Efficient Data Processing and Trustworthy Decision Making through Structured Task Representation

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autonomous SYSTEMS GROUP

Motivation

Autonomous agents in real world

- Decision making under partial knowledge
- Access to large-scale, multi-modal, and noisy data

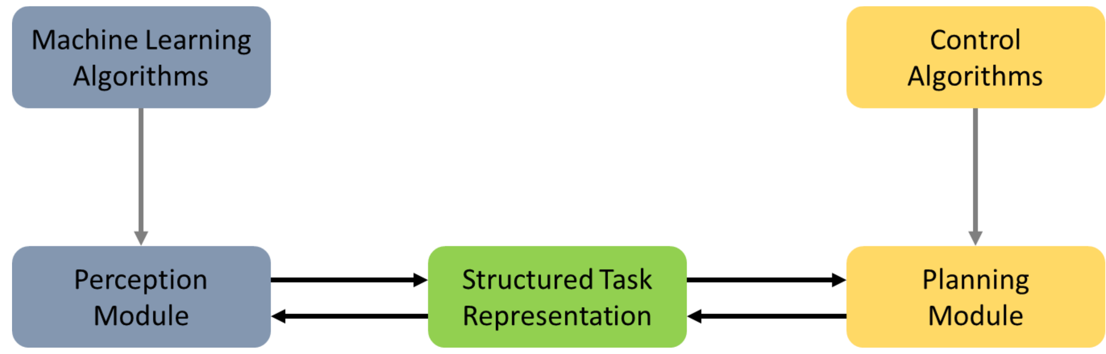
Question: How to process data efficiently and make decisions trustworthily?

