Automated Planning Tools for Intelligent Decision Making

3. AI Planning, Part II: Planners and Extensions

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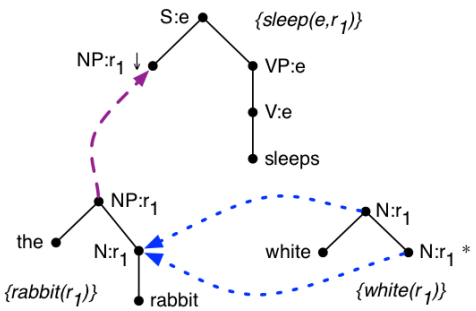
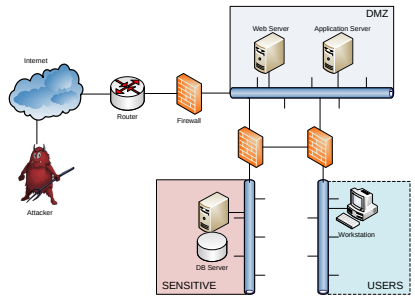
Agenda

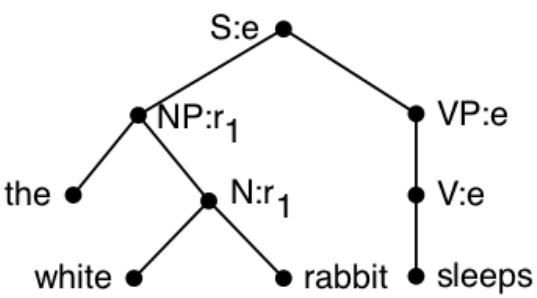
Planning

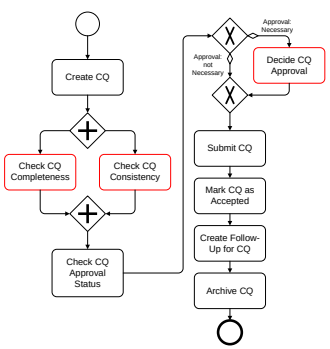


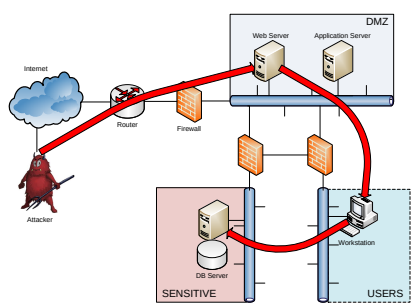
Action name	precondition	effect
Check CQ Completeness	CQ.archiving:notArchived	CQ.completeness:complete OR CQ.completeness:notComplete
Check CQ Consistency	CQ.archiving:notArchived	CQ.consistency:consistent OR CQ.consistency:notConsistent
Check CQ Approval Status	CQ.archiving:notArchived AND CQ.approval:notChecked AND CQ.completeness:complete AND CQ.consistency:consistent	CQ.approval:necessary OR CQ.approval:notNecessary
Decide CQ Approval	CQ.archiving:notArchived AND CQ.approval:necessary	CQ.approval:granted OR CQ.approval:notGranted
Submit CQ	CQ.archiving:notArchived AND (CQ.approval:notNecessary OR CQ.approval:granted)	CQ.submission:submitted
Mark CQ as Accepted	CQ.archiving:notArchived AND CQ.submission:submitted	CQ.acceptance:accepted
Create Follow-Up for CQ	CQ.archiving:notArchived AND CQ.acceptance:accepted	CQ.followUp:documentCreated
Archive CQ	CQ.archiving:notArchived	CQ.archiving:archived



Planning Domain Definition Language (PDDL) $\mapsto$ Planning System







STRIPS Planning: Syntax

Definition (STRIPS Planning Task). *A STRIPS planning task, short planning task, is a 4-tuple $\Pi = (P, A, I, G)$ where:*

- P *is a finite set of facts (aka propositions).*
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Note: We assume unit costs for simplicity: every action has cost 1.

PDDL

- Action-centric language:
  - Preconditions: when can actions be executed
  - Effects: how actions affect the world

Open Discussion

- Homework: Round of Discussion

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- What are your first impressions? UPAAL, ILP, PDDL

The International Planning Competition (IPC)

Competition?

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- 1998, 2000, 2002, 2004, 2006, 2008, 2011, 2014, 2018
- PDDL [McDermott *et al.* (1998); Fox and Long (2003); Hoffmann and Edelkamp (2005); Gerevini *et al.* (2009)]
- ≈ 70 domains, > 1500 instances, 74 planning systems in 2011
- Optimal track vs. satisficing track
- Various others: uncertainty, learning, ...

`http://ipc.icaps-conference.org/`

PDDL Support

List of PDDL features (sorted by how well are they supported by current planners):

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Modelling Advice: Use the simpler model possible

How (most) planners work?

Why? Is this relevant for the user?

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Two phases:

- Preprocessing (Grounding)
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- Search
  →Finds an (optimal) plan

Grounding

PDDL:

```
(:predicates
   (at ?t - truck ?l - loc)
)

(:action drive
   :parameters  (?t - truck ?l1 - loc ?l2 - loc)
   ...
)
```

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Grounded Representation (Strips):

```
(at truck1 Aalborg) (at truck1 Aarhus) (at truck1 Copenhagen)
(at truck2 Aalborg) (at truck2 Aarhus) (at truck2 Copenhagen)
...

(drive truck1 Aalborg Aarhus) (drive truck1 Aarhus Aalborg)
(drive truck1 Aarhus Copenhagen) ...
```

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PDDL:

