Reinforcement Learning with Limited Reinforcement

Using Bayes Risk for Active Learning in POMDPs

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We desire an agent that

- **adapts** to new environments,
- behaves **robustly** in novel situations,
- and is **natural** to train.

How do we do this?

- risk-averse action selection
- particle filtering to track our world knowledge.
- asking for help!
Reinforcement Learning Paradigm

- Agent performs actions, receives observations and rewards.
- Assume a Markov world; world dynamics consists of reward $R(s,a)$, transition $T(s'|s,a)$, and observation $O(o|s,a)$ models.
- Agent must trade between learning about the world (exploration) and getting rewards (exploitation).
Common issues with RL

- Must make mistakes to learn.
Common issues with RL

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- Aside from model/policy convergence, no reasoning about partial information.
Common issues in RL

- Must make mistakes to learn.
- Aside from model/policy convergence, no reasoning about partial information.
- Format of required reinforcement may be unnatural.
Our Approach

- **POMDP framework:** a Bayesian approach to model uncertainty.
  - The agent is **aware of its model uncertainty.**
- **Meta-queries:** Ask for policy information when confused.
  - The agent can **actively reduce model uncertainty.**
- Resulting approach **combines Bayesian and inverse reinforcement learning.**
The POMDP Planning Process

When solved, the POMDP optimally trades between gathering information about the state and gathering reward.
Planning with Uncertain Models

However, models are hard to come by! One option is to keep an estimate of the true model.
Planning with Uncertain Models

But, if we think of the model as hidden state, dealing with model uncertainty is equivalent to dealing with state uncertainty.
Planning with Uncertain Models

Ignore uncertainty: fast, not robust

Plan with parameters as hidden state: optimal but slow
Planning with Uncertain Models

- Ignore uncertainty: **fast, not robust**
- Approximate planning with Bayes risk, policy queries
- Plan with parameters as hidden state: **optimal but slow**
The Model-Uncertainty POMDP

Planning

Belief over world dynamics, objective

Belief over the world state

Belief Update

action

observation

State of the world

True world dynamics

Agent

World
Action Selection

- Use Bayes Risk to find the safest action.
Action Selection with Bayes Risk

• Find the action with the minimal risk:

\[ a = \arg\min_{a \in A} \int_M (Q_m(b_m, a) - Q_m(b_m, a')) p(m) \, dm \]

• Evaluate the Bayes Risk integral approximately using sampled POMDPs:

\[ a = \arg\min_{a \in A} \sum_i (Q_i(b_i, a) - Q_i(b_i, a')) w_i \]

(We can bound the approximation error.)
Action Selection with Bayes Risk

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(We can bound the approximation error.)

**But what if the safest action is still pretty risky?**
Action Selection

- Use Bayes Risk to find the safest action.
- If this action is too risky, ask for help.
Asking for Help: Policy Queries

But what if the risk is too large? Ask for help so

- Agent does not need to take large risks to determine that a particular decision may be poor.
- User only needs to provide reinforcement when the agent is sufficiently confused.

... plus allows us to provide bounds on performance throughout the learning process!
Asking for Help: Implementation

Questions of the form:

- “I think you **might** want to go to the printer. Should I go to the printer?”
- “I'm **certain** you want to go to the printer. Should I go to the printer?”
- “Instead, should I ask for you to confirm your location?”

Ask these questions to determine the correct action; thus a query results in discovering the optimal action.
We need to incorporate two sources of information:

- h: Most recent history of actions and observations
- Q: Set of (query, response) pairs that we have asked
Belief Update

- Need to maintain a posterior over models:

\[ p(m|h, Q) \propto p(Q|m) p(h|m) p(m) \]

- History information can be updated in closed form (via an online EM-like update), but query information cannot.
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Belief Update: During a Trial

- We want to update the posterior quickly, without solving additional POMDPs, so we don't sample new models, only reweight models based on query information.

- In theory, $p(Q|m)$ should be 0-1, but we use a binomial function to account for approximations in the solver.

original set  reweighted set
Belief Update: Between Trials

- Resample POMDPs.
- Use a transition kernel that incorporates history information by either replacing or perturbing current samples with samples from $p(m|h)$.

original set \[\rightarrow\] resample based on weights \[\rightarrow\] perturb based on $p(m|h)$ \[\rightarrow\] reweighted set
Performance Guarantees

- We can lower bound the performance of our approach \textit{in expectation} with respect to the optimal policy:

\[
V' > \eta (V - \frac{\xi}{1-\gamma}) + (1-\eta)\left(\frac{R_{\text{min}}}{1-\gamma}\right), \quad \eta = \frac{(1-\gamma)(1-\delta)}{1-\gamma(1-\delta)}
\]

- We will eventually converge to a transition, observation, and reward model.
Results
Results: Standard POMDP Problems

The active learner maintains good performance from the start.

<table>
<thead>
<tr>
<th>Problem</th>
<th>States</th>
<th>Control</th>
<th>Passive</th>
<th>Active</th>
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<tbody>
<tr>
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</table>

Mean difference between obtained reward and optimal reward over 50 trials (smaller is better)
Results: Simulated Dialog Domain

The active learner performs well without informative priors.
Results: Short User Dialog

Early Conversation:
User: Give me the forecast.
Robot: I'm confused. What action should I take now?
<User indicates that the robot should provide the weather forecast>
Robot: Showers

Later Conversation:
User: What's the forecast for today?
Robot: Do you want the weather?
User: Yup.
Robot: Showers
Conclusions and Future Work

- Although POMDP models require many parameters, we can learn those parameters online.
  - **Bayes risk action** selection lets the agent act robustly in the face of model uncertainty
  - The learning process can be further improved by incorporating policy queries.

