

Iterative Planning: A Survey

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- 1 Background and Motivation
 - Automated Planning
 - Motivation for Iterative Planning
 - Plan Representation
 - Related Problems
- 2 Existing Approaches
 - Deductive Approaches
 - Non-Deductive Approaches
 - Summary of Different Approaches
- 3 Underlying Theory
 - Finite Verification
 - Identification in the Limit
- 4 Possibilities for Future Work

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- Automated Planning
 - Given a formal specification of a dynamical system, the initial state and a goal condition, find an action strategy that realizes the goal.
- Different types of planning
 - Classical planning: STRIPS [Fikes *et al.* 71], ADL [Pednault 89];
 - Sequential extensions: numerics and time [Fox and Long 03], temporally extended goals [Gerevini and Long 05], *etc.*;
 - Conformant planning [Smith and Weld 98];
 - Conditional planning [Petrick and Bacchus 98; Bertoli *et al.* 98].

Motivation for Iterative Planning

- Planning tasks above are concerned with *individual* problems, e.g.
 - Three blocks are on the table. Stack them into a tower!
 - A tree can be felled with no more than two chops. Chop it down!

What if we have 5 blocks on table or a tree needing 4 chops?

- It is desirable to find a solution to a *class* of problems. Then solving a problem in the class is simply an instantiation of the solution. This requires loops [Levesque 05]!
- Learn from small problems so as to more efficiently solve larger ones.

Robot Programs

- Ideally, a plan is a deterministic procedure to follow without further deliberation.
- Robot programs are defined inductively for representing loopy plans [Levesque 96]
 - 1 **nil** is a robot program;
 - 2 if A is a primitive action and P is a robot program, then **seq**(A, P) is also a robot program;
 - 3 if A is a sensing action with sensing results R_1, \dots, R_n , and P_1, \dots, P_n are robot programs, then **case**($A, [\mathbf{if}(R_1, P_1), \dots, \mathbf{if}(R_n, P_n)]$) is also a robot program;
 - 4 if P and Q are robot programs, and P' is the result of replacing some of the occurrences of **nil** by **exit** and the rest by **next**, then **loop**(P', Q) is a robot program.

An Example

```
loop(  
  case(look,  
    [if(down,exit),  
     if(up,seq(chop,next))  
    ],  
  ),  
  seq(store,nil)  
)
```

- Program synthesis [Manna and Waldinger 92; 80]
Given a constraint on valid input $P(x)$ and the relationship between input and output $R(x, y)$, find a program $f(x)$ such that for any input a satisfying $P(a)$, the output $z = f(a)$ satisfies $R(a, z)$.
- Grammar induction [Section 8.7 of Duda *et al.* 01]
Find the underlying grammar that can generate the observed strings from a language.
- Repeated-attempt problems
 - Pick up block with success probability p [Haddawy and Ngo 95]
 - The probability of getting a good egg is p [Bonet and Geffner 01]

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Generate a loopy plan as a by-product of proving a mathematical theorem.

- Tableau-based sequent calculus [Manna & Waldinger 80; 87]
 - Use an $\langle \text{assertion}, \text{goal}, \text{output} \rangle$ triple (sequent) to represent theorems
 - A set of derivation rules to obtain correct new sequents
 - Recursion introduced by a well-founded induction rule

- Deduction-based refinement planning [Stephan & Biundo 96]
 - Problem specification and executable plan represented in a unified language
 - Refinement rules to gradually substitute specification with executable plan
 - Loop structure exists in the original non-executable problem specification

Non-Deductive Approaches

KPLANNER: Generate and Test [Levesque 05]

- Solves a class of planning problems parameterized by an integer (plan parameter)
- Generate a loopy plan that works for a small integer N_1 (the generation bound)
 - Exhaustively search for a conditional plan that works for N_1
 - Wind the conditional plan into a loopy plan
- Test the resulting plan with a larger integer N_2 (the test bound)
 - If it passes the test, the plan is returned.
 - If it fails, go back to the generation phase.
- Correctness
 - The returned plan is guaranteed to work for N_1 and N_2 only, but in practice, it usually works for all integers.
 - For problems with certain properties, the returned plan is guaranteed to work in general.

loopDISTILL: Identifying Regularity in Partial-Order Plans [Winner & Veloso 07]

- Given a partial order plan for a planning problem, find instances of a same action.
- Greedily identify a largest matching subplan by considering neighboring actions.
- Conditionals and loops are constructed from the matching subplans

Role-Based Abstraction [Srivastava *et al.* 08]

- Characterize the role of an object by the truth values of all unary predicates applied to the object.
- Given a concrete plan for an example problem, construct an abstract plan where objects are replaced by their roles.
- Based on the repetition pattern of actions in the abstract plan, identify loops.
- Guaranteed correctness for extended-LL domains.

Explanation-Based Generalization

- BAGGER2 generates recursive concepts as explanation-based learning with the ability of “generalization-to- N ” [Shavlik 90].
- With a similar idea, [Schmid & Wysotzki 00] learns recursive macro operators for planning domains.
 - Predefined data-type structures (natural numbers, lists, sets, *etc.*);
 - Explore problems of small complexity to generate loops that work for all, like in KPLANNER.

Summary of Different Approaches

- Deductive approach
 - Provable correctness
 - Slow and may require human expertise
- Non-deductive approach
 - Efficient and automatic
 - Weak guarantee of correctness

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Underlying Theory: Finite Verification

- Finitely verifiable theories have the property that whether a sentence is a theorem can be checked wrt a finite set of models of the theory [Lin 2007].
- Applied to planning domains, to see if a loopy plan works for a finitely verifiable problem
 - Identify the models that is sufficient for the judgment
 - Correctness verified by finite model checking

Underlying Theory: Identification in the Limit

- Provable correctness relies on the assumption that there is a complete characterization of legal initial states.
- When no such complete characterization is available, finding loopy plans resembles “identification in the limit” [Caldon & Martin 07; Gold 67].
 - There is an infinite supply of instances of a concept
 - The goal is to learn the concept
 - The learner has a hypothesis that explains the observations so far
 - The learner revises its hypothesis when it does not explain the newly observed instance
 - The concept is considered learnable if the learner identifies it after finite mind changes

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Possibilities for Future Work

- Find algorithms that
 - are more efficient
 - solve more problems
- Identify classes of problems with provable correctness guarantees
- Applications to learning for planning (IPC learning track)