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(:predicates
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(drive truck1 Aarhus Copenhagen) ...
```

→Size of the grounded representation is much bigger than the original PDDL (exponential in the number of parameters of predicates and action schemas)

Grounding: Finite-domain variables

(at truck1 Aalborg) (at truck1 Aarhus) (at truck1 Copenhagen)

What have these three facts in common?

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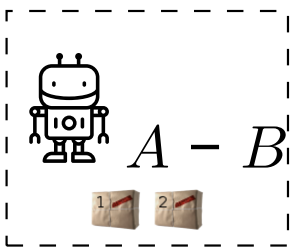
Most planners use finite-domain variables internally (instead of only Boolean).

Example: Variable at-truck1 has 3 values: Aalborg, Aarhus, Copenhagen

History of Planning Algorithms

- Compilation into Logics/Theorem Proving: (popular: Stone Age – 1990)
- Partial-Order Planning: (popular: 1990 – 1995)
- GraphPlan: (popular 1995 – 2000)
- Planning as SAT: (popular 1996 – today)
- Planning as Heuristic Search: (popular 1996 – today)
- Planning as Symbolic Search (with BDDs): (popular 2000 – today)

How to solve planning tasks? Search!



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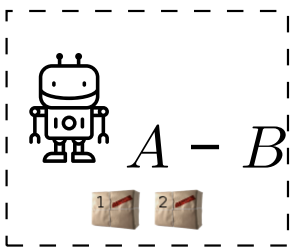

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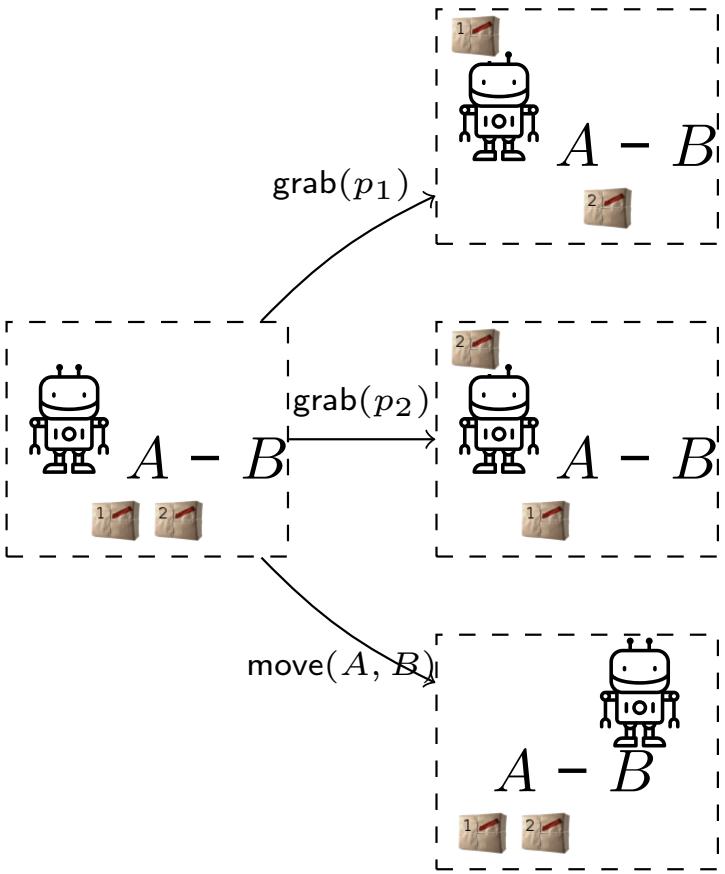

