

Principles of AI Planning

Computational complexity

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Computational Complexity

Motivation

- We have seen that planning in transition systems can be done in time **polynomial** in the size of the transition system
 - This appears not to be true for planning in **succinct transition systems** (= planning tasks)
- ① What is the precise **computational complexity** of the **planning problem**?
 - ② How does the computational complexity vary with the **expressiveness** of the planning language?
 - ③ What is the computational complexity of **planning in a particular domain** (e.g. blocks world)?

AI Planning

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Computational Complexity

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Computational Complexity

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Why Computational Complexity?

- **understand** the problem
- know what is **not** possible
- find interesting **subproblems** that are easier to solve
- distinguish **essential features** from **syntactic sugar**

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Deterministic planning: NP-hardness

Definition

The decision problem SAT: test whether a given propositional formula ϕ is satisfiable.

Reduction from SAT to deterministic planning

- A = the set of propositional variables occurring in ϕ
- I = any state, e.g. all state variables have value 0
- O = $(\{\top\} \times A) \cup (\{\langle \top, \neg a \rangle \mid a \in A\})$

There is a plan for $\langle A, I, O, \phi \rangle$ if and only if ϕ is satisfiable.

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Deterministic planning: NP-hardness

- Because there is a polynomial-time translation from SAT into deterministic planning, and SAT is an NP-complete problem, there is a polynomial time translation from **every decision problem in NP** into deterministic planning. Hence the problem is NP-hard.
- 1 Does NP-hardness depend on having Boolean formulae as preconditions?
 - 2 Does deterministic planning have the power of NP, or is it still more powerful?
 - 3 We show that it is more powerful: The decision problem of testing whether a plan exists is **PSPACE-complete**.

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Alternating Turing Machines

Definition: Alternating Turing Machine

Alternating Turing Machine (ATM) $\langle \Sigma, \square, Q, q_0, l, \delta \rangle$:

- ① **input alphabet** Σ and **blank symbol** $\square \notin \Sigma$
 - alphabets always non-empty and finite
 - **tape alphabet** $\Sigma_{\square} = \Sigma \cup \{\square\}$
- ② finite set Q of **internal states** with **initial state** $q_0 \in Q$
- ③ state labeling $l : Q \rightarrow \{Y, N, \exists, \forall\}$
 - **accepting, rejecting, existential, universal** states
 $Q_Y, Q_N, Q_{\exists}, Q_{\forall}$
 - **terminal** states $Q_{\star} = Q_Y \cup Q_N$
 - **nonterminal** states $Q' = Q_{\exists} \cup Q_{\forall}$
- ④ **transition relation** $\delta \subseteq (Q' \times \Sigma_{\square}) \times (Q \times \Sigma_{\square} \times \{-1, +1\})$

AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

(Non-) Deterministic Turing Machines

Definition: Non-deterministic Turing Machine

A **non-deterministic Turing Machine (NTM)** is an ATM where all nonterminal states are existential.

- no universal states

Definition: Deterministic Turing Machine

A **deterministic Turing Machine (DTM)** is an NTM where the transition relation is functional.

- for all $(q, a) \in Q' \times \Sigma_{\square}$, there is exactly one triple (q', a', Δ) with $((q, a), (q', a', \Delta)) \in \delta$
- notation: $\delta(q, a) = (q', a', \Delta)$

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B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Turing Machine Configurations

Let $M = \langle \Sigma, \square, Q, q_0, l, \delta \rangle$ be an ATM.

Definition: Configuration

A **configuration** of M is a triple $(w, q, x) \in \Sigma_{\square}^* \times Q \times \Sigma_{\square}^+$.

- w : tape contents before tape head
- q : current state
- x : tape contents after and including tape head

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B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Turing Machine Transitions

Let $M = \langle \Sigma, \square, Q, q_0, l, \delta \rangle$ be an ATM.

