AI Planning for Autonomy

5. Width Based Planning

Searching for Novelty
and How to Plan with Simulators

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Agenda

Structure

Planning is **PSPACE-complete**, but current planners can **solve most of benchmarks in a few seconds**

Question:

- Can we explain why planners perform well?
- Can we characterize the line that separates **'easy'** from **'hard'** domains?

Our Answer

A new width notion and planning algorithm exponential in problem width:

- Benchmark domains have **small width** when **goals** restricted to **single atoms**
- Joint goals **easy to serialize** into a sequence of single goals

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Do you want Hard Problems?

- problems with **high atomic width** (apparently no benchmark in this class)
- **multiple goal** problems that are **not easy to serialize** (e.g. Sokoban)

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Definition: Novelty

Key definition: the **novelty** $w(s)$ **of a state** s is the size of the smallest subset of atoms in s that is true for the first time in the search.

- e.g. $w(s) = 1$ if there is **one** atom $p \in s$ such that s is the first state that makes p true.
- Otherwise, $w(s) = 2$ if there are **two** different atoms $p, q \in s$ such that s is the first state that makes $p \wedge q$ true.
- Otherwise, $w(s) = 3$ if there are **three** different atoms...

Iterated Width (*IW*)

Algorithm

- *IW*(k) = breadth-first search that prunes newly generated states whose $novelty(s) > k$.
- IW is a sequence of calls *IW*(k) for $i = 0, 1, 2, \ldots$ over problem P until problem solved or i exceeds number of variables in problem

Properties

$IW(k)$ expands at most $O(n^k)$ states, where n is the number of atoms.

Is IW any good in Classical Planning?

- *IW*, while simple and blind, is a pretty good algorithm over benchmarks when goals restricted to single atoms
- This is no accident, width of benchmarks domains is small for such goals

We tested domains from previous IPCs. For each instance with N goal atoms, we created N instances with a single goal

- Results quite remarkable:

# Instances	*IW*	*ID*	*BrFS*	$GBFS + h_{add}$
37921	91%	24%	23%	91%

Why *IW* does so well?

Key theory of *IW*(k) in terms of width:

Properties

For problems $\Pi \in \mathcal{P}$, where $\boldsymbol{width(\Pi) = k}$:

- $IW(k)$ solves Π in time $O(n^k)$;
- $IW(k)$ solves Π optimally
- $IW(k)$ is complete for Π

Theorem

Blocks, Logistics, Gripper, and n-puzzle have a bounded width independent of problem size and initial situation, provided that goals are single atoms.

In practice, $IW(k \leq 2)$ solves 88.3% IPC problems with single goals:

# Instances	$k = 1$	$k = 2$	$k > 2$
37921	37.0%	51.3%	11.7%

IW in Classical Planning?

Primary question: *IW* solves atomic goals, how do we extend the blind procedure to multiple atomic goals?

Serialized Iterated Width (SIW)

- Simple way to **use *IW*** for solving real benchmarks P with **joint goals** is by simple form of **"hill climbing"** over goal set G with $|G| = n$, achieving atomic goals one at a time

Serialized Iterated Width (SIW)

- ***SIW* uses *IW*** for both **decomposing** a problem into subproblems and for **solving** subproblems
- It's a **blind search** procedure, **no heuristic** of any sort, *IW* **does not even know next goal** G_i "to achieve"

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Blind *SIW* better than GBFS + h_{add} !

Summary (so far)

***IW*:** sequence of novelty-based pruned breadth-first searches

- **Experiments:** excellent when goals restricted to atomic goals
- **Theory:** such problems have low width w and *IW* runs in time $O(n^w)$

***SIW*:** *IW* serialized, used to attain top goals one by one

- **Experiments:** faster, better coverage and much better plans than GBFS planner with h_{add}
- **Intuition:** goals easy to serialize and have atomic low width w

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Classical Planning

State-of-the-art methods for **satisficing planning** rely on:

- heuristics derived from problem
- plugged into Greedy Best-First Search (GBFS)
- extensions (like helpful actions and landmarks)

Shortcoming of GBFS: Exploration and Exploitation

GBFS is pure greedy "exploitation"; often gets **stuck in local minima**

- Recent approaches improve performance by adding exploration

Exploration required for optimal behavior in RL and MCTS

- Such methods perform flat exploration that **ignores structure of states**

We study impact of **width-based exploration methods** that take structure of states into account

Best-First Width Search (BFWS)

BFWS(f)

BFWS(f) for $f = \langle w, f_1, ..f_n \rangle$ where w is a novelty-measure, is a plain best-first search where nodes are ordered in terms of novelty function w, with ties broken by functions f_i in that order.

