Challenges of Human-in-the-Loop Planning and Decision Support

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Automated Planning

- Foundations of automated planning
- Planning under a variety of domain models
  - Classical, temporal, stochastic, partially-observable
- Current Focus: Human-in-the-loop planning

Information Fusion/Integration

- Integrating structured and semi-structured data to support effective query processing
- Structured data: Probabilistic methods for imputation, rectification.
- Semi-structured data: Trust and Relevance based source selection
- Unstructured data: Analyzing and aligning social media data with event transcripts, sentiment analysis
Planning Involves Deciding a Course of Action to achieve a desired state of affairs

- Environment
- Perception
- Goals
  - (Static vs. Dynamic)
  - (Observable vs. Partially Observable)
  - (Deterministic vs. Stochastic)
  - (Instantaneous vs. Durative)
  - (Full vs. Partial satisfaction)
  - (Perfect vs. Imperfect)

What action next?

The $$$$$$ Question:

A: A Unified Brand-name-Free Introduction to Planning

Subbarao Kambhampati
"Classical" Planning

(:action pick-up
 :parameters (?obl)
 :precondition (and (clear ?obl)
 (on-table ?obl)
 (arm-empty)
 (block ?obl)))
 :effect
 (and (not (on-table ?obl)))
 (not (clear ?obl))
 (not (arm-empty))
 (holding ?obl)))

Blocks world

State variables:
- Onetable(x, y)
- On(x, y)
- Clear(x)
- hand-empty
- holding(x)
- Stack(x, y)

Prec:
- holding(x), clear(y)
- Onetable(x, y)

eff:
- not holding(x), not onetable(x), hand-empty, clear(y)

Goal:
- ~clear(B), hand-empty

Initial state:
Complete specification of T/F values to state variables
--By convention, variables with F values are omitted

Goal state:
A partial specification of the desired state variable/value combinations
--desired values can be both positive and negative

Init:
- Onetable(A), Onetable(B), Clear(A), Clear(B), hand-empty

Goal:
- ~clear(B), hand-empty

Pickup(x)
Prec:
- hand-empty, clear(x), onetable(x)

eff:
- holding(x), ~onetable(x), ~hand-empty, ~clear(x)

Putdown(x)
Prec:
- holding(x)

eff:
- Onetable(x), hand-empty, clear(x), ~holding(x)

Stack(x, y)
Prec:
- holding(x), clear(y)

eff:
- on(x, y), ~clear(y), ~holding(x), hand-empty

Unstack(x, y)
Prec:
- on(x, y), hand-empty, clear(x)

eff:
- holding(x), ~onetable(x), clear(y), ~hand-empty

P-Space Complete
Scalability was the big bottle-neck…
We have figured out how to scale synthesis..

- Before, planning algorithms could synthesize about 6 – 10 action plans in minutes
- Significant scale-up in the last decade
  - Now, we can synthesize 100 action plans in seconds.

The primary revolution in planning in the recent years has been methods to scale up plan synthesis

Problem is Search Control!!!

Realistic encodings of Munich airport!
Cost of computing the heuristic

Cost of searching with the heuristic

Not always clear where the total minimum occurs
• Old wisdom was that the global min was closer to cheaper heuristics
• Current insights are that it may well be far from the cheaper heuristics for many problems
  • E.g. Pattern databases for 8-puzzle
  • Plan graph heuristics for planning

Scalability came from sophisticated reachability heuristics based on planning graphs..

..and not from any hand-coded domain-specific control knowledge

“Optimistic projection of achievability”
Planning Graph and Projection

- Envelope of Progression Tree (Relaxed Progression)
  - Proposition lists: Union of states at $k^{th}$ level
  - Mutex: Subsets of literals that cannot be part of any legal state

- Lowerbound reachability information

Planning Graphs can be used as the basis for heuristics!

[Blum&Furst, 1995] [ECP, 1997][AI Mag, 2007]
Heuristics for Classical Planning

Heuristic Estimate = 2

Relaxed plans are solutions for a relaxed problem
How far have we got?

How planners from past IPCs would have performed in IPC-8?

- In Sequential Satisficing track, LAMA-11 (winner of Sequential Satisficing track of IPC-7) would have been 12th out of 21.
- In Agile track, LPG and FF would have been, respectively, 13th and 17th out of 17.
..and we have done our fair bit...
So why the continued fascination with classical planning?

• ...of course, the myriad applications for classical STRIPS planning 😊

• But more seriously, because classical planners have become a customized substrate for “compiling down” other more expressive planning problems
  – Effective approaches exist for leveraging classical planners to do partial satisfaction planning, conformant planning, conditional planning, stochastic planning etc.
So, what next?