Definition: Yields relation

A configuration c of M **yields** a configuration c' of M , in symbols $c \vdash c'$, as defined by the following rules, where $a, a', b \in \Sigma_{\square}$, $w, x \in \Sigma_{\square}^*$, $q, q' \in Q$ and $((q, a), (q', a', \Delta)) \in \delta$:

$$(w, q, ax) \vdash (wa', q', x) \quad \text{if } \Delta = +1, |x| \geq 1$$

$$(w, q, a) \vdash (wa', q', \square) \quad \text{if } \Delta = +1$$

$$(wb, q, ax) \vdash (w, q', ba'x) \quad \text{if } \Delta = -1$$

$$(\epsilon, q, ax) \vdash (\epsilon, q', \square a'x) \quad \text{if } \Delta = -1$$

AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Turing Machine Transitions

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Acceptance (Time)

Let $M = \langle \Sigma, \square, Q, q_0, l, \delta \rangle$ be an ATM.

Definition: Acceptance (time)

Let $c = (w, q, x)$ be a configuration of M .

- M **accepts** $c = (w, q, x)$ with $q \in Q_Y$ **in time n** for all $n \in \mathbb{N}_0$.
- M **accepts** $c = (w, q, x)$ with $q \in Q_\exists$ **in time n** iff M accepts **some** c' with $c \vdash c'$ in time $n - 1$.
- M **accepts** $c = (w, q, x)$ with $q \in Q_\forall$ **in time n** iff M accepts **all** c' with $c \vdash c'$ in time $n - 1$.

AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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Let $c = (w, q, x)$ be a configuration of M .

- M **accepts** $c = (w, q, x)$ with $q \in Q_Y$ **in space n** iff $|w| + |x| \leq n$.
- M **accepts** $c = (w, q, x)$ with $q \in Q_\exists$ **in space n** iff M accepts some c' with $c \vdash c'$ in space n .
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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Accepting Words and Languages

Let $M = \langle \Sigma, \square, Q, q_0, l, \delta \rangle$ be an ATM.

Definition: Accepting words

M **accepts the word** $w \in \Sigma^*$ **in time (space)** $n \in \mathbb{N}_0$
iff M accepts (ϵ, q_0, w) in time (space) n .

- Special case: M accepts ϵ in time (space) $n \in \mathbb{N}_0$
iff M accepts (ϵ, q_0, \square) in time (space) n .

Definition: Accepting languages

Let $f : \mathbb{N}_0 \rightarrow \mathbb{N}_0$.

M **accepts the language** $L \subseteq \Sigma^*$ **in time (space)** f
iff M accepts each word $w \in L$ in time (space) $f(|w|)$,
and M does not accept any word $w \notin L$.

AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

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Definition: Accepting languages

Let $f : \mathbb{N}_0 \rightarrow \mathbb{N}_0$.

M **accepts the language** $L \subseteq \Sigma^*$ **in time (space)** f
iff M accepts each word $w \in L$ in time (space) $f(|w|)$,
and M does not accept any word $w \notin L$.

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Motivation

NP-hardness

Turing
Machines

ATMs
(N)TMs
Computations
Acceptance

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Time Complexity

Definition: DTIME, NTIME, ATIME

Let $f : \mathbb{N}_0 \rightarrow \mathbb{N}_0$.

Complexity class $\text{DTIME}(f)$ contains all languages accepted in time f by some DTM.

Complexity class $\text{NTIME}(f)$ contains all languages accepted in time f by some NTM.

Complexity class $\text{ATIME}(f)$ contains all languages accepted in time f by some ATM.

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Measures

Complexity
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Measures

Complexity
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Measures

Complexity
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Measures

Complexity
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Measures

Complexity
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Measures

Complexity
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Measures

Complexity
Classes
Relationships

Complexity
Results

Domain-
Dependent
Planning

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AI Planning

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Measures

Complexity
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

Polynomial Complexity Classes

Let \mathcal{P} be the set of polynomials $p : \mathbb{N}_0 \rightarrow \mathbb{N}_0$.

Definition: P , NP , \dots

$$P = \bigcup_{p \in \mathcal{P}} \text{DTIME}(p)$$

$$NP = \bigcup_{p \in \mathcal{P}} \text{NTIME}(p)$$

$$AP = \bigcup_{p \in \mathcal{P}} \text{ATIME}(p)$$

$$\text{PSPACE} = \bigcup_{p \in \mathcal{P}} \text{DSpace}(p)$$

$$\text{NPSPACE} = \bigcup_{p \in \mathcal{P}} \text{NSpace}(p)$$

$$\text{APSPACE} = \bigcup_{p \in \mathcal{P}} \text{ASpace}(p)$$

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Measures

Complexity
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

Exponential Complexity Classes

Let \mathcal{P} be the set of polynomials $p : \mathbb{N}_0 \rightarrow \mathbb{N}_0$.