Basic BFWS($\langle w, h \rangle$) scheme obtained with $\mathbf{h} = \mathbf{h_{add}}$ or $\mathbf{h_{ff}}$, and novelty-measure $\mathbf{w} = \mathbf{w_h}$, where

- $w_h(s)$ = size of smallest new tuple of atoms generated by s for the first time in the search relative to previously generated states s' with $h(s) = h(s')$.

$\rightarrow$ BFWS($\langle w, h \rangle$) much better than purely greedy BFS(h)

Some BFWS(f) variants yield state-of-the-art performance:

- 1st place in Agile track, Runner-Up Satisficing track IPC-2018
- more info: `https://ipc2018-classical.bitbucket.io/`

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Classical Planning

The status quo:

- Model usually represented in compact form (STRIPS, PDDL)

Introduction & Motivation

For more than 40 years, research focused on **exploiting** information about **action preconditions and effects** in order to plan efficiently

- GPS, POP, GraphPlan, SAT, OBDD, heuristic-search planning, ...

We showed that same level of efficiency can be obtained with **simulators**: **without** a representation of **action preconditions and effects**

Introduction & Motivation

This has been shown by:

- Developing a planner that uses action structure **only** to define
  - the set A(s) of **applicable actions** in state s, and
  - state **transition function** f(a,s)

  The **planner does not see action preconditions and effects** but just the functions A(s) and f(a,s)

- We showed that its **performance matches** the performance of state of the art **planners that make use of PDDL** representations, over the existing PDDL benchmarks

Many consequences follow from this radical departure

Modeling

Modeling

Many problems fitting **classical planning** model but **difficult to describe in PDDL** are easily modeled now: Pacman, Tetris, Pong, etc.

- **Expressive language features** easily supported: functions, conditional effects, derived predicates, state constraints, quantification, ...
- Any element of the problem can be modeled through logical symbols attached to **external procedures** (e.g. C++).
- Action effects can be given as **fully-black-box procedure** taking the state as input.

Introduction & Motivation

Declarative languages also have their **downsides**:

- **Model $\neq$ Language**. Many problems fit Classical Planning model, but hard to express in PDDL-like languages.

- Recent development of **simulation platforms** such as
  - Atari Learning Environment,
  - GVG-AI,
  - Universe, etc.

> Need for planners that work **without complete declarative** representations.

Algorithm: Simulated BFWS

Framework **Best-first width search** (**BFWS**):

- Novelty measures w also used in best-first algorithms (BFWS)
- Best results when w-measures combined with goal directed heuristics h (Lipovetzky and Geffner, 2017)
- BFWS(h) picks node from OPEN with least w_h measure, breaking ties with h
  - $w_h(s) = k$ if s is first state to make some set of k atoms true, among those with heuristic $h = h(s)$

BFWS(h) much better than standard BFS(h)

Use of heuristics couples algorithm with *declarative representations*.

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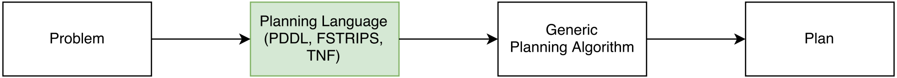
Use of heuristics couples algorithm with *declarative representations*.

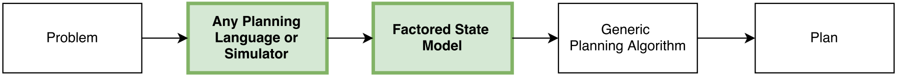
- In (Frances et al. 2017) we lift this requirement

Implications: Modeling and Control

- **Traditional** toolchain



- Results suggest **alternative**



- No **need** for planning languages that reveal **structure** of actions (e.g. action preconditions and effects)
- **Not much** efficiency appears to be **lost** in **second** pathway

These algorithms open up **Exciting possibilities** for **modeling beyond PDDL**

Width-Based planning over Simulators

Challenges:

- Non-linear dynamics
- Perturbation in flight controls
- Partial observability
- Uncertainty about opponent strategy

