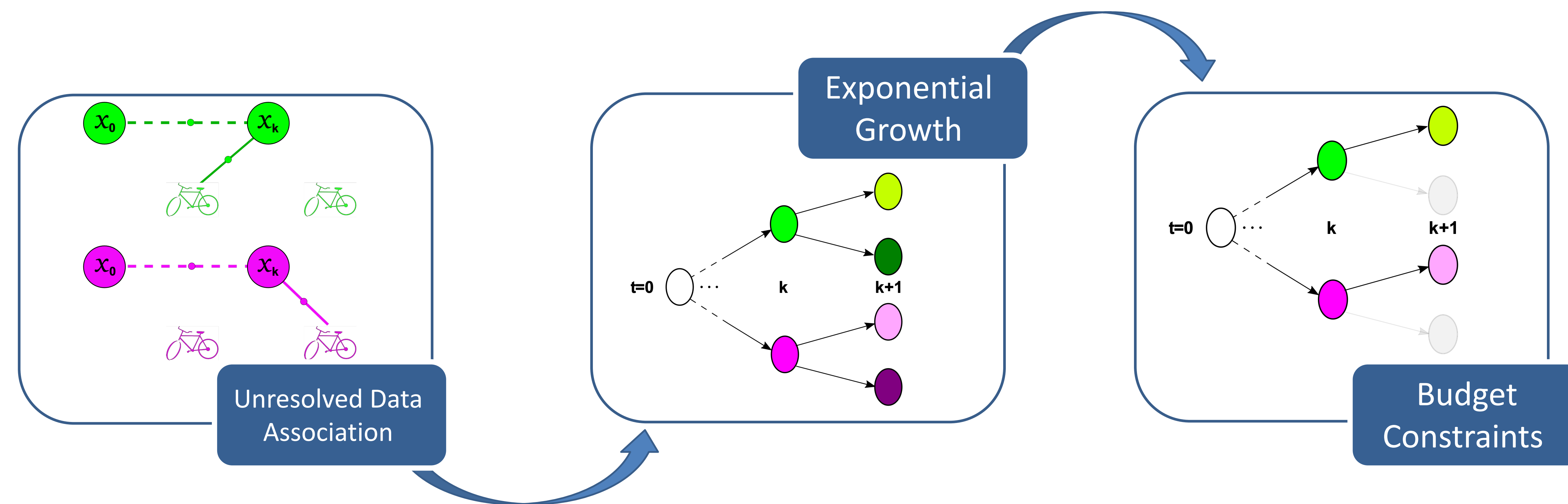


Motivation



- In ambiguous and perceptually aliased environments agents cannot assume that data association is solved
- Explicitly considering all possible data associations, the number of hypotheses grows exponentially
- Under hard computational budget constraints, some hypotheses must eventually be pruned
- There are typically no guarantees on the loss in solution quality in planning

Our Contributions

- D2A-BSP**: A novel planning approach that utilizes only a distilled subset of hypotheses
- Bounds**: Over the true analytical solution considering all possible hypotheses
- Budget Free**: Use bounds to reduce computational complexity while preserving action selection
- Budget Constraints**: Use bounds to provide performance guarantees under budget constraints

Problem Formulation

- Considering Data Associations, the belief at time k is a linear combination of $M_k \in \mathbb{N}$ weighted hypotheses

$$b_k = \sum_{j=1}^{M_k} \underbrace{\mathbb{P}(x_k | \beta_{1:k}^j, H_k)}_{b_k^j} \underbrace{\mathbb{P}(\beta_{1:k}^j | H_k)}_{w_k^j}$$

- The goal of Belief Space Planning is to find the optimal action sequence with respect to a user defined objective function

$$u_{k:k+N-1}^* = \underset{\mathcal{U}}{\operatorname{argmin}} J(b_k, u_{k:k+N-1})$$

- Our goal is to solve an easier problem that bounds the objective function using a *simplified* belief and provides performance guarantees $\underline{J}(b_k, b_k^s, u_k) \leq J(b_k, u_k) \leq \bar{J}(b_k, b_k^s, u_k)$

Approach

Simplified Belief

Select a subset of hypotheses

- The *simplified* belief at time step k is defined by the selected distilled subset of hypotheses of size M_k^s as $b_k^s \triangleq \sum_{j=1}^{M_k^s} w_k^{s,j} b_k^j$, $w_k^{s,j} \triangleq \frac{w_k^j}{w_k^m}$. Weights are re-normalized according to $w_k^{m,s} \triangleq \sum_{m \in M_k^s} w_k^m$