Definition: EXP, NEXP, ...

$$\text{EXP} = \bigcup_{p \in \mathcal{P}} \text{DTIME}(2^p)$$

$$\text{NEXP} = \bigcup_{p \in \mathcal{P}} \text{NTIME}(2^p)$$

$$\text{AEXP} = \bigcup_{p \in \mathcal{P}} \text{ATIME}(2^p)$$

$$\text{EXPSPACE} = \bigcup_{p \in \mathcal{P}} \text{DSpace}(2^p)$$

$$\text{NEXPSPACE} = \bigcup_{p \in \mathcal{P}} \text{NSpace}(2^p)$$

$$\text{AEXPSPACE} = \bigcup_{p \in \mathcal{P}} \text{ASpace}(2^p)$$

AI Planning

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Measures

Complexity
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

Doubly Exponential Complexity Classes

Let \mathcal{P} be the set of polynomials $p : \mathbb{N}_0 \rightarrow \mathbb{N}_0$.

Definition: 2-EXP, ...

$$2\text{-EXP} = \bigcup_{p \in \mathcal{P}} \text{DTIME}(2^{2^p})$$

...

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Measures

Complexity
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

Standard Complexity Classes Relationships

Theorem

$$\begin{array}{lcl} P \subseteq & NP & \subseteq AP \\ PSPACE \subseteq & NPSPACE & \subseteq APSPACE \\ EXP \subseteq & NEXP & \subseteq AEXP \\ EXPSPACE \subseteq & NEXPSPACE & \subseteq AEXPSPACE \\ 2-EXP \subseteq & \dots & \end{array}$$

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Measures

Complexity
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

The Power of Nondeterministic Space

Theorem (Savitch 1970)

$\text{NSPACE}(f) \subseteq \text{DSpace}(f^2)$, and thus:

$$\begin{aligned}\text{PSPACE} &= \text{NPSPACE} \\ \text{EXPSPACE} &= \text{NEXPSPACE}\end{aligned}$$

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Measures

Complexity
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

The Power of Alternation

Theorem (Chandra et al. 1981)

$$AP = PSPACE$$

$$APSPACE = EXP$$

$$AEXP = EXPSPACE$$

$$AEXPSPACE = 2-EXP$$

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Measures

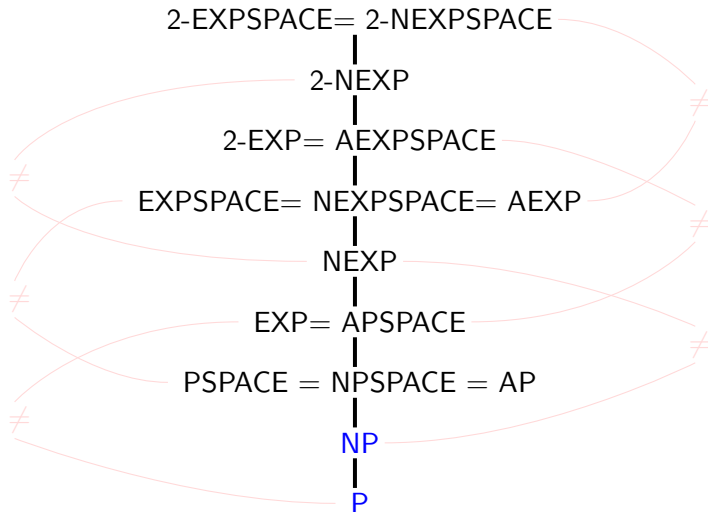
Complexity
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

