# Robot Safety in Partially Observable Domains: Challenges & Opportunities

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ICRA'25 Workshop on Robot Safety Under Uncertainty from Intangible Specifications

May 19, 2025

# Advanced Autonomy

### Perception and Inference

Where am I? What is the surrounding environment?

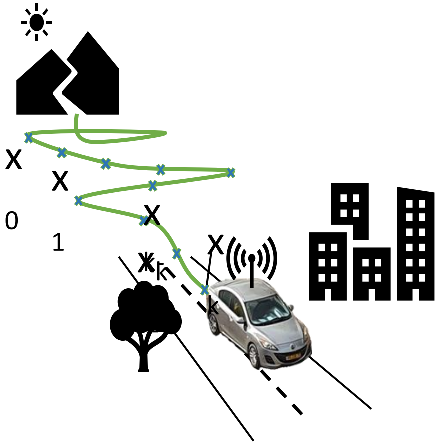
**Key required capabilities**

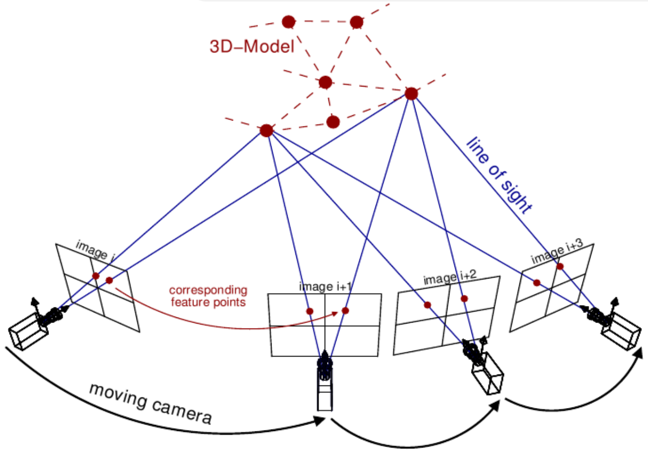
### Decision-Making Under Uncertainty

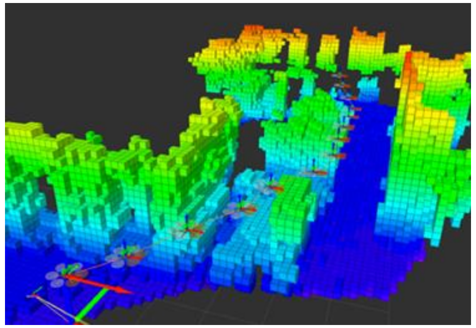
What should I be doing next?

Determine best action(s) to accomplish a task, account for different sources of uncertainty

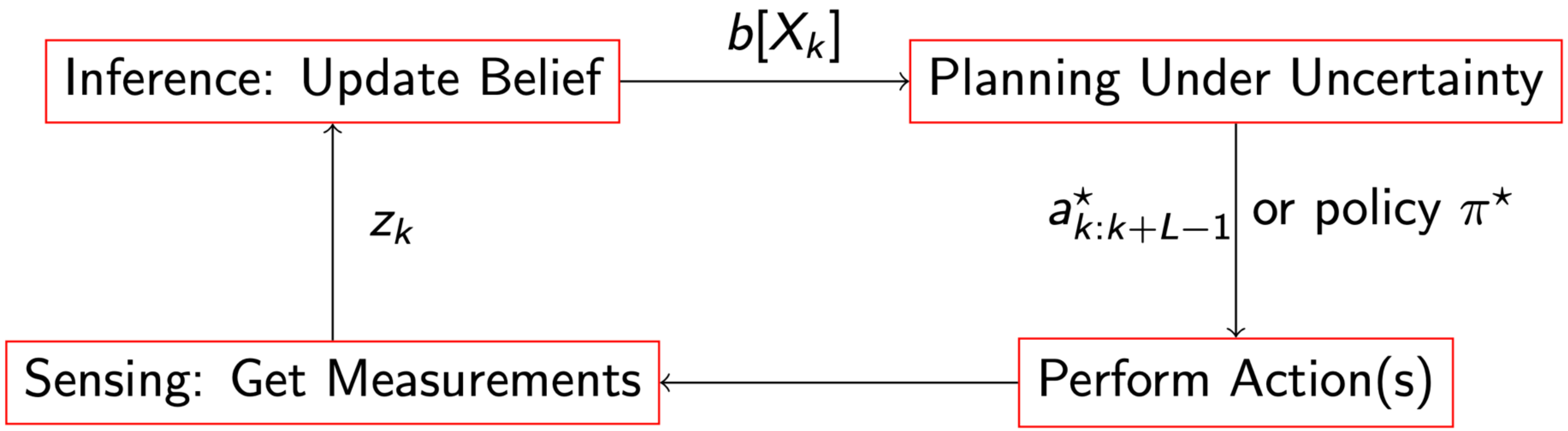
**Perception and Inference** ⟷ **Decision-Making Under Uncertainty**





# Autonomy Loop



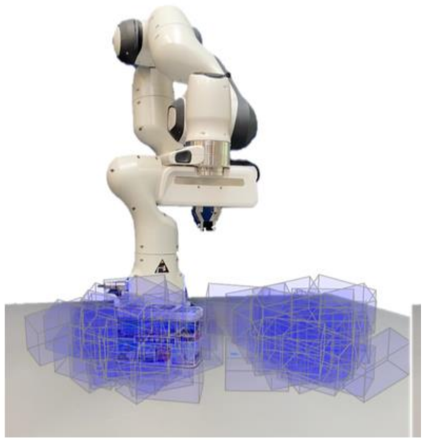
# Perception and Inference

- Posterior belief at time k: $b_k \triangleq b[X_k] = \mathbb{P}(X_k \mid \overbrace{a_{0:k-1}, z_{1:k}}^{\mathcal{H}_k})$

  state/variables at time instant k

  actions

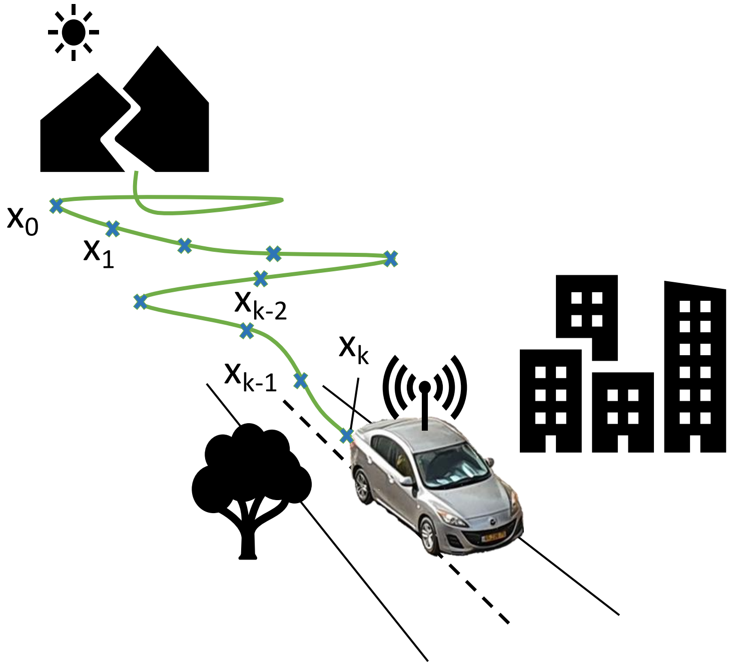
  observations

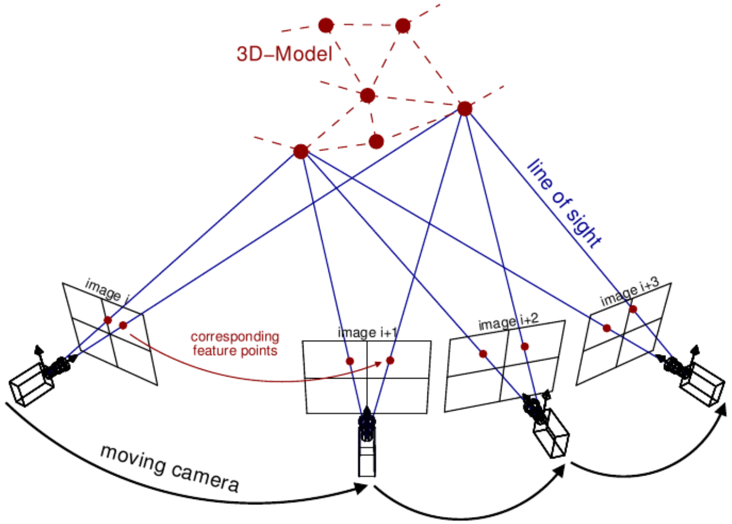


- Example: $X_k \doteq \{\underline{x_0, \ldots, x_k}, \underline{L_k}\}$

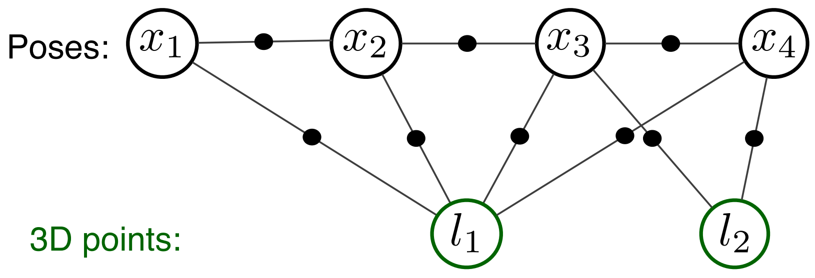
  **Past & current robot states**

  **Environment representation, e.g. Landmarks**




Can be represented with graphical models, e.g. a Factor Graph



# Partially Observable Markov Decision Process (POMDP)

- POMDP tuple:

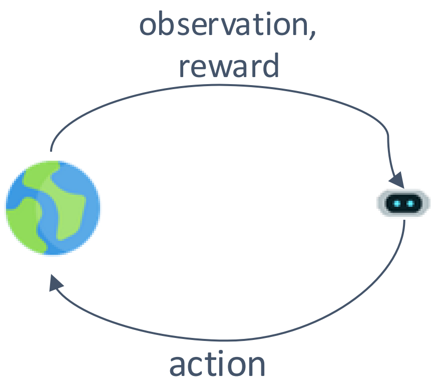
$$\langle \mathcal{X}, \mathcal{Z}, \mathcal{A}, T, O, \rho, b_k \rangle$$

state, observation, and action spaces

transition and observation models

Belief-dependent reward function

Belief at planning time instant k




- Value function

$$V^{\pi}(b_k) = \underset{z_{k+1:k+L}}{\mathbb{E}}\left[\sum_{l=k}^{k+L} \rho(b_l, \pi_l(b_l))\right]$$

Belief-dependent reward function

s.t. safety constraint $\geq 1 - \epsilon$

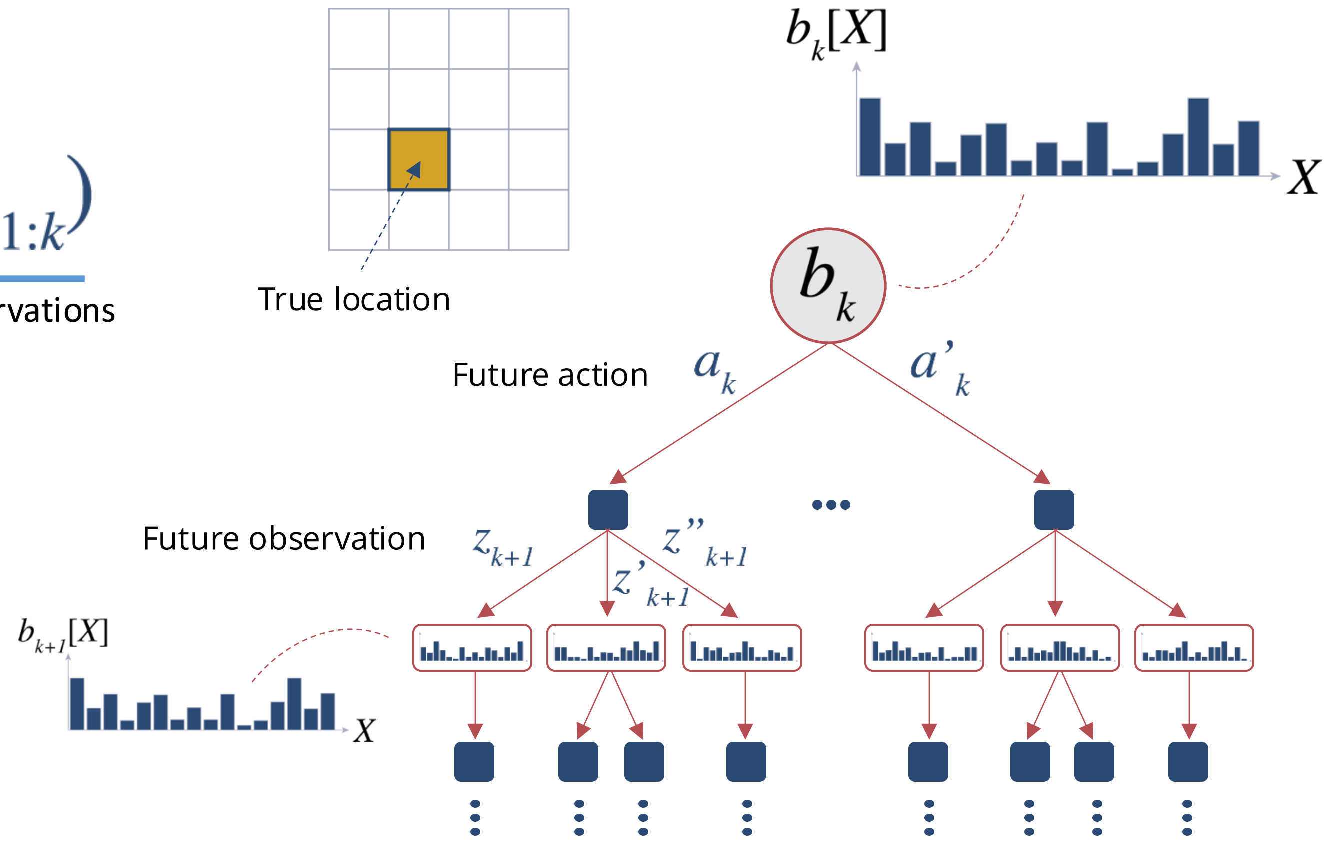
# Challenge

## Probabilistic Inference

Maintain a distribution over the state given data

$$b_k \triangleq b[X_k] = \mathbb{P}(\underbrace{X_k}_{\text{state}} \mid \underbrace{a_{0:k-1}}_{\text{actions}}, \underbrace{z_{1:k}}_{\text{observations}})$$

**Example – grid world**

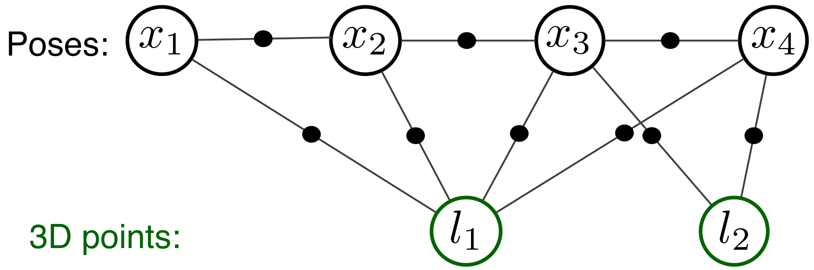



## Decision-making under uncertainty

Involves reasoning about the entire observation and action spaces along planning horizon

## Computationally intractable

More so, in high dimensional settings




**ct autonomously online and efficiently**
**tasks in a safe and reliable fashion??**

# Agenda

POMDP Planning with Hybrid Beliefs

- Semantic Risk Awareness
- Ambiguous Environments

Anytime Constrained POMDP Planning

Multi-agent POMDP Planning with Inconsistent Beliefs

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**Semantic Risk Awareness**

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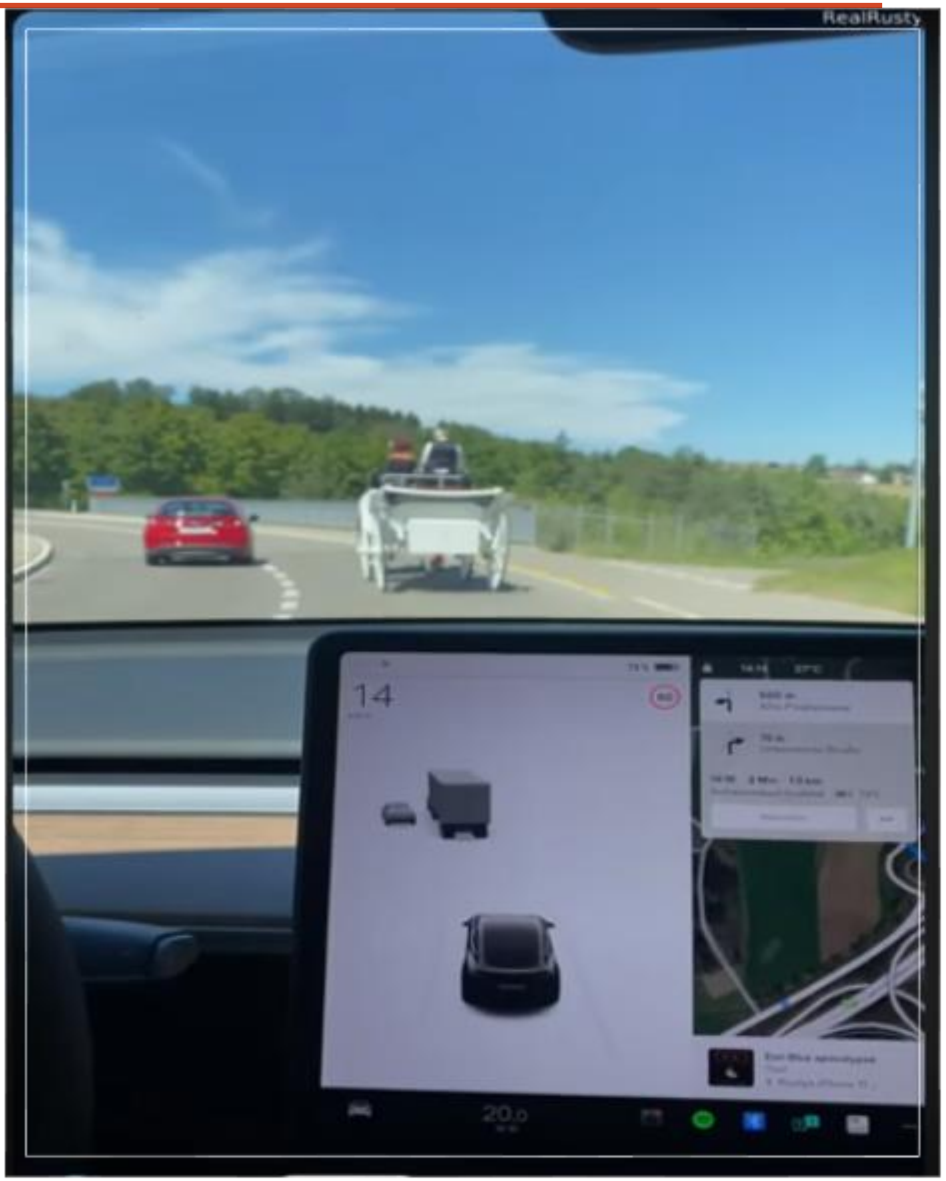
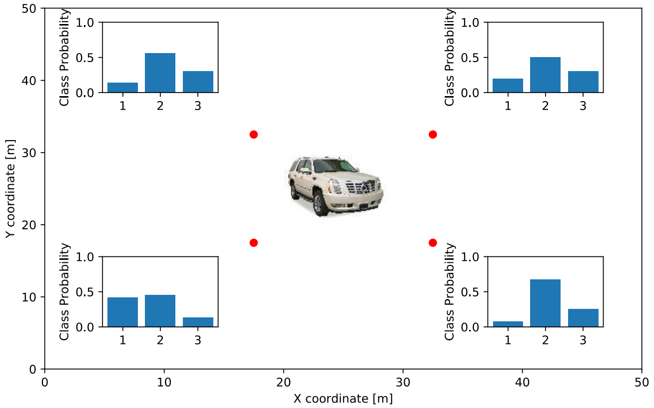
# Semantic Perception & SLAM