Cost Function

For autonomous active disambiguation of hypotheses

- An information theoretic term over data association hypotheses weights using the Shannon entropy $\mathcal{H} \triangleq - \sum_{i=1}^n w^i \log(w^i)$

Bounds

Analytically developed for the considered cost function

- In the myopic case, the considered cost function is bounded by

$$\mathcal{LB}[c(b_{k+1})] \triangleq \mathcal{LB}[\mathcal{H}] = \frac{\eta^s w_k^{m,s}}{\mathcal{UB}[\eta]} [\mathcal{H}^s - \log(\eta^s)] - \frac{w_k^{m,s}}{\mathcal{UB}[\eta]} \sum_i^{|L|} \sum_j^{M_k^s} \tilde{\zeta}_{k+1}^{i,j} w_k^{s,j} \log\left(\frac{w_k^{m,s}}{\mathcal{LB}[\eta]}\right),$$

$$\mathcal{UB}[c(b_{k+1})] \triangleq \mathcal{UB}[\mathcal{H}] = \frac{\eta^s w_k^{m,s}}{\mathcal{LB}[\eta]} [\mathcal{H}^s - \log(\eta^s)] - \frac{w_k^{m,s}}{\mathcal{LB}[\eta]} \sum_i^{|L|} \sum_j^{M_k^s} \tilde{\zeta}_{k+1}^{i,j} w_k^{s,j} \log\left(\frac{w_k^{m,s}}{\mathcal{UB}[\eta]}\right) - \gamma \log\left(\frac{\gamma}{|L| - |M_k^s|}\right)$$

- For each candidate action, the bounds over the objective function are evaluated given the *simplified* belief. With fewer hypotheses, the computational complexity is reduced