The Hierarchy of complexity classes



AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity

Measures

Complexity

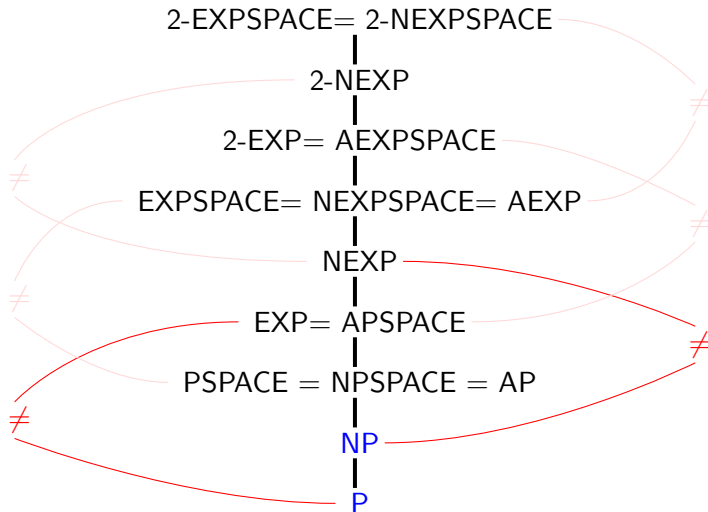
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

The Hierarchy of complexity classes



AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity

Measures

Complexity

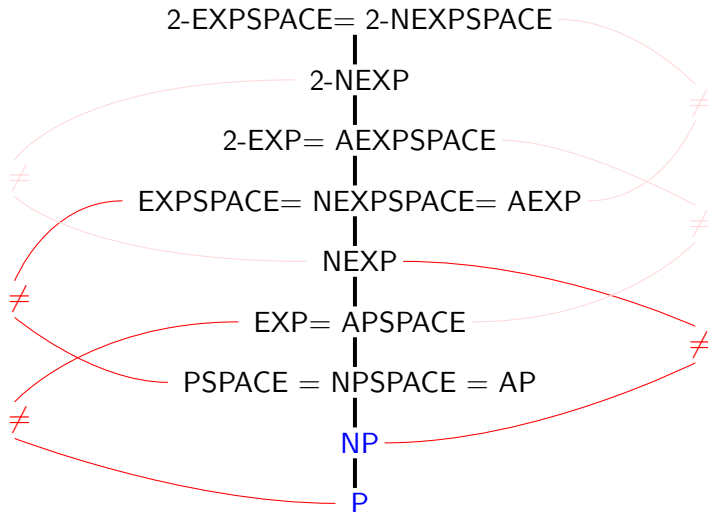
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

The Hierarchy of complexity classes



AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity

Measures

Complexity

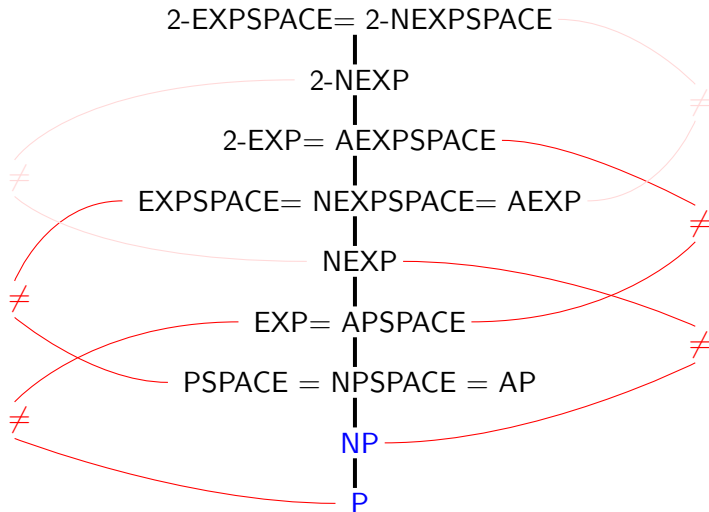
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

The Hierarchy of complexity classes



AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity

Measures

Complexity

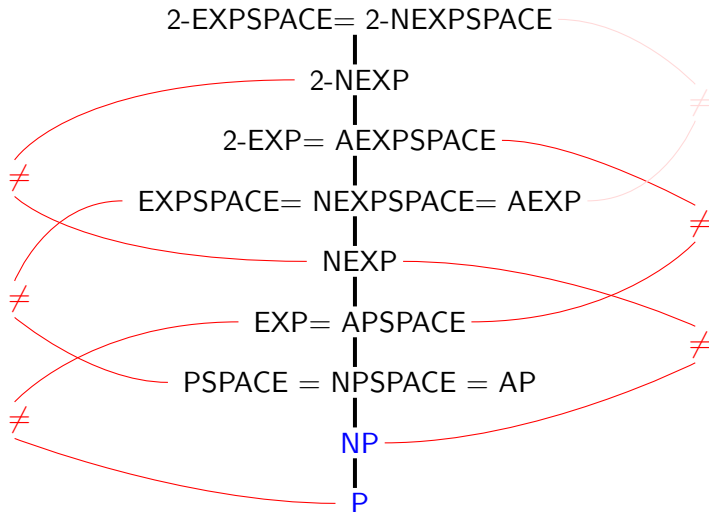
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

