Towards Scalable Online Decision Making Under Uncertainty in Partially Observable Environments

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MIT Robotics Seminar

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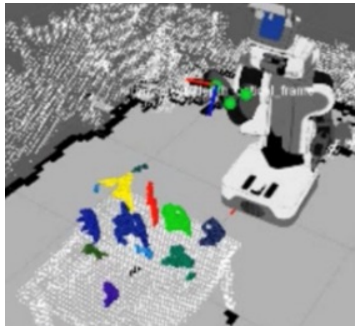
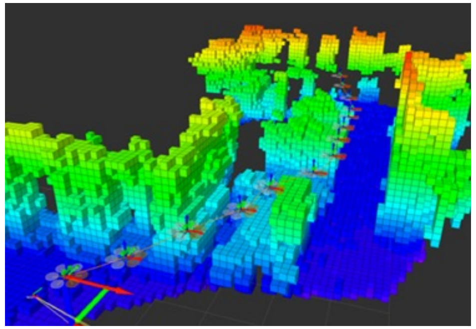
Advanced Autonomy

Involves autonomous navigation, active SLAM, informative gathering, active sensing, etc.





Advanced Autonomy

Perception and Inference

Where am I? What is the surrounding environment?

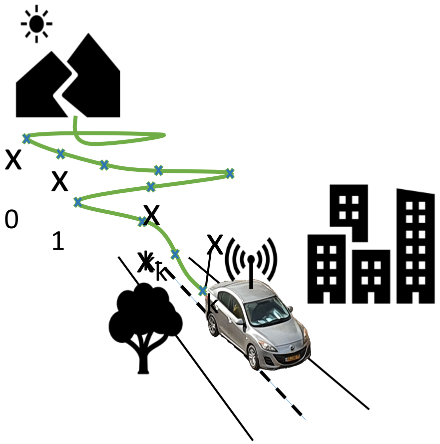
Key required capabilities

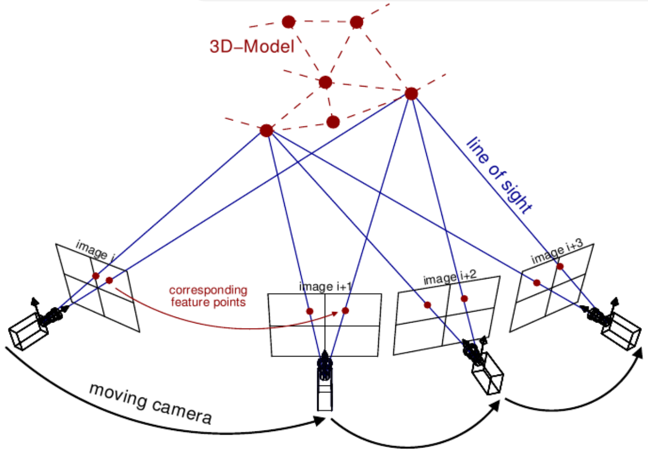
Decision-Making Under Uncertainty

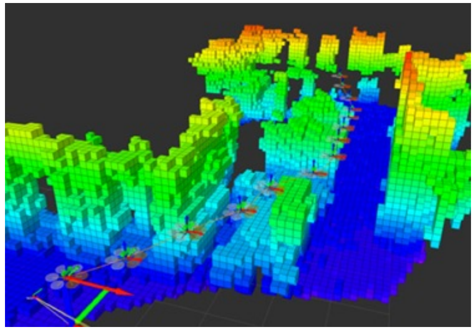
What should I be doing next?

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

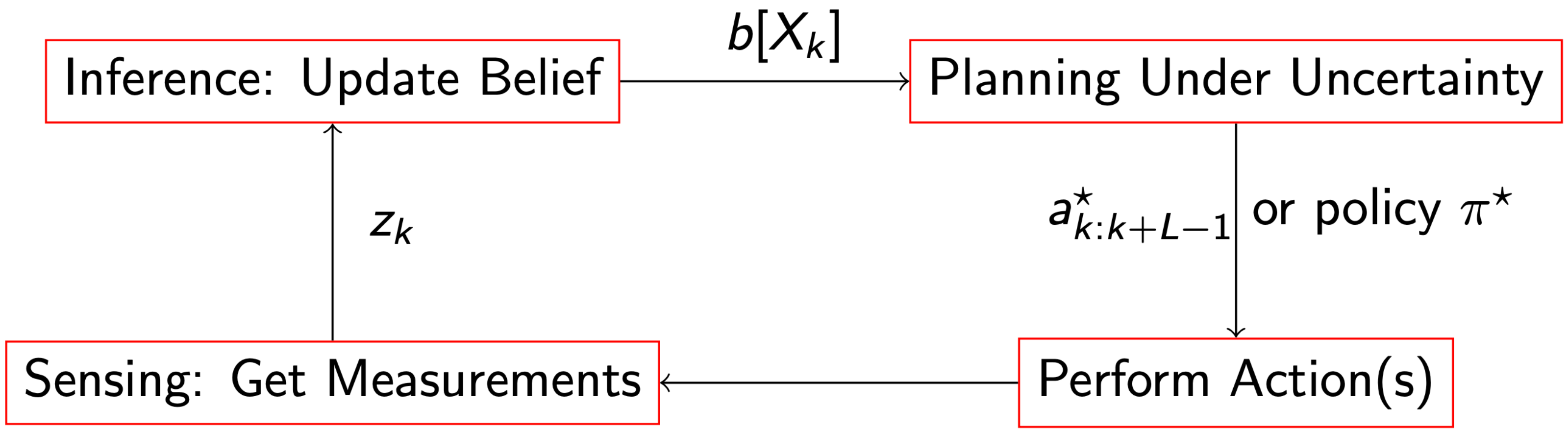
Perception and Inference ⟷ **Decision-Making Under Uncertainty**







Autonomy Loop



Perception and Inference

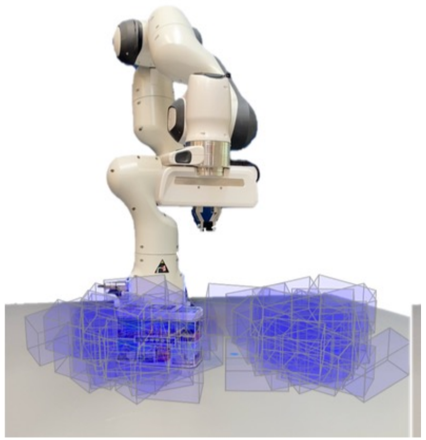
- Posterior belief at time k:

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

state/variables at time instant k

actions

observations

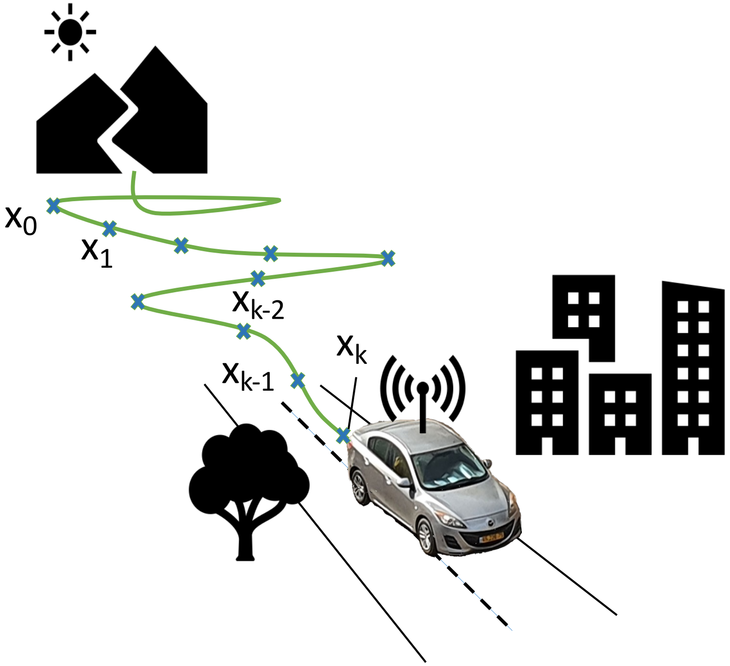


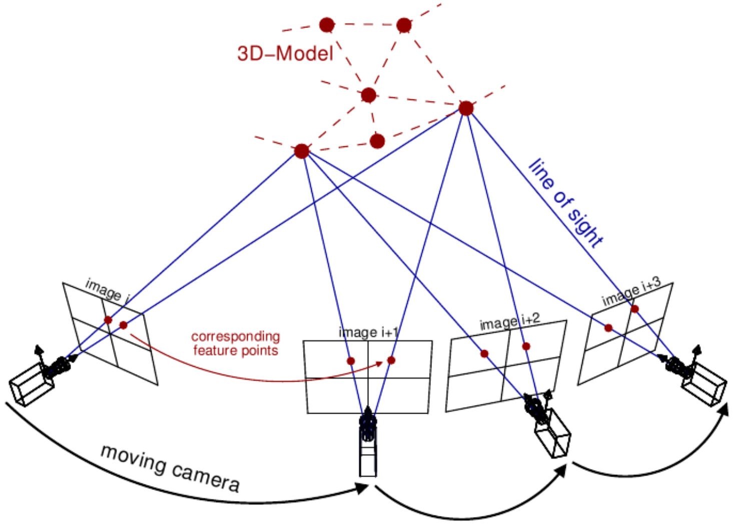
- Example:

$$X_k \doteq \{\underbrace{x_0, \ldots, x_k}, \underbrace{L_k}\}$$

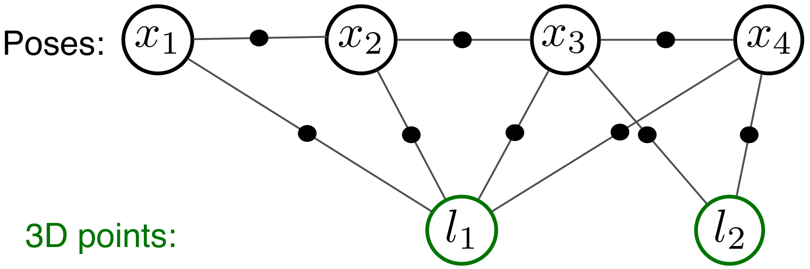
Past & current robot states

Environment representation, e.g. Landmarks





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



Partially Observable Markov Decision Process (POMDP)

- POMDP tuple:

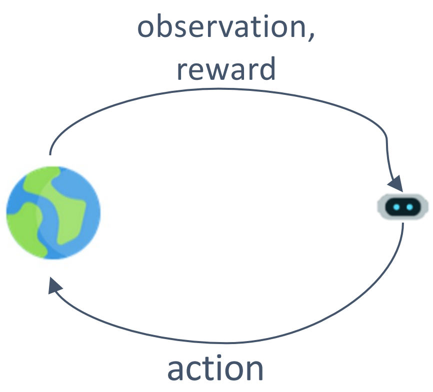
$$\langle \mathcal{X}, \mathcal{Z}, \mathcal{A}, T, O, \rho, b_k \rangle$$

state, observation, and action spaces

transition and observation models

Belief-dependent reward function

Belief at planning time instant k



- Value function

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

Belief-dependent reward function

Partially Observable Markov Decision Process (POMDP)

- Value function

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

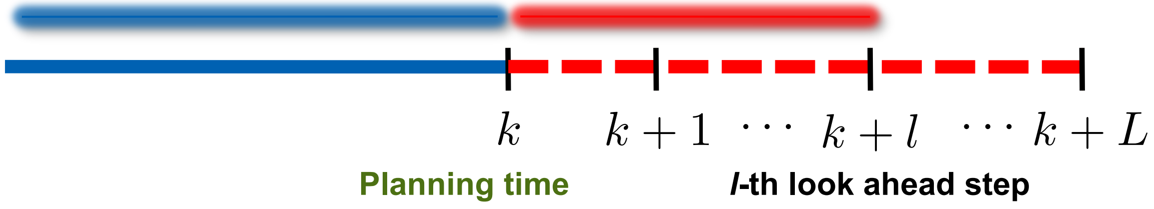
Belief-dependent reward function

- Belief at the ℓ-th look-ahead step: $b_{k+\ell} \triangleq b[X_{k+\ell}] = \mathbb{P}(X_{k+\ell} \mid a_{0:k-1}, z_{0:k}, a_{k:k+\ell-1}, z_{k+1:k+\ell})$

State at the *l*-th look ahead step

Past actions & observations

Future actions & observations



- Examples for reward function $\rho(b, a)$:
  - Expected distance to goal (navigate to a goal)
  - Information theoretic reward (reduce uncertainty)
  - …

Challenge

Probabilistic Inference

Maintain a distribution over the state given data

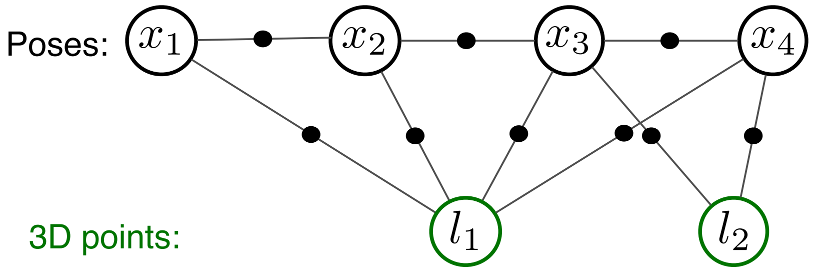
$$b_k \triangleq b[X_k] = \mathbb{P}(\underbrace{X_k}_{\text{state}} \mid \underbrace{a_{0:k-1}}_{\text{actions}}, \underbrace{z_{1:k}}_{\text{observations}})$$