- Usually, semantics and geometry are considered **separately**
- Cannot use coupled observation models or priors
- Can lead to absurd & **unsafe** performance



# Coupled Models

- View-dependent semantic observation model:




$$\mathbb{P}(z^s \mid c, \mathcal{X}^{rel})$$

Semantic observation (from a classifier)

Object class

Agent's viewpoint relative to object

- Class and poses can be coupled via learned prior probabilities.
- Reward/constraint can depend on both classes and poses


Y. Feldman and V. Indelman, "Bayesian Viewpoint-Dependent Robust Classification under Model and Localization Uncertainty," ICRA'18.
V. Tchuiev, Y. Feldman, and V. Indelman, "Data Association Aware Semantic Mapping and Localization via a Viewpoint Dependent Classifier Model," IROS'19.
V. Tchuiev and V. Indelman, "Epistemic Uncertainty Aware Semantic Localization and Mapping for Inference and Belief Space Planning," Artificial Intelligence, 2023.
T. Lemberg and V. Indelman, "Online Hybrid-Belief POMDP with Coupled Semantic-Geometric Models and Semantic Safety Awareness", arXiv'25.

# Hybrid Belief

- **Hybrid Belief** at time instant k:

$$b[X_k, C] = \mathbb{P}(X_k, C \mid \mathcal{H}_k)$$

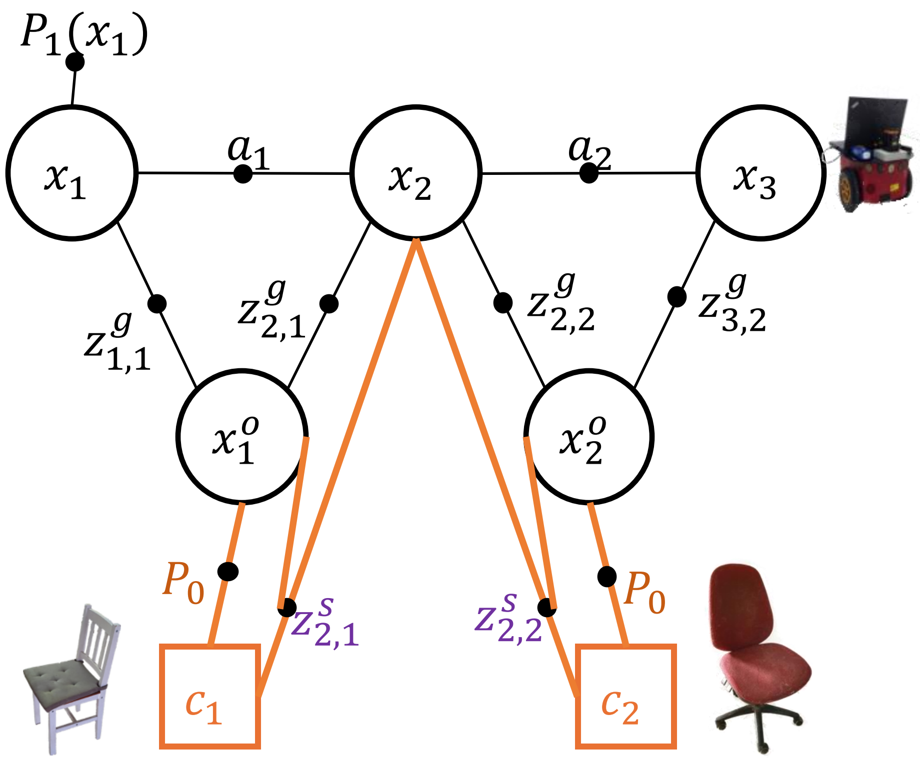
Robot's and objects' poses

Objects' classes

History (actions, geometric & semantic observations)

- Classes and agent poses are <u>dependent</u>
- Classes of different objects are <u>dependent</u>

- As opposed to:
  - Per-frame classification
  - Modeling semantic observations as viewpoint **independent**





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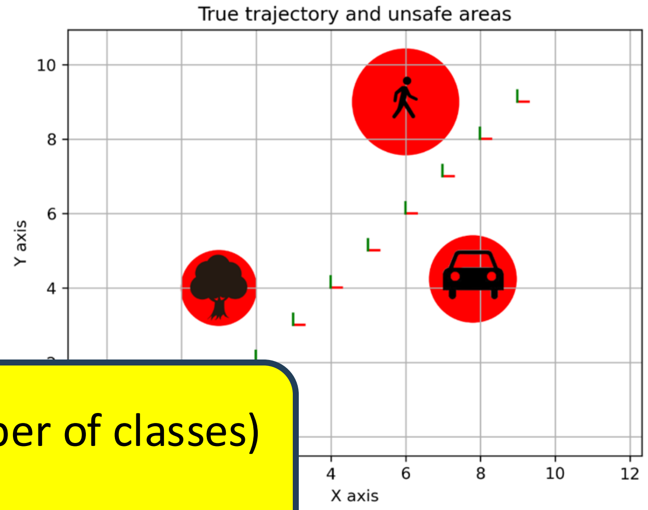
# POMDP Planning with Hybrid Semantic-Geometric Beliefs

- Value function $$V^{\pi}(b_k) = \mathbb{E}_{z_{k+1:k+L}}[\sum_{l=k}^{k+L-1} \rho(b_l, \pi_l(b_l), b_{l+1}]$$

- **Semantic Risk Awareness**

$$\mathbb{P}_{safe} \triangleq \mathbb{P}(\{\wedge_{t=k+1}^{L} x_t \notin \mathcal{X}_{unsafe}(C, X^o)\} \mid \boxed{b_k[x_k, C, X^o]}, \pi)$$

Objects' classes Objects' poses




The number of classification hypotheses is $M^N$ (N: number of objects, M: number of classes)
How to sample w/o pruning hypotheses? How to estimate $\mathbb{P}_{safe}$ ?

T. Lemberg and V. Indelman, "Online Hybrid-Belief POMDP with Coupled Semantic-Geometric Models and Semantic Safety Awareness," arXiv'25.

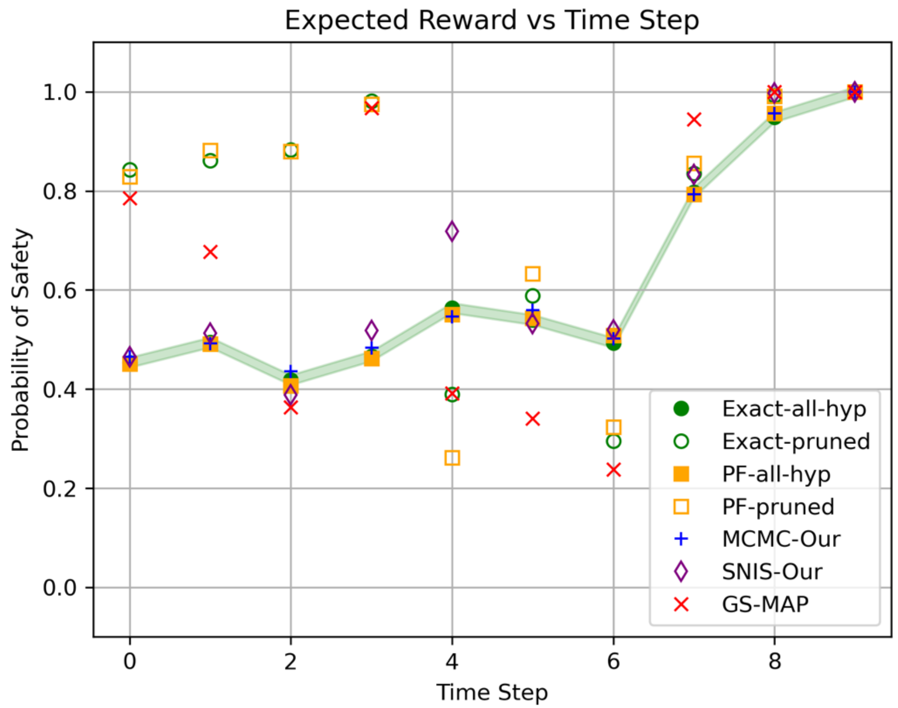
# POMDP Planning with Hybrid Semantic-Geometric Beliefs