The Hierarchy of complexity classes



AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity

Measures

Complexity

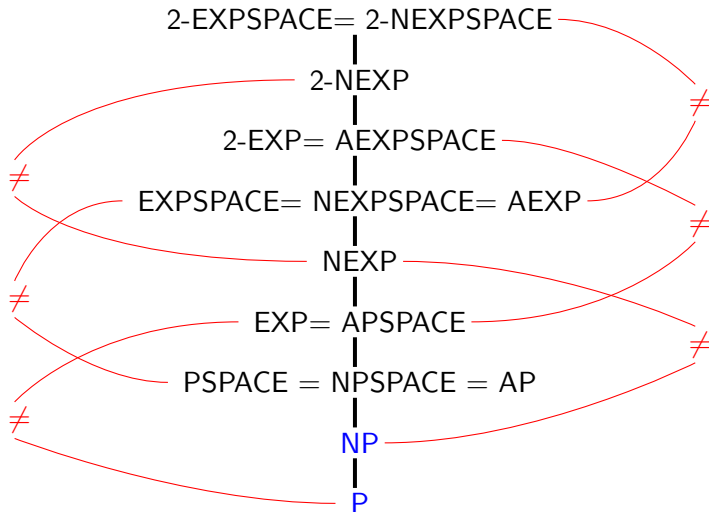
Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

The Hierarchy of complexity classes



AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity

Measures

Complexity

Classes

Relationships

Complexity
Results

Domain-
Dependent
Planning

The Planning Problem

PLANEX (Plan Existence)

GIVEN: Planning task $\langle A, I, O, G \rangle$

QUESTION: Is there a plan for $\langle A, I, O, G \rangle$?

PLANLEN (Bounded Plan Existence)

GIVEN: Planning task $\langle A, I, O, G \rangle$, bound $K \in \mathbb{N}_0$

QUESTION: Is there a plan for $\langle A, I, O, G \rangle$ of length at most K ?

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning
PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

Plan Existence vs. Bounded Plan Existence

$$\text{PLANEX} \leq_p \text{PLANLEN}$$

A planning task with n state variables has a plan
iff it has a plan of length at most $2^n - 1$.

\rightsquigarrow polynomial reduction

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

**Propositional
Planning**

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

Membership in PSPACE

PLANLEN \in PSPACE

Show PLANLEN \in NPSPACE and use Savitch's theorem.

Nondeterministic algorithm:

```
def plan( $\langle A, I, O, G \rangle, K$ ):  
     $s := I$   
     $k := K$   
    repeat until  $s \models G$ :  
        guess  $o \in O$   
        reject if  $o$  not applicable in  $s$   
        set  $s := app_o(s)$   
        reject if  $k = 0$   
        set  $k := k - 1$   
accept
```

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

Hardness for PSPACE

Idea: **generic reduction**

- For a fixed polynomial p , given DTM M and input w , generate planning task which is solvable iff M accepts w in space $p(|w|)$
- For simplicity, restrict to TMs which never move to the left of the initial head position (no loss of generality)

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

Reduction: State Variables

Let p be the space-bound polynomial.

Given DTM $\langle \Sigma, \square, Q, q_0, l, \delta \rangle$ and input $w_1 \dots w_n$,
define **relevant tape positions** $X = \{1, \dots, p(n)\}$.

State variables

- state_q for all $q \in Q$
- head_i for all $i \in X \cup \{0, p(n) + 1\}$
- $\text{content}_{i,a}$ for all $i \in X, a \in \Sigma \cup \square$

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

Reduction: Initial State

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define **relevant tape positions** $X = \{1, \dots, p(n)\}$.