Decision-making under uncertainty

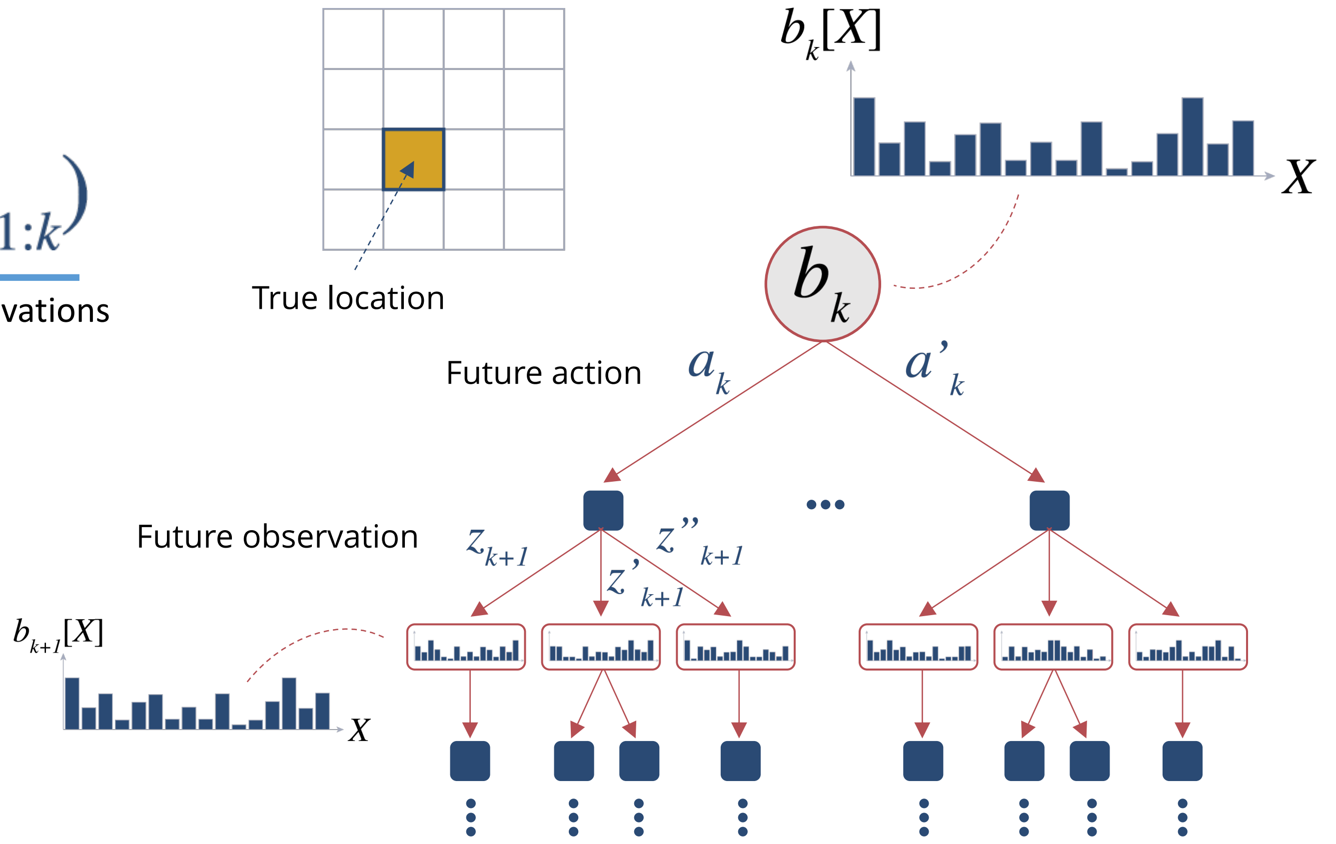
Involves reasoning about the entire observation and action spaces along planning horizon

Computationally intractable

More so, in high dimensional settings



Example – grid world



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

Agenda

Experience Reuse in POMDP Planning

POMDP Planning with Hybrid Beliefs

Simplification of POMDP with Formal Guarantees

Multi-agent POMDP Planning with Inconsistent Beliefs

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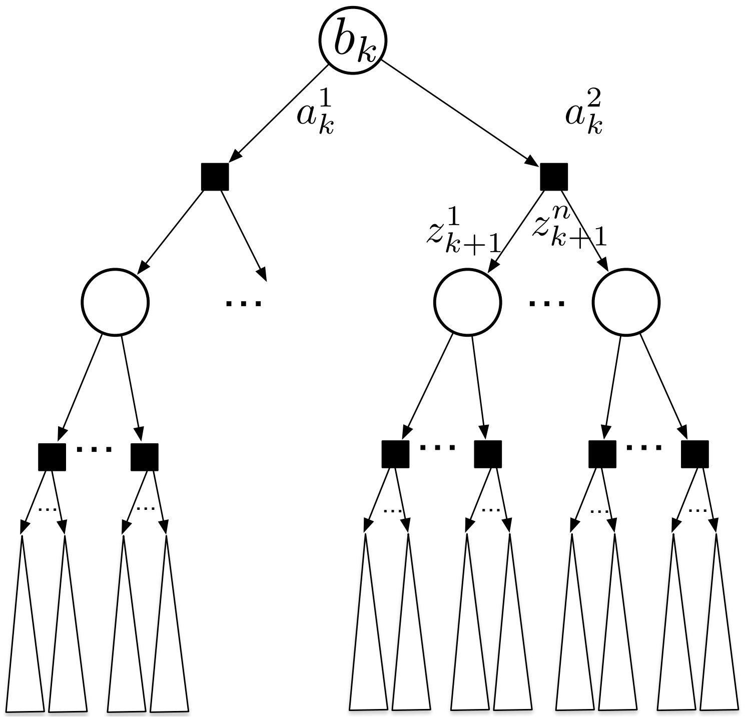
Experience Reuse in POMDP Planning

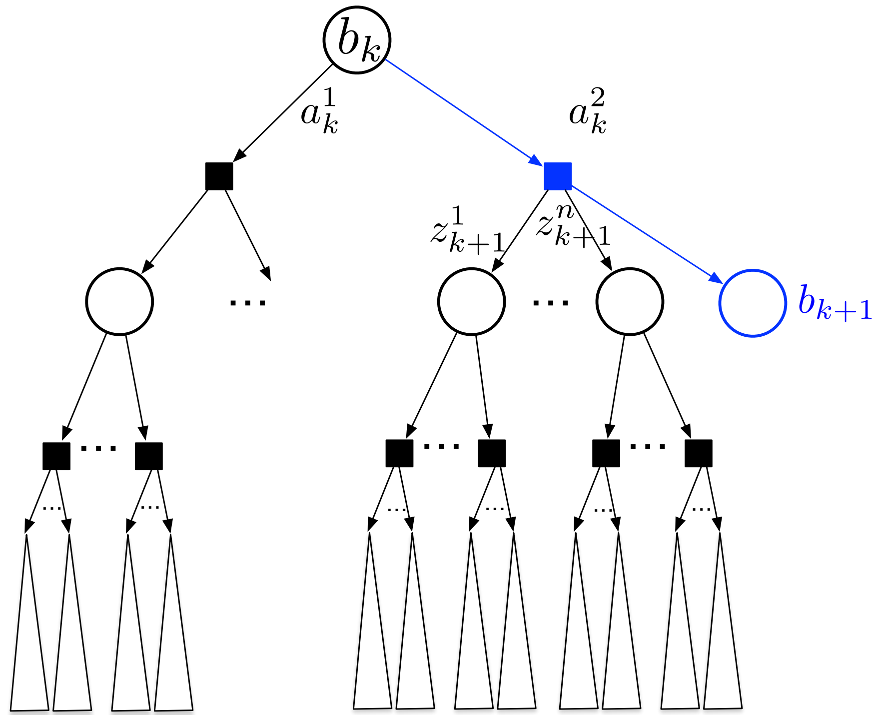
- Consider POMDPs with continuous state, action, and observation spaces



E. Farhi and V. Indelman, "iX-BSP: Incremental Belief Space Planning," ICRA'19, arXiv'21.
M. Novitsky, M. Barenboim, and V. Indelman, "Previous Knowledge Utilization In Online Anytime Belief Space Planning," arXiv'24.

Experience Reuse in POMDP Planning

- Consider POMDPs with continuous state, action, and observation spaces
- The probability of sampling the same belief/observation twice is zero



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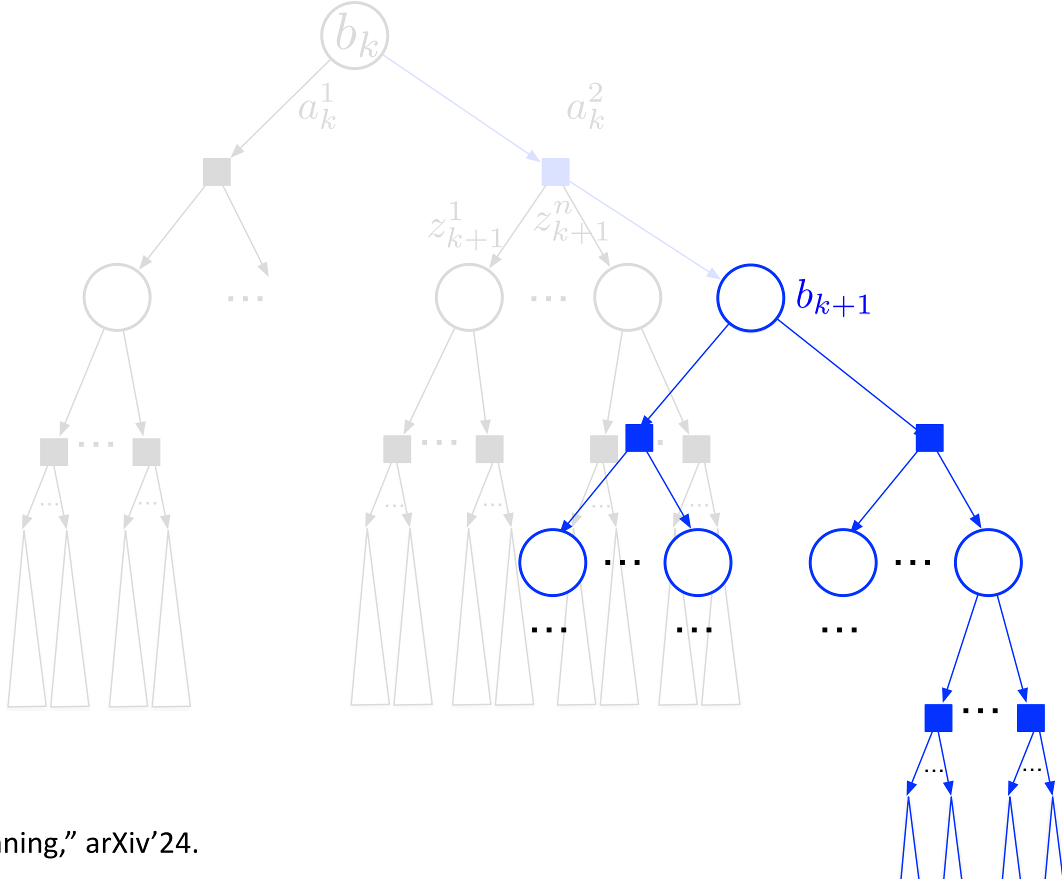
Online SOTA POMDP solvers typically perform calculations from **scratch at each planning session**



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Experience Reuse in POMDP Planning

- Consider POMDPs with continuous state, action, and observation spaces
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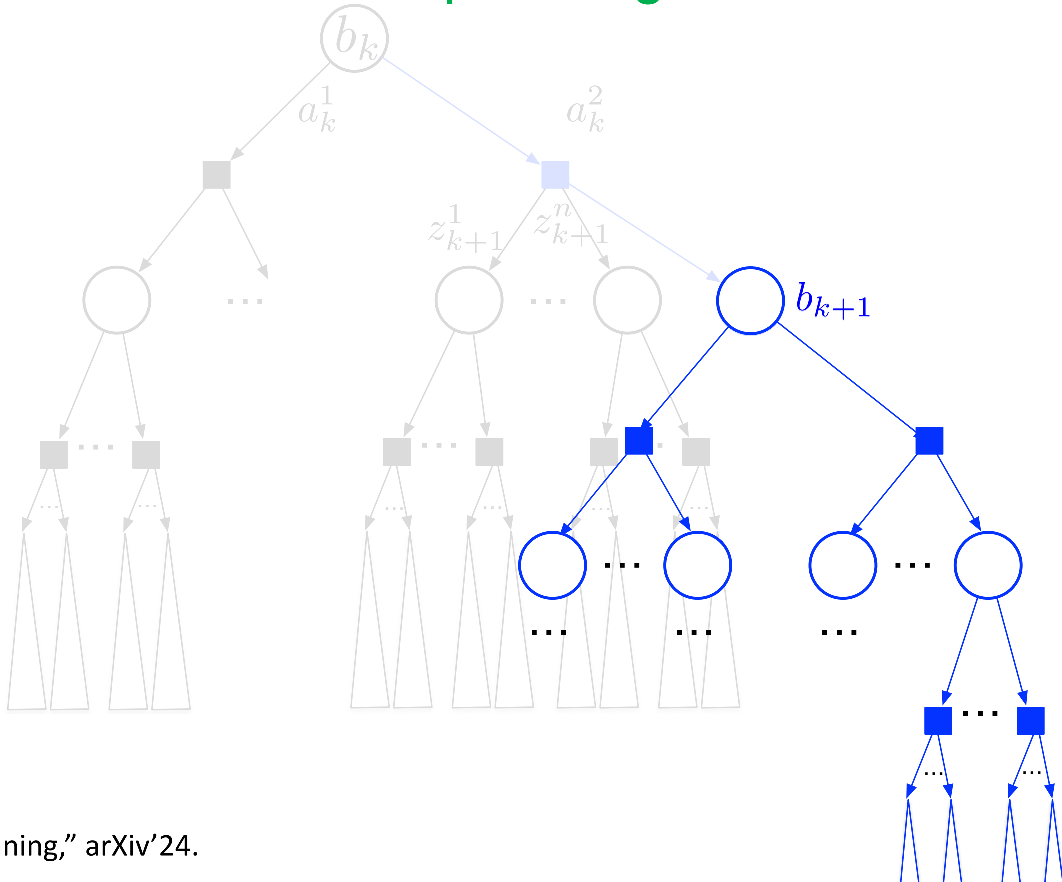

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Experience Reuse in POMDP Planning

- Consider POMDPs with continuous state, action, and observation spaces
- The probability of sampling the same belief/observation twice is zero
- Previously sampled beliefs can still provide useful info in the current planning session

Key idea: Reuse previous trajectories/calculations to get an efficient estimation of

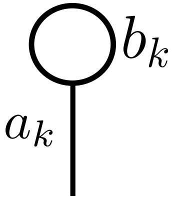
$$Q^{\pi}(b,a) = \mathbb{E}_{\pi}[\sum_{i=k}^{k+L-1} \gamma^{i-k} r(b_i, \pi_i(b_i), b_{i+1}) \mid b_k = b, a_k = a] \triangleq \mathbb{E}_{\pi}[G \mid b_k = b, a_k = a]$$

- Instead of calculating each planning session from scratch (state of the art)

E. Farhi and V. Indelman, "iX-BSP: Incremental Belief Space Planning," ICRA'19, arXiv'21.
M. Novitsky, M. Barenboim, and V. Indelman, "Previous Knowledge Utilization In Online Anytime Belief Space Planning," arXiv'24.