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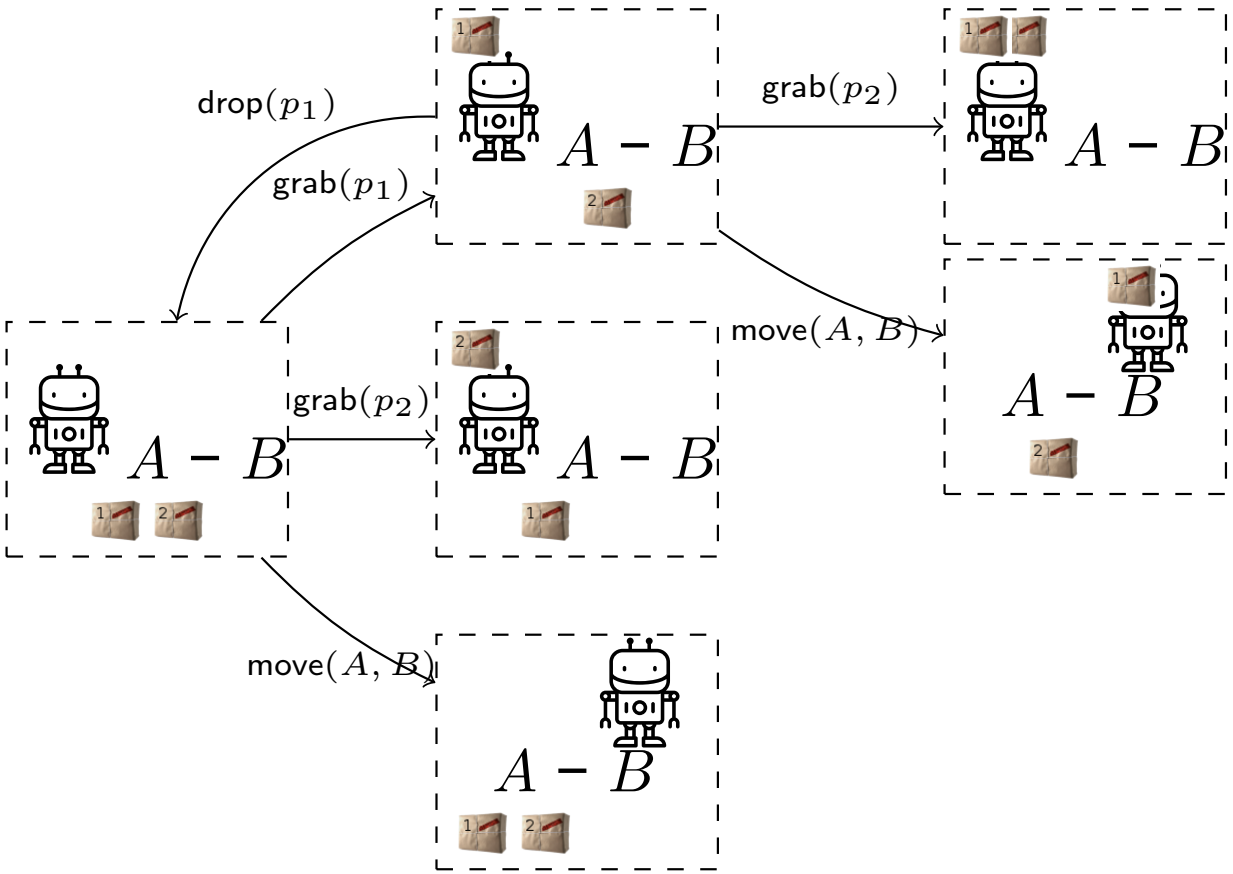
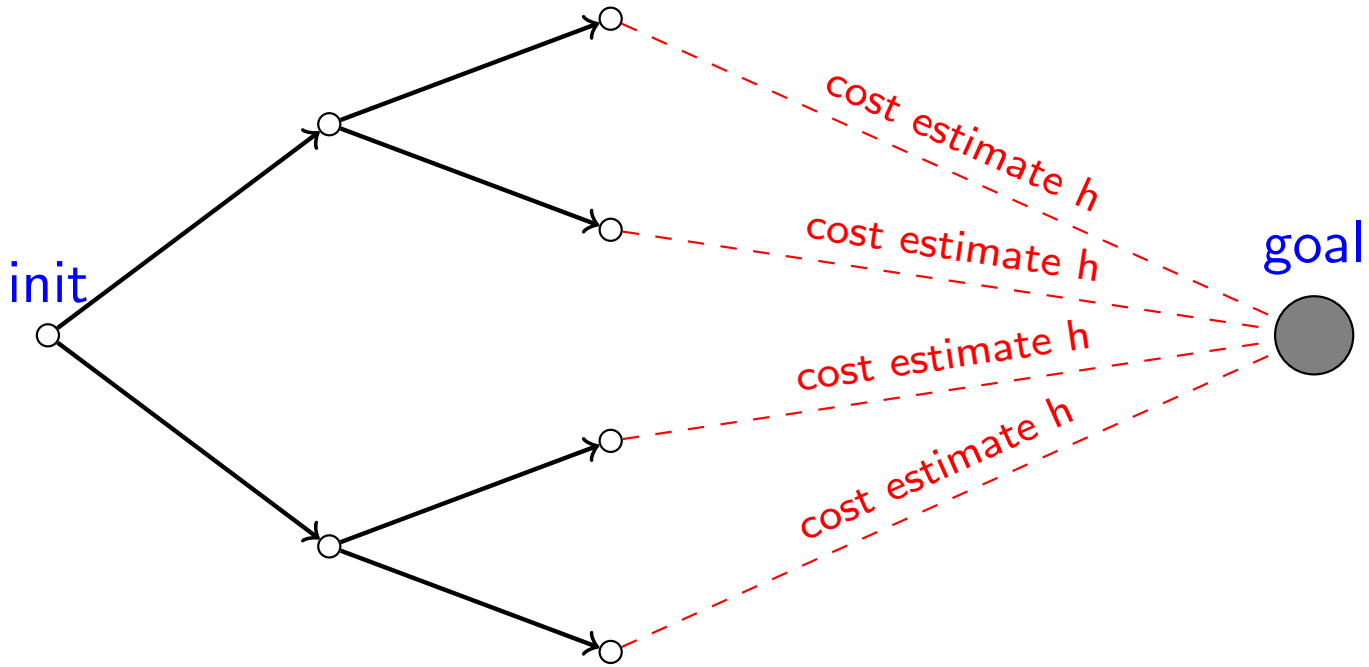


Heuristic Search



$\rightarrow$ Heuristic function h estimates the cost of an optimal path from a state s to the goal; search prefers to expand states s with small $h(s)$.

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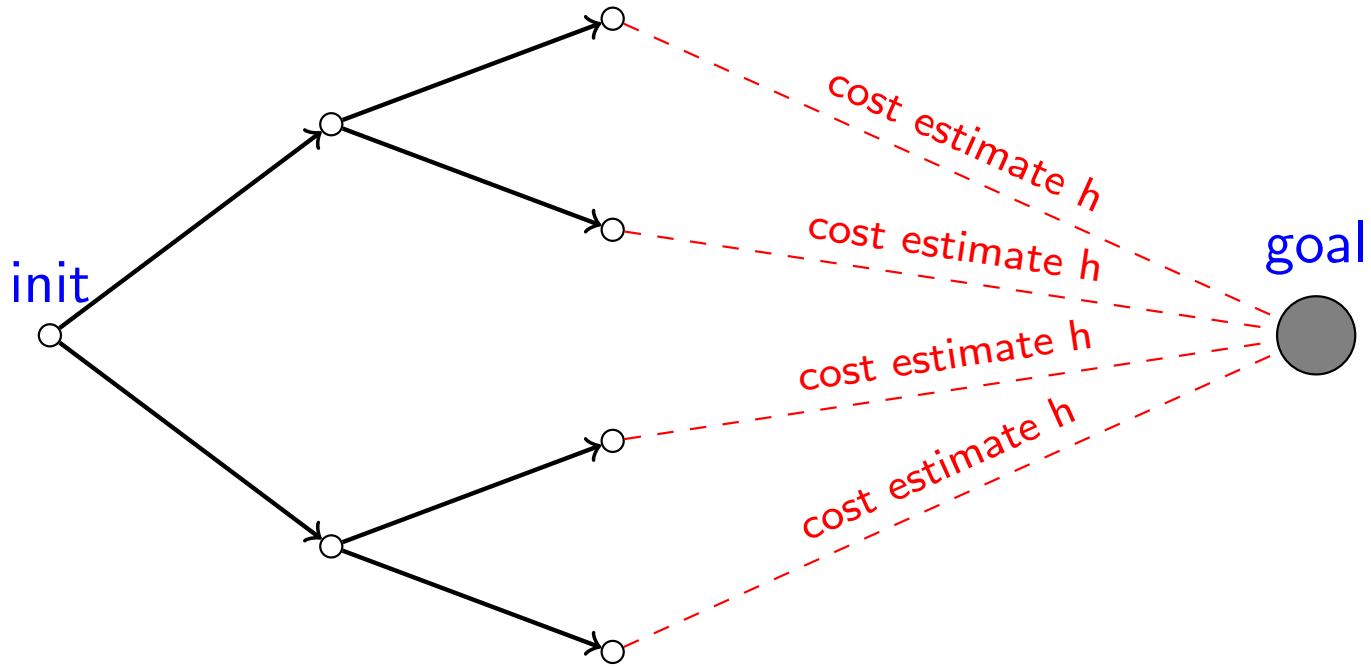

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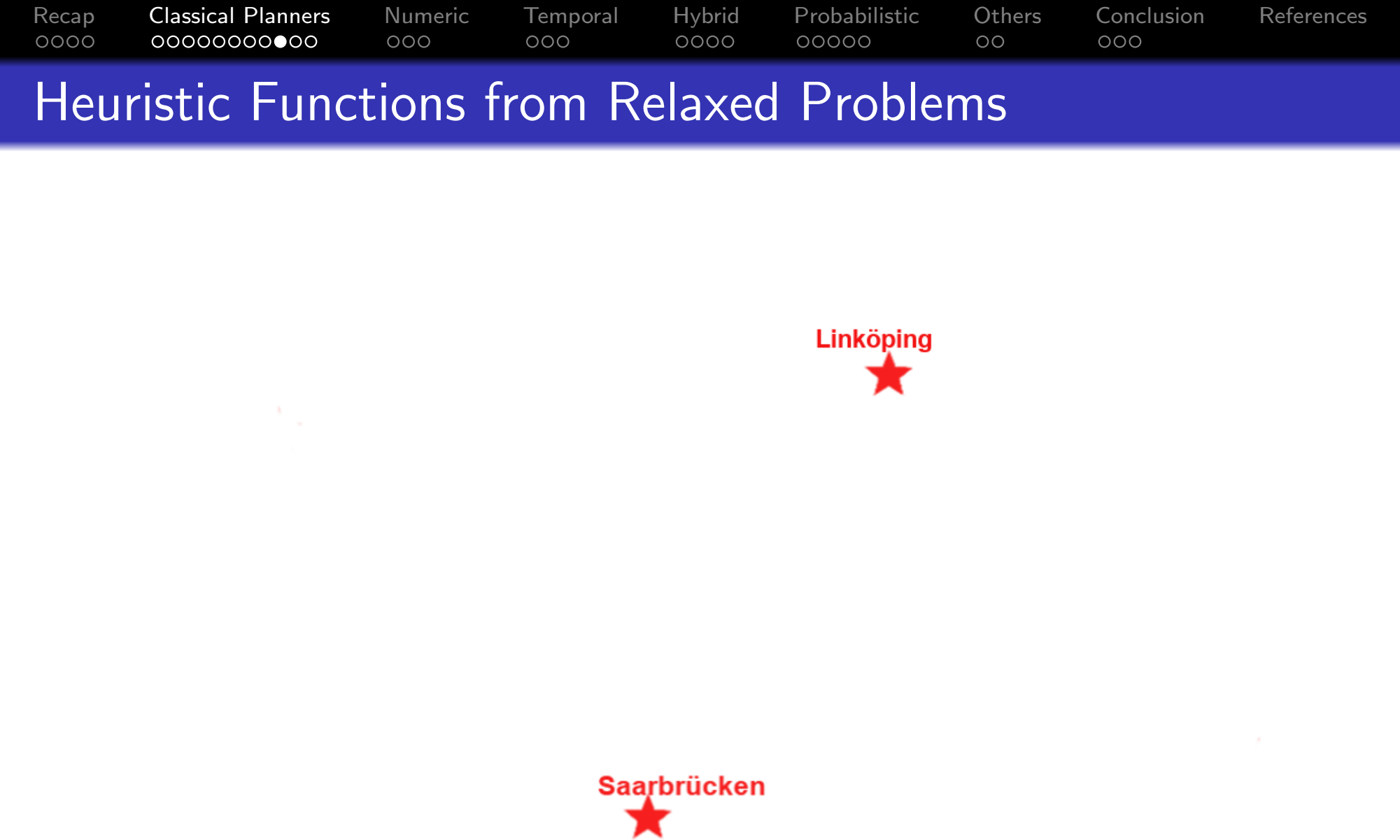
Live Demo vs. Breadth-First Search:

`http://qiao.github.io/PathFinding.js/visual/`

Heuristic Functions from Relaxed Problems

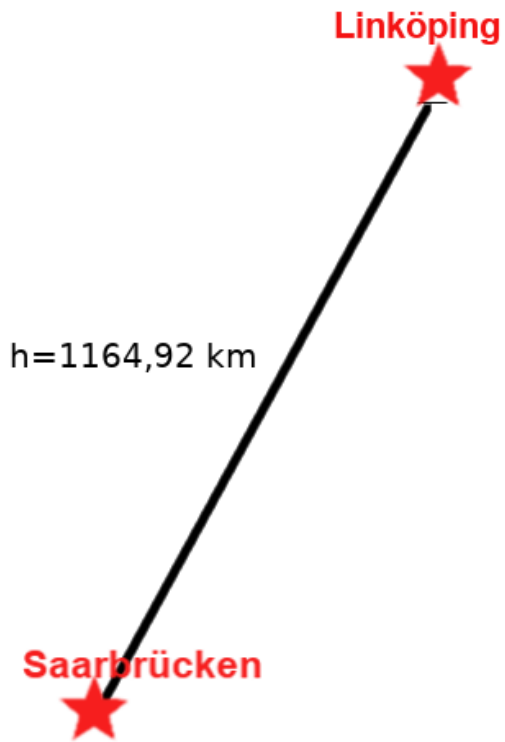
Problem II: Find a route from Saarbruecken To Edinburgh.