- Dynamic
- Stochastic
- Partially Observable
- Durative
- Continuous

- Replanning
- Situated Plans
- MDP Policies
- POMDP Policies
- Contingent/Conformant Plans, Interleaved execution
- Semi-MDP Policies
- Temporal Reasoning
- Numeric Constraint reasoning (LP/ILP)

- Static
- Deterministic
- Observable
- Instantaneous

“Classical Planning”
Compilation Substrates for Planning

**SAT**
- First of the substrates
  - Kautz & Selman got the classic paper award honorable mention
- Continued work on fast SAT solvers
- Limited to bounded length planning
- (Not great for metric constraints)

**IP/LP**
- Followed closely on the heels of SAT
- Can go beyond bounded length planning
  - Allows LP Relaxation
  - (Has become the basis for powerful admissible heuristics)
- IP solvers evolve much slower..

**(Classical) Planning**
- Tremendous progress on heuristic search approaches to classical planning
- A currently popular approach is to compile expressive planning problems to classical planning
  - Conformant planning, conditional planning
  - (even plan recognition)
Applications—sublime and mundane

- Mission planning (for rovers, telescopes)
- Military planning/scheduling
- Web-service/Work-flow composition
- Paper-routing in copiers
- Gene regulatory network intervention
Planning: The Canonical View

A fully specified problem
-- Initial state
-- Goals
  (each non-negotiable)
-- Complete Action Model

The Plan
**Need for Human-in-the-Loop/Human-Aware Planning & Decision Support**

- Planners are increasingly embedded in systems that include both humans and machines
  - Human Robot Teaming
    - Petrick et al, Veloso et al, Williams et al, Shah et al, Kambhampati et al
  - Decision support systems; Crowd-planning systems; Tutorial planning systems
    - Allen et al, Kambhampati et al; L

- **Necessitates Human-in-the-Loop Planning**
  - But, isn’t it just “Mixed-Initiative Planning”?
    - ..a lot of old MIP systems had the “Humans in the land of Planners” paradigm (the humans help planners)
    - In effective human-aware planning, planners realize they inhabit the land of humans..
Human-Robot Teaming

- Search and report (rescue)
- Goals incoming on the go
- World is evolving
- Model is changing

- Infer instructions from Natural Language
- Determine goal formulation through clarifications and questions
Commander View

Structured Data

Unstructured Data Stream (e.g., short text)
Recognition

Goal / Intent Recognition, Model learning
Model-lite plan recognition and model acquisition [1-7]

Decision Model

BayesWipe [11,12,13,17]

Data Reformulator

T*
T
R(T*)|Q*

Relevance Estimator

Generative & Error Model of Data

Query Reformulator

Q*
Q

Query

Results & Explanations

Suggested Actions

Structured, aligned, Unstructured

Actions

Alignment and Aggregation

Based on ET-LDA [14,15]

Structured Source

Unstructured Source

Latent topic

Inferring similarity

Latent topic

Data Support

SourceRank [8,9]
- Vertical integration
- Agreement based
- Handles unstructured data sources

SmartINT [10]
- Horizontal integration
- Handles fragmented data sources

Tweet Rank [16]
- Incorporates Trust
- 3 layers of signals: user, tweet and links

Unstructured Sources

( Includes documents and short text)

Structuring and semi-structured Sources

Decision Support

RADAR
Tour Request

Going to New York City for only a day in about a month. Where is a must to eat at that I can make reservations at? With so little time, I don't exactly want to spend it waiting for hours to get seated/get food. Also, what are the must things I should do and see in NYC? Off the beaten path things are preferred! :) I've been to NYC before, so perhaps new speakeasies, restaurants and nightlife recommendations would be awesome.

- Have a quick light lunch. Budget is $50. #lunch
- Do some shopping for a maximum of 2 hours. I can spend up to $300 on shopping. #shop
- Take a walk in some touristy place. #walk #touristy
- Have dinner and drinks at a good local restaurant. I want to spend a maximum time of 3 hours here. #dinner

TO DO Tags:
- manhattan_gettingto
- Getting to manhattan
- museum
- lunch

Existing Activities:
- manhattan_gettingto
  - Macy's: Awesome clothes and the head quarters (10:00 hrs) (1 hours) #shop
  - Manhattan: Walk near the NY public library and the charging bull (14:00 hrs) #walk

Google Map of New York City
Results: Role of Planner Module

VOTED ICAPS 2014 BEST DEMO BY ... THE CROWD!
Planning: The Canonical View

A fully specified problem
--Initial state
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  (each non-negotiable)
--Complete Action Model

The Plan
Challenges in Human-in-the-Loop/Human-Aware Planning & Decision Support

- Interpret what humans are doing
  - Plan/goal/intent recognition
- Plan with incomplete domain models
  - Robust planning with “lite” models
  - (Learn to improve domain models)
- Continual planning/Replanning
  - Commitment sensitive to ensure coherent interaction
- Explanations/Excuses
  - Excuse generation can be modeled as the (conjugate of) planning problem
- Asking for help/elaboration
  - Reason about the information value
Effective ways to handle the more expressive planning problems by exploiting the deterministic planning technology.