**Experiments -** Estimation of $\mathbb{P}_{safe}$ with different methods

- **Exact-all-hyp** – belief computed exactly
- **Exact-pruned** – pruned version
- **PF-all-hyp** – Particle filter
- **PF-pruned** – pruned version

**Our methods**

- **MCMC-Our** – MCMC samples
- **SNIS-Our** – self-normalized importance sampling
- **GS-MAP** – separate semantic and geometric

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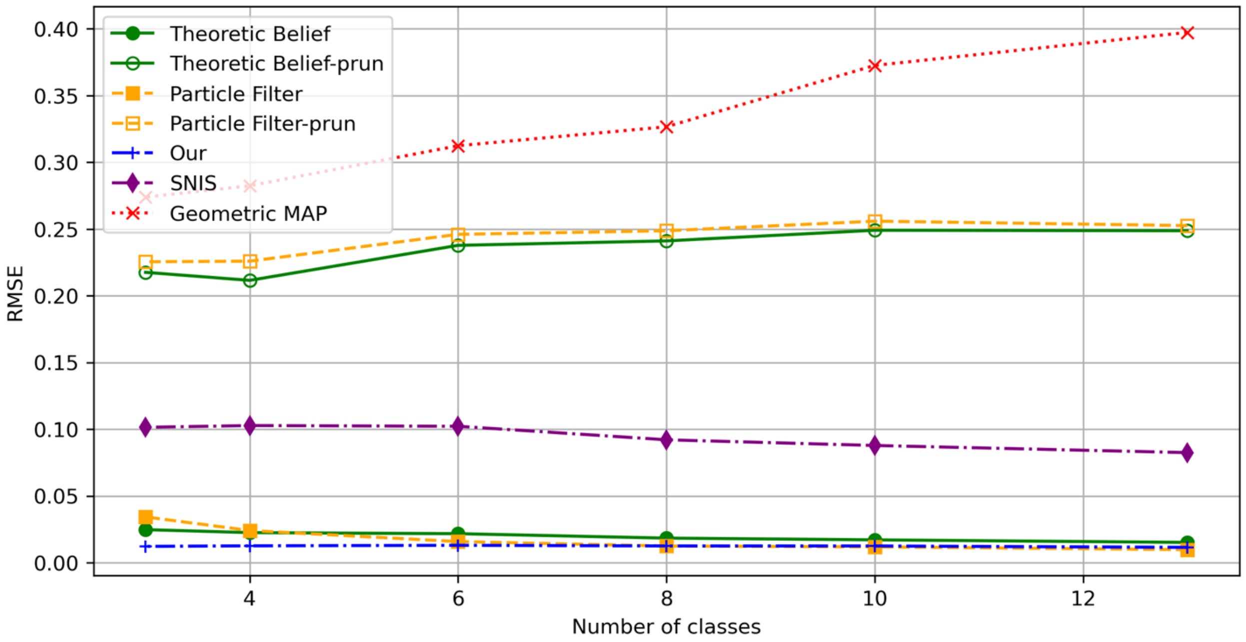
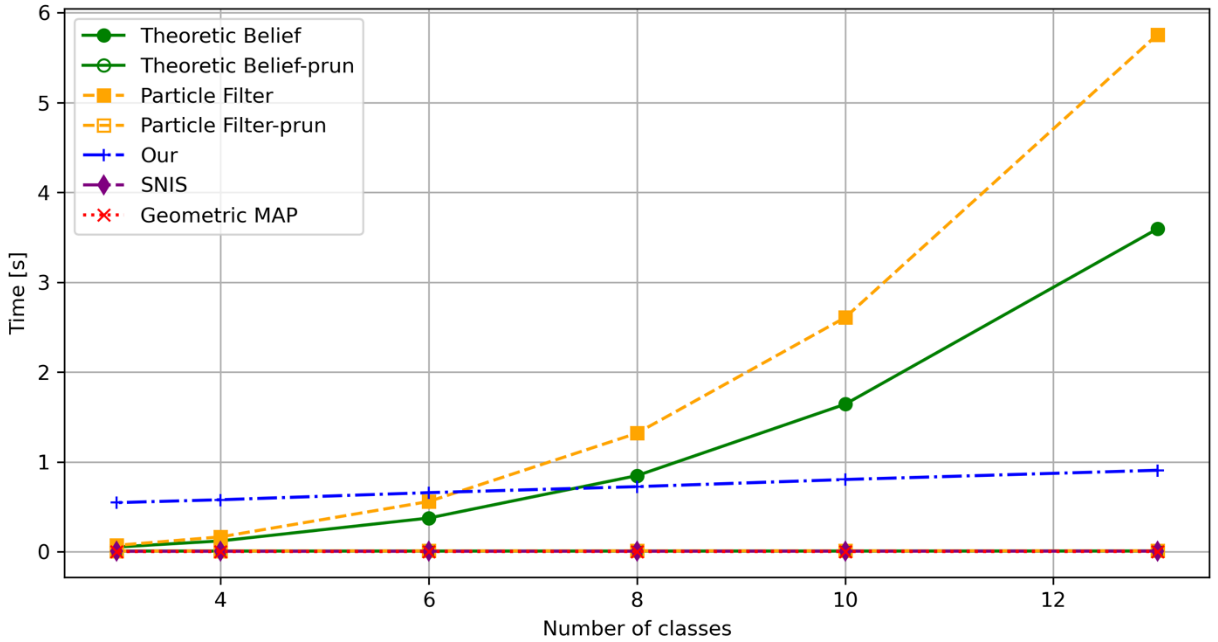
<u>Sensitivity to number of classes</u>

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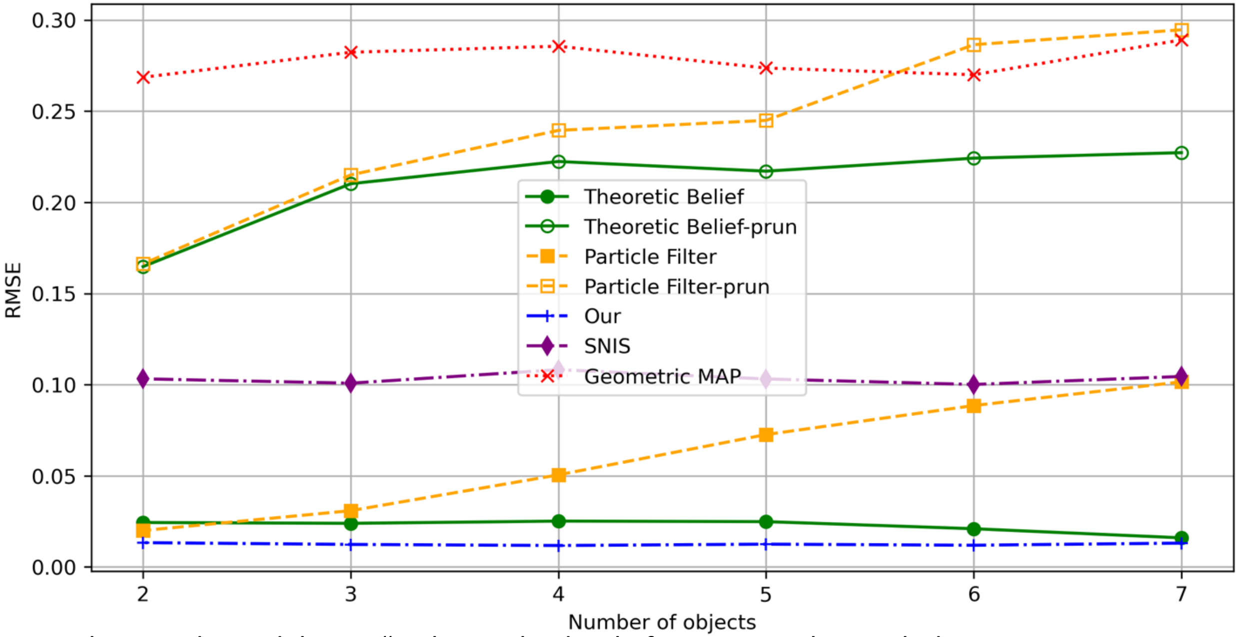
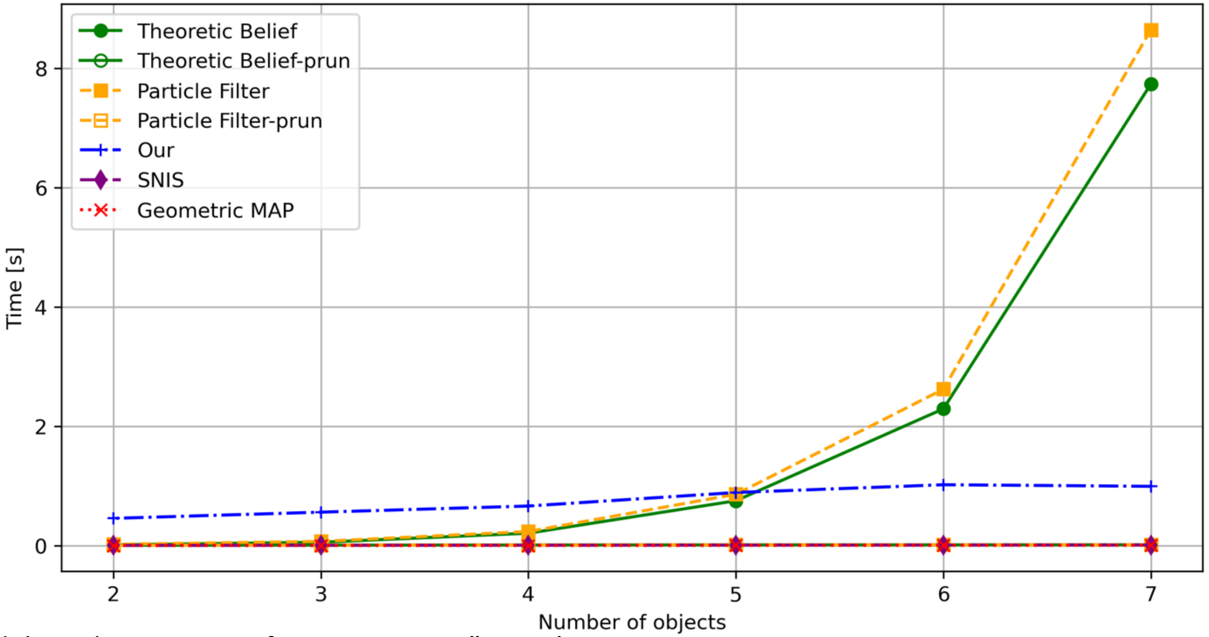
Sensitivity to number of objects