Heuristic Functions from Relaxed Problems



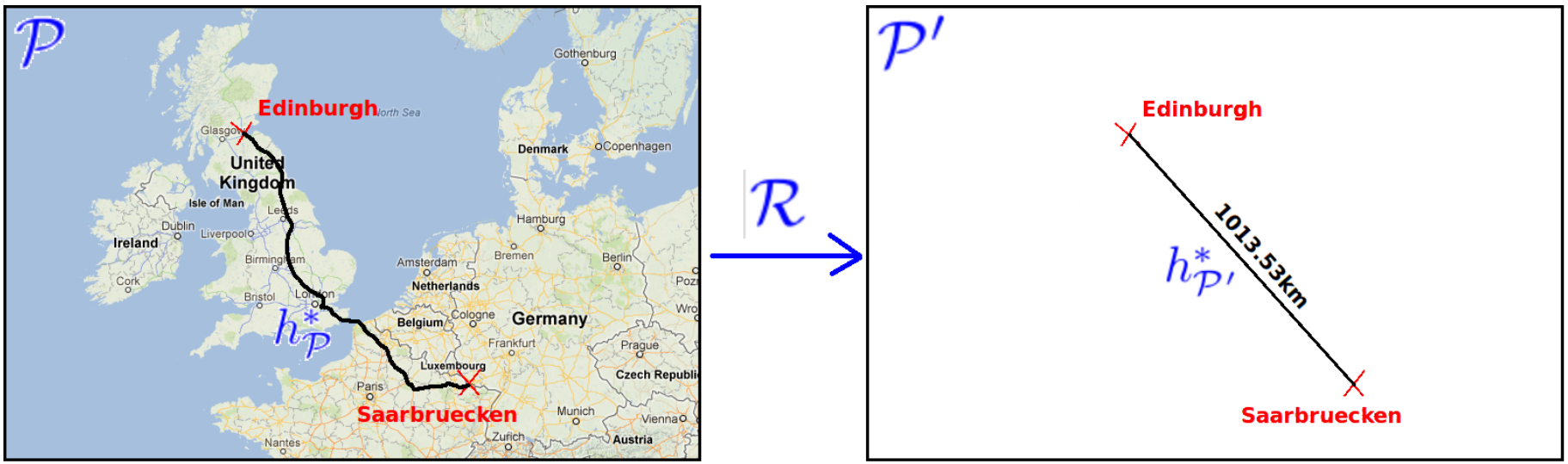
Relaxed Problem Π': Throw away the map.

Heuristic Functions from Relaxed Problems



Heuristic function h: Straight line distance.

Relaxation in Route-Finding



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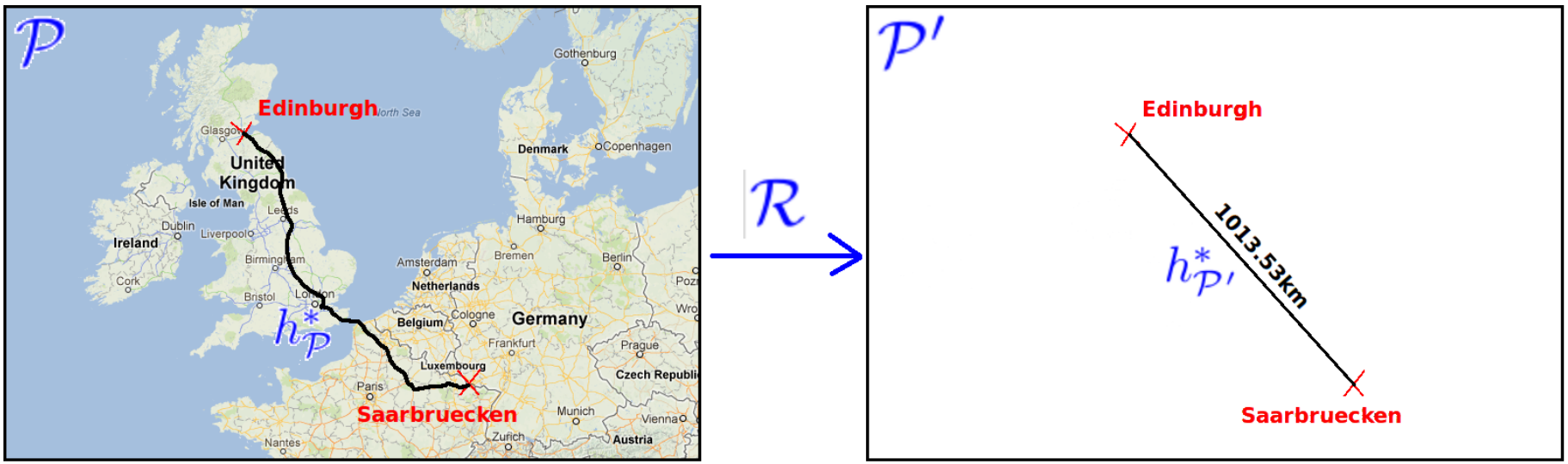

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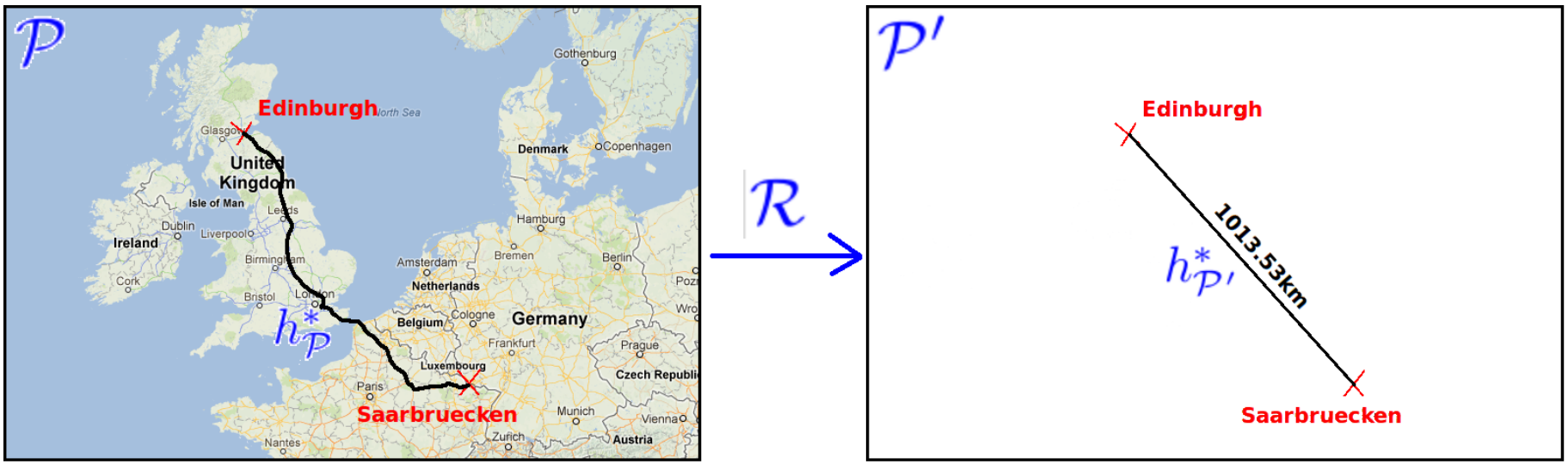

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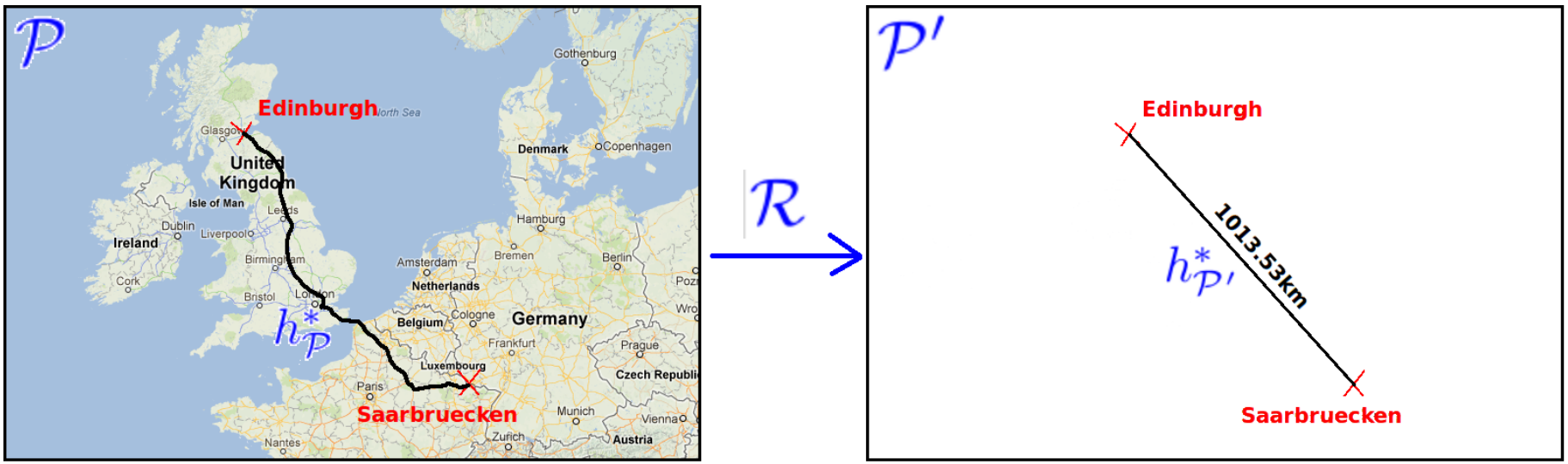

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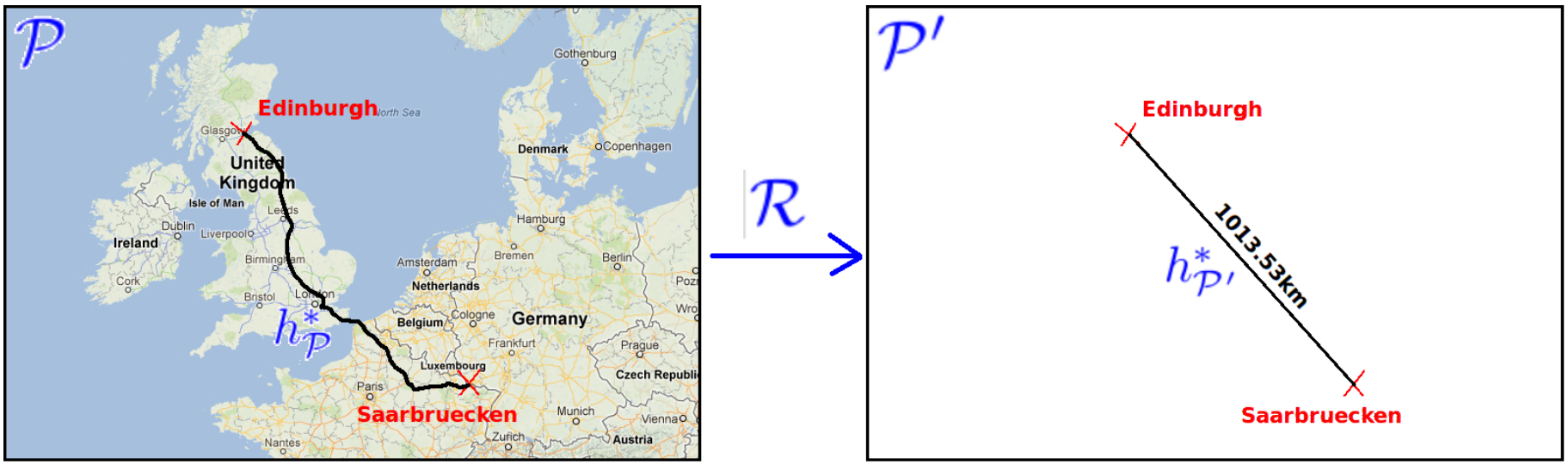

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5. Operator Counting
   $\rightarrow$Use LP methods to estimate how many actions need to be applied

Numeric Planning (PDDL 2.1)

In the real world: We have numbers!

Numeric STRIPS Planning: Extends STRIPS by introducing numeric variables V_n with rational values in $\mathbb{Q}$.

- Numeric expressions: We can do simple arithmetic $(+, -, \times, \div)$ with the values of variables and/or constants.

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ENHSP: (`https://sites.google.com/view/enhsp/`)

(examples in the next slides were taken from the ENHSP webpage)

Simple Linear Numeric Planning (Example)