Violated Assumptions:
- Complete Action Descriptions (fallible domain writers)
- Fully Specified Preferences (uncertain users)
- Packaged planning problem (Plan Recognition)
- One-shot planning (continual revision)

Planning is no longer a pure inference problem 😞

But humans in the loop can ruin a really a perfect day 😞
A tempting way to handle incompleteness is to say that we should wait until the full model is obtained

- Either through learning
  - (We do have work in Model Learning: E.g. Zhuo et al. IJCAI 2013)
- Or by the generosity of the domain writer..

Problem: Waiting for complete model is often times not a feasible alternative

- The model may never become complete...
- We need to figure out a way of maintaining incomplete models, and planning with them (pending learning..)
MODELS V. PLANNING CAPABILITIES

I/O types
Task dependency
(e.g. workflows management, web service composition)

Missing some preconditions/effects of actions
(e.g. Garland & Lesh, 2002)
**Approaches for Planning with Incomplete Models (1)**

**Incompleteness annotations are available**

- One way to make-up for model incompleteness is to expect annotations circumscribing the extent of incompleteness.

- In this case, we can explicitly reason with the correctness of candidate plans over all possible models.
  - Nguyen et. al. ICAPS 2014; NIPS 2013

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**Problem Formulation**
- Incomplete domain: $\overline{D} = (F, A)$
- Each partially specified action $a \in A$:
  - Known preconditions, effects: $Pre(a), Add(a), Del(a)$
  - Possible preconditions, effects: $\overline{Pre}(a), \overline{Add}(a), \overline{Del}(a)$
  - Optional weights: $w_{a}^{pre}(p), w_{a}^{add}(p), w_{a}^{del}(p) \in (0,1)$
- Exponential number of candidate complete models: $\ll \overline{D} \gg$
- One of which is the true model.
- Planning problem: $\bar{P} = (\overline{D}, I, G)$

**Robustness measure for plans**

$$R(\pi, \bar{P}; (\overline{D}, I, G)) = \sum_{D_1 \in \ll \overline{D} \gg, \gamma(\pi, I, D_1) = G} \Pr(D_1)$$

**A Spectrum of robust planning problems**
- Robustness assessment
- Maximally robust plan generation
- Generating plan with desired level of robustness
- Cost-sensitive robust plan generation
- Incremental robustification
Robustness Assessment as Weighted Model Counting

- Causal-proof based correctness constraints \( \Sigma \)
  - Establishment constraints
    - Unsupported known preconditions must be supported:
    - So do possible preconditions, if realized:
  - Protection constraints
    - Known preconditions deleted by realized effects must be re-established:
    - So do possible preconditions, if realized:

Plan robustness = Weighted model counting WMC(\( \Sigma \)).

Complexity: Assessing plan robustness is \#P-complete.

Robust Plan Synthesis: A Compilation Approach

- Incomplete model
  - Complete model
    - Complete world state
      - Initial belief state

(Conformant Probabilistic Planning)

\[ x_p (0.5) \land x_q (0.7) \land x_r (0.2) \]

Resulting action \( a' \) with eight conditional effects.

Cond: \( x_p \land p \land x_q \land x_r \)
Eff: \( q \land \neg r \)

Robust Plan Synthesis: A Heuristic Approach

- Anytime approach
  1. Initialize: \( \delta = 0 \)
  2. Repeat
    - Find plan \( \pi \) s.t. \( R(\pi) > \delta \)
    - If plan found: \( \delta = R(\pi) \)
  3. Return \( \pi \) and \( R(\pi) \) if plan found

- Costly!