Initial state

Initially true:

- state_{q_0}
- head_1
- $\text{content}_{i,w_i}$ for all $i \in \{1, \dots, n\}$
- $\text{content}_{i,\square}$ for all $i \in X \setminus \{1, \dots, n\}$

Initially false:

- all others

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

Reduction: Operators

Let p be the space bound polynomial.

Given DTM $\langle \Sigma, \square, Q, q_0, l, \delta \rangle$ and input $w_1 \dots w_n$, define **relevant tape positions** $X = \{1, \dots, p(n)\}$.

Operators

One operator for each transition rule $\delta(q, a) = (q', a', \Delta)$ and each cell position $i \in X$:

- precondition: $\text{state}_q \wedge \text{head}_i \wedge \text{content}_{i,a}$
- effect: $\neg \text{state}_q \wedge \neg \text{head}_i \wedge \neg \text{content}_{i,a}$
 $\wedge \text{state}_{q'} \wedge \text{head}_{i+\Delta} \wedge \text{content}_{i,a'}$

AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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Let p be the space bound polynomial.

Given DTM $\langle \Sigma, \square, Q, q_0, l, \delta \rangle$ and input $w_1 \dots w_n$,
define **relevant tape positions** $X = \{1, \dots, p(n)\}$.

Goal

$\bigvee_{q \in Q_Y} \text{state}_q$

AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

PSPACE-completeness for STRIPS

Theorem (PSPACE-completeness (Bylander))

PLANEX and PLANLEN are PSPACE-complete even if the planning task is given in STRIPS form (preconditions and goals are conjunctions of literals and no conditional effects).

Proof.

Hardness and membership for the general formalism follows from the above. Hardness holds for **STRIPS** as well because of the style of the reduction: only simple preconditions and no conditional effects. The only problem is the disjunction in the goal formula. This can be eliminated by transforming the TM beforehand, though. □

AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

Polynomial plan size

The PSPACE result depends on the fact that plans can become exponentially long. What if restrict them to be only of **polynomial length**?

Theorem (NP-completeness for polynomial plan size)

PLANEX and PLANLEN are NP-complete even if the planning task is given in STRIPS form provided only plans of length polynomial in the size of the planning task are permitted.

Membership follows easily by using a **guess-and-check** algorithm.

Hardness needs a bit more ...

Note: Answers earlier questions whether we need the Boolean precondition formula for NP-hardness

AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

First-Order Tasks

- we considered
propositional state variables (0-ary predicates) and
grounded operators (0-ary schematic operators)
- reasonable: most planning algorithms
work on grounded representations
- predicate arity is typically small (a constant?)

How do the complexity results change if we introduce
first-order predicates and schematic operators?

AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

**First-Order
Tasks**

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

**First-Order
Tasks**

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

Membership in EXPSPACE

PLANEX, PLANLEN \in EXPSPACE

- input size n
- \rightsquigarrow at most 2^n grounded state variables
- \rightsquigarrow at most 2^n grounded operators
- can ground the task in exponential time, then use the earlier PSPACE algorithms

AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

Hardness for EXPSPACE

Idea: Adapt the earlier reduction from PLANEX to encode Turing Machine contents more **succinctly**. Assume **relevant tape positions** are now $X = \{1, \dots, 2^n\}$. We need to encode the computation as a planning task in **polynomial time**!

Objects

0, 1

Predicates

- $\text{state}_q()$ for all $q \in Q$
- $\text{head}(?b_1, \dots, ?b_n)$
- $\text{content}_a(?b_1, \dots, ?b_n)$ for all $a \in \Sigma$ \square

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M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

Reduction: Example Operator

Operator example

Schematic operator for transition rule $\delta(q, a) = (q', a', +1)$

- parameters: $?b_1, \dots, ?b_n$
- precondition:
 - state_q
 - $\wedge \text{head}(?b_1, \dots, ?b_n)$
 - $\wedge \text{content}_a(?b_1, \dots, ?b_n)$
- effect:
 - $\neg \text{state}_q$
 - $\wedge \neg \text{head}(?b_1, \dots, ?b_n)$
 - $\wedge \neg \text{content}_a(?b_1, \dots, ?b_n)$
 - $\wedge \text{state}_{q'}$
 - $\wedge \text{advance-head}$
 - $\wedge \text{content}_{a'}(?b_1, \dots, ?b_n)$