```
(define (domain fn-counters)
    ;(:requirements :strips :typing :equality :adl)
    (:types counter)

    (:functions
        (value ?c - counter);; - int   ;; The value shown in counter ?
        (max_int);; -  int ;; The maximum integer we consider - a sta
    )

    ;; Increment the value in the given counter by one
    (:action increment
        :parameters (?c - counter)
        :precondition (and (<= (+ (value ?c) 1) (max_int)))
        :effect (and (increase (value ?c) 1))
    )

    ;; Decrement the value in the given counter by one
    (:action decrement
        :parameters (?c - counter)
        :precondition (and (>= (value ?c) 1))
        :effect (and (decrease (value ?c) 1))
    )
)
```

Simple Linear Numeric Planning (Example)

```
(define (problem instance_4)
  (:domain fn-counters)
  (:objects
    c0 c1 c2 c3 - counter
  )

  (:init
    (= (max_int) 8)
        (= (value c0) 0)
        (= (value c1) 0)
        (= (value c2) 0)
        (= (value c3) 0)
  )

  (:goal (and
    (<= (+ (value c0) 1) (value c1))
        (<= (+ (value c1) 1) (value c2))
        (<= (+ (value c2) 1) (value c3))
  ))
)
```

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- POPF: `https://nms.kcl.ac.uk/planning/software/popf.html`
- Optic: `https://nms.kcl.ac.uk/planning/software/optic.html`
- IBaCOP: `https://icenamor.github.io/portfolio/Temporal/`

Temporal Planning (Example Fox and Long (2003))

```
(:durative-action heat-water
   :parameters (?p - pan)

   :duration (= ?duration (/ (- 100 (temperature ?p)) (heat-rate)))

   :condition (and (at start (full ?p))
                   (at start (onHeatSource ?p))
                   (at start (byPan))
                   (over all (full ?p))
                   (over all (onHeatSource ?p))
                   (over all (heating ?p))
                   (at end (byPan)))

   :effect (and (at start (heating ?p))
                (at end (not (heating ?p)))
                (at end (assign (temperature ?p) 100)))
           )
```

Temporal Planning (Example Fox and Long (2003))

We can also encode continuous effects:

```
(:durative-action heat-water
   :parameters (?p - pan)

   :duration ()

   :condition (and (at start (full ?p))
                   (at start (onHeatSource ?p))
                   (at start (byPan))
                   (over all (full ?p))
                   (over all (onHeatSource ?p))
                   (over all (heating ?p))
                   (over all (<= (temperature ?p) 100))
                   (at end (byPan)))

    :effect (and (at start (heating ?p))
                 (at end (not (heating ?p)))
                  (increase (temperature ?p) (* #t (heat-rate))))
)
```

Hybrid Planning (PDDL +)

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- ENHSP: `https://sites.google.com/view/enhsp/`
- SMTPlan: `http://kcl-planning.github.io/SMTPlan/`
- Dino: `http://kcl-planning.github.io/Dino/`

Example in the next slides from: `http://planning.wiki`

Hybrid Planning (Example)

```
(define (domain car_nonlinear_mt_sc)
 (:predicates (engine_running) (engine_stopped) )
 (:functions
    (d) (v) (a) (drag_coefficient) (max_speed)
    (max_acceleration) (min_acceleration) )

 (:constraint speed_limit
  :condition (and (>= (v) (* -1 (max_speed))) (<= (v) (max_speed))))

 (:process displacement
   :precondition (and (engine_running) (> (v) 0))
   :effect (increase (d) (* #t (v))))

 (:process moving_drag
  :precondition (engine_running)
   :effect (increase (v) (* #t (a)) )  ;; acceleration  )

 (:process drag_ahead
    :precondition (and (engine_running) (> (v) 0))
    :effect (decrease (v) (* #t (* (^ (v) 2) (drag_coefficient)
) ) ) ) )
```

Hybrid Planning (Example)

```
(:action accelerate
    :precondition (and (< (a) (max_acceleration)) (engine_running) )
    :effect (increase (a) 1.0)
)

(:action stop_car
 :precondition (and (> (v) -0.1) (< (v) 0.1) (= (a) 0.0) (engine_run
 :effect (and  (assign (v) 0.0)
               (engine_stopped)
               (not (engine_running))) )

(:action start_car
    :precondition (engine_stopped)
    :effect (and (engine_running)
                 (not (engine_stopped))))

(:action decelerate
    :precondition (and (> (a) (min_acceleration)) (engine_running))
    :effect (decrease (a) 1.0)
)
)
```

Hybrid Planning (Example)

```
(define (problem instance_1_300_01_100)
  (:domain car_nonlinear_mt_sc)

  (:init
    (= (d) 0.0)
       (= (v) 0.0)
       (engine_stopped)
       (= (a) 0.0)
       (= (max_acceleration) 1)
       (= (min_acceleration) -1)
       (= (drag_coefficient) 0.1)
       (= (max_speed) 10.0)
  )