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Semantic Risk Awareness

**Ambiguous Environments**

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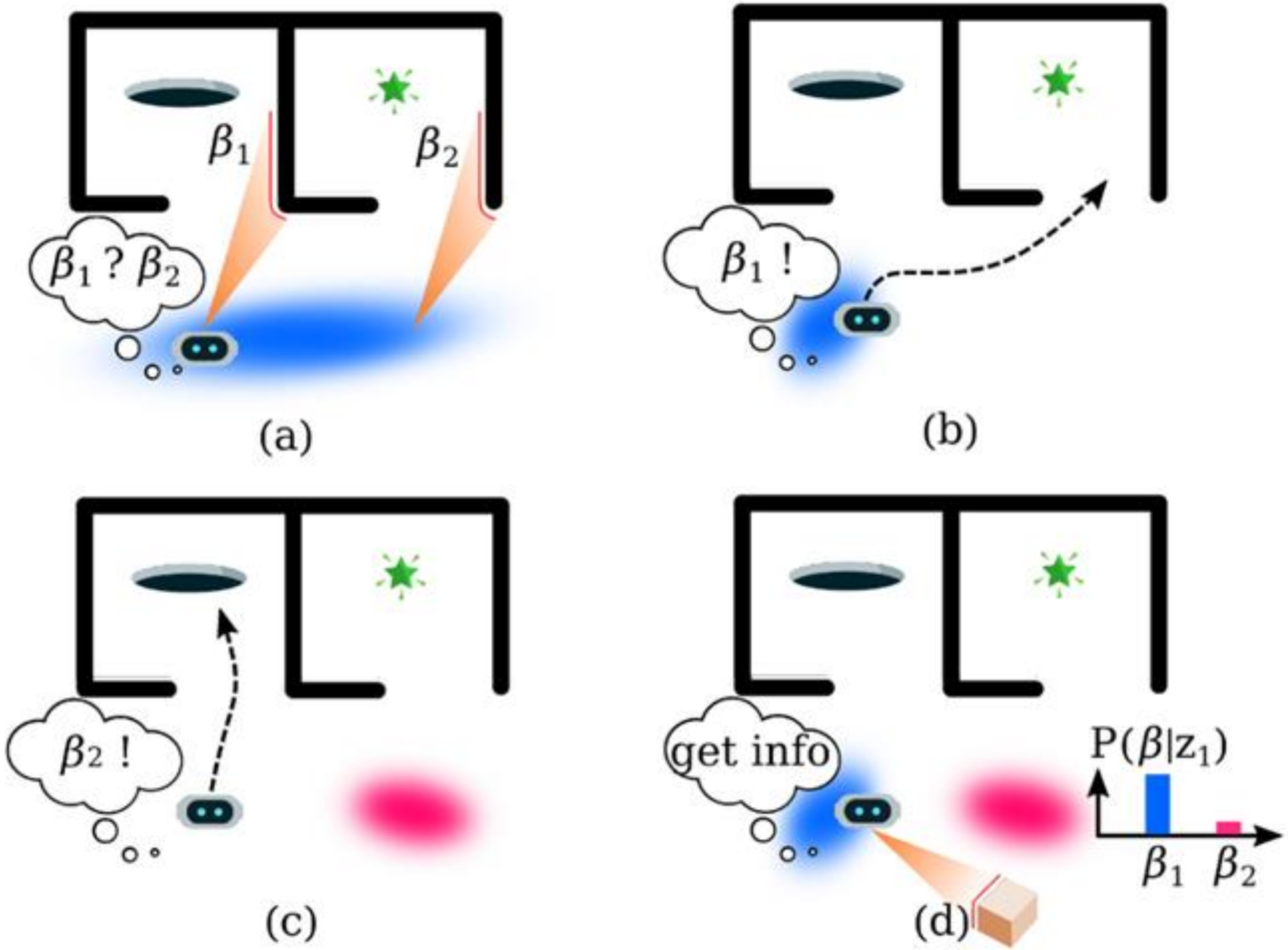
# Ambiguous Scenarios

- Have to reason about data association hypotheses within inference and planning

An observation:
(e.g. LIDAR)

How should the agent act?

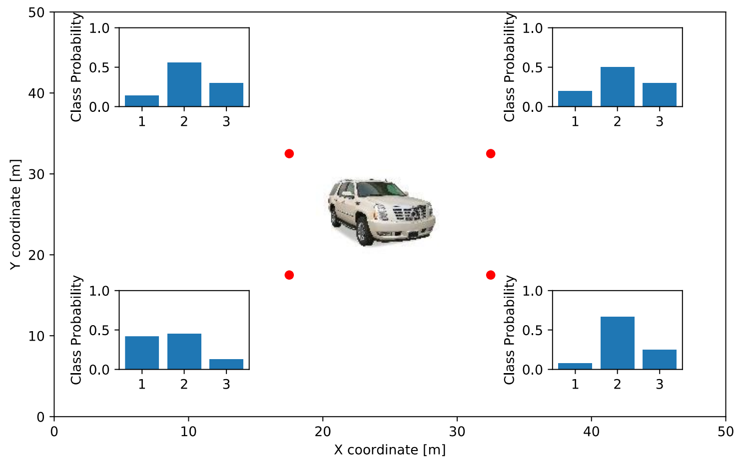
Unsafe!



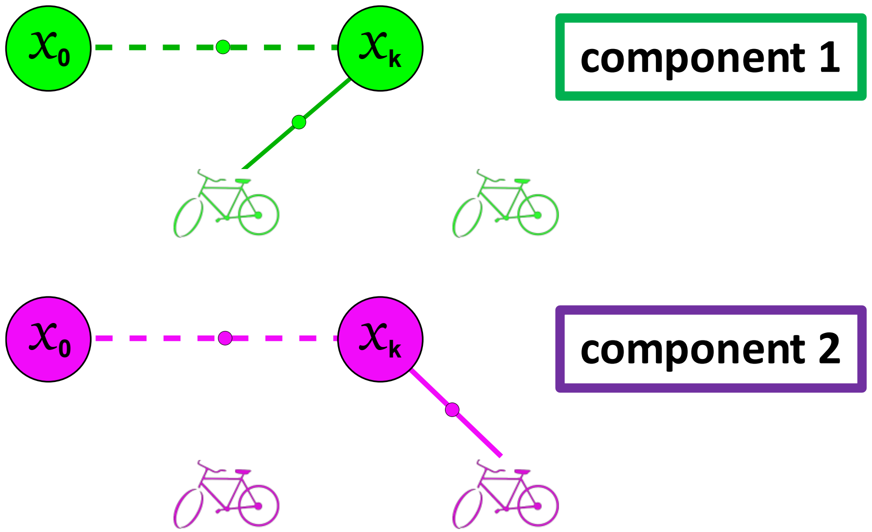

S. Pathak, A. Thomas, and V. Indelman, “A Unified Framework for Data Association Aware Belief Space Planning and Perception”, IJRR’18.