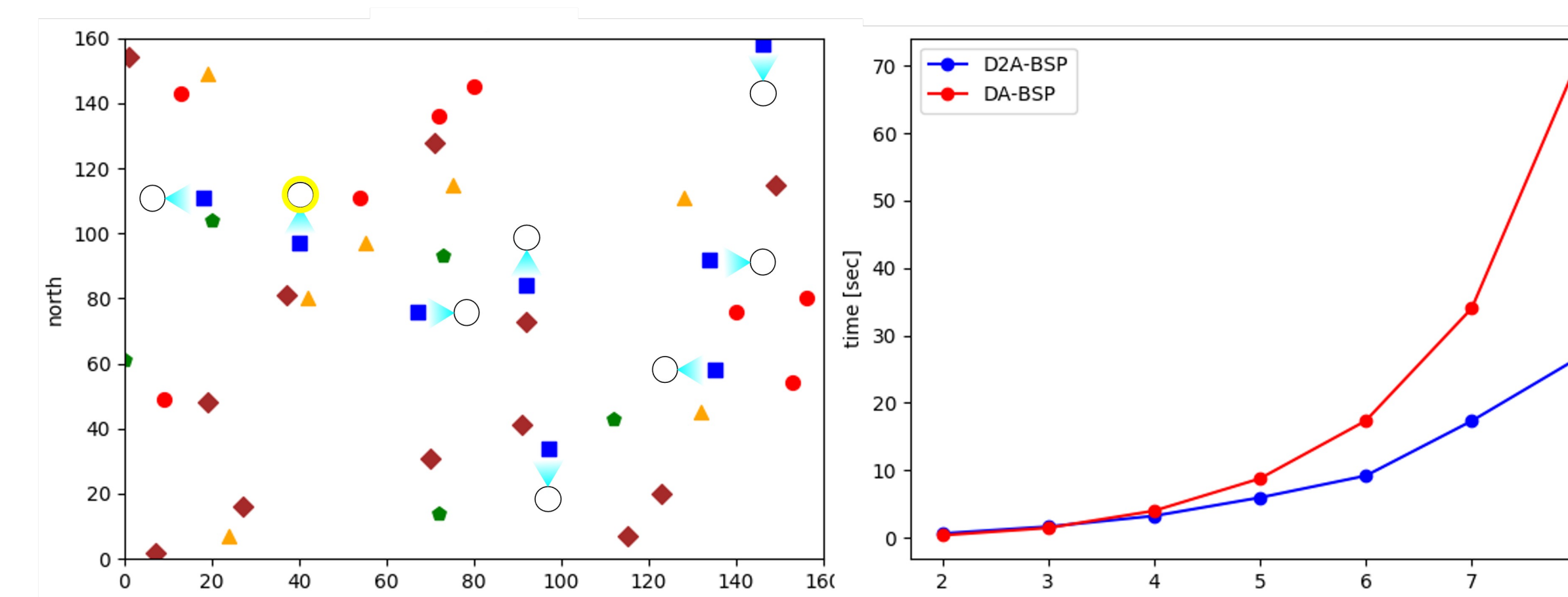
Performance Guarantees

Derived from bounds

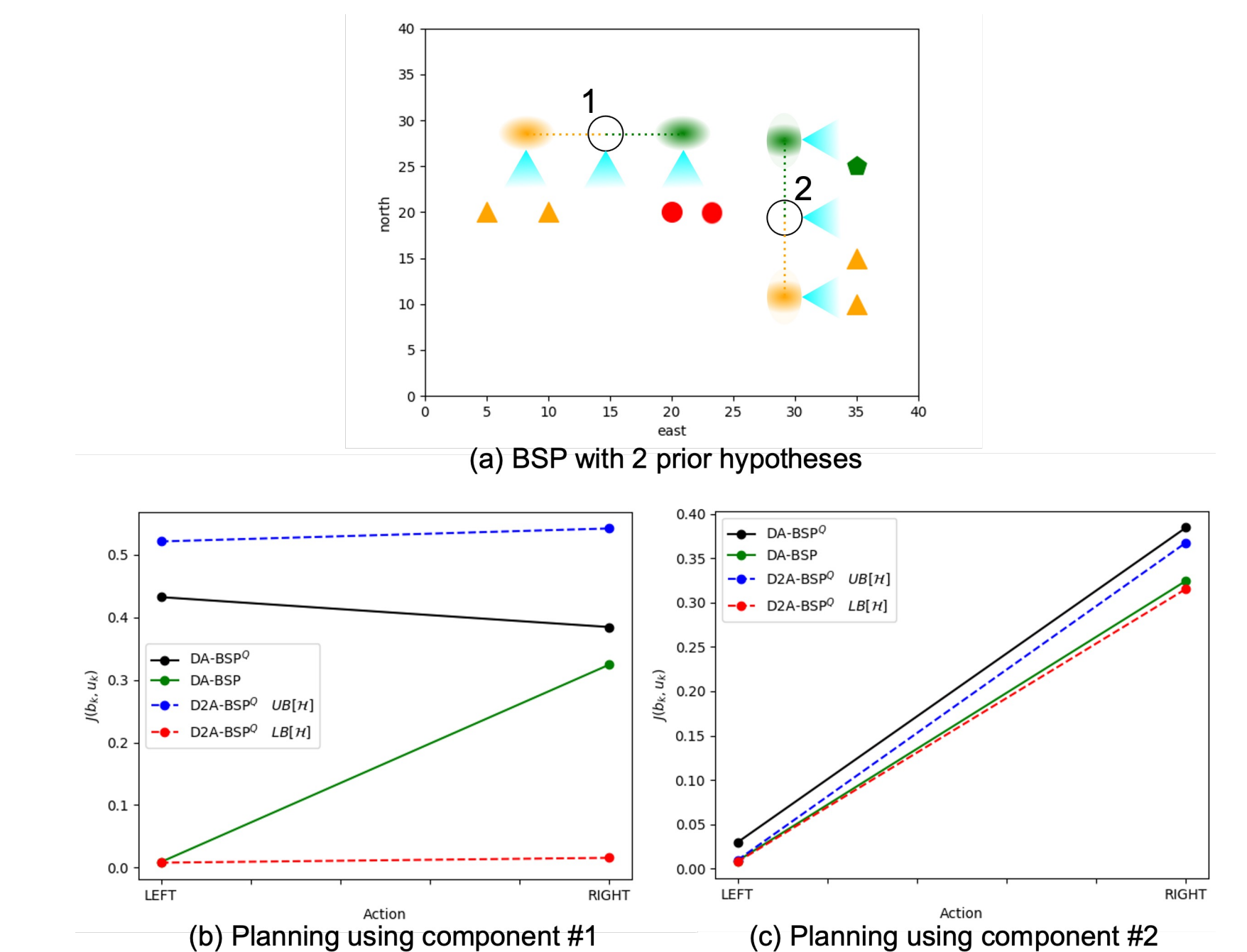
- Planning using these bounds we can either guarantee to select the same optimal action as in the original problem or derive a loss on the quality of the solution when bounds overlap

Results

Goal Fully disambiguate between all prior hypotheses (no budget constraints)



Goal Disambiguate between hypotheses (weighted equally) under budget constraints



- A kidnapped robot scenario
- The initial belief is multi-modal
- The agent's goal is to fully disambiguate between hypotheses
- The higher the level of ambiguity within the environment, the more prominent our approach becomes

- While DA-BSP can only rely on heuristics to decide which hypothesis to use
- Our approach can guarantee that going left is the optimal action as the bounds do not overlap