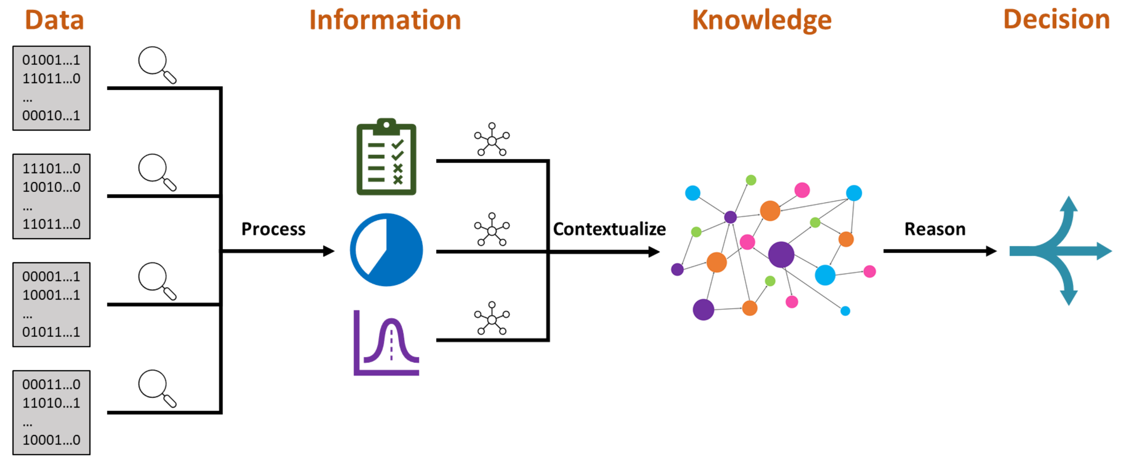
Machine learning algorithms

- Handling large-scale high-dimensional data
- Fusing heterogeneous data

Control algorithms

- Providing performance guarantees
- Ensuring safety constraints





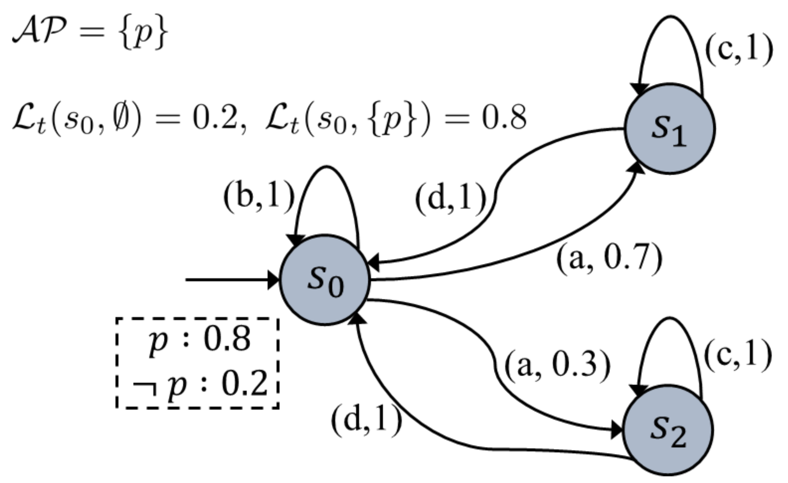
Contributions

1. Characterize information utility
2. Guide active perception while planning
3. Provide runtime guarantee on task success

Modeling Framework

System dynamics

A Markov decision process $\mathcal{M} = (\mathcal{S}, s_{init}, \mathcal{A}, \mathcal{T})$



Environment model

A set of state attributes (atomic propositions)

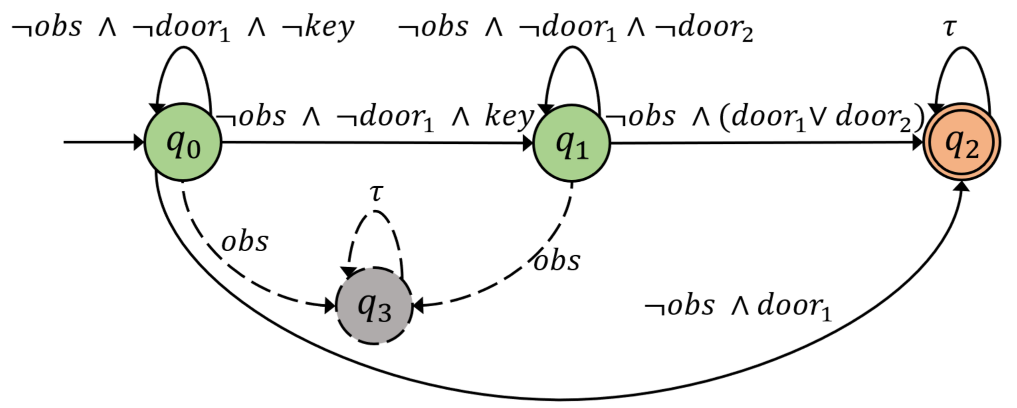
A true labeling function $\hat{\mathcal{L}} : \mathcal{S} \to 2^{\mathcal{AP}}$