Experience Reuse in POMDP Planning

- Consider a planning session at time instant k



$$Q^{\pi}(b_k, a_k)$$

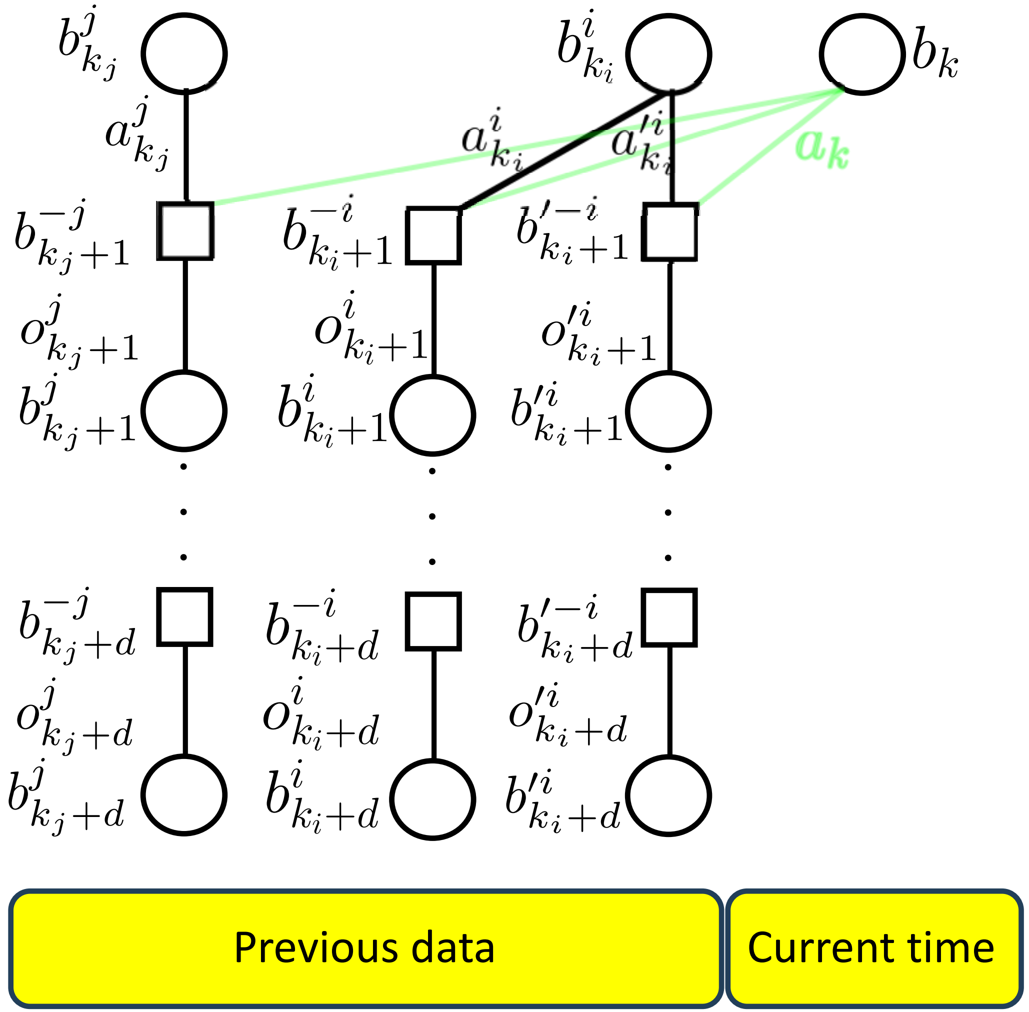
Current time

E. Farhi and V. Indelman, “iX-BSP: Incremental Belief Space Planning,” ICRA’19, arXiv’21.
M. Novitsky, M. Barenboim, and V. Indelman, “Previous Knowledge Utilization In Online Anytime Belief Space Planning,” arXiv’24.

Experience Reuse in POMDP Planning

- Consider a planning session at time instant k

$$Q^\pi(b_k, a_k)$$



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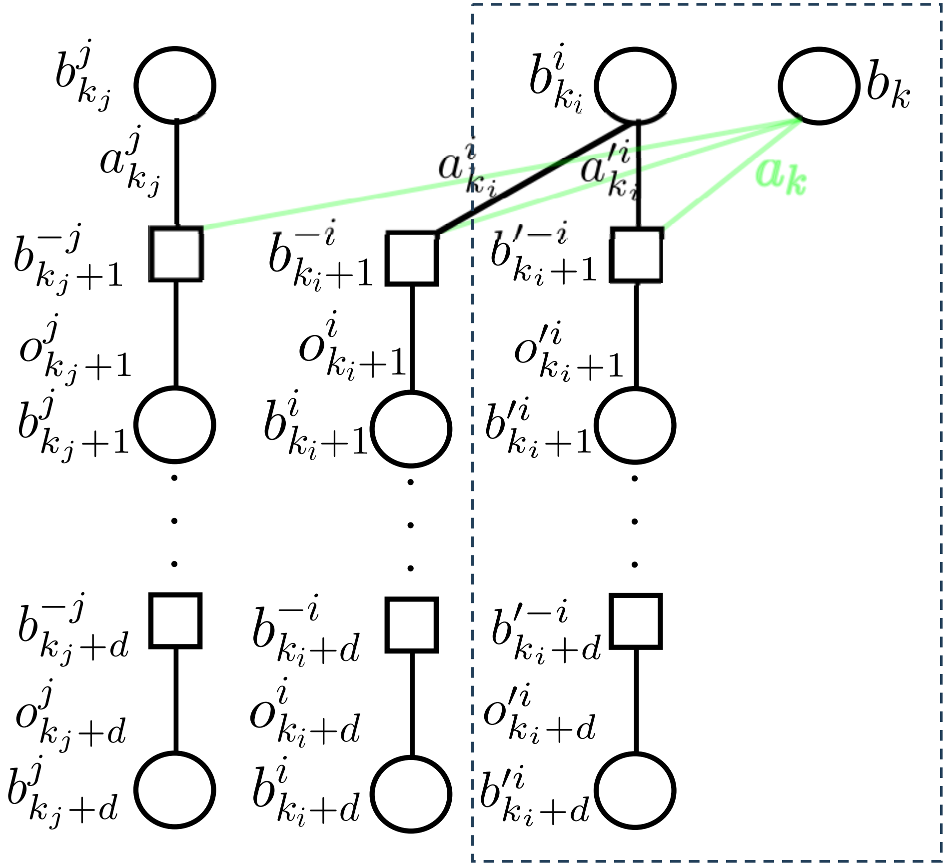
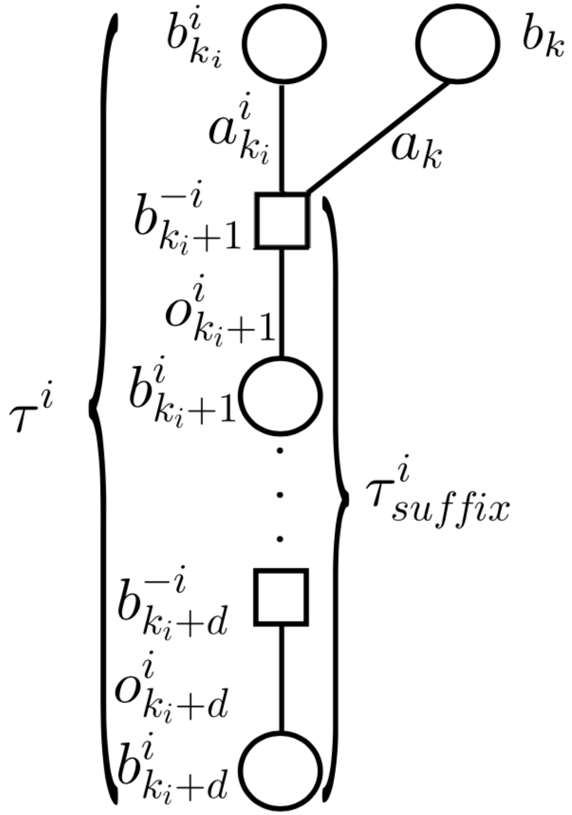
Experience Reuse in POMDP Planning

- **Key idea**: multiple importance sampling (MIS) estimator





$$w_i \triangleq \frac{\mathbb{P}(\tau^i_{suffix}|b_k, a_k, \pi)}{\mathbb{P}(\tau^i_{suffix}|b^i_{k_i}, a^i_{k_i}, \pi)}$$

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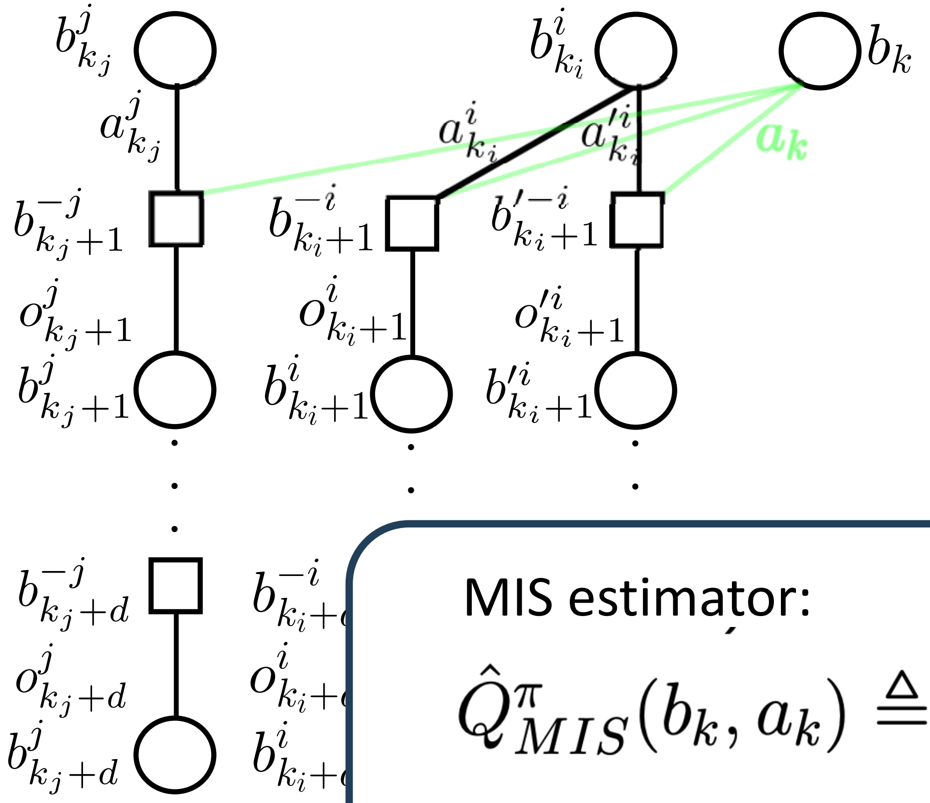
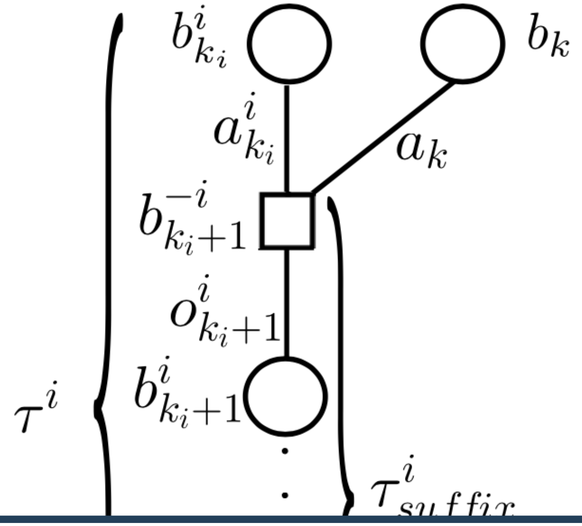




$$w_i \triangleq \frac{\mathbb{P}(\tau^i_{suffix} | b_k, a_k, \pi)}{\mathbb{P}(\tau^i_{suffix} | b^i_{k_i}, a^i_{k_i}, \pi)}$$

MIS estimator:

$$\hat{Q}^{\pi}_{MIS}(b_k, a_k) \triangleq \sum_{m=1}^{M} \sum_{l=1}^{n_m} \frac{\mathbb{P}(\tau^{l,m}_{suffix} | b_k, a_k, \pi)\tilde{G}^{l,m}}{\sum_{j=1}^{M} n_j \cdot \mathbb{P}(\tau^{l,m}_{suffix} | b^j_{k_j}, a^j_{k_j}, \pi)}.$$

return

E. Farhi and V. Indelman, “iX-BSP: Incremental Belief Space Planning,” ICRA’19, arXiv’21.
M. Novitsky, M. Barenboim, and V. Indelman, “Previous Knowledge Utilization In Online Anytime Belief Space Planning,” arXiv’24.

Experience-Based Value Function Estimation

MIS estimator:

$$\hat{Q}^{\pi}_{MIS}(b_k, a_k) \triangleq \sum_{m=1}^{M} \sum_{l=1}^{n_m} \frac{\mathbb{P}(\tau^{l,m}_{suffix}|b_k,a_k,\pi)\tilde{G}^{l,m}}{\sum_{j=1}^{M} n_j \cdot \mathbb{P}(\tau^{l,m}_{suffix}|b^j_{k_j},a^j_{k_j},\pi)}.$$

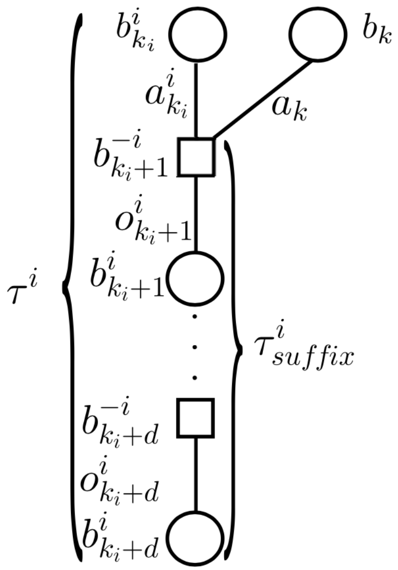
Theorem 1

$$\frac{\mathbb{P}(\tau^i_{suffix}|b_k,a_k,\pi)}{\mathbb{P}(\tau^i_{suffix}|b^i_{k_i},a^i_{k_i},\pi)} = \frac{\mathbb{P}(b^{-i}_{k_i+1}|b_k,a_k)}{\mathbb{P}(b^{-i}_{k_i+1}|b^i_{k_i},a^i_{k_i})}$$

Proof.

$$\frac{\mathbb{P}(\tau^i_{suffix}|b_k,a_k,\pi)}{\mathbb{P}(\tau^i_{suffix}|b^i_{k_i},a^i_{k_i},\pi)} = \frac{\mathbb{P}(b^{-i}_{k_i+1},o^i_{k_i+1},\ldots,b^i_{k_i+L}|b_k,a_k,\pi)}{\mathbb{P}(b^{-i}_{k_i+1},o^i_{k_i+1},\ldots,b^i_{k_i+L}|b^i_{k_i},a^i_{k_i},\pi)} =$$

$$\frac{\mathbb{P}(b^{-i}_{k_i+1}|b_k,a_k)}{\mathbb{P}(b^{-i}_{k_i+1}|b^i_{k_i},a^i_{k_i})} \cdot \cancel{\frac{\mathbb{P}(o^i_{k_i+1},\ldots,b^i_{k_i+L}|b^{-i}_{k_i+1},\pi)}{\mathbb{P}(o^i_{k_i+1},\ldots,b^i_{k_i+L}|b^{-i}_{k_i+1},\pi)}} = \frac{\mathbb{P}(b^{-i}_{k_i+1}|b_k,a_k)}{\mathbb{P}(b^{-i}_{k_i+1}|b^i_{k_i},a^i_{k_i})} \quad \square$$

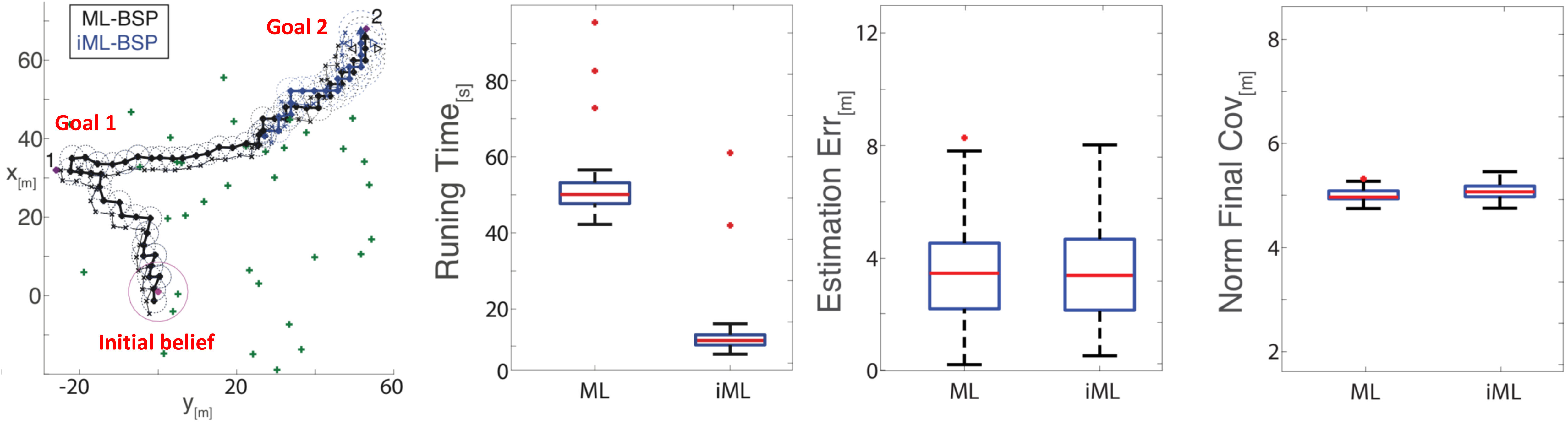


M. Novitsky, M. Barenboim, and V. Indelman, “Previous Knowledge Utilization In Online Anytime Belief Space Planning,” arXiv’24.

