Explaining the Behavior of POMDP-based Agents Through the Impact of Counterfactual Information

Saaduddin Mahmud[1], Marcell Vazquez-Chanlatte[2], Stefan Witwicki[2] and Shlomo Zilberstein[1]

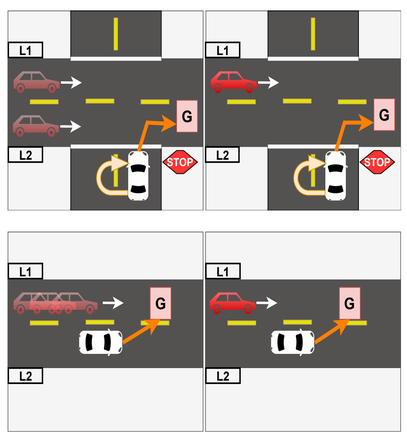
[1] University of Massachusetts Amherst, [2] Nissan Advanced Technology Center Silicon Valley

Introduction

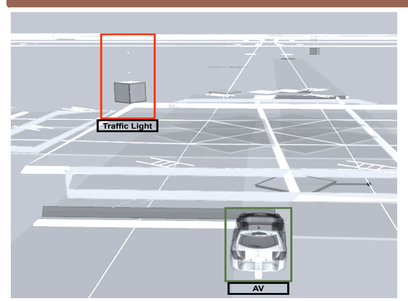
- **What?** We introduce a novel framework called SIP: Sequential Information Probing to explain how uncertainty about state features affect agents behavior.
- **Why?** Most real-world decision-making scenarios contain partially observed features.
  - While ubiquitous scenario no prior works has attempted to explain this class of problems.
  - The sequential nature of POMDPs makes it difficult to apply existing feature attribution methods.
- **How?** We probe agent with a sequence of perfect counterfactual information about state features. Then we quantify the effect on agents' behavior.
- **Works?** We both theoretically and quantitatively analyze the properties of our method. We also run a case study on a working AV system for demonstration.

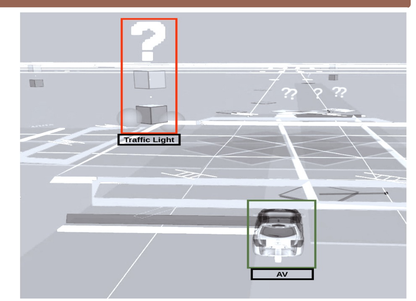
Example

- **One-Step Information**
  - The White car on the left waits to make a more accurate estimation of the lane position of the oncoming red vehicle before making a right turn.
  - If we probe with white care with the lane position information it can avoid waiting.
- **Sequential Information**
  - Estimation of both position and speed needed when changing lane. Further, each step degrades estimation.
  - Therefore, a single step of information probing might not be sufficient to elicit lane-changing behavior.



Case Study

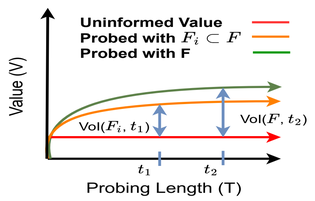


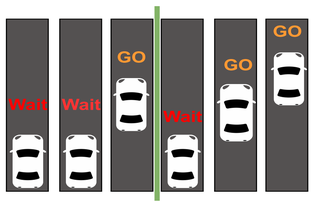


- **Details**
  - We run a case study on an Autonomous vehicle in an urban environment.
  - The vehicle models the world with a set of POMDP using the MODIA framework.
- **VoI Visualization**
  - We put a '?' on object corresponding to each feature. We control the opacity based on the normalized magnitude of VoI
  - The AV is waiting in the intersection for the traffic light to change.
  - Sudden change of the traffic light state causes uncertainty and lights up (right).