# Autonomous Semantic Perception & Ambiguous Environments

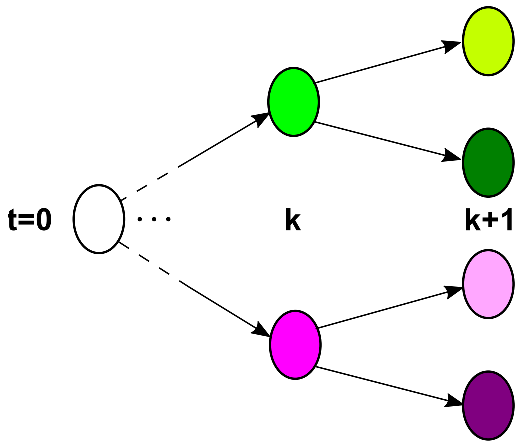
Viewpoint dependent semantic models




Data association hypotheses

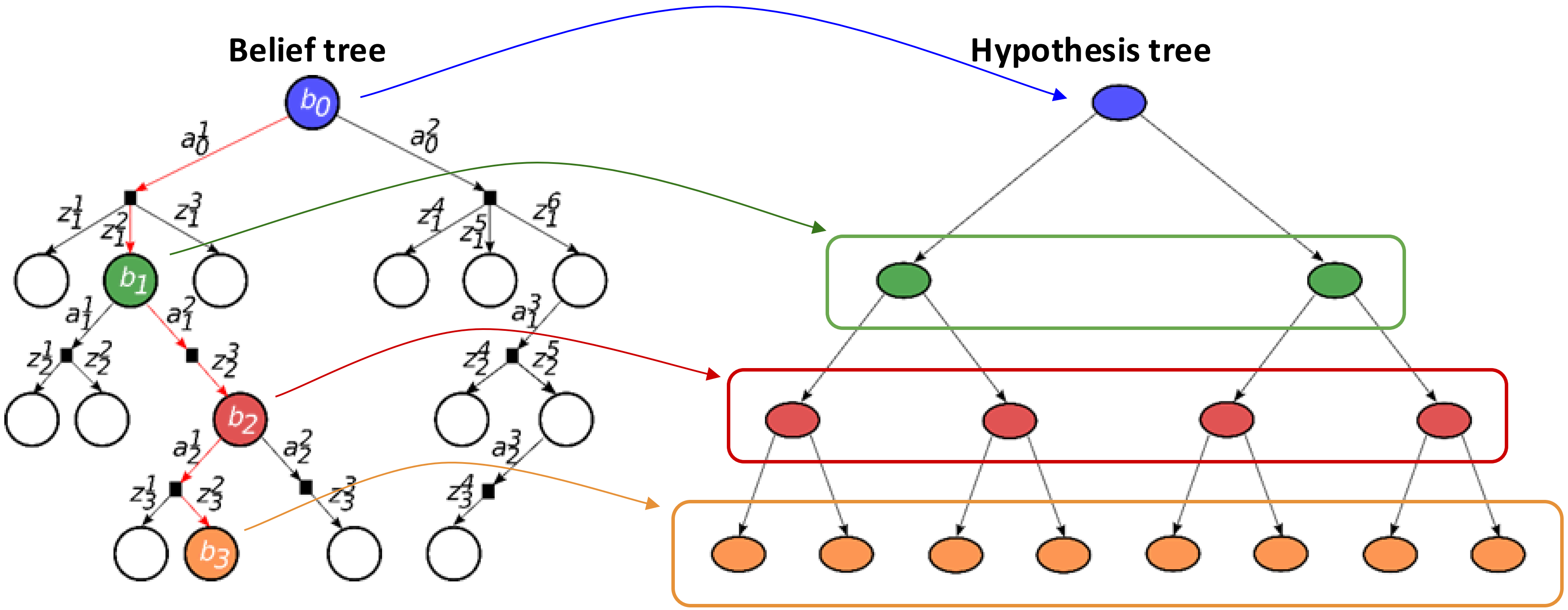



- Hybrid beliefs (over continuous and discrete RVs)
- The number of hypotheses can grow exponentially
- Impact on **safe** decision making?



# Continuous-Discrete State Spaces - the Challenge

- The number of hypotheses may grow **exponentially** with the planning horizon!




M. Barenboim, M. Shienman, and V. Indelman, "Monte Carlo Planning in Hybrid Belief POMDPs," IEEE RA-L'23.

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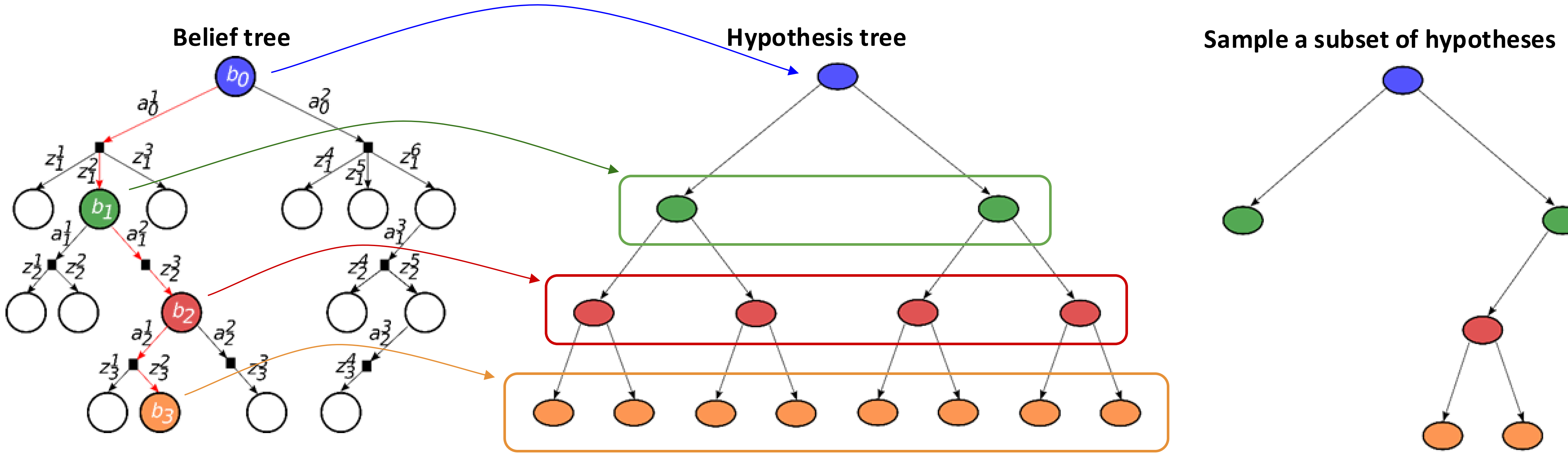


Impact on **safe** decision making?

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# Simplification of POMDP with Hybrid Beliefs

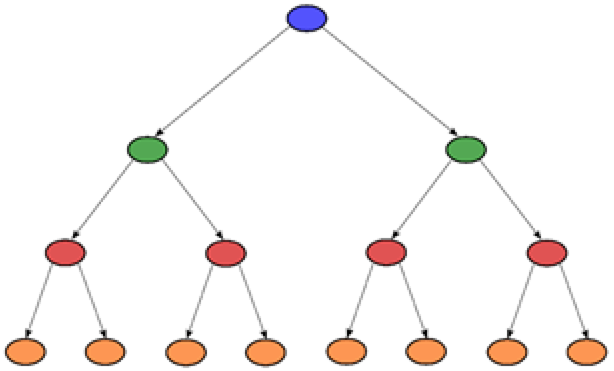
- Deterministic bound to relate the full set of hypotheses to a subset thereof,

**Corollary**

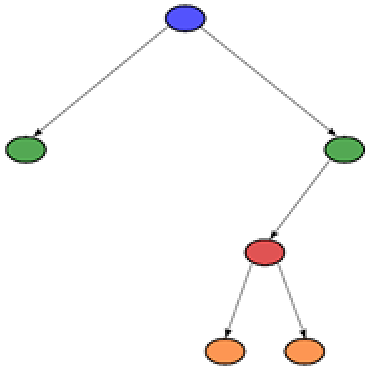
*For any policy $\pi$, and selection of hypotheses set $\{\beta^i_{0:\mathcal{T}}\}_{i=0}^{|\mathcal{B}|}$ the following holds,*

$$\left|V^{\pi}(b_0) - \bar{V}^{\pi}(\bar{b}_0)\right| \leq \mathcal{R}_{max}\left[\mathcal{T}\delta_0^{\beta} + \sum_{k=1}^{\mathcal{T}}\sum_{\tau=1}^{k}\overline{\mathbb{E}}_{z_{1:\tau}}\left[\delta_\tau^{\beta}\right]\right].$$

Full tree



Any subset



Importantly, the bound relies on the available hypotheses

Can bound the theoretical value with access only to the simplified tree

Bounds can be evaluated online

M. Barenboim, I. Lev-Yehudi, and V. Indelman, “Data Association Aware POMDP Planning with Hypothesis Pruning Performance Guarantees,” IEEE RA-L’23.

# Simplification of Decision-Making Problems

**Concept**:

- Identify and solve a **simplified (computationally) easier** decision-making problem
- Provide (adaptive) performance guarantees

**Specific simplifications include**:

- Sparsification of Gaussian beliefs (high dim. state)
- Topological metric for Gaussian beliefs (high dim. state)
- Utilize a subset of samples (nonparametric beliefs)
- Utilize a subset of hypotheses (hybrid beliefs)
- Simplified models and spaces
- Simplification of Risk-Averse POMDP Planning
- Simplification in a multi-agent setting

[Indelman RAL'16; Elimelech & Indelman IJRR'22; Sztyglic & Indelman IROS'22, Zhitnikov & Indelman AIJ'22, TRO'24; Shienman & Indelman ICRA'22; Kitanov & Indelman IJRR'24; Zhitnikov et al. IJRR'24, Barenboim & Indelman NIPS'23; Lev-Yehudi, Barenboim & Indelman AAAI'24, Kong & Indelman ISRR 2024]

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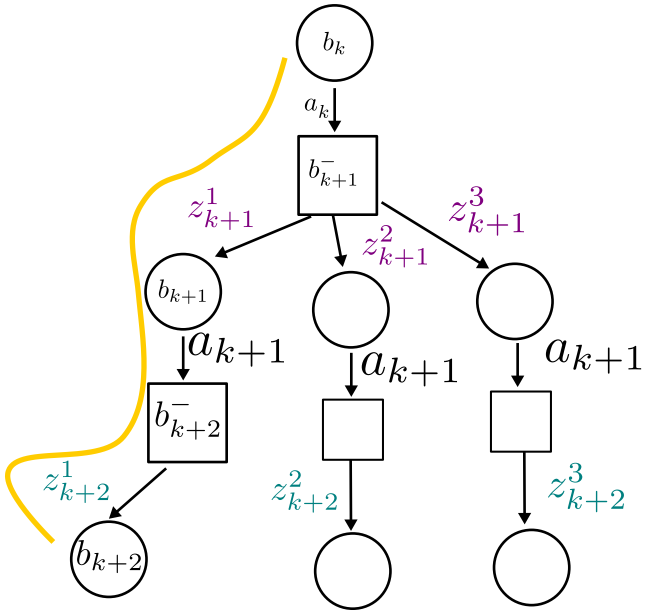
# Anytime Probabilistically Constrained Belief Space Planning

$$\max_{\pi_{k+}} \mathbb{E}\left[\sum_{\ell=k}^{k+L-1} \rho_{\ell+1} \middle| b_k, \pi_{k+}\right]$$

$$\text{subject to } \mathrm{P}(c(b_{k:k+L};\phi,\delta)=1|b_k,\pi_{k+}) \geq 1-\epsilon$$