Incremental Belief Space Planning

Basic simulation – autonomous navigation in unknown environments:

ML-BSP: BSP with ML observations
(one sample per look ahead step)



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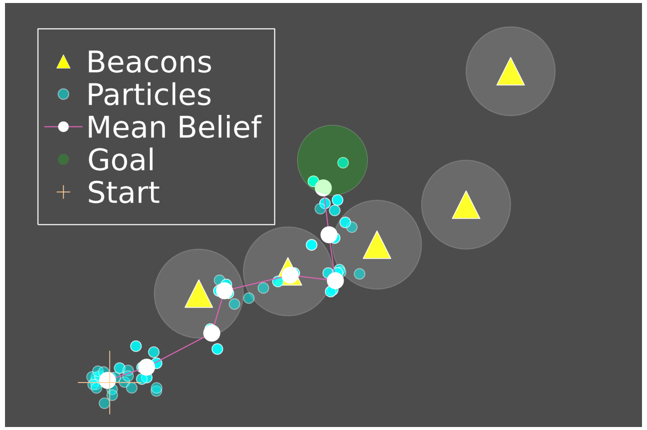
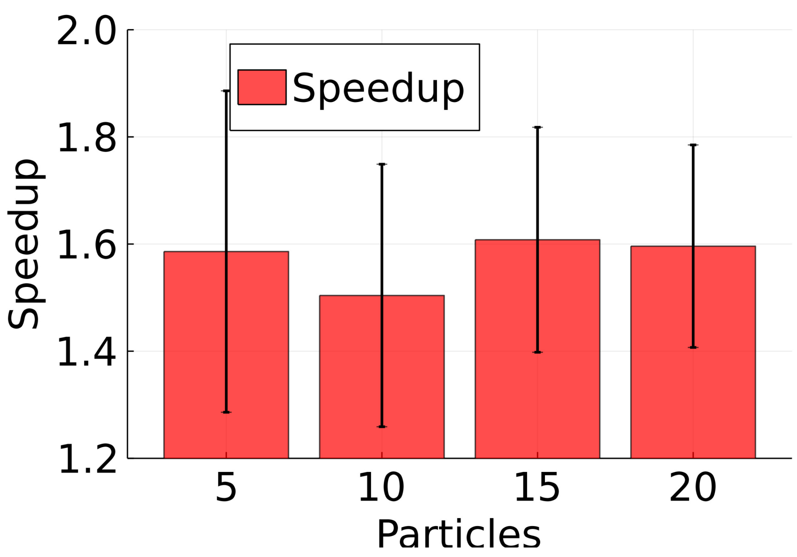
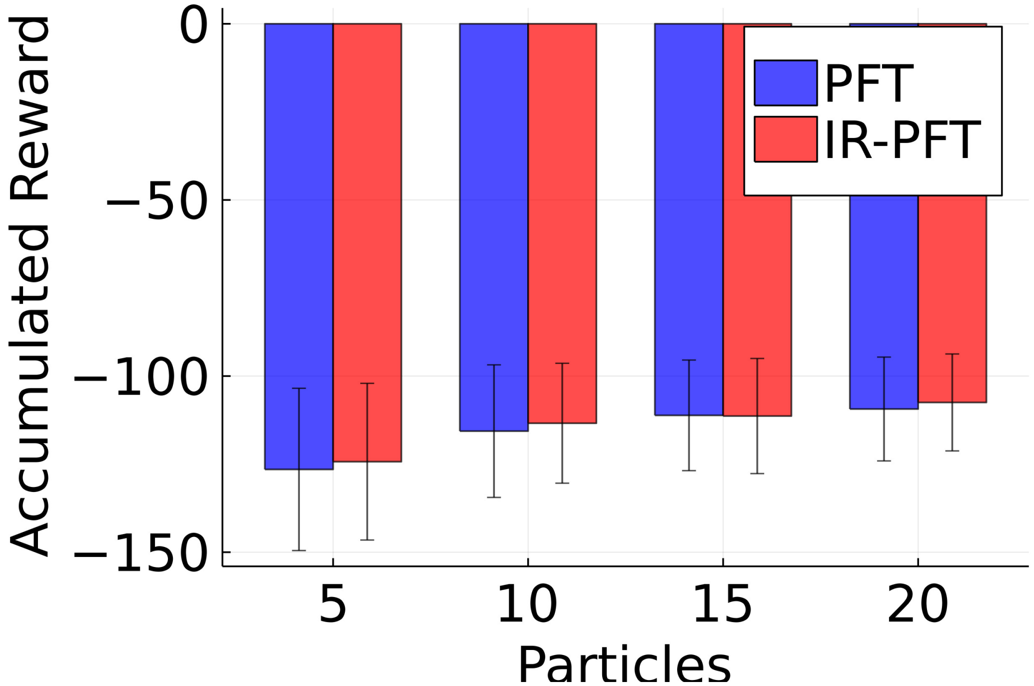
M. Novitsky, M. Barenboim, and V. Indelman, "Previous Knowledge Utilization In Online Anytime Belief Space Planning," arXiv'24.

Incremental Reuse Particle Filter Tree (IR-PFT)

- Extend PFT-DPW[1] , incorporating trajectories from previous planning sessions for fast estimation of $Q(b_k, a_k)$



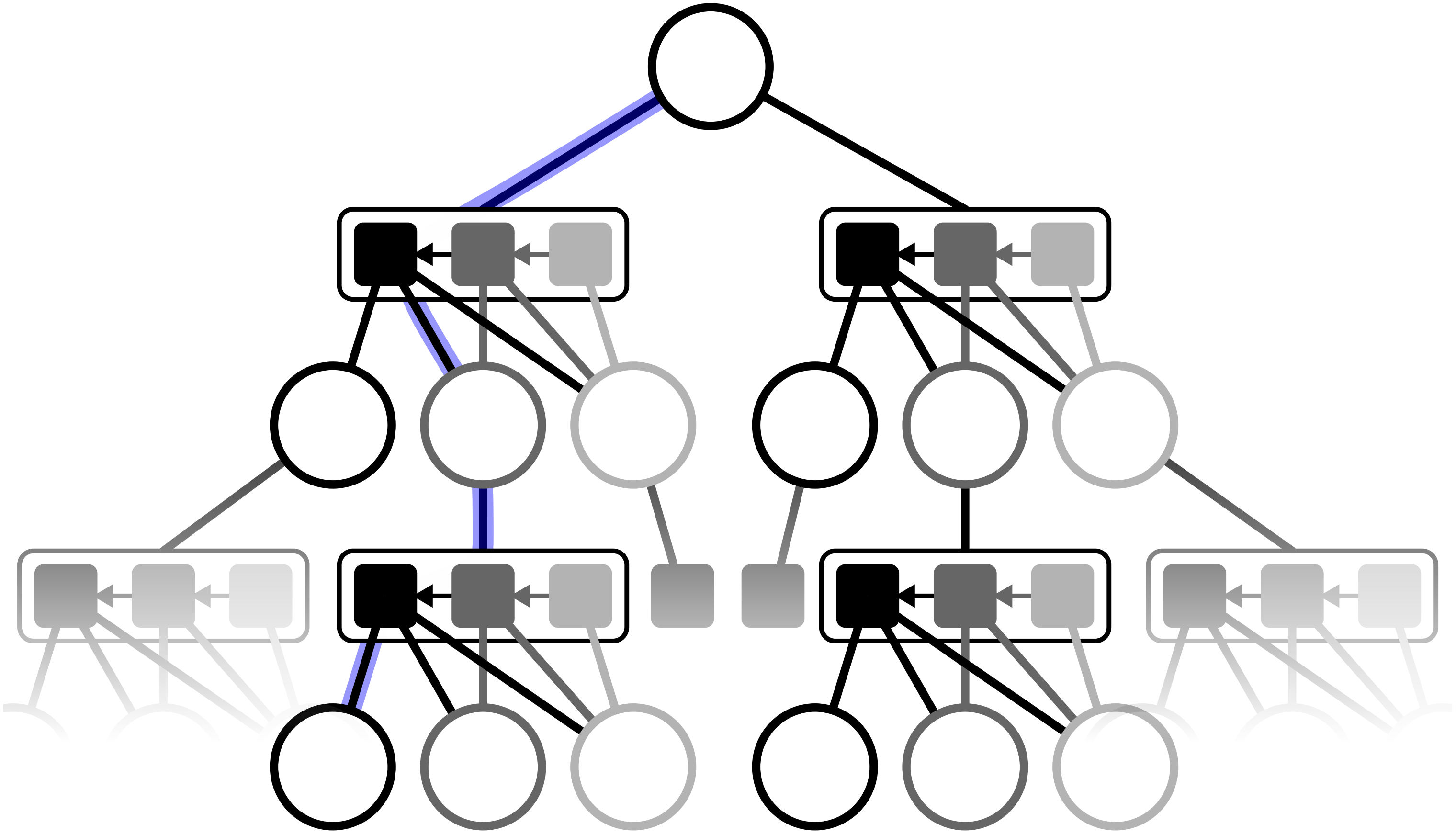




[1]Z. Sunberg and M. Kochenderfer. "Online algorithms for POMDPs with continuous state, action, and observation spaces." ICAPS, 2018.

E. Farhi and V. Indelman, “iX-BSP: Incremental Belief Space Planning,” ICRA’19, arXiv’21.
M. Novitsky, M. Barenboim, and V. Indelman, “Previous Knowledge Utilization In Online Anytime Belief Space Planning,” arXiv’24.

Value Gradients with Action Adaptive Search Trees in Continuous (PO)MDPs



I. Lev-Yehudi, M. Novitsky, M. Barenboim, R. Benchetrit, and V. Indelman, “Value Gradients with Action Adaptive Search Trees in Continuous (PO)MDPs”, arXiv’25.

Agenda

Experience Reuse in POMDP Planning

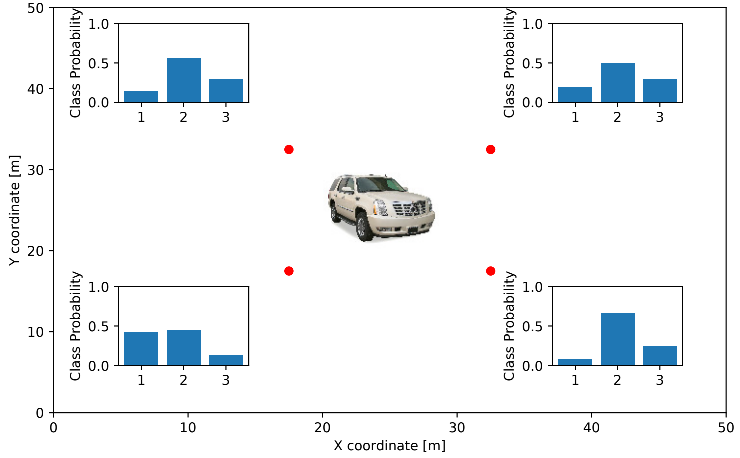
POMDP Planning with Hybrid Beliefs

Simplification of POMDP with Formal Guarantees

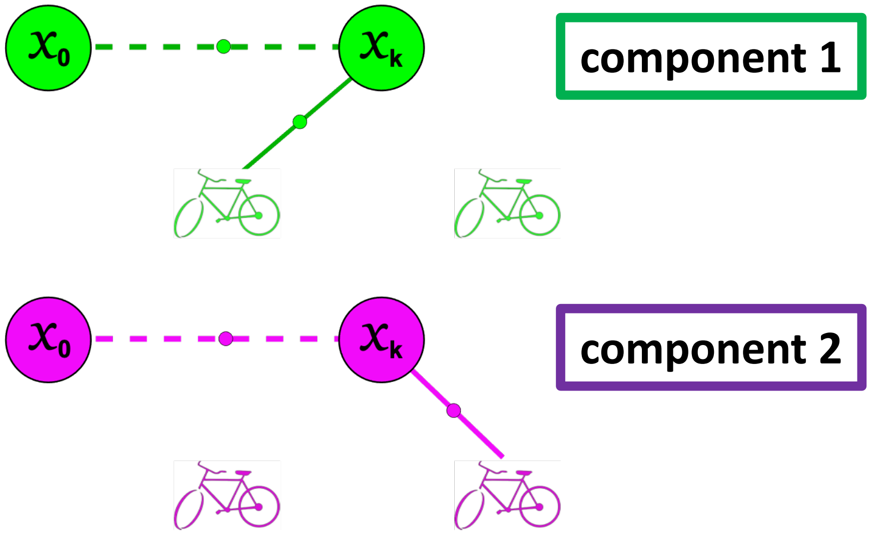
Multi-agent POMDP Planning with Inconsistent Beliefs

Autonomous Semantic Perception & Ambiguous Environments

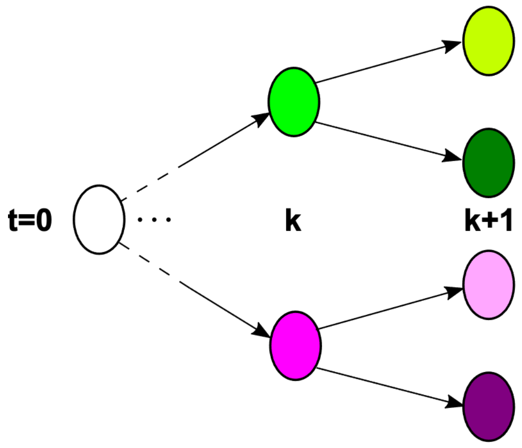
Viewpoint dependent semantic models



Data association hypotheses



- Hybrid beliefs (over continuous and discrete RVs)
- The number of hypotheses can grow exponentially
- How do we do probabilistic inference and POMDP planning?