- Extensions
  - Improve POMDP sampling techniques (or find a closed-form approximation to the POMDP posterior).
  - Approaches to finding policy information from humans (improved meta-queries).
Thank-you!
Results: Direct Solution

Total Reward in Directly Solved Model-Uncertainty POMDP

<table>
<thead>
<tr>
<th>Total Reward</th>
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<tbody>
<tr>
<td>100</td>
</tr>
<tr>
<td>95</td>
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<tr>
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<td>80</td>
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<tr>
<td>75</td>
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<td>70</td>
</tr>
</tbody>
</table>

- MetaQueries and Direct Solution
- No MetaQueries
- MetaQueries and Bayes Risk
BR Action Selection (Continuous Models)

Observation Learning

Reward Learning

Mean difference between optimal and system rewards when learning the observation spaces

Median Reward Aggregated Over 100 trials, Permuted Model

- opt
- no learning
- reweight only
- reweight and meta-action
User Test Results: Example Dialog 2

Early Conversation:
User: I want some tea from the kitchen.
Robot: How can I help you?
User: The tea is in the kitchen near the coffee machine. <The system hears "copy" instead of "coffee" and is confused about "tea" and "kitchen." >
Robot: How can I help you?
User: Go to the kitchen.
Robot: I'm confused. What action should I take now?
<User indicates "Confirm the coffee machine area" is the correct action.>
Robot: Do you want to go to the coffee machine area?
User: Yup.

<The system asks a few more (non-meta) questions>
Robot: Do you want to go to the coffee machine area?
User: Yup.
Robot: Going to the coffee machine area.

Later Conversation:
User: Take me to the kitchen. <The system hears "Nick" and "kitchen." >
Robot: How can I help you?
User: I want some coffee. <The system hears "copy" instead of "coffee." >
Robot: Do you want to go to the coffee machine area?
User: Yup.
Robot: Going to the coffee machine area.
Related Work in Bayesian Model Learning

- Dearden et. al.: Bayesian MDP model learning
- Beetle (Poupart et. al.): frame unknown MDP as a continuous state POMDP
- Medusa (Jaulmes et. al.): sample from a distribution over POMDPs; use the sample for action selection
Solving a known POMDP Model

Value of a belief

\[ V_n(b) = \max_a Q_n(b, a) \]

Value of belief, action pair

\[ Q_n(b, a) = R(b, a) + \gamma \sum_{b' \in B} T(b'|b, a) V_{n-1}(b') \]

\[ Q_n(b, a) = R(b, a) + \gamma \sum_{o \in O} O(o|b, a) V_{n-1}(b^o) \]

Current reward

Future Reward
Error in Approximating Bayes Risk

- If we want to estimate if the Bayes Risk is greater than \( \zeta \) with confidence \( \delta \), two error sources exist:
  - Error due to approximating risk from samples:
    \[
    n_m = \frac{(R_{max} - \min(\zeta, R_{min}))^2}{2(1-\gamma)^2 \epsilon_m^2} \log \frac{1}{\delta}
    \]
  - Error due to approximate POMDP solutions:
    \[
    \epsilon_{pb} = 2 \delta_b \frac{(R_{max} - R_{min})}{(1-\gamma)^2}
    \]
- Noting that \( \zeta = \epsilon_m + \epsilon_{pb} \), set \( \epsilon_m \) and \( \epsilon_{pb} \) to trade between the number of belief samples and model samples.
Details for Particle Filter

- In general, given a kernel $K(m, m')$, particles are sampled and assigned weights according to:

$$m_t \sim K(m_{t-1}, m_t)$$

$$w_t = w_{t-1} \frac{p_M(t)(m_t)}{p_{M, t-1}(m_{t-1}) K(m_{t-1}, m_t)}$$

- During trials: $K(m, m') = \delta(m, m')$

$$w_t = w_{t-1} p(Q_t| m)$$

- Between trials: Sample $m''$ from $p(m|h)$, replace $m$ with $m''$ with probability $p$; else $K(m, m') = am + (1-a)m''$.

$$w_t = \frac{p(Q|m') p_{M|h}(m')}{p(Q|m) p_M(m) K(m, m')}$$
Termination Procedure

To estimate if the probability of asking a meta-query after n more interactions is greater than \( \zeta \) with confidence \( \delta \), we can:

- Compute “worst posterior” by assigning interaction counts to make a flat Dirichlet posterior.
- Sample POMDPs from the posterior.
- Sample beliefs from the POMDPs.
- Reject if \( f(\zeta) \)-proportion beliefs require meta-queries.

We can set the number of POMDP, belief samples required, as well as \( f(\zeta) \), based on our desired confidence.
Discrete Models: Why few policies?

In the special case where:

- Only rewards are unknown
- Simple dialog model

The policies for a variety of parameter values are similar; the main degree of freedom is how certain we must be before acting, which translates to how many times to confirm a choice.
Sometimes, POMDPs can be solved quickly

Doshi and Roy, AAMAS 2008