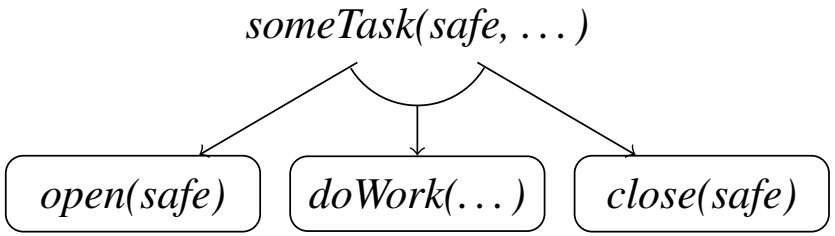

Consider an execution error after opening the safe but before closing it. What happens?

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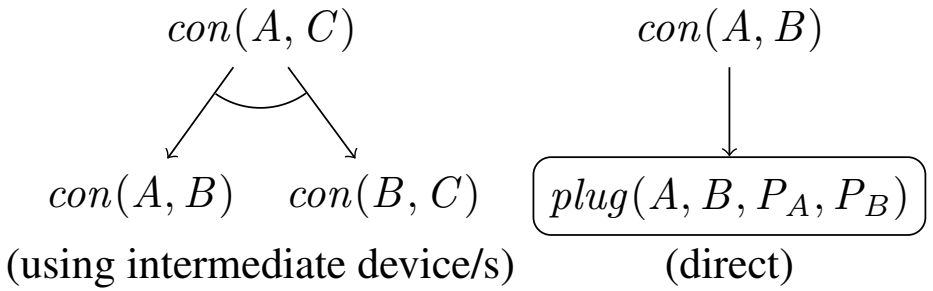

Here, the signal flow is modeled via the hierarchy, not the state.
What happens with replanning?

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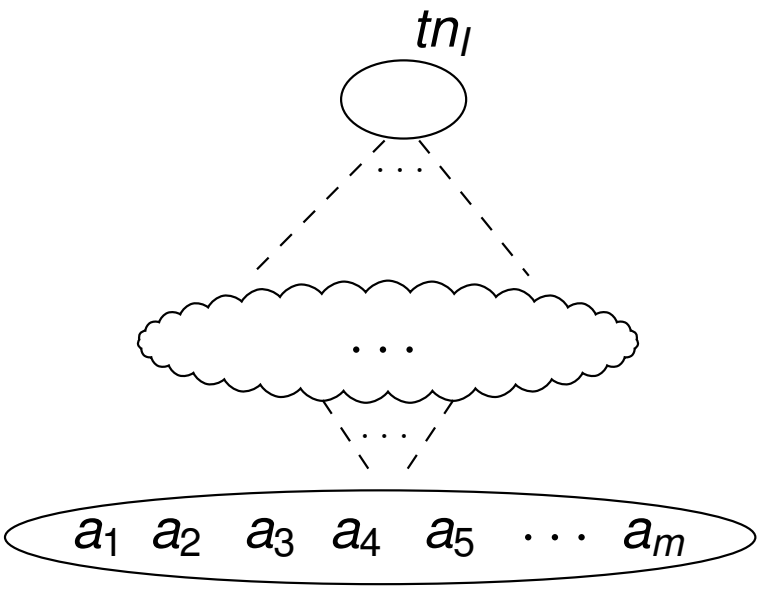
  - it produces exactly the unforeseen state changes.

Plan Repair as Planning



$a_1, \ldots, a_m$ is the solution found.

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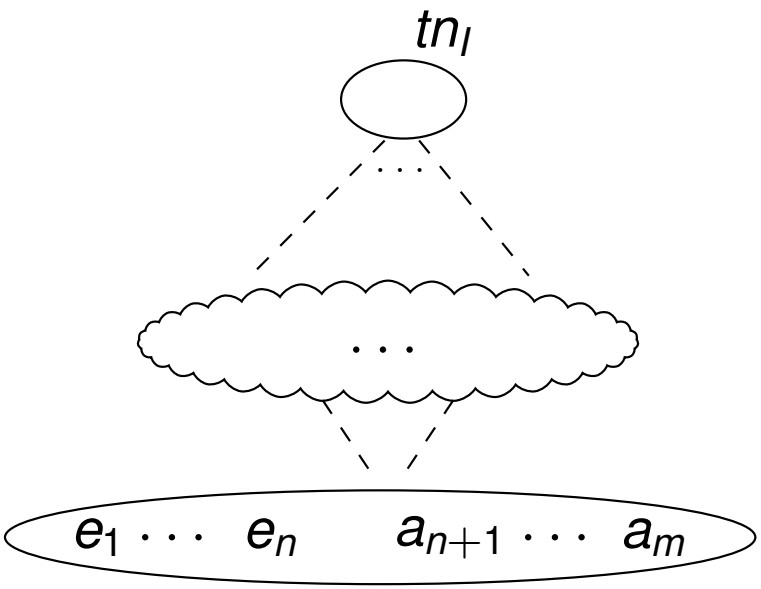

$e_1, \ldots, e_n = a_1, \ldots, a_n$ are the action already *executed* before the failure.

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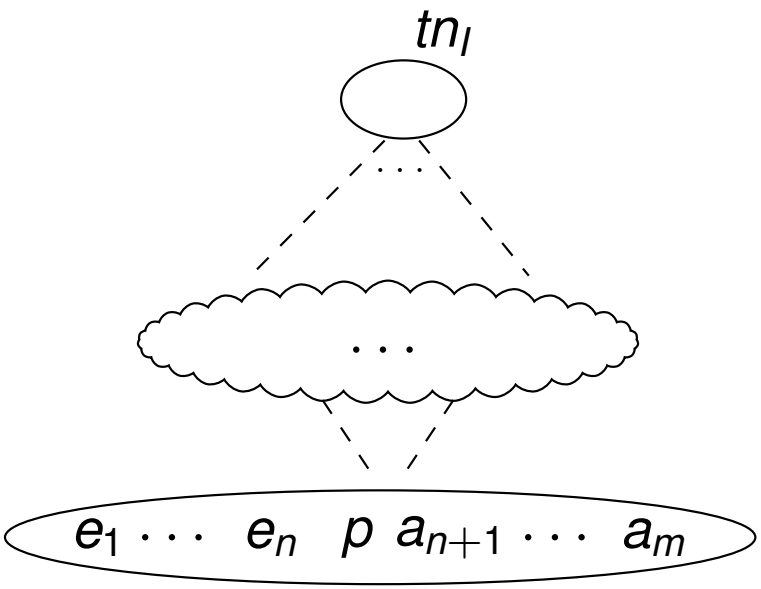

p is the novel *process* action encoding the state space.

