Anticipatory On-line Planning

Ethan Burns\textsuperscript{1}, J. Benton\textsuperscript{2}, Wheeler Ruml\textsuperscript{1}, Sungwook Yoon\textsuperscript{3}, and Minh Do\textsuperscript{4}

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Consider a UAV fulfilling observation requests:

- Observation requests (start–end locations) arrive over time
  - Requests draw from known distribution
- Minimize time to service observations
  - Re-planning may reduce cost.
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Observations:
- Life is more than one goal—others will come
- “Planner” can run, even before goal arrives

Other examples:
- Life (e.g., insurance)
- Satellite planning
- Taxi/ambulance dispatching
- Manufacturing
- PARC printer

Opportunity:
- Estimate of future goals
Contributions

- Simple and clean formalization of on-line planning
  - Exposes key issues, yet very approachable
- Show that hindsight optimization applies easily
  - Not just for probabilistic planning any more!
- Show that simple HOP is better than “reactive” planning
  - Many avenues for future work
Formalization
Like classical planning:
- Action effects are deterministic

but, on-line:
- Goals arrive stochastically, distribution is known

Like MDP:
- Minimize total cost, approximate over a fixed horizon, $H$
- When evaluating actions:

$$V_H^*(s_1) = \min_{a_1, \ldots, a_H} \mathbb{E} \left[ \sum_{i=1}^{H} C(s_i, a_i) \right]$$

- State incorporates unachieved goals

Simple and clean formulation of on-line planning
1. Plan for the current goals
2. Execute the plan until the goals change
3. Repeat
A Simple Approach: Reactive Planning

1. Plan for the current goals
2. Execute the plan until the goals change
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Doesn’t take advantage of knowledge about future goals
Hindsight Optimization
Consider possible future goals when planning actions
Solve for all possible future goals

\[ V_H^*(s_1) = \min_{a_1,\ldots,a_H} E \left[ \sum_{i=1}^H C(s_i, a_i) \right] \]

A 3x3 UAV with \( \leq 3 \) requests has tens of millions of states.
Hindsight optimization — solve a sample of future goals

\[ \hat{V}_H(s_1) = \mathbb{E}_{s_2, \ldots, s_H} \left[ \min_{a_1, \ldots, a_H} \sum_{i=1}^{H} C(s_i, a_i) \right] \]
Hindsight optimization – solve a sample of future goals

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Hindsight optimization – solve a sample of future goals

\[ V_H(s_1) = \min_{a_1, \ldots, a_H} \sum_{i=1}^{H} C(s_i, a_i) \]

Deterministic Planning
1. Sample future goal arrivals
2. For each action
   Evaluate mean plan cost over sampled futures
3. Take the best action
4. Repeat
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Simple, and uses knowledge about goal arrivals
HOP has been applied to:

- On-line scheduling (Chong, Givan, Chang 2000)
- Stochastic integer programs (Mercier and van Hentenrych 2007)
- Probabilistic planning (Yoon et al. 2008)

Now:

- On-line Planning
Experiments
Goal: **gain the most reward**

How do we know our technique is doing well?
Goal: gain the most reward

How do we know our technique is doing well?

- How does it compare to optimal?
  - Imagine we have an oracle that knows the future

- How does it compare to a simple planner?
  - Greedy: evaluate cost-to-go heuristic on each successor
  - Go to the state with the lowest heuristic value
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Normalized reward:
reward normalized between optimal (1) and greedy (0)
UAV Domain

Introduction
Formalization
Hindsight Opt.
Experiments
- How?
  - UAV Domain
    - UAV Results
    - Manufacturing
    - Manu. Results
Conclusion
Reactive ∼ greedy, HOP gives the most reward
Manufacturing Domain

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HOP is close to optimal and gives the most reward
Pros:

■ HOP simple to implement (just need deterministic planner)
■ Better than the simple reactive approach
■ Better than MDP solvers for these problems

◆ 3x3 UAV: LRTDP 100x slower and worse than greedy

Cons:

■ HOP slower than reactive

◆ Finds many plans instead of just one
◆ Reactive: ~ 0 seconds, HOP: 0.002–10 seconds
◆ But, see (Yoon et al. ICAPS 2010)
Many problems are on-line continual planning problems.
We can take advantage of the known goal distribution.
Hindsight optimization is simple and works well.
Tell your students to apply to grad school in CS at UNH!

- friendly faculty
- funding
- individual attention
- beautiful campus
- low cost of living
- easy access to Boston, White Mountains
- strong in AI, infoviz, networking, systems