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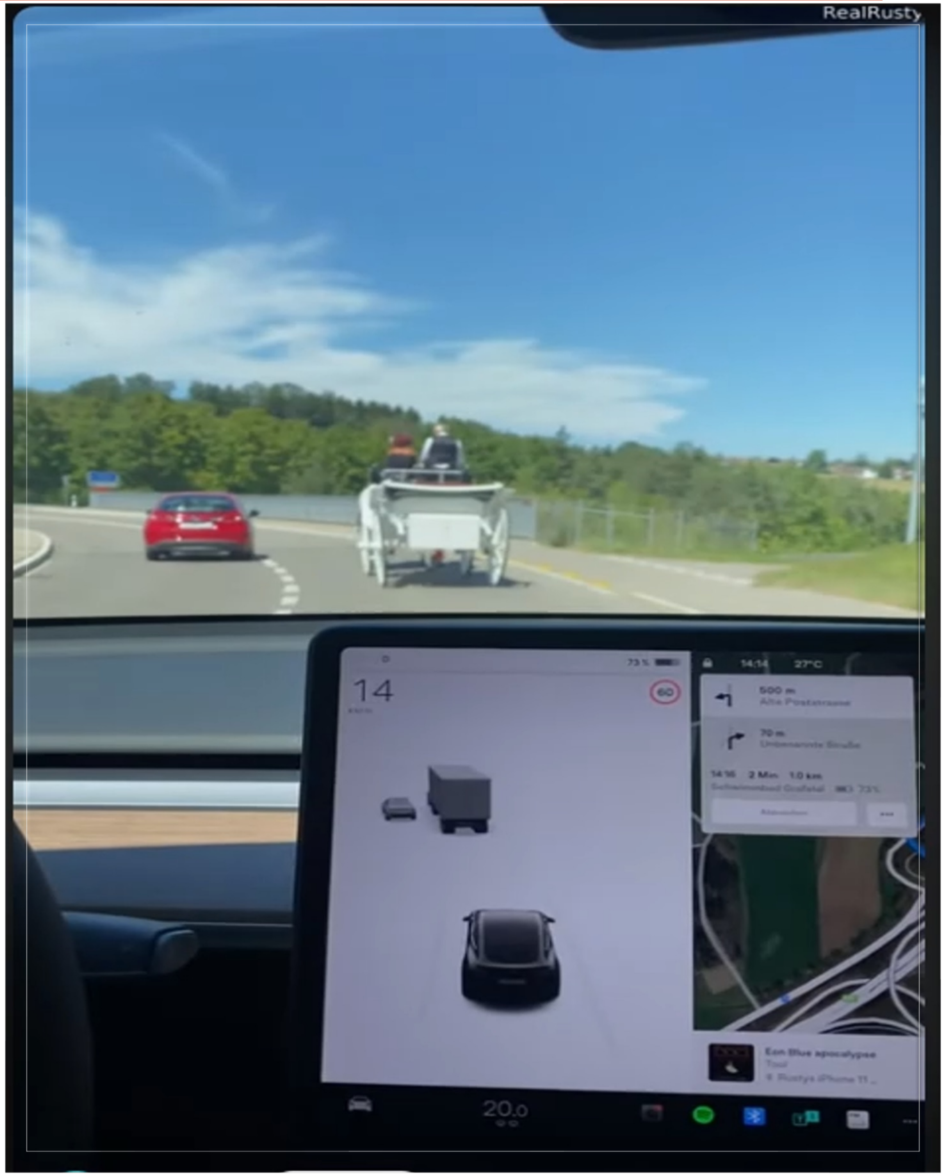
Semantic Perception & SLAM

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

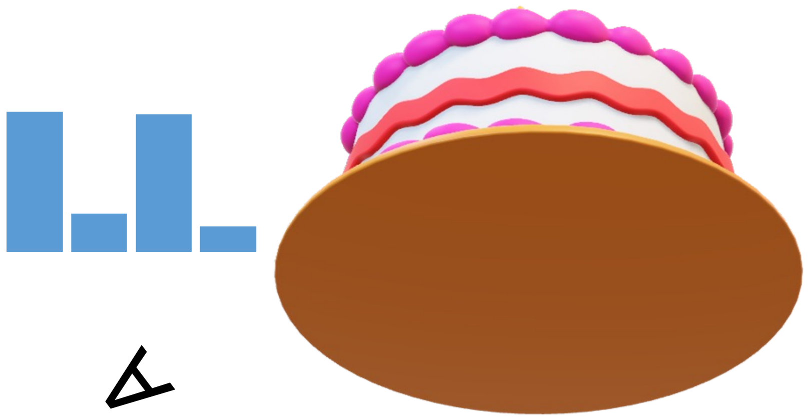


Class- and Viewpoint-Dependency

- Is it a floor or a roof?
- Depending on the viewpoint of the viewer!
  - Looking on the people below - it's a floor
  - Looking on the people above - it's a roof
- How do we know the viewpoint?

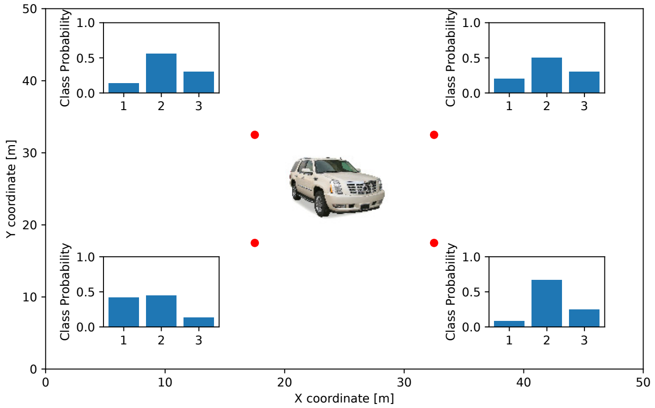
Class- and Viewpoint-Dependency

- Another example:



Coupled Models

- View-dependent semantic observation model:

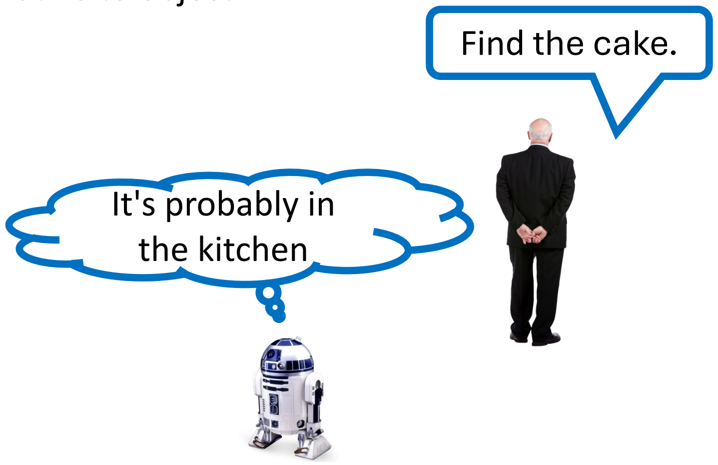


$$\mathbb{P}(z^s \mid c, \mathcal{X}^{rel})$$

Object class

Semantic observation (from a classifier)

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 (e.g., object search)

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

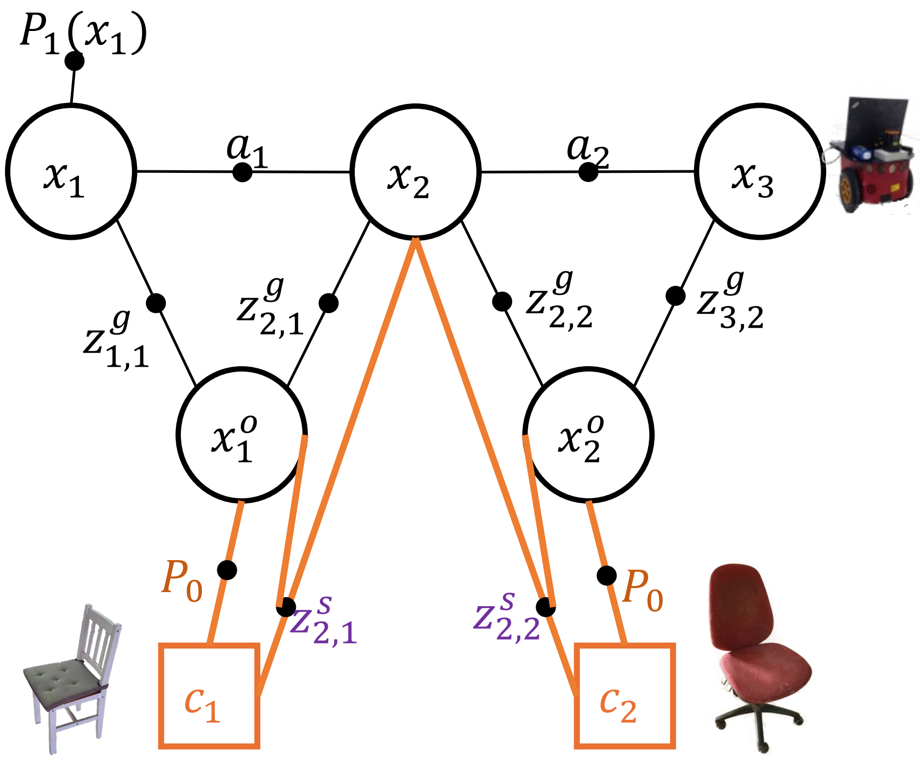
- **Hybrid Belief** at time instant k:

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

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**

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.

POMDP Planning with Hybrid Semantic-Geometric Beliefs

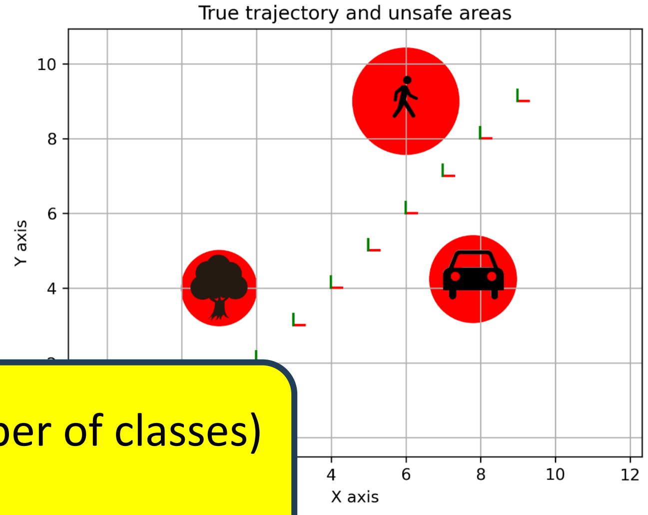
- Value function

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

- 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

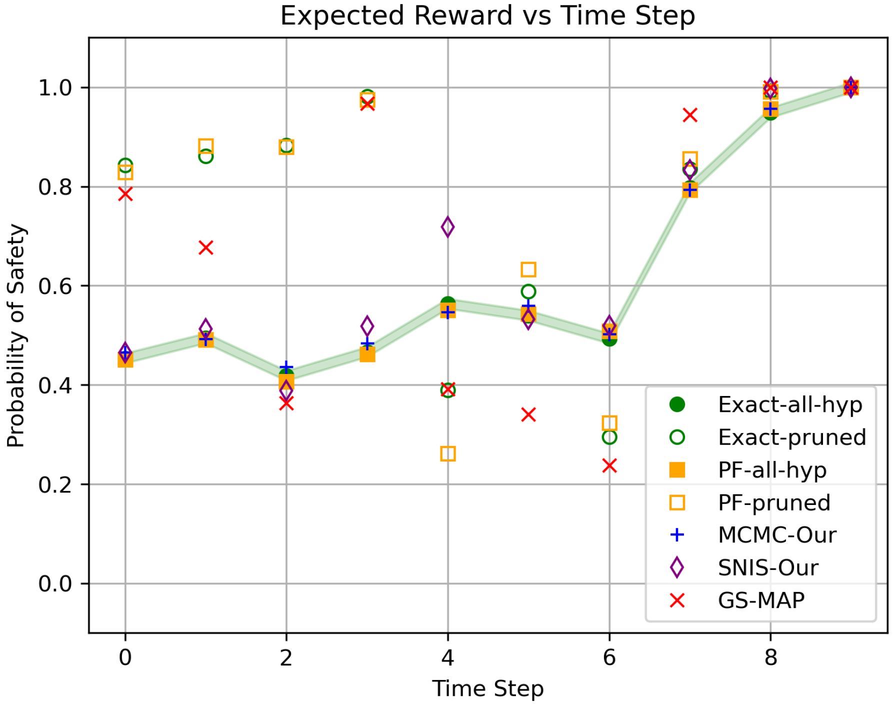
Experiments - Estimation of $\mathbb{P}_{safe}$ with different methods

- **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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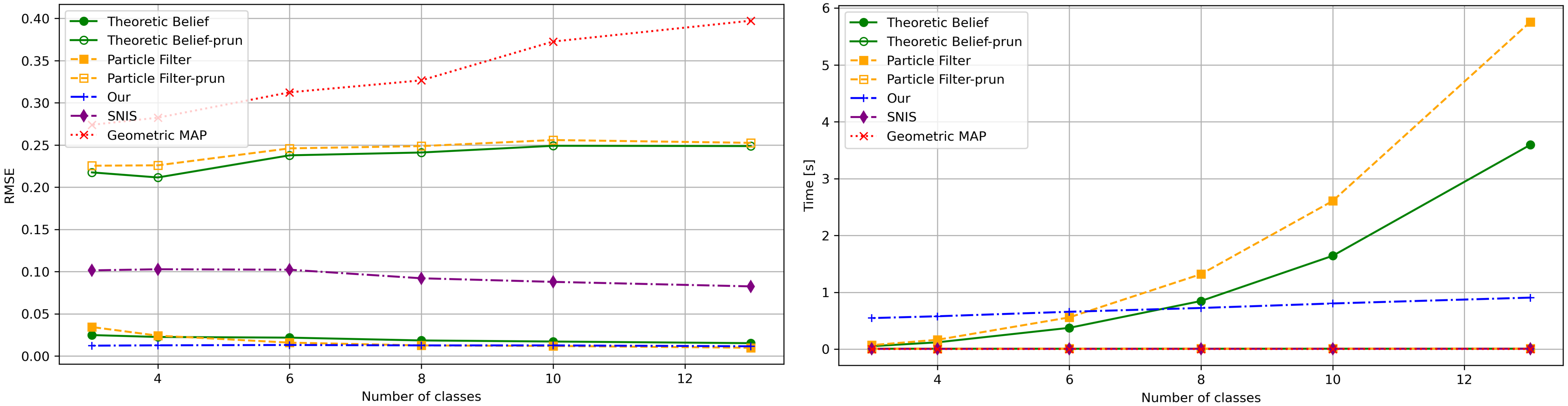
Sensitivity to number of classes



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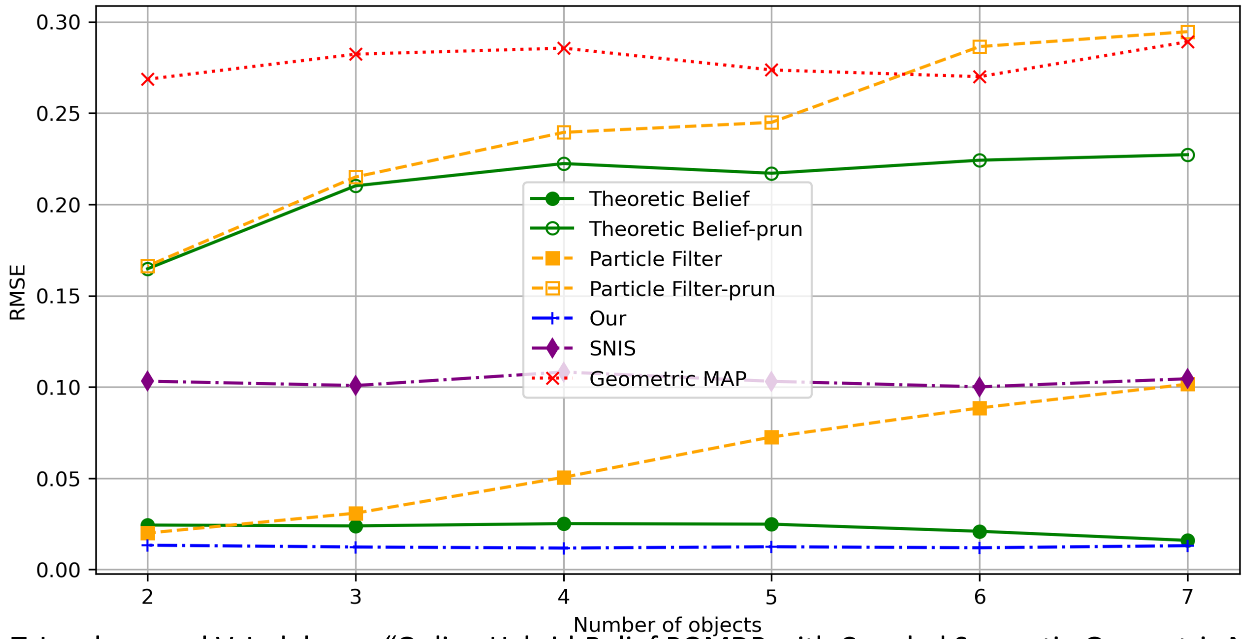