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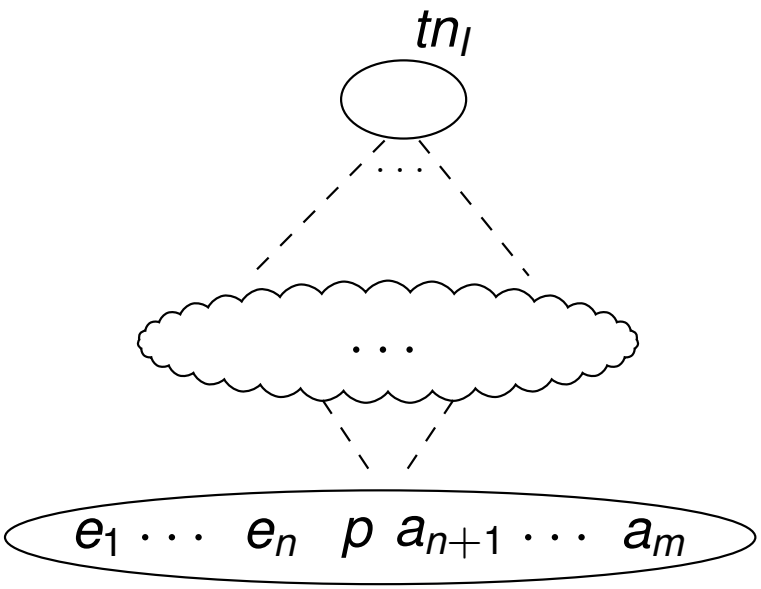

However, to keep it simpler, we do not represent the process p with a novel action but instead add all its effects to the action a_n. Then, define $e_1, \ldots, e_n$ as the observed action from plan recognition and solve the plan recognition problem with tn as the single possible goal (task) network.

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  - to use existing standard heuristics without adapting them to the repair setting.

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  - In which order to convey the actions? ($\rightarrow$ Plan linearization, see next section)

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We now assume that the (original) input is given in a *lifted* fashion, e.g.:

describes a *ground instance* of a primitive action used to plugin a CINCH cable in an AV-Receiver to establish an audio signal.

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So, how to convey it to a user?

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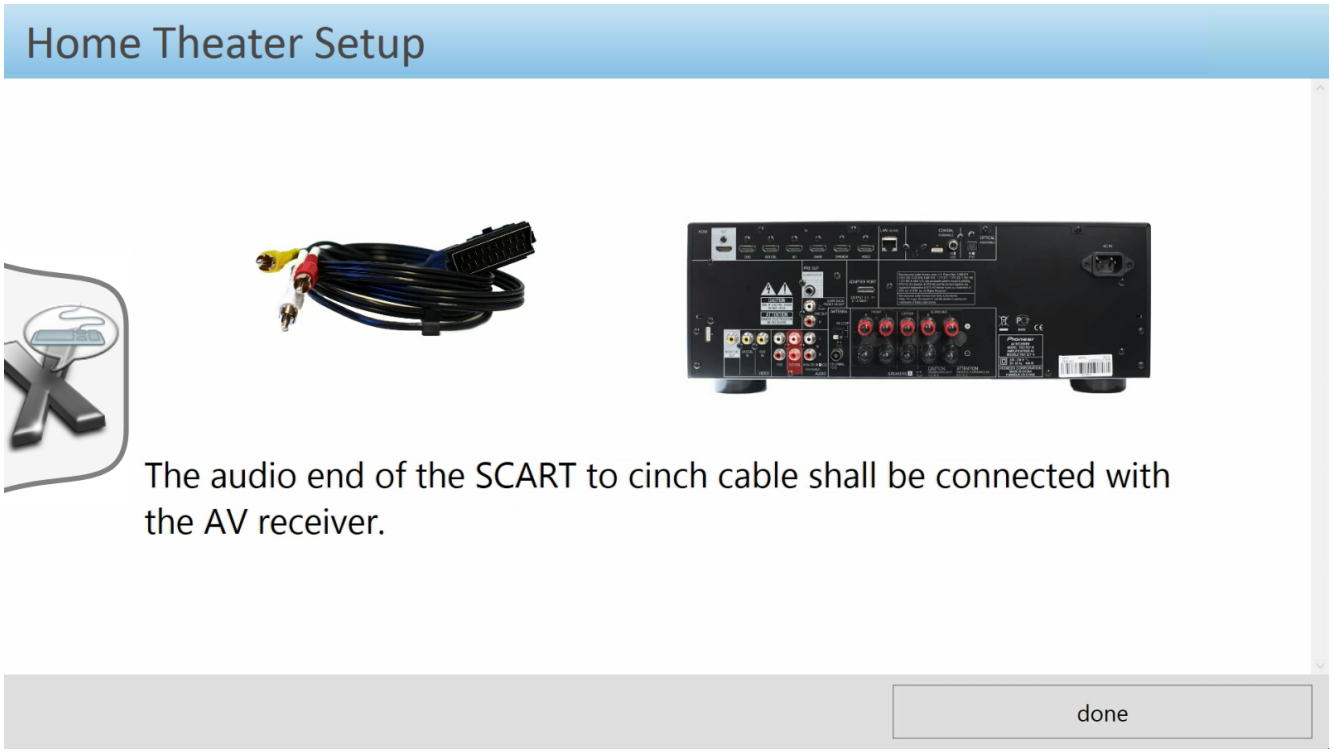
- Use pictures and/or videos to illustrate the involved objects., e.g.



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  - There are extensions in which abstract tasks have effects as well, see next lecture.
  - When we want to convey abstract tasks, we need to re-infer such abstract tasks from the solution.

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- It is obviously decidable whether such a linearization of abstract tasks exists, because the decomposition tree is finite.

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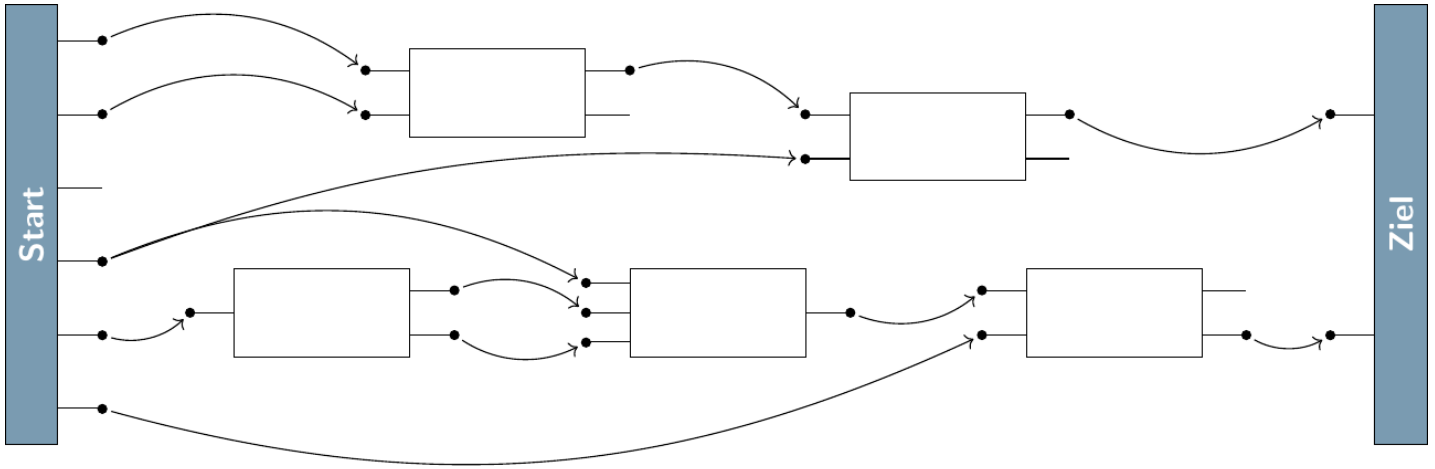
- Note: This question is *also* relevant in case we convey abstract tasks.