Value and Influence of Information (VoI and IoI)

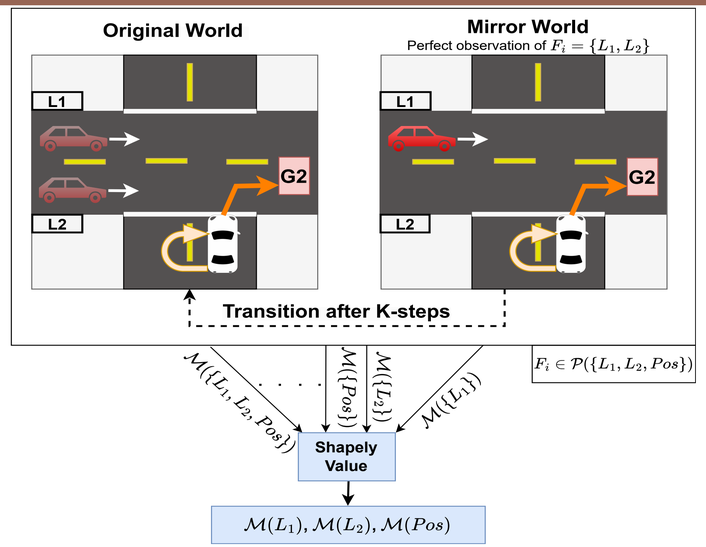
- **VoI: Value of Information**
  - Expected difference between uninformed value function and information probed value function.
  - As we increase the probing length and provide information about a larger subset of the features we gain more value.
- **IoI: Influence of Information**
  - Expected change in negative log-likelihood of observing a given trajectory.
  - The likelihood of observing ***WAIT*** $-$ ***WAIT*** $-$ ***GO*** goes down and ***WAIT*** $-$ ***GO*** $-$ ***GO*** goes up when we probe the agent with lane position information (Example 1).





- **Probing Strategy**
  - **[*KS*]**: The agent stays exactly ***K*** steps in the mirror world.
  - **[*GE*]**: The agent stays ***K*** steps in expectation in the mirror world where $\boldsymbol{K} \sim \textbf{\textit{Geometric}}(\mathbf{1} - \lambda)$
  - **[*MY*]**:: The agent remains in the mirror world for ***K*** steps but the agent is not aware of the probing.
- **Calculating VoI and IoI**
  - Discrete State Space: We construct a new probing augmented POMDP. Solving this augmented POMDP allows $\boldsymbol{O}(|\boldsymbol{S}|)$ calculation of VoI, and $\boldsymbol{O}(|\boldsymbol{S}||\boldsymbol{T}|)$.
  - Continues State Space: We propose Meta-CDQL algorithm, a deep Q-learning-based algorithm for estimating counterfactual information probed values.

SIP: Sequential Information Probing



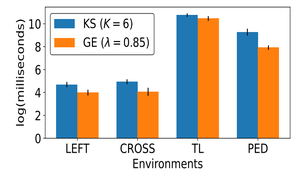
- Step 1: Prob POMDP-agent with a sequence of information about different subsets of state features.
- Step 2: Calculate metrics such as VoI and IoI by contrasting the probed agents with the uninformed agent.
- Step 3: Compute and present the marginal contribution of each feature using the Shapley value method.

Additional Results and Takeaway Message

- **Theoretical Analysis**
  - We present several theoretical properties of VoI and IoI including a direct relation between VoI and IoI:

$$|\textbf{\textit{IoI}}(\tau) - \sum_{t=0}^{T} [\textbf{\textit{VoI}}(b_t) - \textbf{\textit{QoI}}(b_t)]| \leq \textbf{\textit{log}}(|\boldsymbol{A}|)$$

- **Quantitative Analysis**
  - We compare the computation requirements of different probing strategies.
  - We evaluate the similarity among VoI and IoI and different probing mechanisms. We find a high correlation between these methods.
  - We analyze the consistency of the generated explanations. We found high consistency in discrete state space. We propose an ensemble as a remedy in continuous state space.



- **Takeaway Messages**
  - We propose a novel method for explaining how uncertainty affects a sequential decision-making agent.
  - We propose two metrics VoI and IoI to quantify the long-term effect of uncertainty.
  - We propose an efficient method to calculate VoI and IoI and apply the Shapley value method to calculate the marginal effect of feature uncertainty.
  - In the future, we want to extend our work to offline RL settings.

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