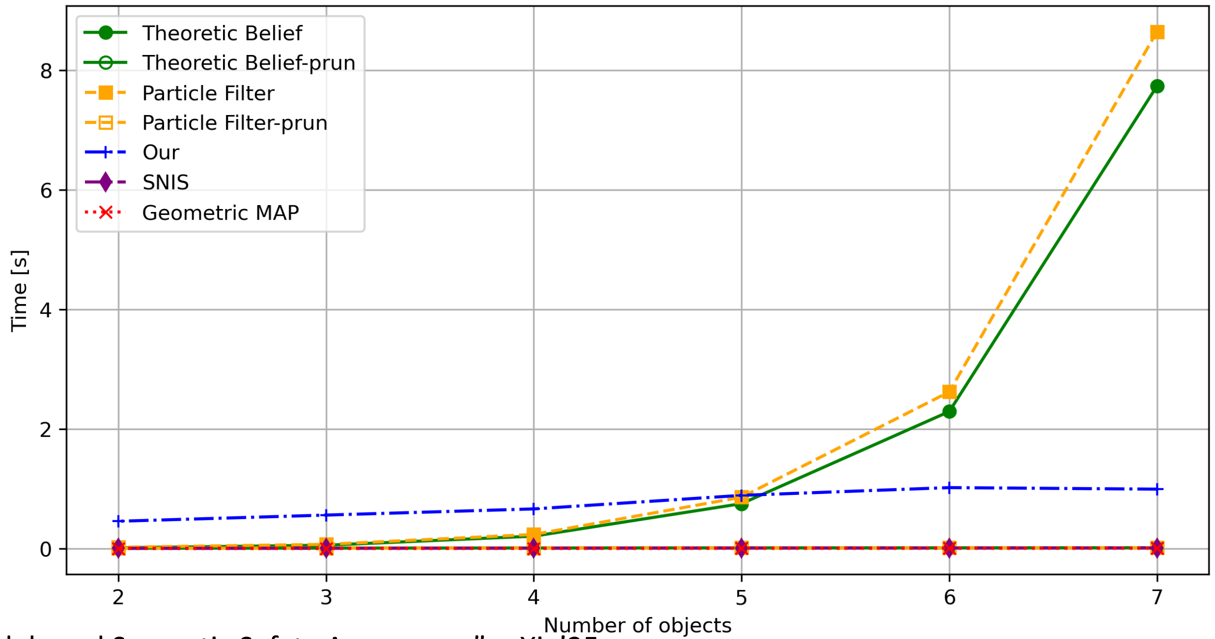

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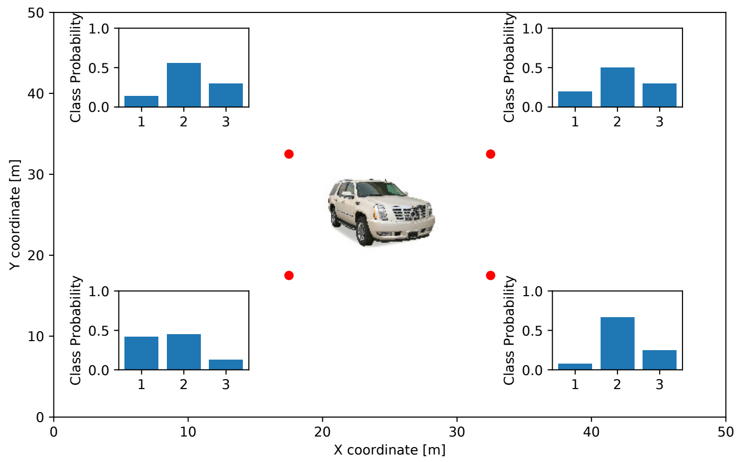
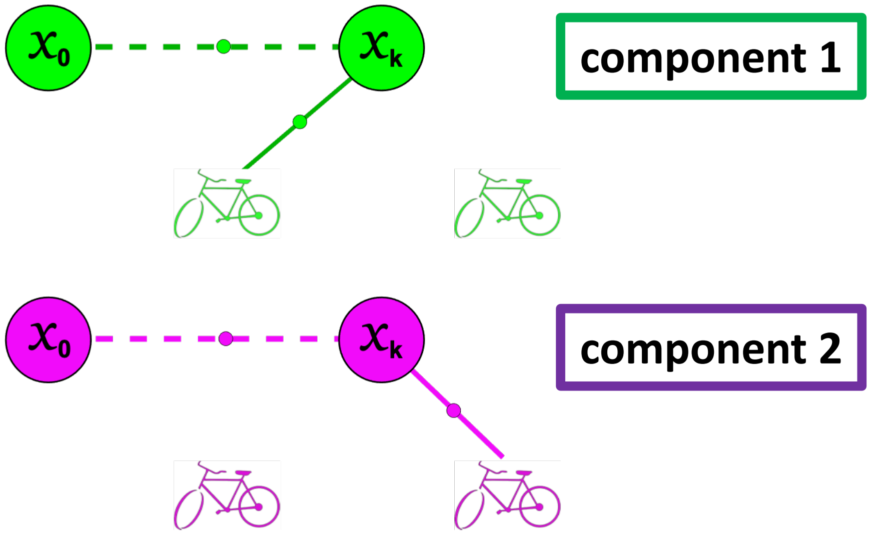
Autonomous Semantic Perception & Ambiguous Environments

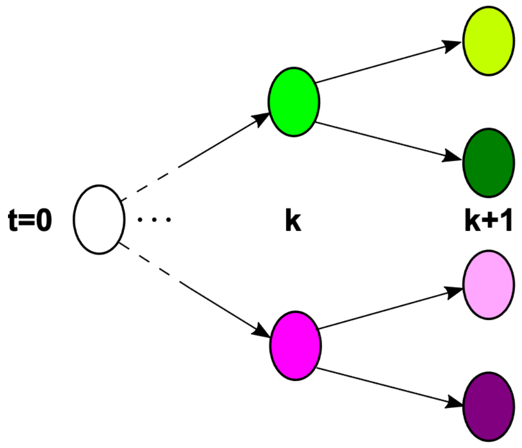
Viewpoint dependent semantic models



Data association hypotheses



- Hybrid beliefs (over continuous and discrete RVs)
- The number of hypotheses can grow exponentially
- How do we do probabilistic inference and POMDP planning?

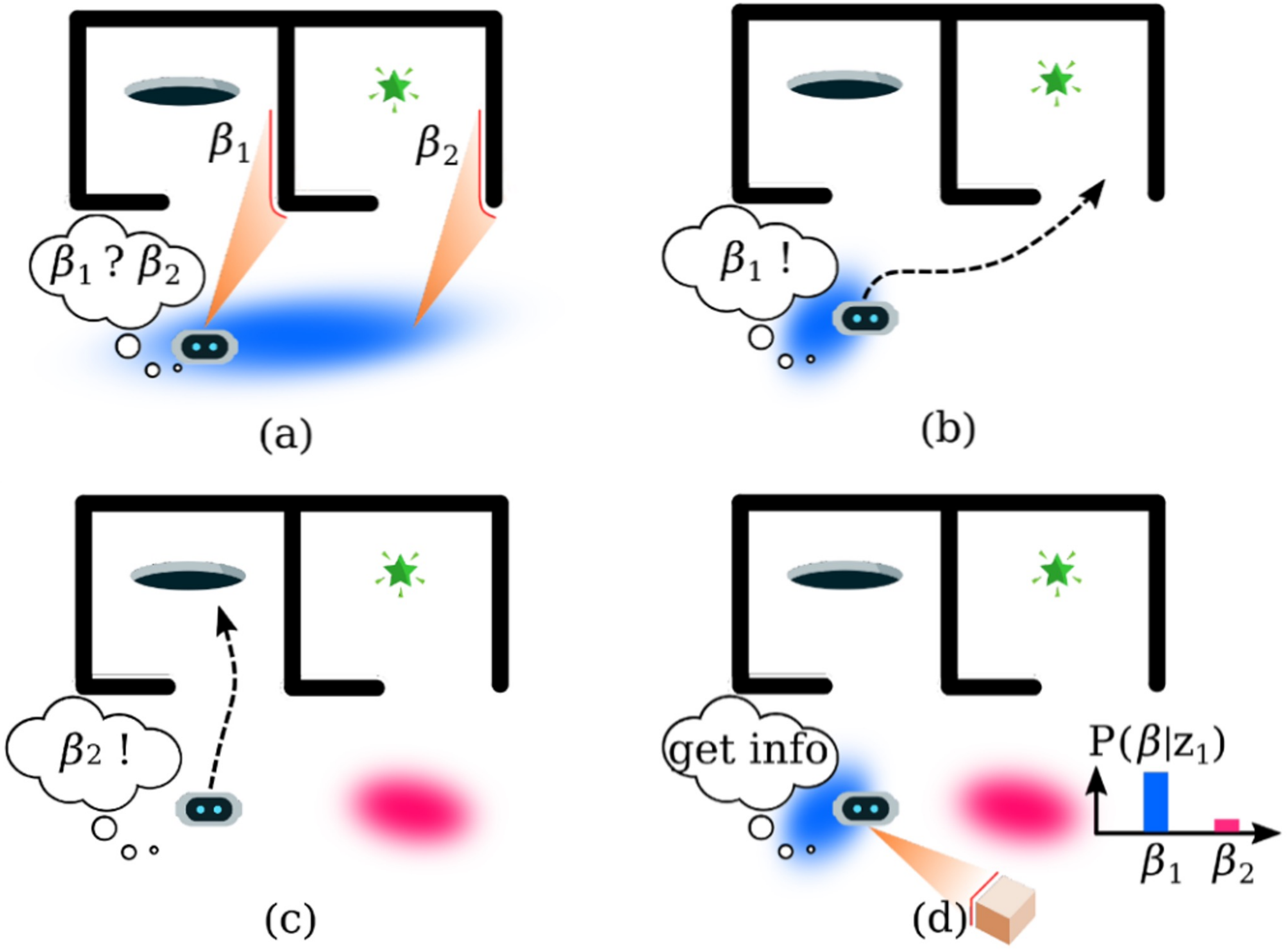


Ambiguous Scenarios

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

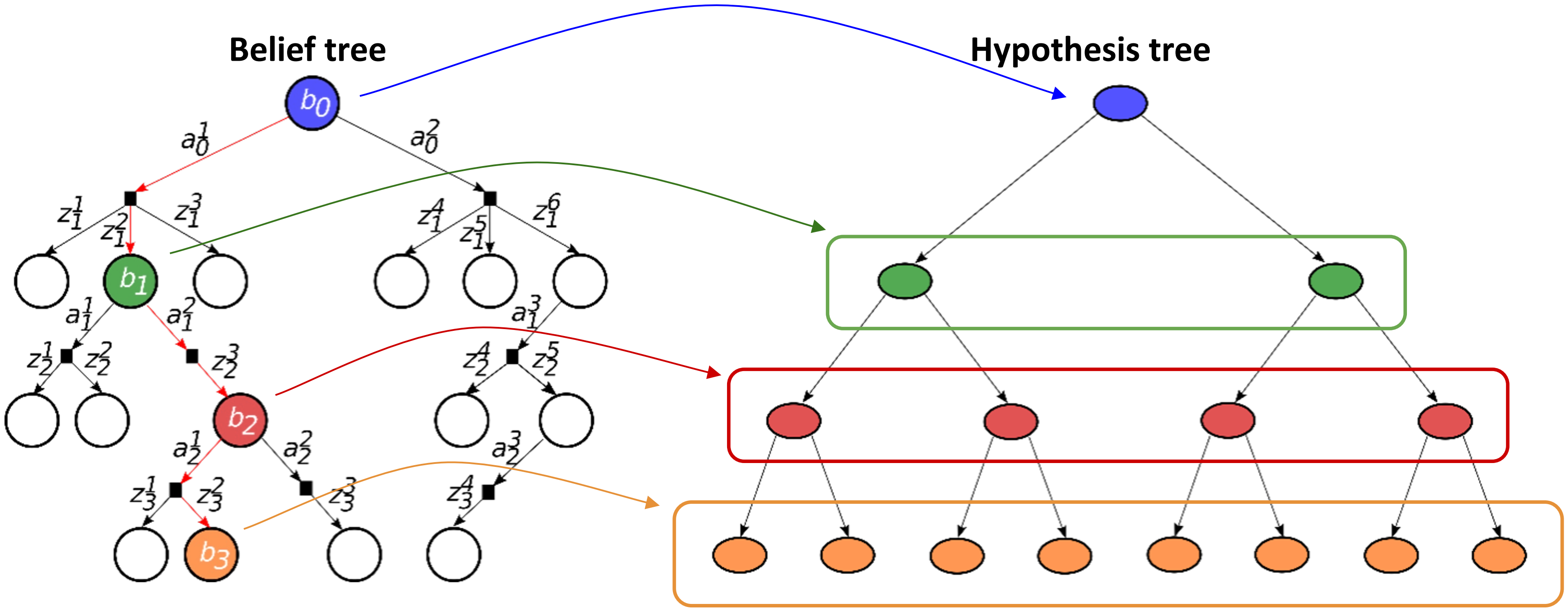
An observation:
(e.g. LIDAR)

How should the agent act?