User-Friendly Plan Linearizations, Motivation

Which linearizations are well-suited for human users?



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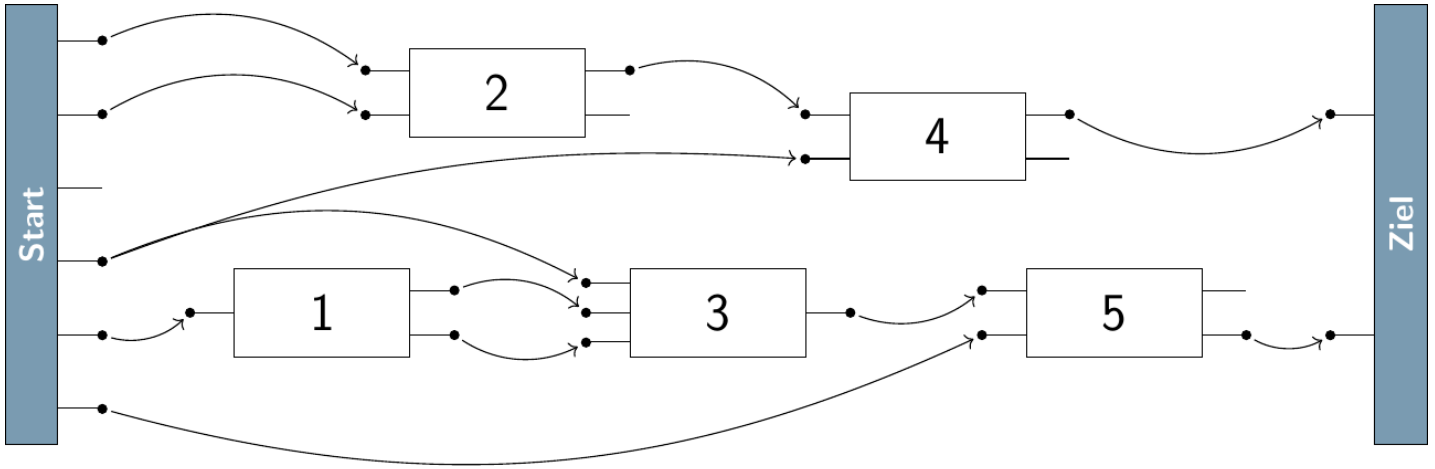

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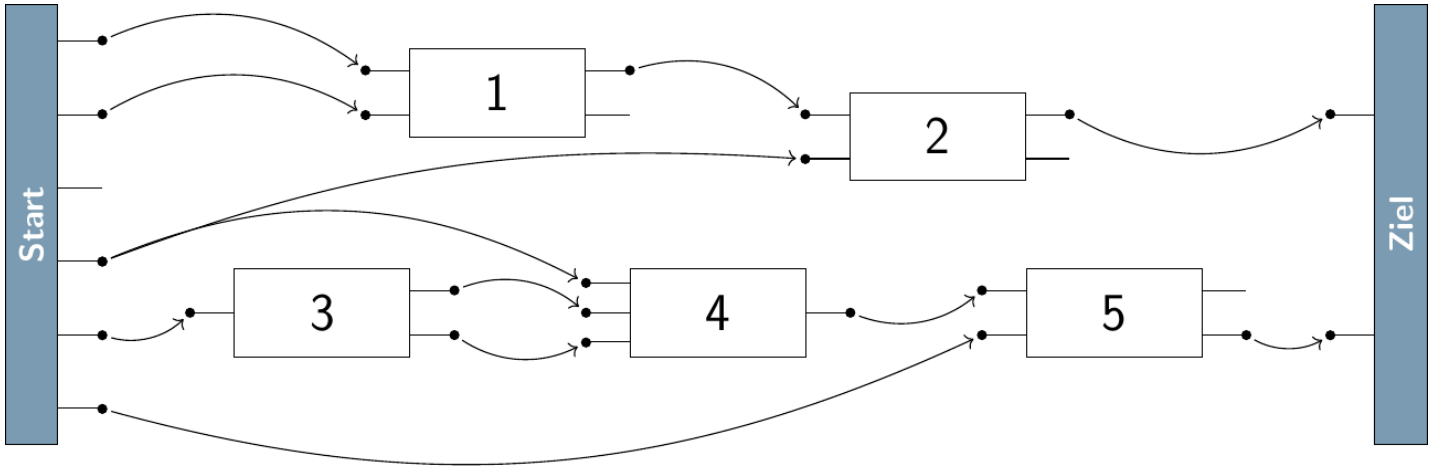

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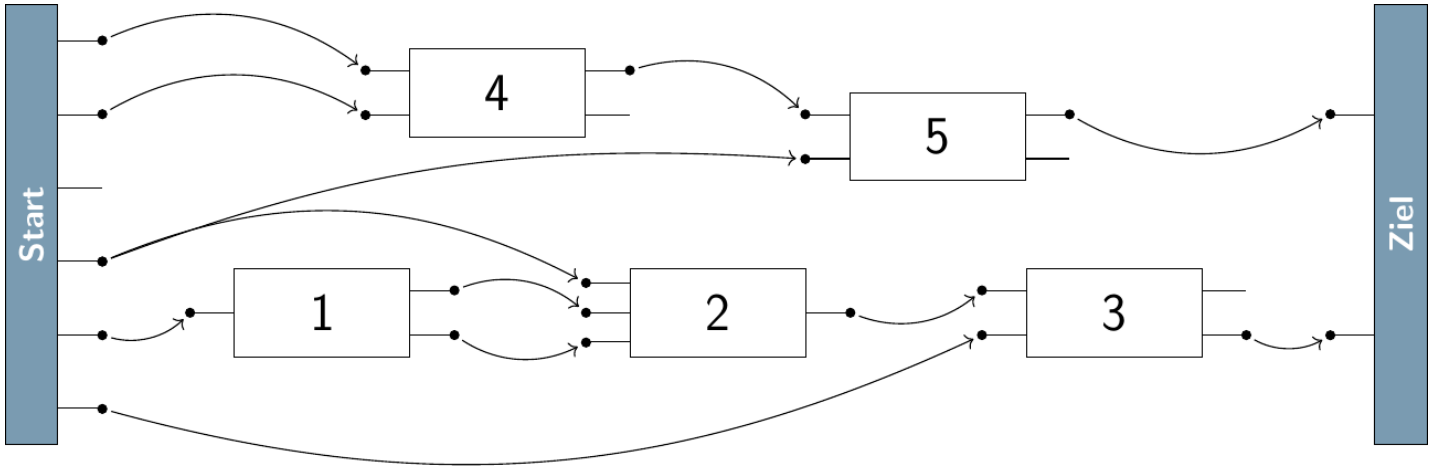