- Approximate plan robustness
  - Lower bound: \( \Sigma \) as monotone clauses
    \[ l(\Sigma) = \prod_{c \in \Sigma} \Pr(c) \leq \text{WMC}(\Sigma) \]
  - Upper bound: divide \( \Sigma \) into independent sets \( \Sigma^i \)
    \[ u(\Sigma) = \prod_{\Sigma^i} \min_{c \in \Sigma^i} \Pr(c) \geq \text{WMC}(\Sigma) \]

- Evaluation
Approaches for Planning with Incomplete Models (2)

**Library of cases is available**

- Sometimes, we may have access to “cases”/previous successful plans
- ML-CBP exploits cases directly during planning (by transferring case fragments into a skeletal plan generated w.r.t. $M'$)
  - Zhuo Et al AAAI 2013
- An alternative approach would be to use the cases $C$ to *refine* the model $M'$ into a more accurate model $M''$ (where $M''$ is a better approximation of $M^*$)
  - $M''$ contains both primitive and macro-operators
  - Zhuo et. Al. IJCAI 2013

**Figure 3: Accuracy w.r.t. number of plan cases.**
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Figure 3: Accuracies w.r.t. completeness of action models.
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COORDINATION IN HUMAN-ROBOT TEAMS USING MENTAL MODELING AND PLAN RECOGNITION

Presented at IROS 2014
Plan Recognition

BELIEF IN GOAL

(conducted_triage commX room1)
(conducted_triage commX room5)

observations -
move commx room3 hall5
move_reverse commx hall5 hall4
move_reverse commx hall4 hall3
move_reverse commx hall3 hall2
move_reverse commx hall2 hall1
move_reverse commx hall1 room1
pick_up_medkit commx mkeast room1
conduct_triage commx room1
Plan Recognition

BELIEF IN GOAL

(\text{conducted\_triage}\ \text{commX}\ \text{room1})

(\text{conducted\_triage}\ \text{commX}\ \text{room5})

Observations -
move\_commx\ \text{room3}\ \text{hall4}
moves\_reverse\ \text{commx}\ \text{hall4}\ \text{hall3}
moves\_reverse\ \text{commx}\ \text{hall3}\ \text{hall2}
moves\_reverse\ \text{commx}\ \text{hall2}\ \text{hall1}
moves\_reverse\ \text{commx}\ \text{hall1}\ \text{room1}
pick\_up\_medkit\ \text{commx}\ \text{mkeast}\ \text{room1}
conducted\_triage\ \text{commx}\ \text{room1}

Talamadupula et al. – Arizona State University & Tufts University
Coordination in Human-Robot Teams Using Mental Modeling & Plan Recognition
AI-MIX: SYSTEM SCHEMATIC

REQUESTER (Human)

COLLABORATIVE BLACKBOARD

PLANNER

CROWD (Turkers)

INTERPRETATION

M: Planner’s Model (Partial)

Analyze the extracted plan in light of M, and provide critiques

STEERING

MANIKONDA et al., Arizona State University
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reward for photograph of something interesting far exceeds penalty for violating drop-off commitment
[DMAP13]

Kartik Talamadupula - Arizona State
| M1  | REPLANNING AS RESTART  
     | (From scratch) | No Constraints |
|-----|----------------------|----------------|
|     | M2  | REPLANNING AS REUSE  
     | (Similarity) | Depends on the similarity metric between plans  
     |     | ACTION SIMILARITY |  
     |     | \[ \min | \pi \Delta \pi' | \]  
     |     | CAUSAL SIMILARITY |  
     |     | \[ \min | CL(\pi) \Delta CL(\pi') | \]  
|     | M3  | REPLANNING TO KEEP  
     | COMMITMENTS | Dependencies between \( \pi \) and other plans  
     |     | Project down into commitments that \( \pi' \) must fulfill  
     |     | Exact nature of commitments depends on \( \pi \)  
     |     | E.g.: Multi-agent commitments (between rovers)  

[DMAP13]

Kartik Talamadupula - Arizona State
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--Human Factors
Minecraft USAR Simulation

- Minecraft was chosen for its ease in flexibility and variability in its virtual environment.
- Office environment created in Minecraft for the purpose of simulating a search and rescue task.
- Minecraft allows for complex and changing environments and many internal participants for future iterations.
Example Maps
Results: Situation Awareness

**External Situation Awareness** = number of rooms correct (i.e., correct number and color of boxes on the map) slightly lower for Intelligent and more variability

Note: *Data collection is in progress - results are preliminary*
Human-in-the-Loop Planning is making inroads at ICAPS..

• Several papers that handle these challenges of Human-Aware Planning have been presented at the recent ICAPS (and AAAI and IJCAI)
  – Significant help from applications track, robotics track and demonstration track
  – Several planning-related papers in non-ICAPS venues (e.g. AAMAS and even CHI) have more in common with the challenges of Human-aware planning
• ..so consider it for your embedded planning applications
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--Human Factors

Tutorial@AAAI 2015