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

Reduction: Example Operator (continued)

Operator example (ctd.)

$$\begin{aligned}\text{advance-head} = & ((?b_n = 0) \\ & \triangleright \text{head}(?b_1, \dots, ?b_{n-1}, 1)) \\ & \wedge ((?b_{n-1} = 0 \wedge ?b_n = 1) \\ & \triangleright \text{head}(?b_1, \dots, ?b_{n-2}, 1, 0)) \\ & \wedge ((?b_{n-2} = 0 \wedge ?b_{n-1} = 1 \wedge ?b_n = 1) \\ & \triangleright \text{head}(?b_1, \dots, ?b_{n-3}, 1, 0, 0)) \\ & \wedge \dots \\ & \wedge ((?b_1 = 0 \wedge ?b_2 = 1 \wedge \dots \wedge ?b_n = 1) \\ & \triangleright \text{head}(1, 0, \dots, 0))\end{aligned}$$

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

Plan Existence vs. Bounded Plan Existence

- Our earlier reduction from PLANEX to PLANLEN no longer works: the shortest plan can have length doubly exponentially in the input size, so that the bound cannot be written down in polynomial time.
- Indeed, PLANLEN is actually **easier** than PLANEX for this planning formalism (NEXP-complete).

AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSpace

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

Planning with function terms

- If we allow in addition **function terms** with arity > 0 , then planning becomes undecidable.
- The state space is **infinite**: $s(0), s(s(0)), s(s(s(0))), \dots$
- We can use function terms to describe (the index of) **tape cells of a Turing machine**.
- We can use operators to describe the **Turing machine control**.
- The existence of a plan is then equivalent to the existence of a **successful computation** on the Turing machine.
- PLANEX for planning tasks with function terms can be used to decide the **Halting problem**.

Theorem

PLANEX for planning tasks with function terms is undecidable.

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

The Planning
Problem

Propositional
Planning

PSPACE

Polynomial Plan
Size

First-Order
Tasks

EXPSPACE

Bounded Plan
Existence?

Undecidability

Domain-
Dependent
Planning

Domain-Dependent Planning

Planning (and its complexity) for particular domains is interesting, since we want to **judge** planning benchmarks ... and perhaps want to go for **domain-dependent planning**. Consider **fixed domains** and determine complexity.

AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning

Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning

Logistics

Logistics:
PLANEX

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PLANLEN

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Domain-Dependent Planning

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning

Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

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A Concrete Domain: Logistics

There are several cities, each containing several locations, some of which are airports. There are also trucks, which drive within a single city, and airplanes, which can fly between airports. The goal is to get some packages from various locations to various new locations [McDermott, 1998].

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning

Logistics

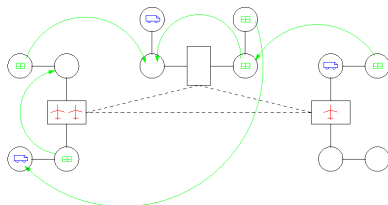
Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

A Concrete Domain: Logistics

There are several cities, each containing several locations, some of which are airports. There are also trucks, which drive within a single city, and airplanes, which can fly between airports. The goal is to get some packages from various locations to various new locations [McDermott, 1998].



AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning

Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

Plan Existence for Logistics

Theorem

PLANEX for Logistics can be decided in polynomial time.

Proof.

Consider the subgraphs formed by the **connected airport networks** (for planes) and **city networks** (for trucks). If at least one vehicle (truck or plane) is in one of the subgraphs, all nodes in the subgraph are internally reachable, otherwise only the externally connected nodes can be reached. Check for each package delivery, whether there are connected subgraphs such that the package can pass through the subgraphs to the target node. This is a simple reachability test, which can be done in **poly. time**. □

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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AI Planning

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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AI Planning

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Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

Optimizing Delivery: Shortest Plans for Logistics

Definition (Feedback Vertex Set)

- Given: a directed graph $G = (V, A)$ and a natural number k
- Question: Does there exist a subset $V' \subseteq V$ with $|V'| \leq k$ such that removing V' results in an acyclic graph?