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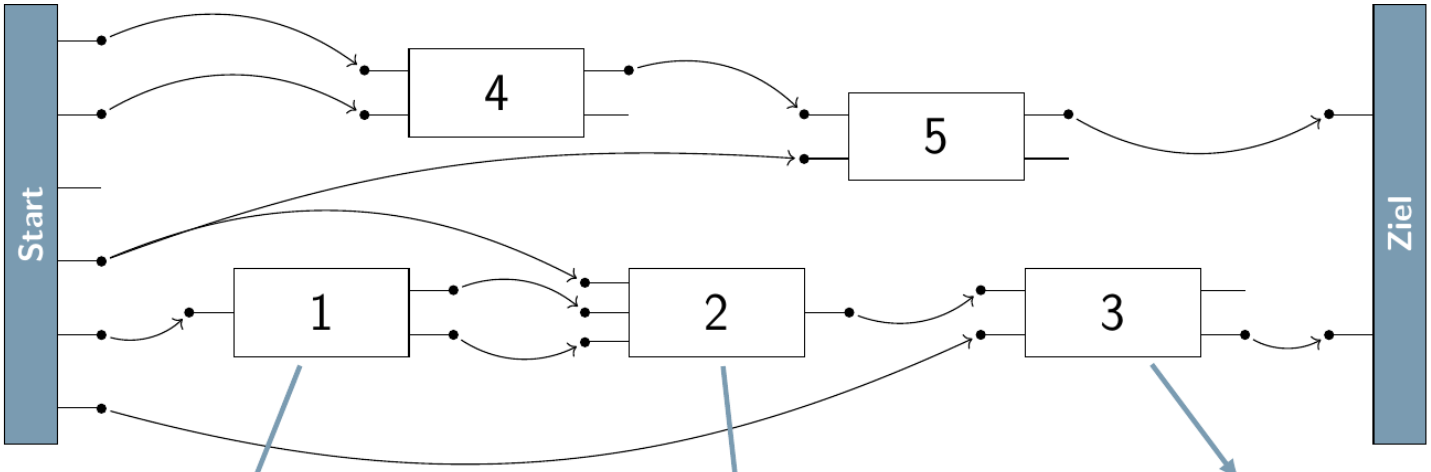

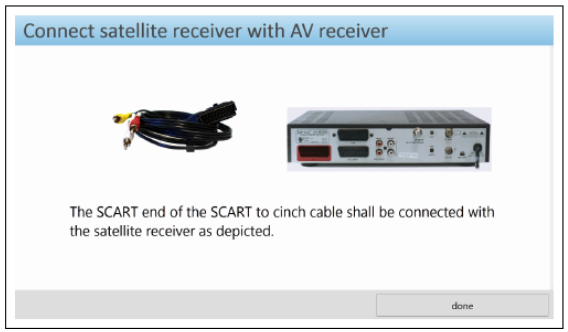

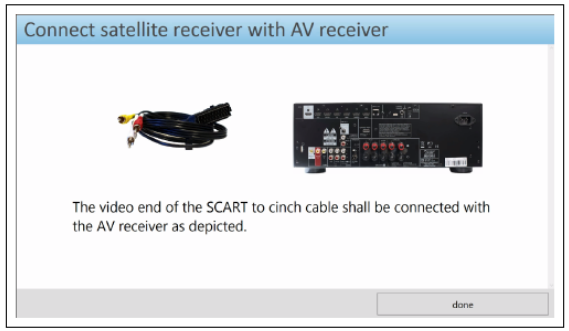

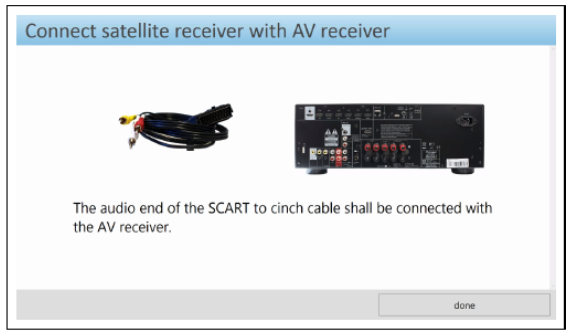

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- Number of identical constants:
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- Number of shared causal links:
  Perform actions that are causally related to each other.

Parameter-based Linearization Strategy

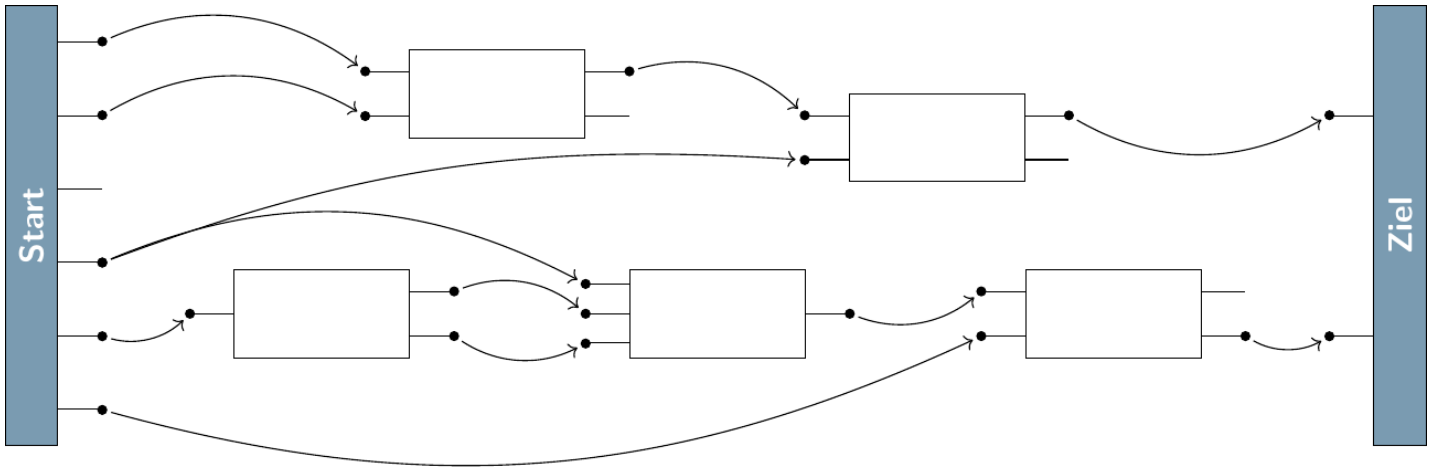
Reasoning behind using parameters for linearization:

- Actions represent activities to do.
- Parameters introduce the items/objects/subjects to use.