  (:goal
    (and
       (>= (d) 29.5 )
       (<= (d) 30.5 )
       (engine_stopped)
       )
  )
)
```

Non-deterministic/Stochastic Environments

In the real world: we cannot always anticipate the effect of our actions!

Differences with respect to classical planning:

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Extensions of PDDL for Probabilistic Planning:

- PPDDL (next slide)
- RDDL (more general)

Probabilistic Planners:

- Prost: `https://github.com/prost-planner/prost`
- IPC: `https://ipc2018-probabilistic.bitbucket.io/`

PPDDL Example

```
(:action try-navigate-l1-l2
 :parameters (?hcur ?hnew - horizon-value ?x - rover)
 :precondition
  (and (horizon ?hcur)
       (horizon-decrement ?hcur ?hnew)
       (can_traverse ?x waypoint1 waypoint2)
       (available ?x)
       (at ?x waypoint1)
       (visible waypoint1 waypoint2)
       (road_isunknown road2))
:effect
   (and (not (horizon ?hcur))
        (horizon ?hnew)
        (increase (total-cost) 1)
        (not (road_isunknown road2))
        (probabilistic
           2/10 (and (road_isblocked road2))
           8/10 (and (road_isfree road2)
                     (not (at ?x waypoint1))
                     (at ?x waypoint2))
    ))
)
```

Online vs. Offline Planning

Given a non-deterministic/probabilistic planning task:
Offline Planning: Plan ahead for every possibility.

- Find contingent plan
- Find (optimal) policy

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Offline Planning: Plan ahead for every possibility.

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- Find (optimal) policy

Online Planning: Decide what to do next: spent some time deciding what action to execute, execute it, observe the result and re-plan if necessary.

Fully-Observable Non-Deterministic Planning (FOND Planning)

In the real world: we cannot always anticipate the effect of our actions! (without probabilities)

PRP:
`https://github.com/qumulab/planner-for-relevant-policies`

Planning Under Partial-Observability (POND)

In the real world: we do not know everything about the initial state! (without probabilities)

- Conformant Planning: A sequence of actions that works for all possible initial states
- Contingent Planning: We can have conditions along our plan

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- Conformant/Contingent-FF: `https://fai.cs.uni-saarland.de/hoffmann/cff.html`
- PO-PRP: `https://github.com/qumulab/planner-for-relevant-policies/wiki/PO-PRP`

Preferences/Soft Goals (PDDL 3)

- Hard goals: In classical planning we must achieve all goal facts
- Soft goals: Facts that are desirable, but not a must (each goal has an associated reward)
- Preferences: sometime-after, sometime-before, always-within, hold-during, hold-after

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Oversubscription Planning: Fixed cost, maximize achieved goals

Net-benefit Planning: Minimize Cost - Reward
$\rightarrow$Compilable to classical planning (give-up action)

Multi-Agent Planning

In the real world: We are not the single and only agent!

Multi-agent planning: Several agents must collaborate to achieve a common goal.

Key: There is some global information known by all agents but each agent has his own private facts, who do not want to share with the rest.

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Multi-Agent STRIPS Planning: A multi-agent STRIPS planning task, is a 5-tuple $\Pi = (P, A, I, G)$ where:

- P is a finite set of facts, divided in private and public facts.
- A is a finite set of actions; each $a \in A$ is a triple of pre, add, and del, divided in private and public actions.
- $I \subseteq P$ is the initial state.
- $G \subseteq P$ is the goal.

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$\rightarrow$Agents must communicate during the planning process to share information about how they will achieve the goal

Planning in the Real World

Question!

If most real-world environments are not deterministic, not fully observable, not discrete, not single agent, and temporal. What is classical planning good for?

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If most real-world environments are not deterministic, not fully observable, not discrete, not single agent, and temporal. What is classical planning good for?

- The model does not try to simulate the environment, it is just a tool to take good decisions.
- Oftentimes, reasoning with a simplified model can still lead to intelligent decisions and solutions are easier to compute than with more complex models.
- Classical planning is a relaxation of the problem so it can be used in heuristics for more complex types of planning.

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- Oftentimes, reasoning with a simplified model can still lead to intelligent decisions and solutions are easier to compute than with more complex models.
- Classical planning is a relaxation of the problem so it can be used in heuristics for more complex types of planning.

My two cents: Ideally, we should always provide an accurate description of the environment so that the AI simplifies it when necessary. However, automatic simplification methods are not powerful enough in all cases yet.

Summary

- You can use planning tools to solve your problems:
  $\rightarrow$Encode them in PDDL and use any planner
- Classical planning is very effective at solving large problems
- Non-classical planning models reason about more complex environments such as non-deterministic, partially-observable, continuous, temporal, etc.
- Solving these problems by computing a complete offline policy is hard (though many non-classical planners are able to do this satisfactorily in some domains). Many approaches are online, planning to decide the next action by looking into the future but without considering all alternatives.
- Classical planning and heuristic search techniques are still an important ingredient of many approaches that deal with complex environments.

Additional Resources

- Editor: `http://editor.planning.domains/`
- Wiki: `https://planning.wiki/`
- Benchmarks:
  `https://github.com/aibasel/downward-benchmarks`
- Visual Studio Plugin:
  `https://github.com/jan-dolejsi/vscode-pddl`
- Planners:
  - Fast Downward: `http://www.fast-downward.org/`
  - IPC-18: `https://ipc2018-classical.bitbucket.io/#planners`
- Domains as examples:
  - STRIPS: FD'All $\rightarrow$ Blocksworld, Logistics
  - Action costs: IPC'11 $\rightarrow$ Woodworking, Transport
  - Discretized numbers: IPC'11 $\rightarrow$ Nomystery (fuel consumption)
  - Forall-when: IPC'18 $\rightarrow$ Nurikabe
  - Complex ADL: FD'All $\rightarrow$ Miconic-ADL (ID114)

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