Principles of AI Planning

1. Introduction

Bernhard Nebel and Robert Mattmüller
October 16th, 2018
About the course
# People

## Lecturers

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- **consultation**: by appointment (email) or just come to my office

**Prof. Dr. Bernhard Nebel**
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Exercises

David Speck
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Dominik Drexler
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- **consultation:** by appointment (email)
**Time & place**

### Lectures
- **time:** Tuesday 16:15-18:00, Friday 16:15-17:00
- **place:** Building 051, seminar room 03-026

### Exercises
- **time:** Friday 17:15-18:00
- **place:** Building 051, seminar room 03-026
Course web site

http://gki.informatik.uni-freiburg.de/teaching/ws1819/aip/

- **main page:** course description
- **lecture page:** slides
- **exercise page:** assignments, software
- **bibliography page:** literature references and papers
no script, but these slides available on the web
three textbooks exist, but not necessary for this course:
- Geffner and Bonet (2013), A Concise Introduction to Models and Methods for Automated Planning
  (comes closest to this course, includes relatively recent research results – a few copies available in the Faculty of Engineering library)
  (very different from this course, quite outdated)
- Ghallab, Nau, and Traverso (2016), Automated Planning and Acting
  (heavily modified rewrite of the above, still quite different from this course)

additional resources: bibliography page on web + ask us!
Teaching materials

Acknowledgments:

- slides based on earlier courses by Jussi Rintanen, Bernhard Nebel and Malte Helmert
- many figures by Gabi Röger
Target audience

Students of Computer Science:

- Master of Science, any year
- Bachelor of Science, ~3rd year

Other students:

- advanced study period (~4th year)
Prerequisites

Course prerequisites:

- **propositional logic**: syntax and semantics
- **foundations of AI**: search, heuristic search
- **computational complexity theory**: decision problems, reductions, NP-completeness
Credit points & exam

- 6 ECTS points
- special lecture in specialization field Cognitive Technical Systems
- oral exam of about 30 minutes for computer science B.Sc. students
- written or oral exam for M.Sc. students and students in study programs other than computer science (likely written)
Exercises

Exercises (written assignments):

- handed out once a week
- due one week later, before the lecture
- discussed in the next exercise session
- may be solved in groups of two students ($2 \neq 3$)
- successful participation prerequisite for exam admission
points can be earned for “reasonable” solutions to exercises.

at least 50% of points prerequisite for admission to final exam.
Plagiarism

What is plagiarism?

- passing off solutions as your own that are not based on your ideas (work of other students, Internet, books, ...)
- http://en.wikipedia.org/wiki/Plagiarism is a good intro

Consequence: no admission to the final exam.

- We may (!) be generous on first offense.
- Don’t tell us “We did the work together.”
- Don’t tell us “I did not know this was not allowed.”
Introduction
Planning in the AI landscape
(hugely simplified …)

Symbolic AI, e.g. …
- Knowledge and symbols
- Often model-based
- Explainability: ✔

Sub-symbolic AI, e.g. …
- Data, no symbols
- Often model-free
- Explainability: ✗

<table>
<thead>
<tr>
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Planning in the AI landscape
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**Symbolic AI, e.g. …**

- Knowledge representation and reasoning
- Logic
- AI planning, search

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  - Explainability: ✔

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Planning

“Planning is the art and practice of thinking before acting.”
— Patrik Haslum

- intelligent decision making: What actions to take?
- general-purpose problem representation
- algorithms for solving any problem expressible in the representation
- application areas:
  - high-level planning for intelligent robots
  - autonomous systems: NASA Deep Space One, ...
  - problem solving (single-agent games like Rubik’s cube)
Why is planning difficult?

- solutions to classical planning problems are **paths from an initial state to a goal state in the transition graph**
  - efficiently solvable by Dijkstra’s algorithm in $O(|V| \log |V| + |E|)$ time
  - Why don’t we solve all planning problems this way?
- state spaces may be **huge**: $10^{10}, 10^{100}, 10^{1000}, \ldots$ states
  - constructing the transition graph is infeasible!
  - planning algorithms try to **avoid constructing whole graph**
- planning algorithms are often much more efficient than obvious solution methods constructing the transition graph and using e.g. Dijkstra’s algorithm
Different classes of problems

- **dynamics**: deterministic, nondeterministic or probabilistic
- **observability**: full, partial or none
- **horizon**: finite or infinite

1. classical planning
2. conditional planning with full observability
3. conditional planning with partial observability
4. conformant planning
5. Markov decision processes (MDP)
6. partially observable MDPs (POMDP)
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Properties of the world: dynamics

Deterministic dynamics
Action + current state uniquely determine successor state.

Nondeterministic dynamics
For each action and current state there may be several possible successor states.

Probabilistic dynamics
For each action and current state there is a probability distribution over possible successor states.

Analogy: deterministic versus nondeterministic automata
Deterministic dynamics example

Moving objects with a robotic hand: move the green block onto the blue block.
Moving objects with an **unreliable** robotic hand: move the green block onto the blue block.
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\[ p = 0.9 \]

\[ p = 0.1 \]
Properties of the world: observability

**Full observability**
Observations determine current world state *uniquely*.

**Partial observability**
Observations determine current world state *only partially*: we only know that current state is one of several possible ones.

**No observability**
There are *no observations* to narrow down possible current states. However, can use knowledge of *action dynamics* to deduce which states we might be in.

**Consequence:** If observability is not full, must represent the *knowledge* an agent has.
What difference does observability make?

Camera A

Camera B

Goal

October 16th, 2018 B. Nebel, R. Mattmüller – AI Planning
Different objectives

1. Reach a goal state.
   - **Example:** Earn 500 Euros.

2. Stay in goal states indefinitely (infinite horizon).
   - **Example:** Never allow bank account balance to be negative.

3. Maximize the probability of reaching a goal state.
   - **Example:** To be able to finance buying a house by 2028, study hard and save money.

4. Collect the maximal expected rewards/minimal expected costs (infinite horizon).
   - **Example:** Maximize your future income.

5. ...
Game theory addresses decision making in multi-agent setting: “Assuming that the other agents are rational, what do I have to do to achieve my goals?”

Game theory is related to multi-agent planning.

In this course we concentrate on single-agent planning.

Some of the techniques are also applicable to special cases of multi-agent planning.

Example: Finding a winning strategy of a game like chess. In this case it is not necessary to distinguish between an intelligent opponent and a randomly behaving opponent.

Game theory in general is about optimal strategies which do not necessarily guarantee winning. For example card games like poker do not have a winning strategy.
What do you learn in this course?

- emphasis on **classical** planning (“simplest” case)
- brief digression to **nondeterministic** planning
- **theoretical background** for planning
  - formal **problem definition**
  - basic **theoretical notions**
  - (e.g., normal forms, progression, regression)
  - computational complexity of planning
- **algorithms** for planning:
  - based on **heuristic search**
  - based on exhaustive search with logic-based data structures such as BDDs (if time permits)

Many of these techniques are applicable to problems outside AI as well.

- **hands-on experience** with a classical planner (probably)