$\rightarrow$ execute actions involving the same parameters consecutively.

Parameter-based Linearization Strategy, Illustrating Example

Solution plan (schematically, with causal structure)



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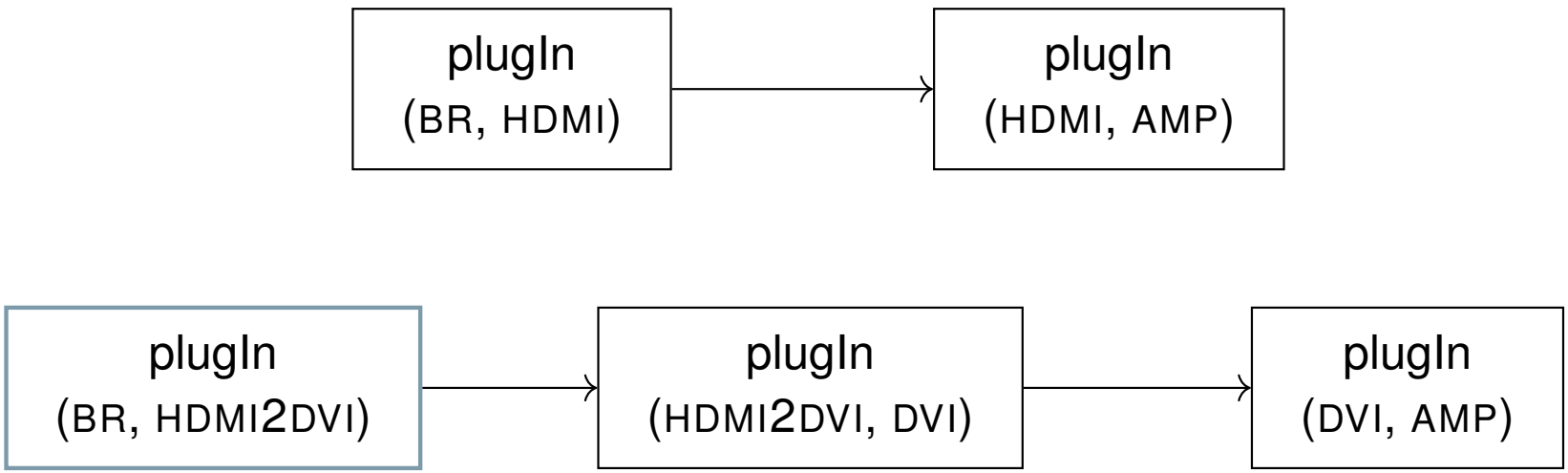
Solution plan (ordering constraints, action schemata)



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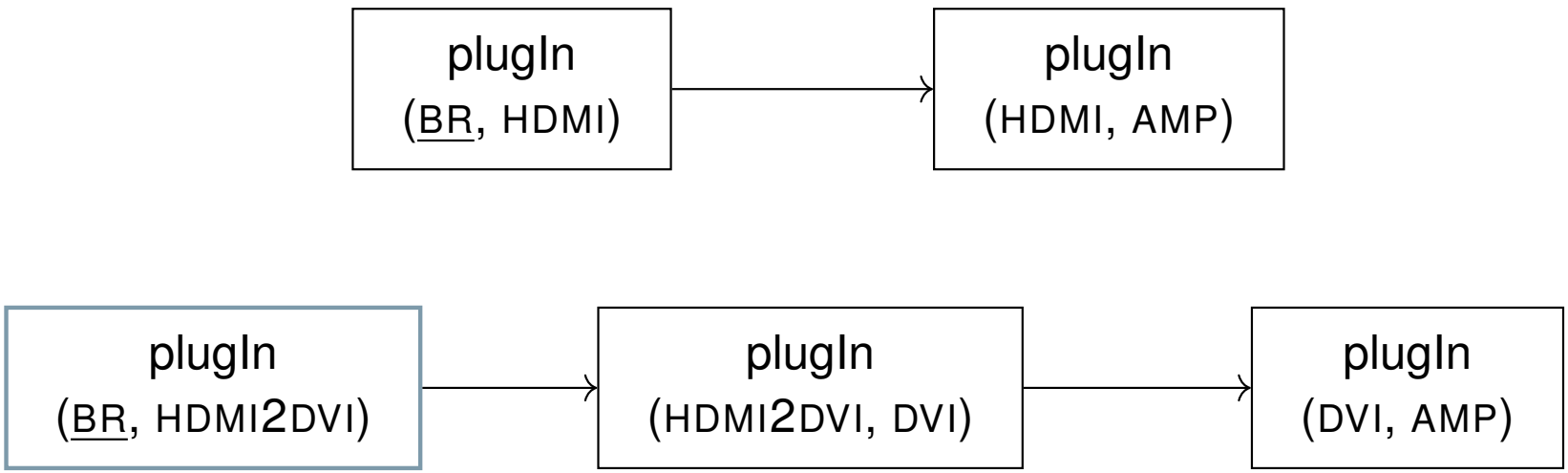