Information gain:

$$c(b_{k:k+L};\phi,\delta) \triangleq \mathbf{1}_{\{\left(\sum_{\ell=k}^{k+L-1}\phi(b_t,b_{t+1})\right)\geq\delta\}}(b_{k:k+L})$$

Safety:

$$c(b_{k:k+L};\phi,\delta) \triangleq \prod_{\ell=k}^{k+L} \mathbf{1}_{\{b_\ell:\phi(b_\ell)\geq\delta\}}(b_\ell)$$

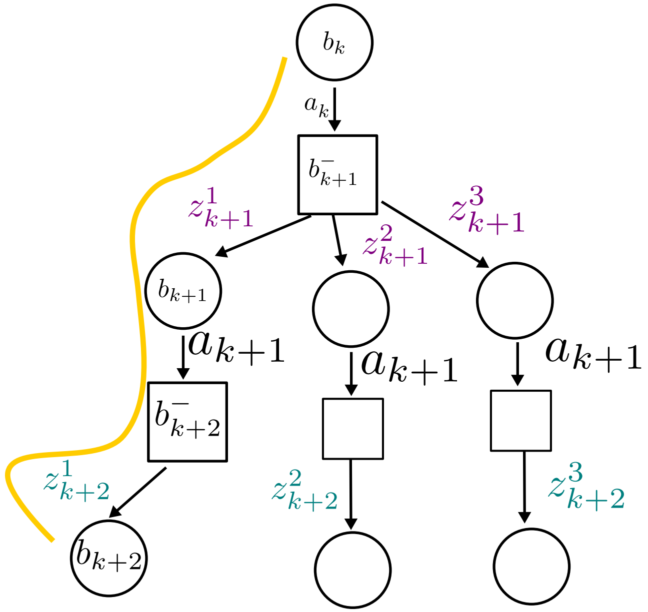
$$\phi(b_\ell) = \mathrm{P}(\mathbf{1}_{\{x_\ell \in \mathcal{X}^{\text{safe}}_\ell\}} = 1|b_\ell)$$


A. Zhitnikov and V. Indelman, "Risk Aware Belief-dependent Constrained Simplified POMDP Planning," arXiv, 2022.
A. Zhitnikov and V. Indelman, "Simplified Continuous High Dimensional Belief Space Planning with Adaptive Probabilistic Belief-dependent Constraints," T-RO'24.
A. Zhitnikov and V. Indelman, "Anytime Probabilistically Constrained Provably Convergent Online Belief Space Planning," arXiv'24.

# Anytime Probabilistically Constrained Belief Space Planning

Probabilistic constraint sample approximation

$$\hat{\mathrm{P}}^{(m)}(c(b_{k:k+L};\phi,\delta)=1|b_k,\pi_{k+})=\frac{1}{m}\sum_{l=1}^{m}c(b^l_{k:k+L};\phi,\delta)$$




$$c^l \sim \mathrm{P}(c|b_k,a_{k+})$$

$$c \in \{0,1\}$$

The inner constraint is violated The inner constraint is satisfied

A. Zhitnikov and V. Indelman, "Risk Aware Belief-dependent Constrained Simplified POMDP Planning," arXiv, 2022.
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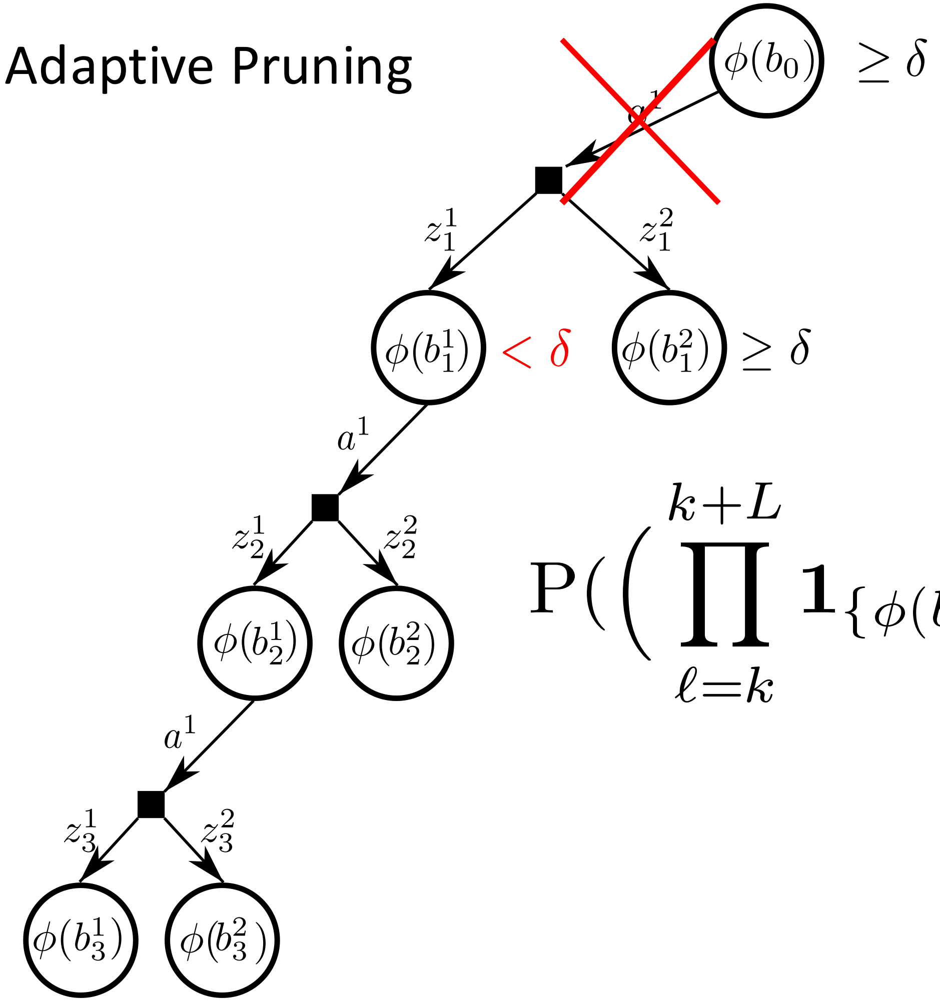
# Anytime Probabilistically Constrained Belief Space Planning

## Fast Adaptive Pruning




$$\mathrm{P}\Big(\Big(\prod_{\ell=k}^{k+L} \mathbf{1}_{\{\phi(b_\ell)\geq\delta\}}(b_\ell)\Big) = 1 | b_k, a_k, \pi^*_{k+1:k+L-1}\Big) \geq 1 - \cancel{\epsilon}$$

0

$$\phi(b_\ell) = \mathrm{P}(\mathbf{1}_{\{x_\ell \in \mathcal{X}_\ell^{\text{safe}}\}} = 1 | b_\ell)$$

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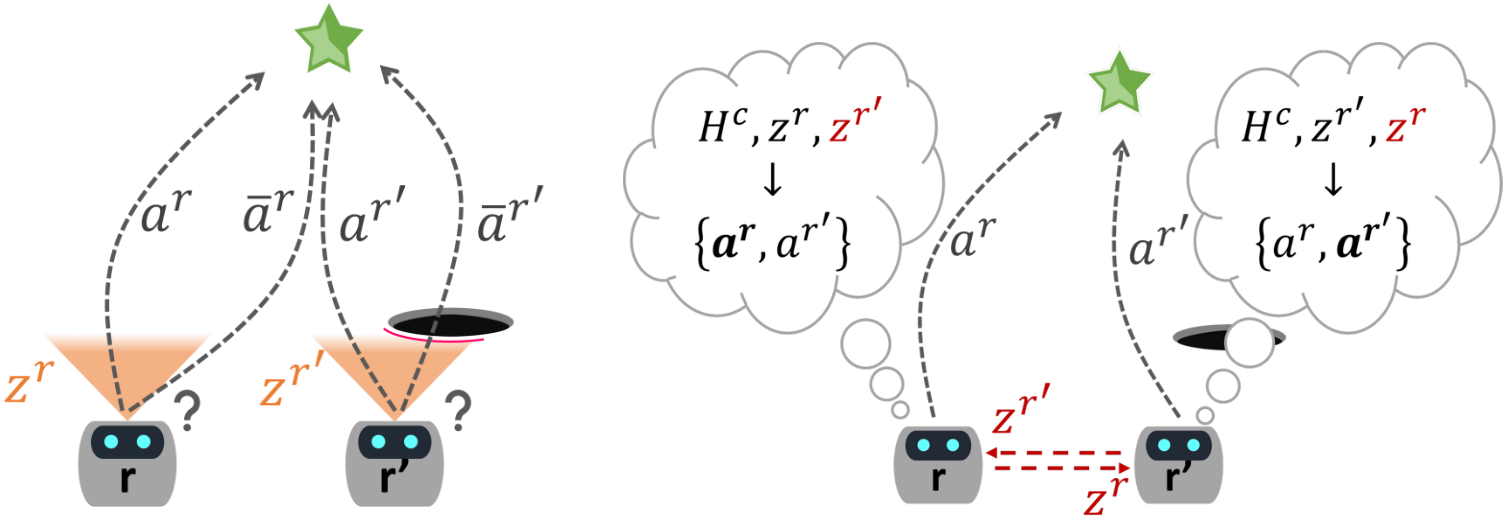
# Multi-Robot Belief Space Planning

- **A common assumption**: Beliefs of different robots are consistent at planning time
- Requires prohibitively frequent data-sharing capabilities!