Agent's belief as a probabilistic labeling function

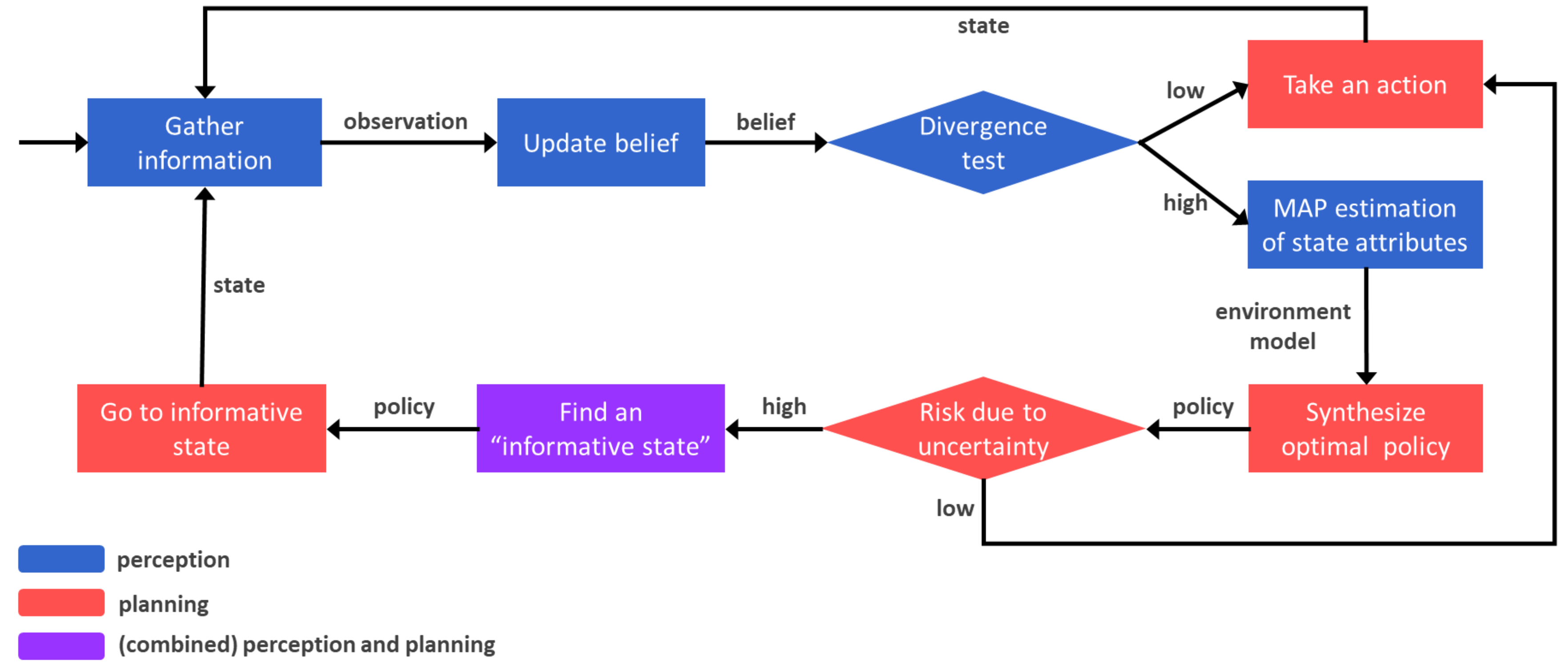
$$\mathcal{L}_t : \mathcal{S} \times 2^{\mathcal{AP}} \to [0, 1]$$

Task specification

A temporal logic formula represented as a deterministic finite automaton



Task-Oriented Active Perception and Planning



Divergence test

$$\underbrace{D_{\mathcal{JSD}}(\mathcal{L}_{t-1} \| \mathcal{L}_t)}_{\text{Jensen-Shannon divergence between consecutive beliefs}} \overset{?}{\geq} \underbrace{\gamma_d}_{\text{A hyperparameter determining the frequency of replanning}}$$

Risk assessment

$$\underbrace{\mathcal{R}(\mathcal{M}_\mathcal{D}, \pi_t, \mathcal{L}_t, \varphi)}_{\text{Risk parameter}} = \left| \underbrace{Pr(\mathcal{M}_\mathcal{D}^{\pi_t} \models \varphi \,|\, \hat{\mathcal{L}}_t)}_{\text{Task success for the estimated environment}} - \underbrace{\mathbb{E}_{\mathcal{L} \sim Dist(\mathcal{L})}\left[Pr\left(\mathcal{M}_\mathcal{D}^{\pi_t} \models \varphi\right)\right]}_{\text{Task success for the environment with partial semantics}} \right| \overset{?}{\geq} \underbrace{\gamma_r}_{\text{Risk tolerance}}$$

Theorem: (computational complexity of exact verification)

Quantitative verification of a Markov chain with m states and n atomic propositions with partial semantics against a reachability specification requires computation over a computation graph of size $O(n2^{nm})$.

Theorem: (sampling complexity for statistical verification)