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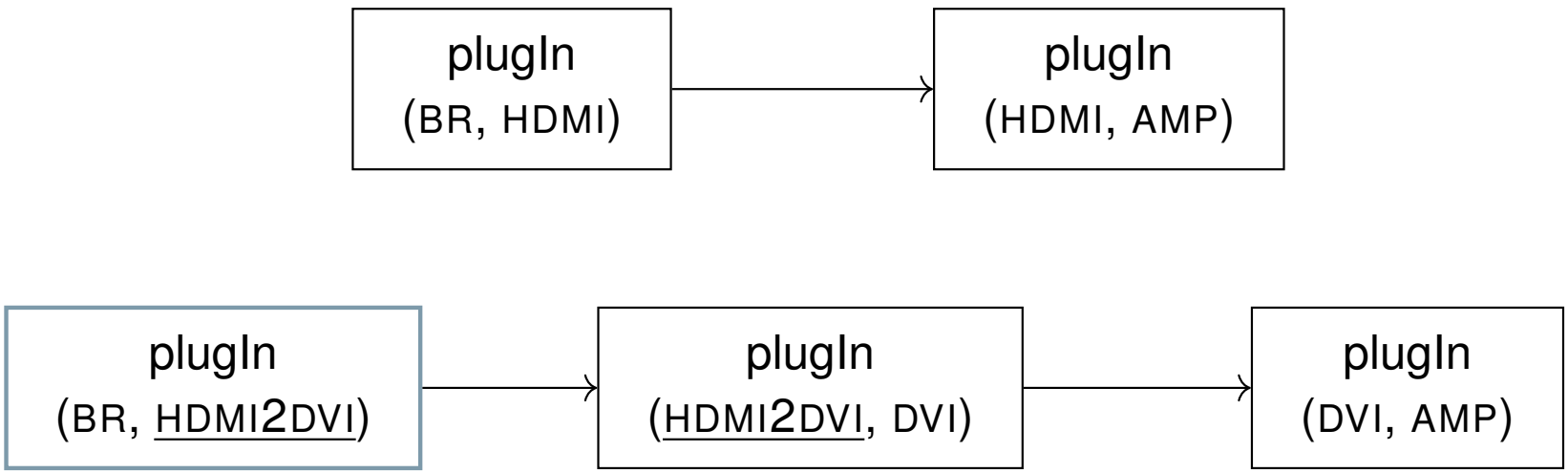
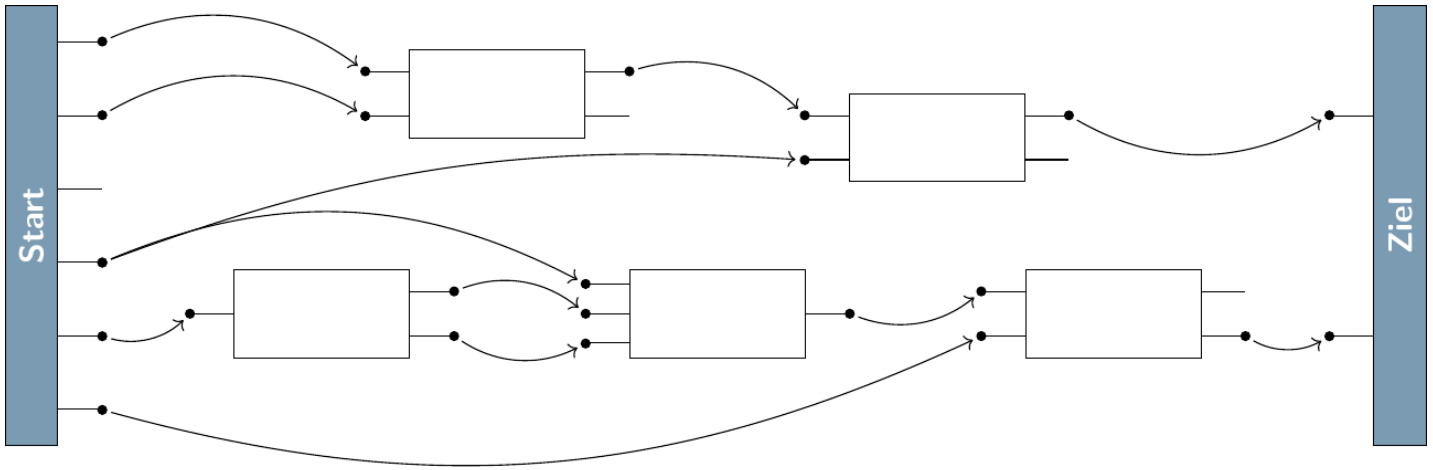


Causal Link-based Linearization Strategy

Reasoning behind using causal links for linearization:

- Causal links explicitly represent the causal dependencies between actions.
- Each link was introduced for a reason – all links are required.

→ Execute connected actions consecutively.



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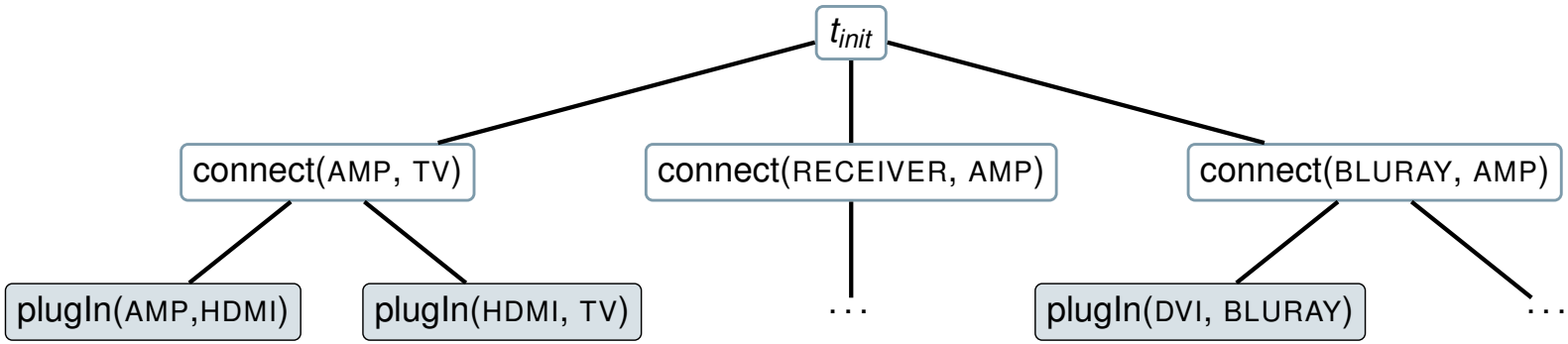

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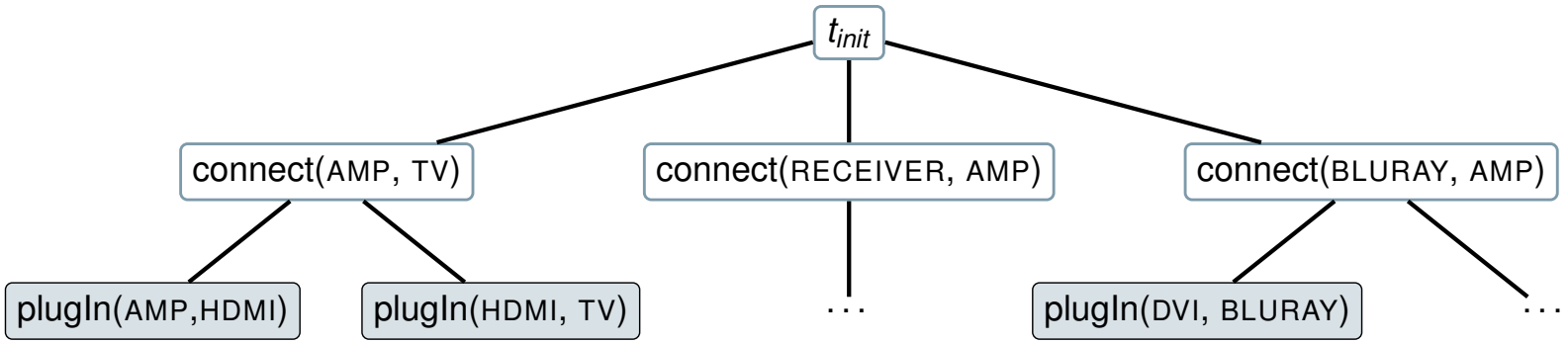