This problem is NP-complete and can be used to prove the following result:

Theorem

PLANLEN for Logistics is NP-complete, even if there is only one complete city graph and one truck in this graph.

Proof.

*Membership follows because there is an obvious polynomial upper bound of moves for all solvable instances.
Hardness is shown using a reduction from FVS.*

AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

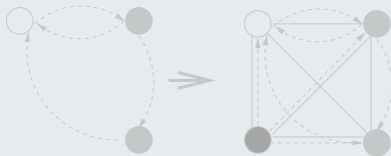
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Other Domains

PLANLEN for Logistics: NP-hardness contd. (1)

Proof. (continued)

Let $G = (V, A)$ be a directed graph and k a natural number. Then G contains a FVS of size k iff the logistics problem constructed below has a plan of length at most $3|V| + 2|A| + k$. Construct a *Logistics* task with just one truck and one city network which is a complete graph containing V and an extra node v_0 , where the truck starts. The truck has to deliver one package from v_0 to each other location and one package from u to v for each $(u, v) \in A$.



AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics
Logistics:
PLANEX

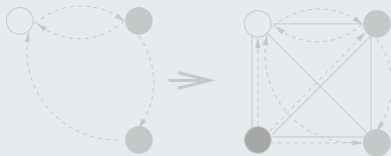
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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics
Logistics:
PLANEX

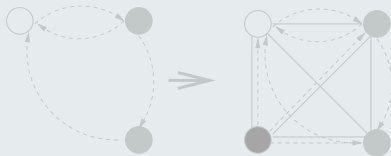
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Other Domains

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics
Logistics:
PLANEX

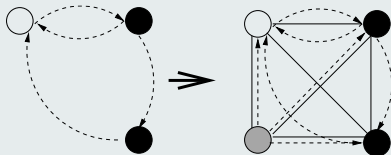
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PLANLEN

Other Domains

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

PLANLEN for Logistics: NP-hardness contd. (2)

Proof. (continued).

Let $V' \subseteq V$ the feedback vertex set. Solve task by moving to V' in any order, then to all $V - V'$ using a topological ordering on these nodes, and finally to V' again. Requires $|A| + |V|$ load and unload actions each, and $|V'| + |V - V'| + |V'|$ movements, i.e., $3|V| + 2|A| + k$ actions if $|V'| = k$.

Conversely, at least $3|V| + 2|A|$ actions are needed. If a plan contains not more than $3|V| + 2|A| + k$, then no more than k nodes are visited twice. These nodes form a FVS of size k . \square

Note: It is not route planning that makes the task difficult, but the interaction of sub-goals!

AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

PLANLEN for Logistics: NP-hardness contd. (2)

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

PLANLEN for Logistics: NP-hardness contd. (2)

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

Other Domains

- Generalizations of all the domains that have been used at the [international planning competition](#) have been analyzed.
- Many show a similar behavior as [Logistics](#): [PLANEX](#) is in [P](#), [PLANLEN](#) is [NP-complete](#), e.g., [Blocks world](#).
- Some are already NP-complete for PLANEX, e.g. [Freecell](#).
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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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AI Planning

M. Helmert,
B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

Summary

- Planning using general **first-order terms** is **undecidable**.
- Planning using a **function free** language is **EXPSpace-complete**.
- Planning with a **propositional language** (no schema variables) is **PSPACE-complete**.
- If we consider only “short” plans, the complexity comes down to **NP-completeness**.
- **Domain-dependent** planning can be easier.
- For **Logistics**, the existence problem is in **P**, while the optimization problem is **NP-complete**, which holds for many other domains as well.

AI Planning

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B. Nebel

Motivation

NP-hardness

Turing
Machines

Complexity
Classes

Complexity
Results

Domain-
Dependent
Planning

Domain-
Dependent
Planning
Logistics

Logistics:
PLANEX

Logistics:
PLANLEN

Other Domains

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- Planning using a **function free** language is **EXPSpace-complete**.
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- If we consider only “short” plans, the complexity comes down to **NP-completeness**.
- **Domain-dependent** planning can be easier.
- For **Logistics**, the existence problem is in **P**, while the optimization problem is **NP-complete**, which holds for many other domains as well.

AI Planning

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Motivation

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Complexity
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Logistics:
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