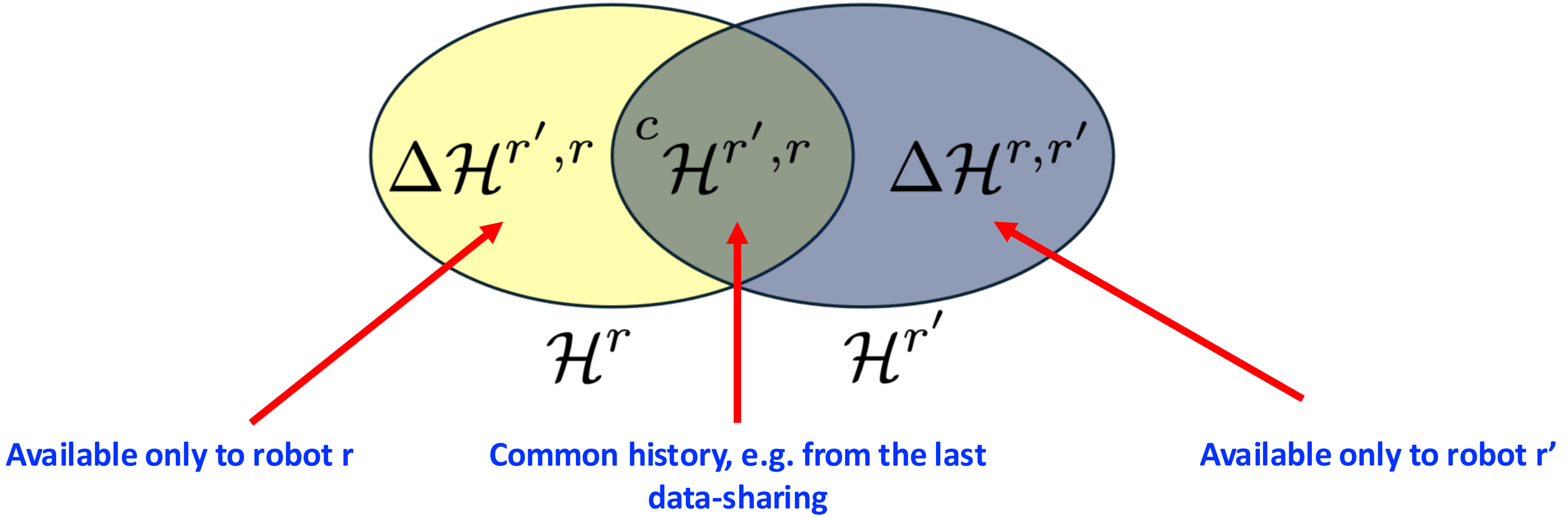


# Multi-Robot Cooperative BSP with Inconsistent Beliefs

**What happens when data-sharing capabilities between the robots are limited?**

- Histories & beliefs of the robots may <u>**differ**</u> due to limited data-sharing capabilities

$b_k^r = \mathbb{P}(x_k \mid \mathcal{H}_k^r)$ $\qquad b_k^{r'} = \mathbb{P}(x_k \mid \mathcal{H}_k^{r'})$ $\qquad \mathcal{H}_k^r \neq \mathcal{H}_k^{r'}$




T. Kundu, M. Rafaeli, and V. Indelman, "Multi-Robot Communication-Aware Cooperative Belief Space Planning with Inconsistent Beliefs: An Action-Consistent Approach," IROS'24.
T. Kundu, M. Rafaeli, A. Gulyaev, and V. Indelman, "Action-Consistent Decentralized Belief Space Planning with Inconsistent Beliefs and Limited Data Sharing: Framework and Simplification Algorithms with Formal Guarantees," arXiv'25.

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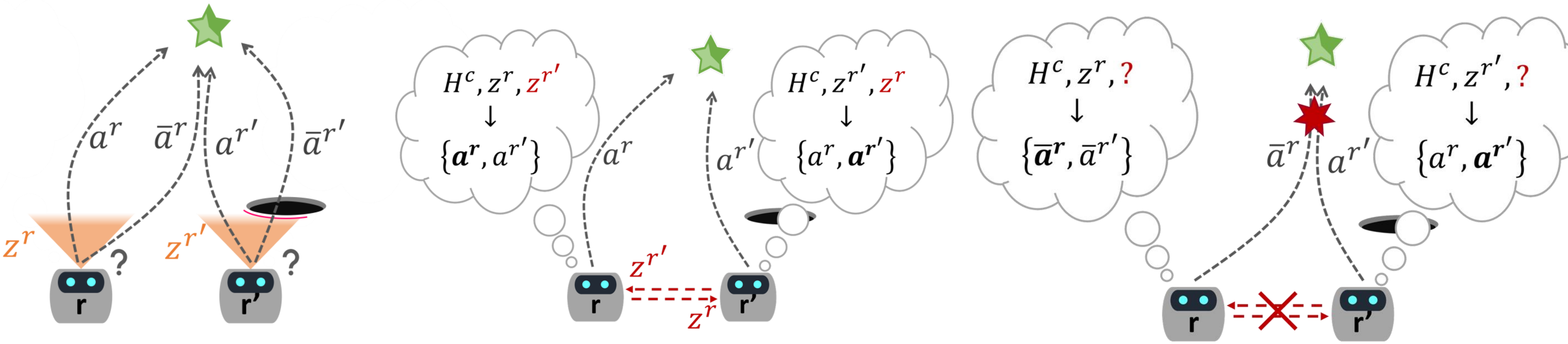
- **Can lead to a lack of coordination and unsafe and sub-optimal actions**




T. Kundu, M. Rafaeli, and V. Indelman, "Multi-Robot Communication-Aware Cooperative Belief Space Planning with Inconsistent Beliefs: An Action-Consistent Approach," IROS'24.
T. Kundu, M. Rafaeli, A. Gulyaev, and V. Indelman, "Action-Consistent Decentralized Belief Space Planning with Inconsistent Beliefs and Limited Data Sharing: Framework and Simplification Algorithms with Formal Guarantees," arXiv'25.

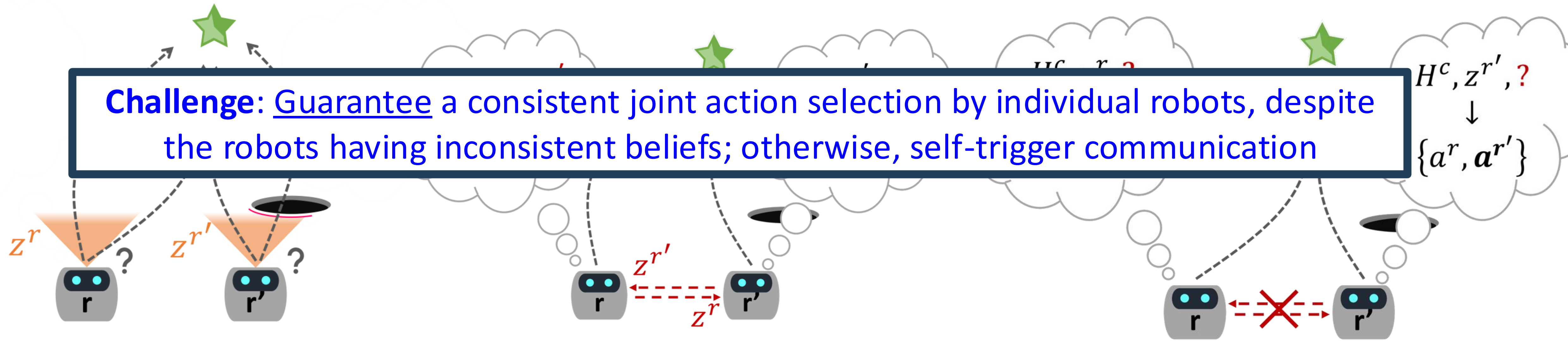
# Multi-Robot Cooperative BSP with Inconsistent Beliefs

**What happens when data-sharing capabilities between the robots are limited?**

- Histories & beliefs of the robots may **<u>differ</u>** due to limited data-sharing capabilities

$$b_k^r = \mathbb{P}(x_k \mid \mathcal{H}_k^r) \qquad b_k^{r'} = \mathbb{P}(x_k \mid \mathcal{H}_k^{r'}) \qquad \mathcal{H}_k^r \neq \mathcal{H}_k^{r'}$$

- **Can lead to a lack of coordination and unsafe and sub-optimal actions**




**Challenge**: <u>Guarantee</u> a consistent joint action selection by individual robots, despite the robots having inconsistent beliefs; otherwise, self-trigger communication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# Agenda

POMDP Planning with Hybrid Beliefs

Semantic Risk Awareness

Ambiguous Environments

Anytime Constrained POMDP Planning

Multi-agent POMDP Planning with Inconsistent Beliefs

**See additional research directions on ANPL website!**

ANPL Autonomous Navigation and Perception Lab

Feel free to reach out to explore **research opportunities**!