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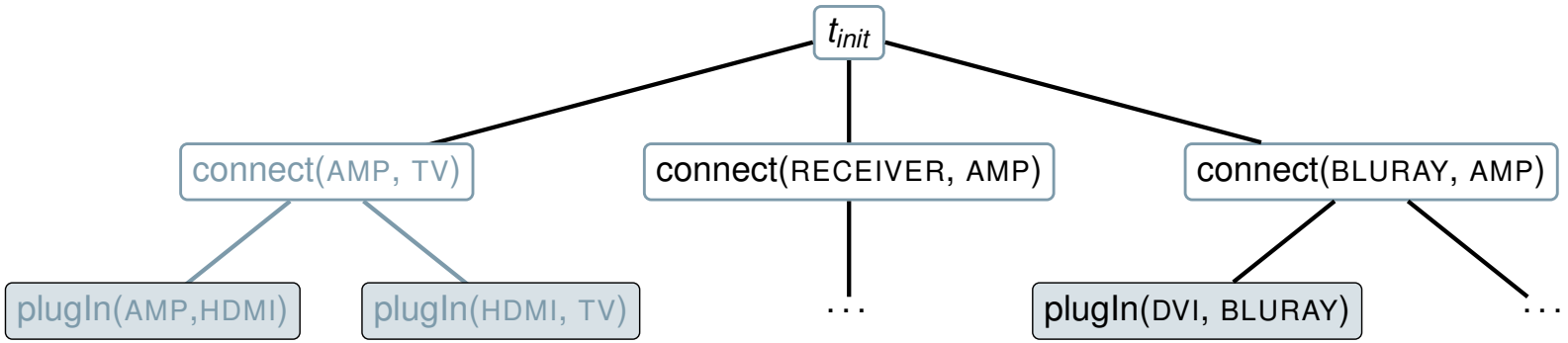

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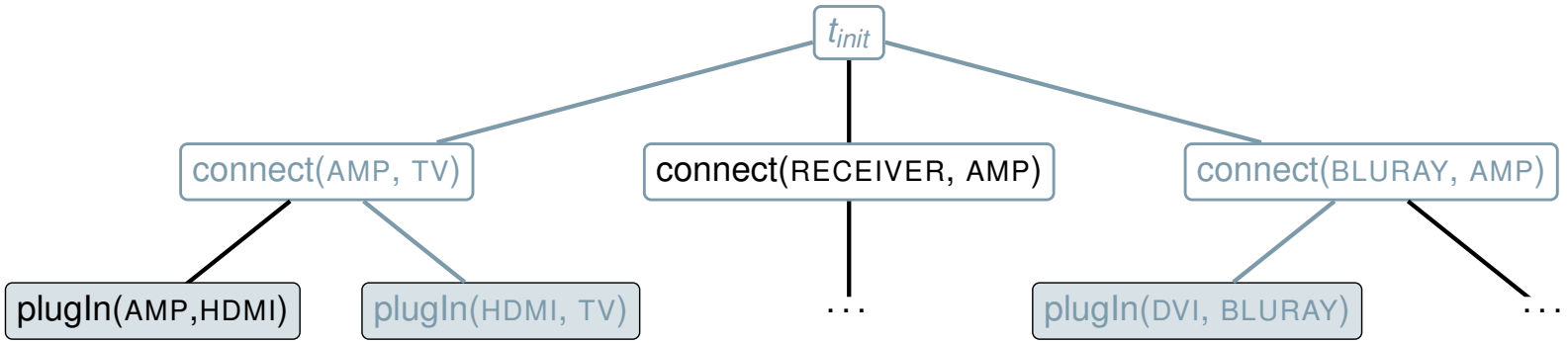

How closely to instruct plugIn(HDMI, TV) and plugIn(DVI, BLURAY) next to each other?

Formal Descriptions of Linearization Criteria

Formal descriptions of these three optimization criteria can be found in the following paper:

Daniel Höller et al. “Finding User-friendly Linearizations of Partially Ordered Plans”. In: *28th PuK Workshop ”Planen, Scheduling und Konfigurieren, Entwerfen” (PuK 2014)*. 2014

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$\rightarrow$ Just asking for *some justification* why a certain property holds is much easier!

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Both “explainable AI” and “explainable planning” became very prominent lately. Still, only a few approaches exist for planning:

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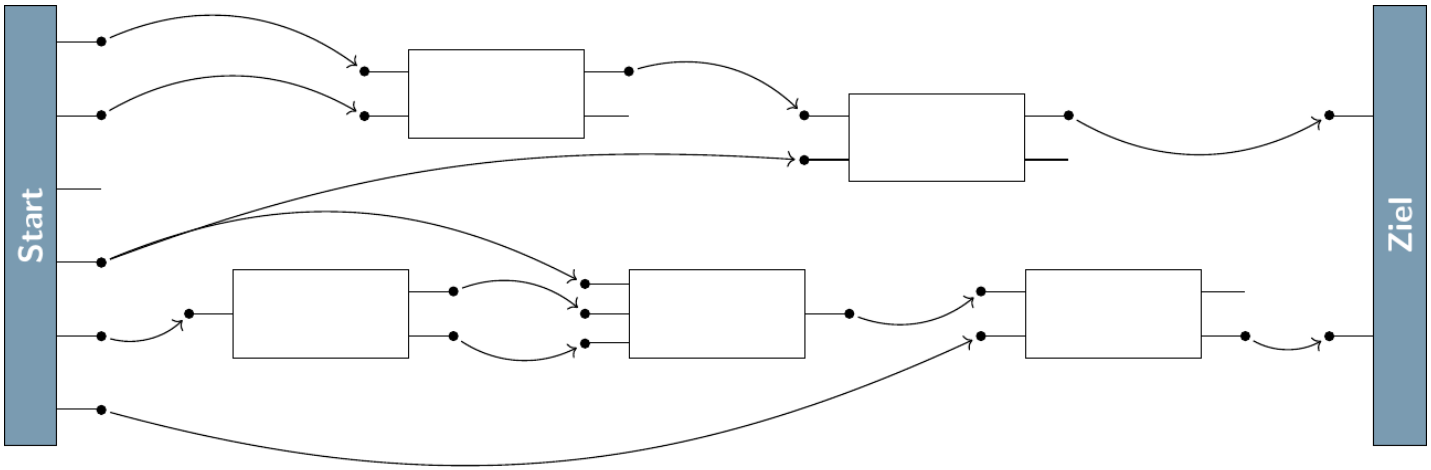
- Another approach considers “excuses” for failed plans:
  Given an unsolvable planning problem, it finds alternative initial states that allow for a solution. The performed alterations to the actual state are referred to as excuses.