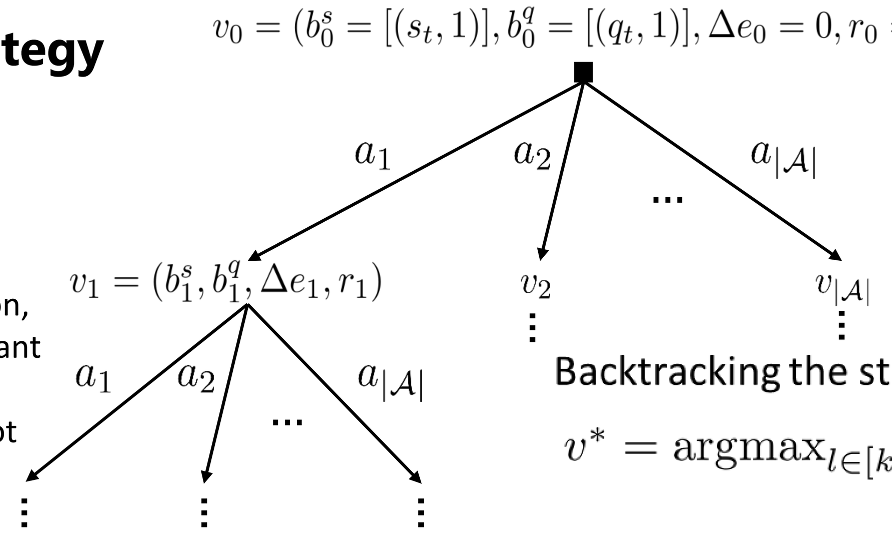
For any $\epsilon_1 \in (0,1)$ and $\epsilon_2 \in (0,1)$, if $N \geq \frac{1}{2\epsilon_1^2} \log \frac{2}{\epsilon_2}$, then it holds that

$$Pr\left(\left| \mathbb{E}_{\mathcal{L} \sim Dist(\mathcal{L})}\left[Pr\left(\mathcal{M}_\mathcal{D}^{\pi_t} \models \varphi\right)\right] - \hat{\mathbb{E}}_{\mathcal{L} \sim Dist(\mathcal{L})}\left[Pr\left(\mathcal{M}_\mathcal{D}^{\pi_t} \models \varphi\right)\right] \right| \geq \epsilon_1 \right) \leq \epsilon_2.$$

Active perception strategy

node $v_i = (b_i^s, b_i^q, \Delta e_i, r_i)$ =

(
belief over states of the MDP,
belief over states of automaton,
uncertainty reduction in relevant atomic propositions,
probability of reaching the root state
)



Backtracking the strategy from the tree:

$$v^* = \operatorname{argmax}_{l \in [k]} \underbrace{\Delta e_l}_{\text{Entropy reduction over related atomic propositions}} + \beta \underbrace{(b_l^q(q_t) + r_l)}_{\text{Exploration safety}}$$

Simulation and Empirical Results

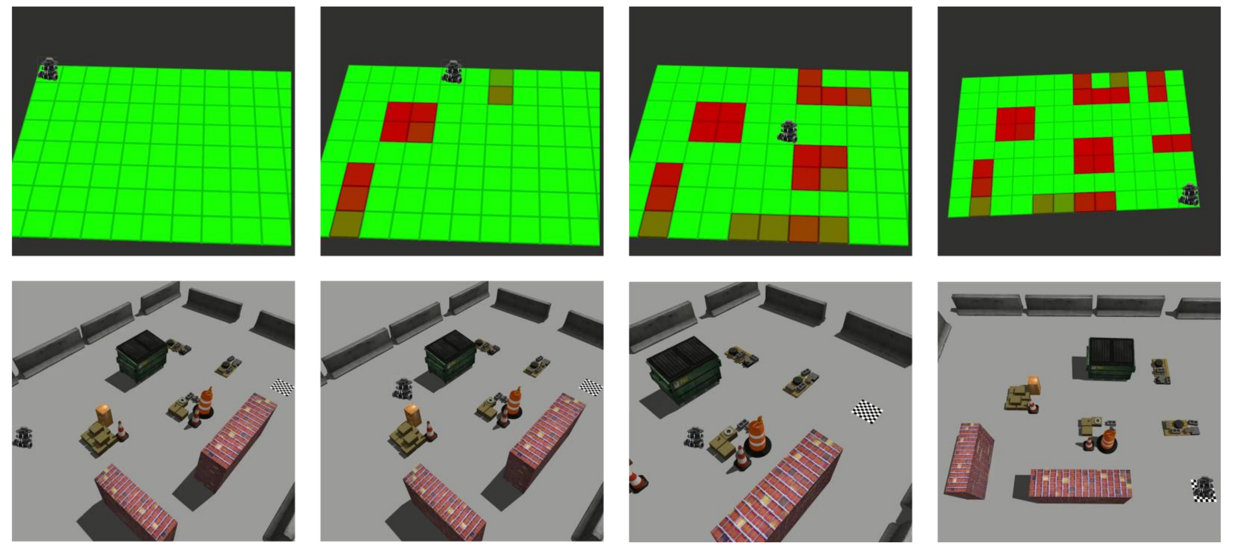
Ablation study in a planar navigation task