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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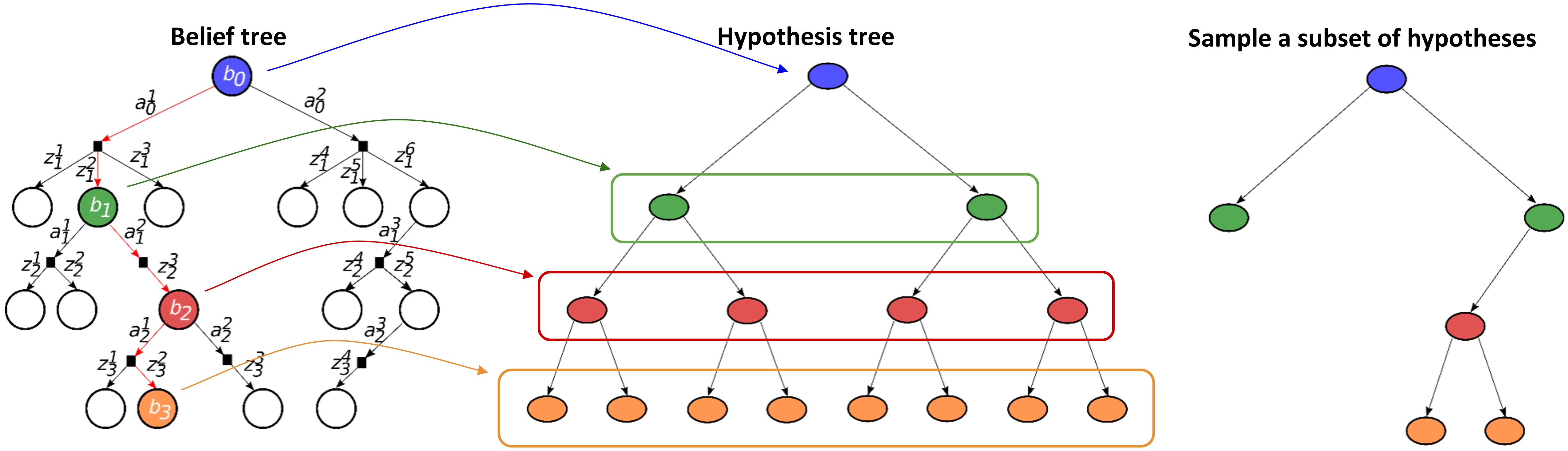


Impact on decision making?

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

Agenda

Experience Reuse in POMDP Planning

POMDP Planning with Hybrid Beliefs

Simplification of POMDP with Formal Guarantees

Multi-agent POMDP Planning with Inconsistent Beliefs

Simplification Framework

Accelerate decision making by adaptive simplification while providing performance guarantees

Break original problem into (computationally) easier problems

Provide performance guarantees

Relate between the original & simplified problems

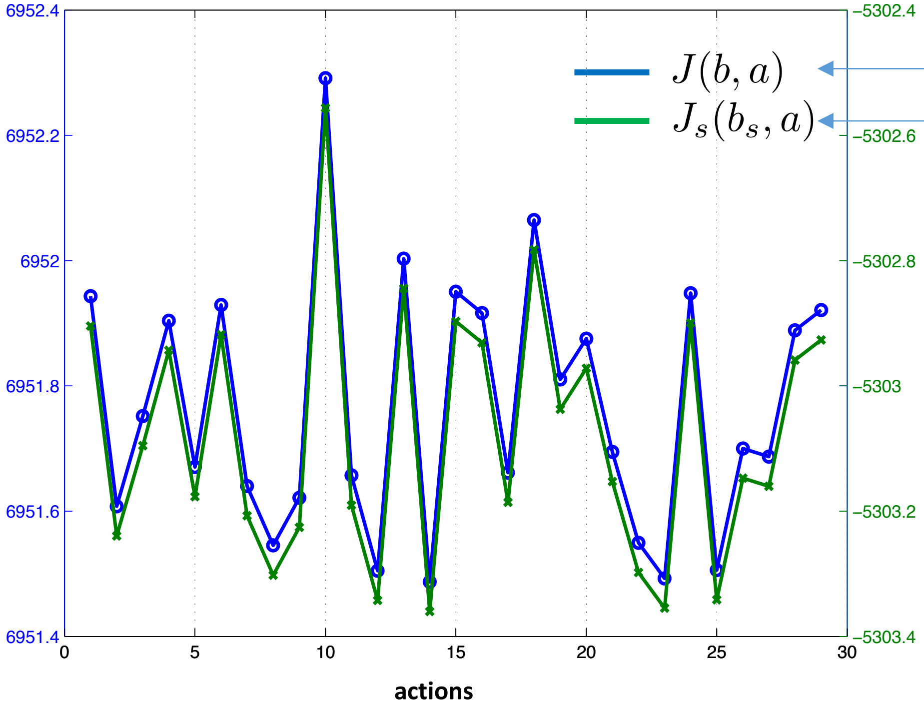
Tradeoff complexity & performance

Develop online adaptation mechanisms

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

Simplification of Decision-Making Problems

- Each element of the decision-making problem can be simplified
- **Action-consistent** simplification preserves order between actions w.r.t. original problem



Original problem

Simplified problem

Same optimal action!

V. Indelman, “No Correlations Involved: Decision Making Under Uncertainty in a Conservative Sparse Information Space,” IEEE RA-L’16.
K. Elimelech and V. Indelman, “Simplified decision making in the belief space using belief sparsification,” IJRR’22.

Simplification of Decision-Making Problems

$$\mathcal{LB}(b,a) \leq Q(b,a) \leq \mathcal{UB}(b,a)$$

Computationally cheap(er) bounds

V. Indelman, “No Correlations Involved: Decision Making Under Uncertainty in a Conservative Sparse Information Space,” IEEE RA-L’16.
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Specific simplifications include:

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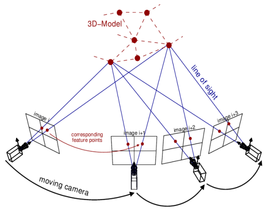
[Indelman RAL'16; Elimelech & Indelman IJRR'22; Sztyglic & Indelman IROS'22, Zhitnikov & Indelman AIJ'22, TRO'24; Shienman & Indelman ICRA'22; Kitanov & Indelman IJRR'24; Zhitnikov et al. IJRR'24, Barenboim & Indelman NIPS'23; Lev-Yehudi, Barenboim & Indelman AAAI'24, Kong & Indelman ISRR 2024]

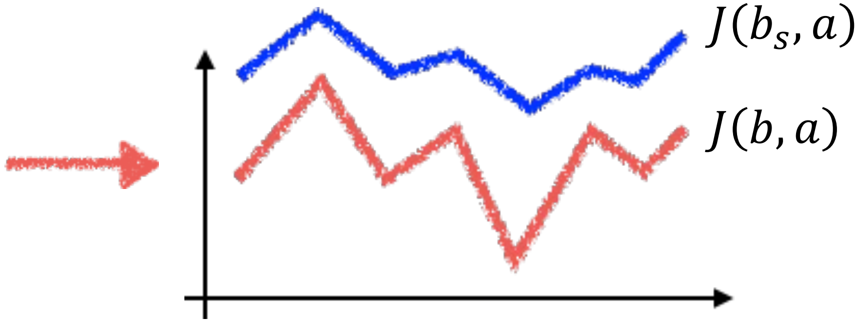
Belief Sparsification for Gaussian BSP

- Find an appropriate **sparsified** (square root) information matrix
- Perform decision making using that, rather the original, information matrix



Setting:

- Gaussian belief over high dim. state $X \in \mathbb{R}^n$: $b[X] = \mathcal{N}(X^\star, \Lambda^{-1}) = \mathcal{N}(X^\star, (R^T R)^{-1})$
- Information-theoretic reward (entropy): $H[X] = \frac{1}{2}\log((2\pi e)^n |\Lambda|^{-1})$

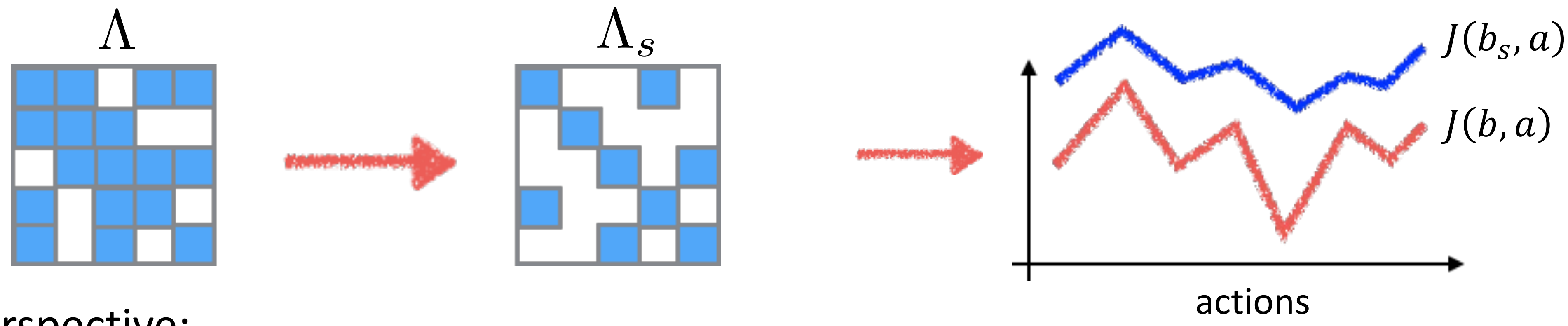


- Do we get the same performance (decisions), i.e. is it action consistent?

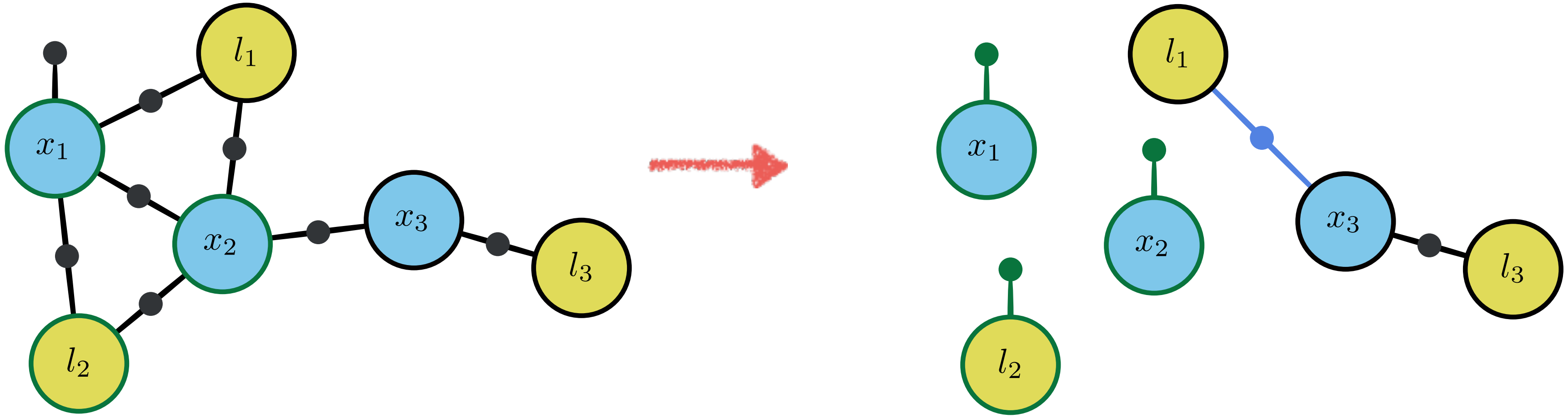
V. Indelman, “No Correlations Involved: Decision Making Under Uncertainty in a Conservative Sparse Information Space,” IEEE RA-L’16.
K. Elimelech and V. Indelman, “Simplified decision making in the belief space using belief sparsification,” IJRR’22.

Belief Sparsification for Gaussian BSP

- **Sparsification** of (square root) information matrix



- Graphical models perspective:



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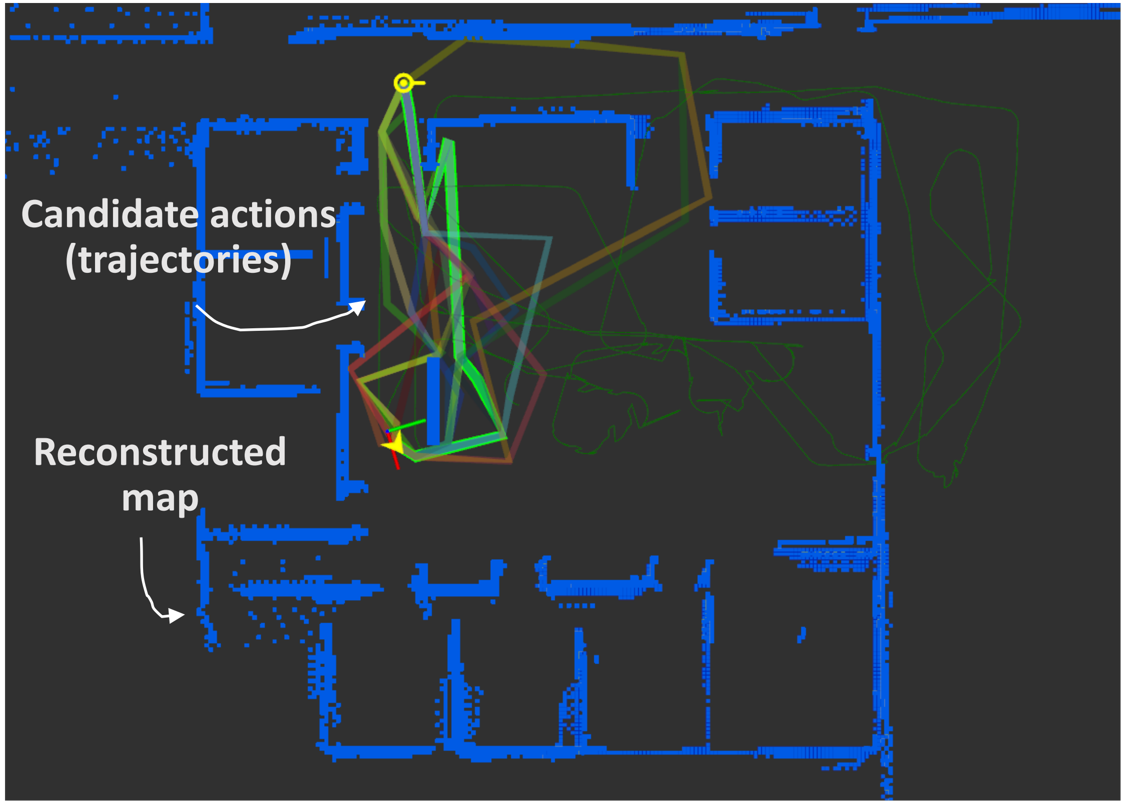
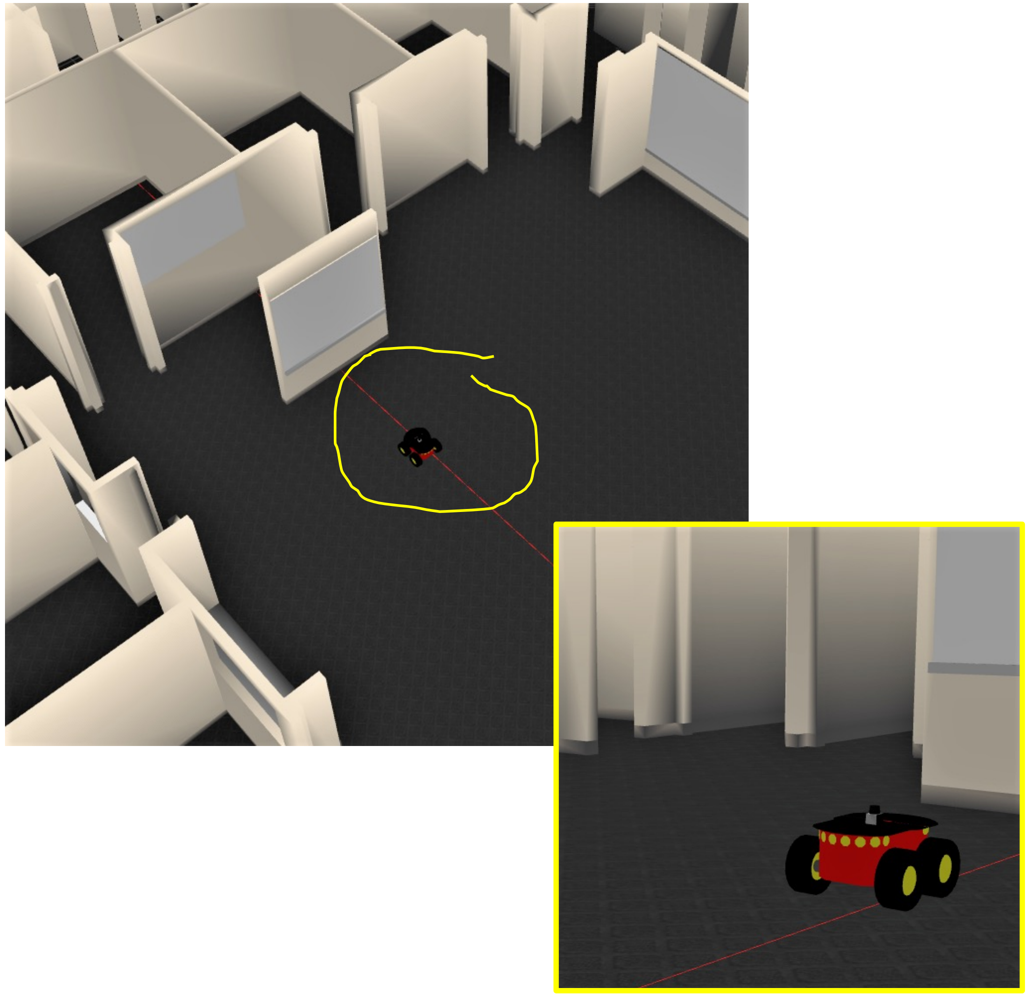
Belief Sparsification for Gaussian BSP