Explanations for Plan Step Necessity

Question: *Why should I perform action X?*



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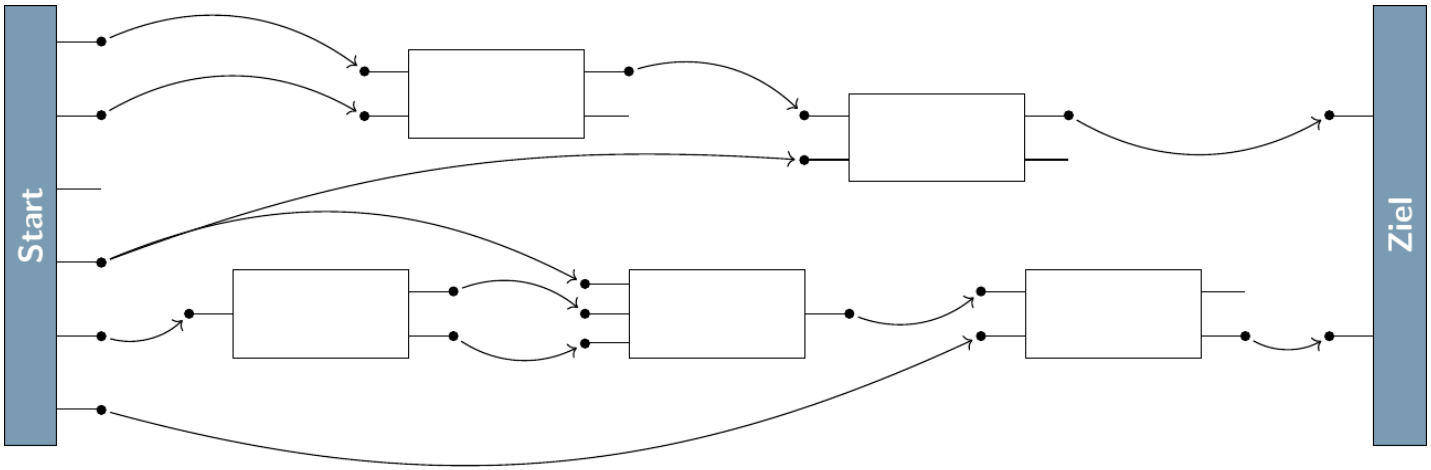

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- Exploit causality: X achieves effect x, which is necessary for action Y, which in turn achieves ...
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An example will be provided in the next section.

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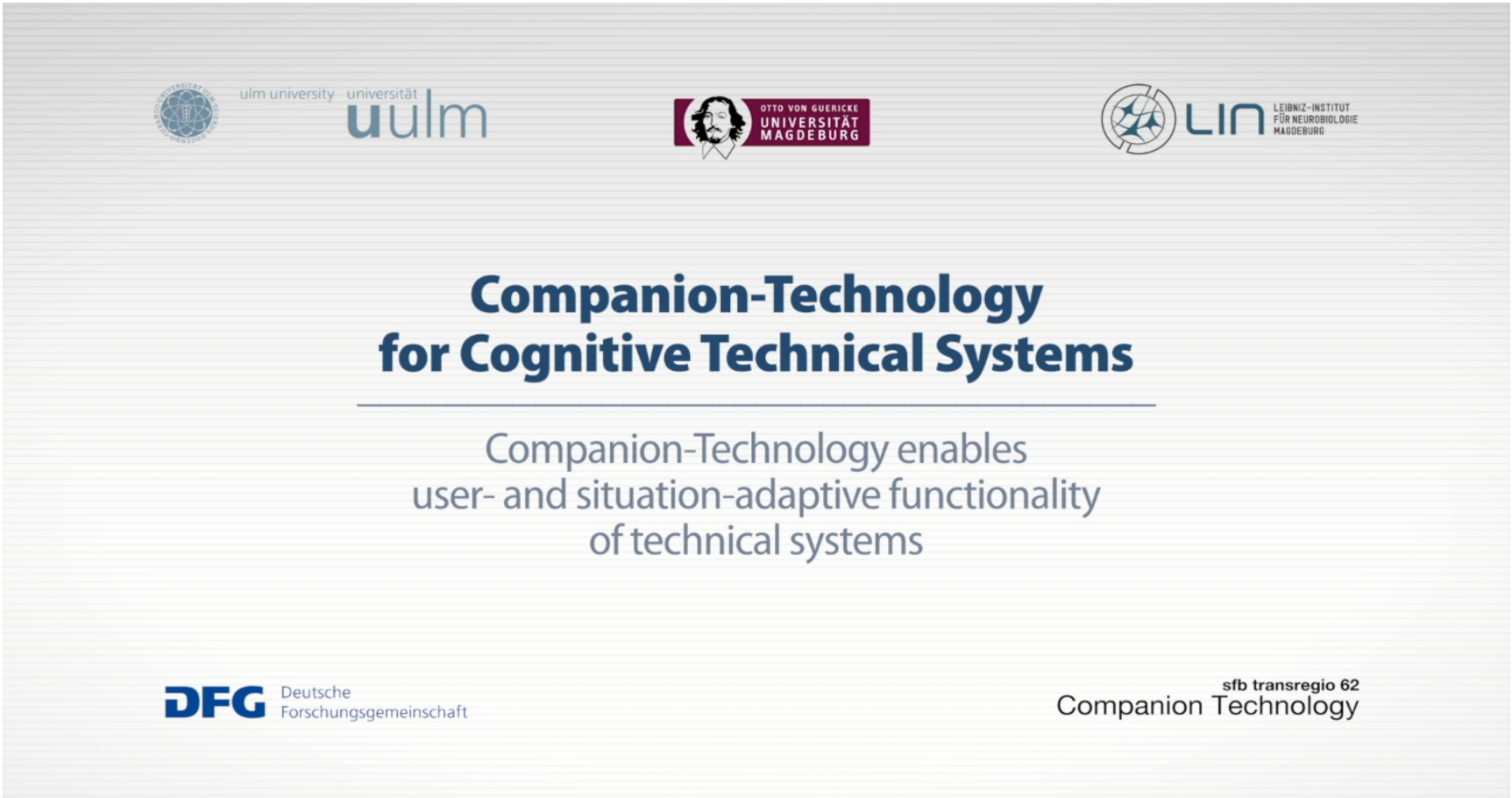
in a prototypical assistance system to assist in setting up a complex home theater.

Home Theater Assembly Assistant, Problem Setting

Four devices:

- Television (requires video)
- Blu-ray player
- Satellite receiver
- audio/video receiver (requires audio)

Home Theater Assembly Assistant, Complete Video



Video available at: `https://www.youtube.com/watch?v=Q25bGmFFc4U`

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  - And more (cf. first lecture)!

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- *Conveying plans.*
  - We showed how it can be done in a step-by-step (action-per-action) fashion.

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  - For this step-by-step presentation, we need to commit to an ordering ($\rightarrow$ plan linearization).

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