Agenda

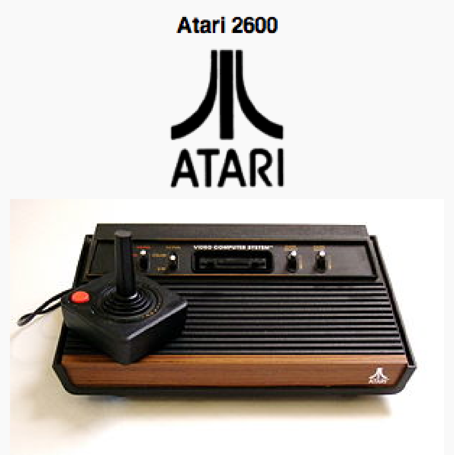
1. Width-Based Search
2. Balancing Exploration and Exploitation
3. Models and Simulators
4. Classical Planning with Simulators
5. Conclusion

Classical Planning with Simulators

Can classical planners work without PDDL?

Classical Planning with Simulators

Can classical planners work without PDDL?



Arcade Learning Environment

http://www.arcadelearningenvironment.org/
The Arcade Learning Environment (ALE) is a simple object-oriented framework that allows researchers and hobbyists to develop *AI agents for Atari 2600 games*.

Recent AI agents:

$\leadsto$ Reinforcement Learning and Deep Learning trained to learn a controller

$\leadsto$ Search algorithm as a lookahead for action selection

Motivation

While planning is the model-based approach to control, planning research is heavily fragmented

- Many models (classical; MDPs, POMDPs; "logical" variants FOND and POND; time, resources, ..)
- Modeling languages vs. Use of Simulators
- Different communities (ICAPS-AAAI; NIPS-UAI-RL ..)

Best way to get communication across and to build on each others' work is common benchmarks and environments such as *ALE*

ALE and Classical Planning

Planning setting in ALE is deterministic and initial state fully known

Yet classical planners can't be used

- no PDDL encoding
- no goals but rewards

→ *Bellemare et al.* consider Breadth-first Search (*BrFS*) and *MCTS (UCT)*

→ Still, "classical" planning algorithms such as *IW* can be applied almost off-the-shelf!

IW in the Atari Games

- *IW*(1) used with the 128 variables (bytes) of 256 values each
- *IW*(1) generates then up to $128 \times 256 \times 18$ (i.e, $589,824$) states
  - Children in *IW*(1) generated in random order
  - Discount factor used $\gamma = 0.995$
- Action leading to most rewarding *IW*(1)-path is executed

IW Playing Atari!

Freeway

Experimental Results

Same setting from Bellemare et al:

- Games are played for 5 minutes maximum (18,000 frames)
- 2BFS and *IW* have a maximum lookahead budget of $150,000$ simulated frames
- UCT has same budget by running 500 rollouts of depth 300
- Score is averaged among 5 runs per game

	IW(1)	2BFS	*BrFS*	UCT
# Times Best (54 games)	26	13	1	19
# Times Better than *IW*	–	16	1	19
# Times Better than 2BFS	34	–	1	25
# Times Better than UCT	31	26	1	–

Search Tree Depths

- *BrFS* search tree results in a lookahead of 0.3 seconds
- *IW*(1) and 2BFS result in lookahead of up to 6–22 seconds

Atari in the Press

IW vs DeepMind

Lookahead Agents VS Learning Agents:

⇝ Still open how to compare them best as they solve different control problems, and different inputs (RAM vs Screen)

But, taking into account gameplay score:

⇝ IW outperforms DeepMind's algorithm in 45 out of 49 games
⇝ Similar results have been reported recently over Screen Inputs [AAAI 2018]

ALE Wrap up

- *IW* makes use of the state structure (atoms) to order exploration
- *IW*(1) is a *BrFS* that keeps states that generate new atoms
- Exploitation of this structure pays off in classical planning and ALE
- First classical planners using simulators
- Youtube videos: Link http://bit.ly/1EuCb9x

Agenda

The Width Conspirators: What's next?

→ Explore new **applications**: Social Sciences, Computational Sustainability, and any other fields rely on simulators

→ Width-based for other **planning computational models**: Uncertainty, Beliefs, Multi-agent

→ Devise new **algorithms** for real-time behavior

→ Bridge connection between **Control, Planning and Learning**

Help us grow the boundaries of AI planning research!

Resources

Literature:

- https://nirlipo.github.io/Width-Based-Planning-Resources/

LAPKT stands for the Lightweight Automated Planning ToolKiT:

- http://lapkt.org

IW-ALE, BFWS source code:

- http://lapkt.org/index.php?title=Projects

Width-based in action featured in ICAPS-19:

- https://icaps19.icaps-conference.org/!