- Replanning improves performance at the cost of more computation
- Active perception improves performance

Algorithm	Success	#Step	#Plan
No perc.	0%	50	1
Perc. w/ no update + replan	0%	38.4	38.4
Perc. w/ update + replan	84%	21.8	21.8
Perc. w/ update + div.	80%	22.8	14.8
Perc. w/ update + replan + info.	92%	19.4	19.4
Perc. w/ update + div. + info.	86%	22.6	14.6

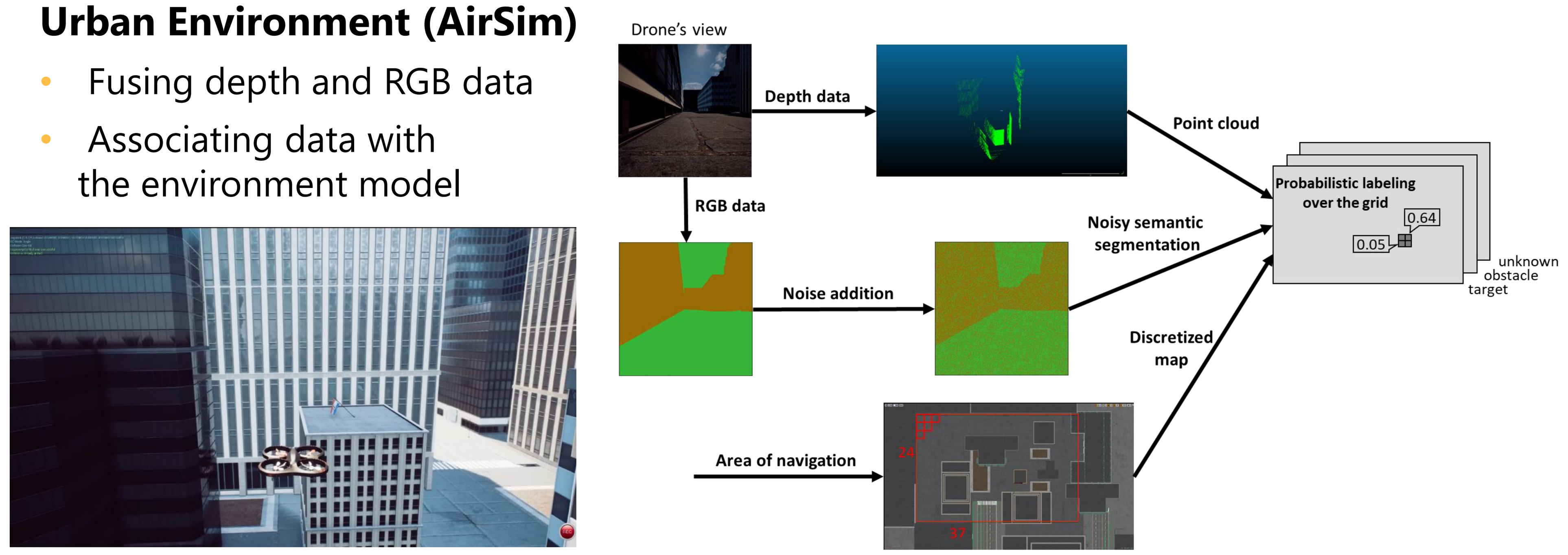
TurtleBot navigation in a Gazebo environment

- Gathering task-relevant information
- Successful navigation with partial environment model



Drone Navigation in Simulated Urban Environment (AirSim)

- Fusing depth and RGB data
- Associating data with the environment model



Conclusion and Future Directions

Conclusion

- Studied decision making in environments with partially known semantics
- Proposed a task-oriented active perception and planning framework that integrates learning through perception with decision-making under uncertainty

Future directions

- Extending to settings with uncertain or unknown dynamics and evolving environments
- Incorporating a priori side knowledge for perception

Paper: *Task-Oriented Active Perception and Planning in Environments with Partially Known Semantics*, International Conference on Machine Learning (ICML), 2020.

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