# Planning and Optimization

B6. Computational Complexity of Planning: Background

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**B6.1** Motivation

**B6.2 Turing Machines** 

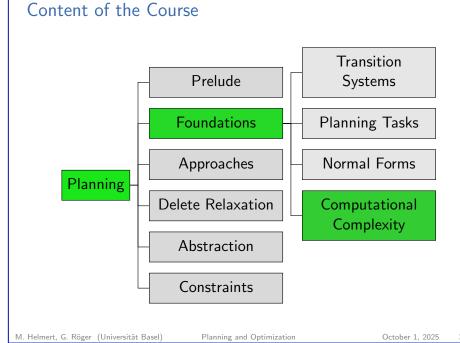
**B6.3 Complexity Classes** 

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Motivation

**B6.1** Motivation

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How Difficult is Planning?

- ► Using state-space search (e.g., using Dijkstra's algorithm on the transition system), planning can be solved in polynomial time in the number of states.
- ► However, the number of states is exponential in the number of state variables, and hence in general exponential in the size of the input to the planning algorithm.
- → Do non-exponential planning algorithms exist?
- → What is the precise computational complexity of planning?

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### 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
  - ▶ Is STRIPS planning easier than general planning?

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### Reminder: Complexity Theory

### Need to Catch Up?

- ► We assume knowledge of complexity theory:
  - languages and decision problems
  - Turing machines: NTMs and DTMs; polynomial equivalence with other models of computation
  - complexity classes: P, NP, PSPACE
  - polynomial reductions
- ▶ If you are not familiar with these topics, we recommend Chapters B11, D1-D3, D6 of the Theory of Computer Science course at https://dmi.unibas.ch/en/studium/ computer-science-informatik/lehrangebot-fs25/ 10948-main-lecture-theory-of-computer-science/

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Turing Machines

**B6.2 Turing Machines** 

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### **Turing Machines**

### Definition (Nondeterministic Turing Machine)

A nondeterministic Turing machine (NTM) is a 6-tuple  $\langle \Sigma, \square, Q, q_0, q_Y, \delta \rangle$  with the following components:

- ▶ input alphabet  $\Sigma$  and blank symbol  $\square \notin \Sigma$ 
  - ► alphabets always nonempty and finite
  - ▶ tape alphabet  $\Sigma_{\square} = \Sigma \cup \{\square\}$
- ▶ finite set Q of internal states with initial state  $q_0 \in Q$ and accepting state  $q_Y \in Q$ 
  - ▶ nonterminal states  $Q' := Q \setminus \{q_Y\}$
- ▶ transition relation  $\delta: (Q' \times \Sigma_{\square}) \to 2^{Q \times \Sigma_{\square} \times \{-1,+1\}}$

Deterministic Turing machine (DTM):  $|\delta(q,s)|=1$  for all  $\langle q,s\rangle\in Q' imes \Sigma_{\square}$ 

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### Turing Machines: Accepted Words

- ► Initial configuration
  - ightharpoonup state  $q_0$
  - ▶ input word on tape, all other tape cells contain □
  - head on first symbol of input word
- ► Step
  - ▶ If in state q, reading symbol s, and  $\langle q', s', d \rangle \in \delta(q, s)$  then
  - $\blacktriangleright$  the NTM can transition to state g', replacing s with s' and moving the head one cell to the left/right (d = -1/+1).
- ▶ Input word  $(\in \Sigma^*)$  is accepted if some sequence of transitions brings the NTM from the initial configuration into state  $q_Y$ .

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Complexity Classes

# B6.3 Complexity Classes

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## Acceptance in Time and Space

Definition (Acceptance of a Language in Time/Space)

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

A NTM accepts language  $L \subseteq \Sigma^*$  in time f if it accepts each  $w \in L$  within f(|w|) steps and does not accept any  $w \notin L$  (in any time).

It accepts language  $L \subseteq \Sigma^*$  in space f if it accepts each  $w \in L$  using at most f(|w|) tape cells and does not accept any  $w \notin L$ .

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Complexity Classes

## Time and Space Complexity Classes

Definition (DTIME, NTIME, DSPACE, NSPACE)

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

Complexity class DTIME(f) contains all languages accepted in time f by some DTM.

Complexity class NTIME(f) contains all languages accepted in time f by some NTM.

Complexity class DSPACE(f) contains all languages accepted in space f by some DTM.

Complexity class NSPACE(f) contains all languages accepted in space f by some NTM.

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### Polynomial Time and Space Classes

Let  $\mathcal{P}$  be the set of polynomials  $p : \mathbb{N}_0 \to \mathbb{N}_0$  whose coefficients are natural numbers.

Definition (P, NP, PSPACE, NPSPACE)

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

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

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

 $\mathsf{NPSPACE} = \bigcup_{p \in \mathcal{P}} \mathsf{NSPACE}(p)$ 

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### Polynomial Complexity Class Relationships

Theorem (Complexity Class Hierarchy)

 $P \subseteq NP \subseteq PSPACE = NPSPACE$ 

#### Proof.

 $P \subseteq NP$  and  $PSPACE \subseteq NPSPACE$  are obvious because deterministic Turing machines are a special case of nondeterministic ones.

 $NP \subseteq NPSPACE$  holds because a Turing machine can only visit polynomially many tape cells within polynomial time.

PSPACE = NPSPACE is a special case of a classical result known as Savitch's theorem (Savitch 1970).

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B6.4 Summary

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Summarv

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### Summary

- ► We recalled the definitions of the most important complexity classes from complexity theory:
  - P: decision problems solvable in polynomial time
  - ▶ NP: decision problems solvable in polynomial time by nondeterministic algorithms
  - ► PSPACE: decision problems solvable in polynomial space
  - ► NPSPACE: decision problems solvable in polynomial space by nondeterministic algorithms
- ▶ These classes are related by  $P \subseteq NP \subseteq PSPACE = NPSPACE$ .

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