- Agent performs simultaneous localization and mapping
- Maintains a multivariate Gaussian belief

$$b[X] = \mathcal{N}(X^{\star}, (R^T R)^{-1})$$

- Task: reach a goal with **minumum uncertainty**





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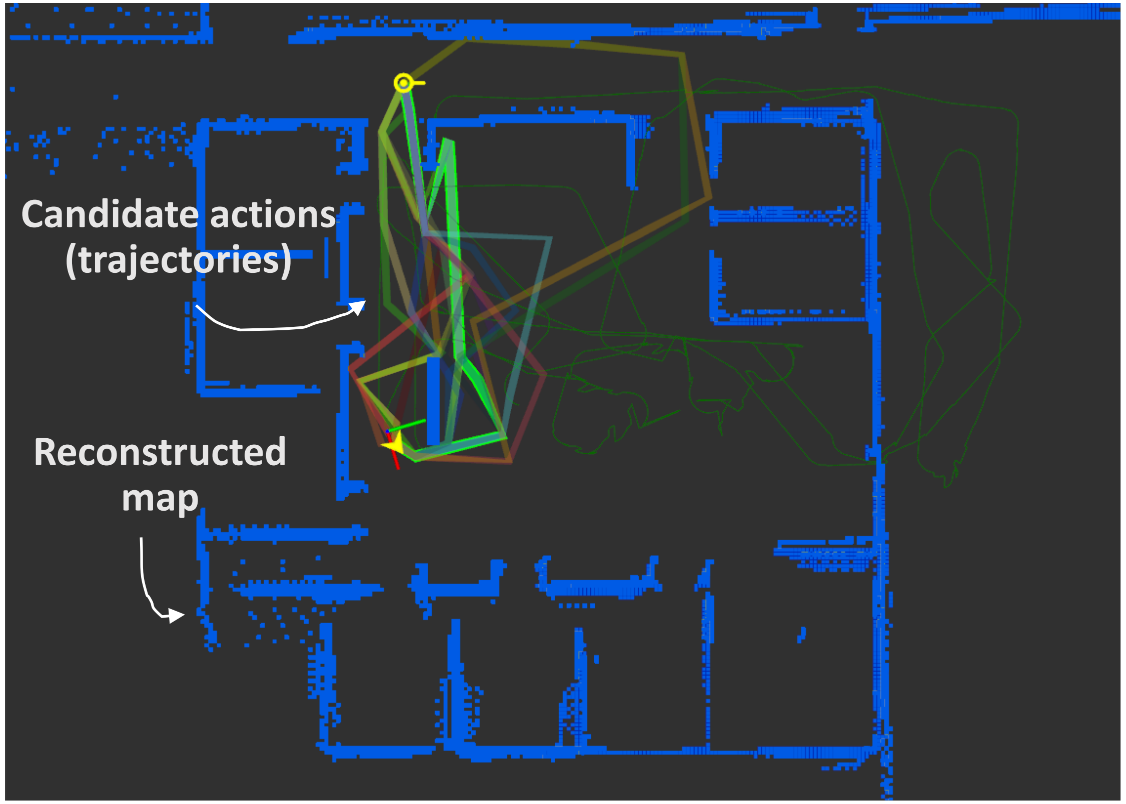

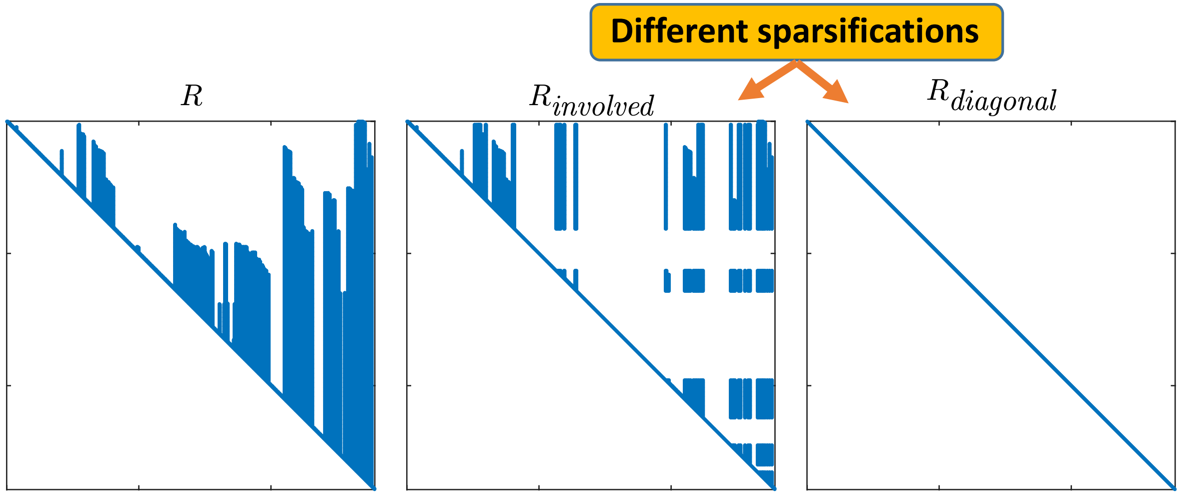

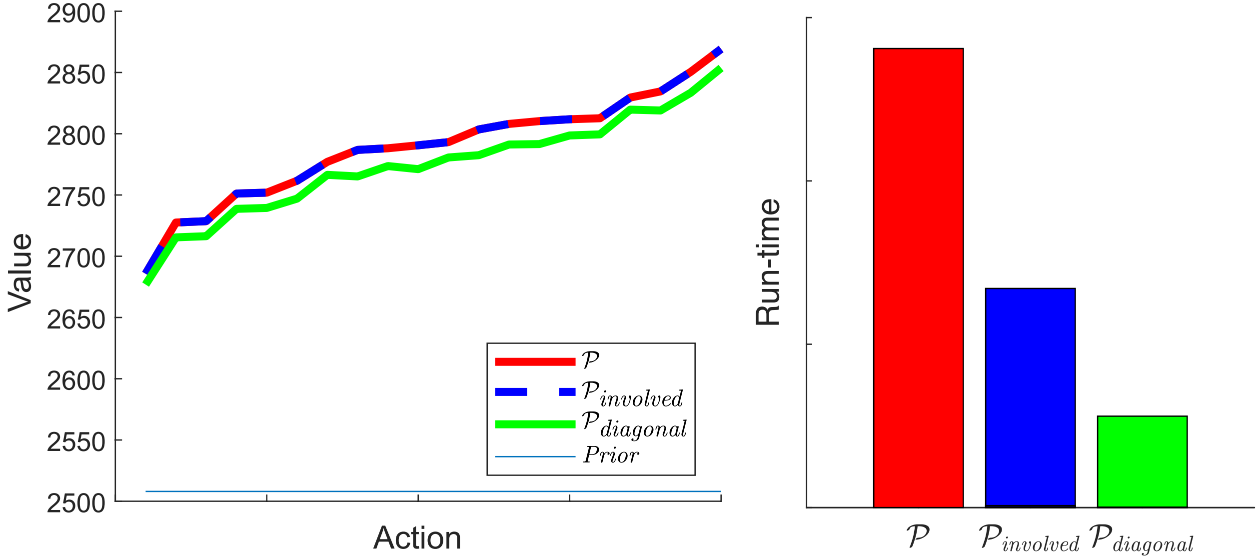

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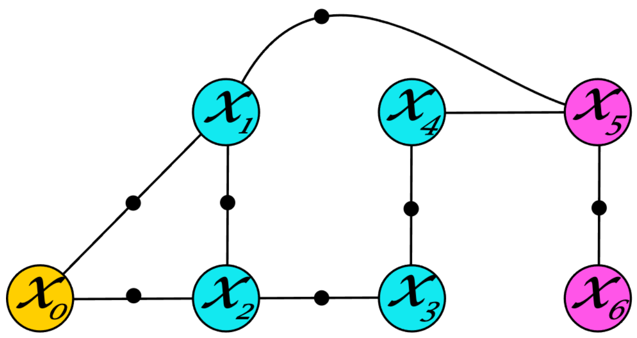
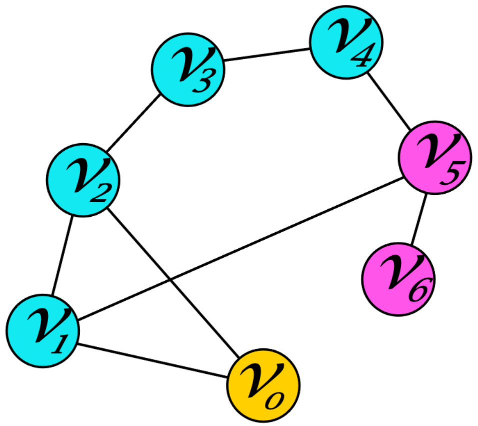
Topological Gaussian Belief Space Planning (t-BSP)

- Topological properties of factor graphs dominantly determine estimation accuracy[1]

Key idea:
- Design a metric of factor graph topology that is strongly correlated with entropy
- Determine best action using that topological metric (instead of entropy)
- **Does not require explicit inference, nor partial state covariance recovery**



Factor graph



Topological graph $G(\Gamma, E)$

topological metric $s(G)$

graph signature

[1]K. Khosoussi, et al. "Reliable graphs for SLAM", IJRR'19.

A. Kitanov and V. Indelman. "Topological belief space planning for active SLAM with pairwise Gaussian potentials and performance guarantees", IJRR'24.
M. Shienman, A. Kitanov, and V. Indelman. "Ft-bsp: Focused topological belief space planning." IEEE RA-L'21.

Topological Gaussian Belief Space Planning (t-BSP)

Topological and info-theoretic metrics are strongly correlated

Metric Space

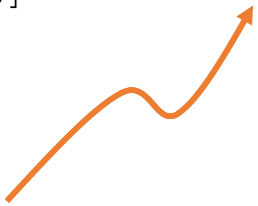
$$J(\mathcal{U}) = \frac{n}{2}\ln(2\pi e) + \frac{1}{2}\ln|\Sigma(X_{k+L})|$$

$$\mathcal{U}^{\star} = \arg\min_{\mathcal{U}} J(\mathcal{U})$$

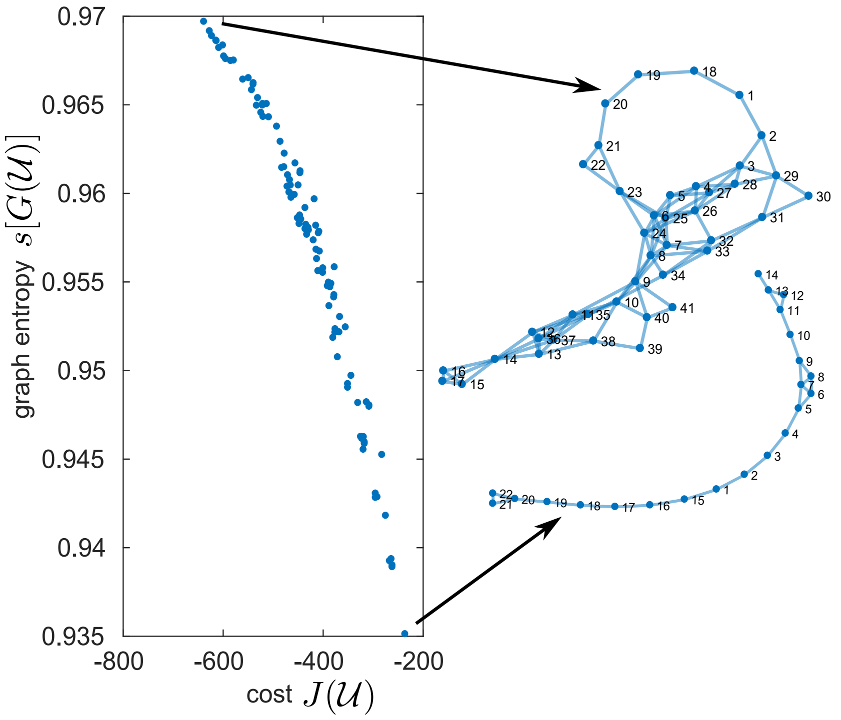
Topological space

$$s(G) = H_{VN}(G) \approx 1 - \frac{1}{|\Gamma|} - \frac{1}{|\Gamma|^2}\sum_{(i,j)\in E}\frac{1}{d(i)d(j)}$$

$$\hat{\mathcal{U}}^{\star} = \arg\max_{\mathcal{U}} s[G(\mathcal{U})]$$



- Cheap to calculate, only a function of node degrees
- Supports incremental calculations
- Provided bounds on the error/loss $\left|J_k\left(\hat{\mathcal{U}}\right) - J_k\left(\hat{\mathcal{U}}^{\star}\right)\right|$



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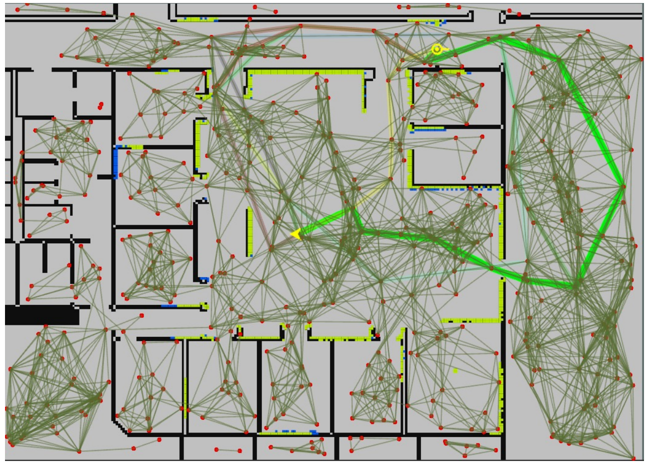
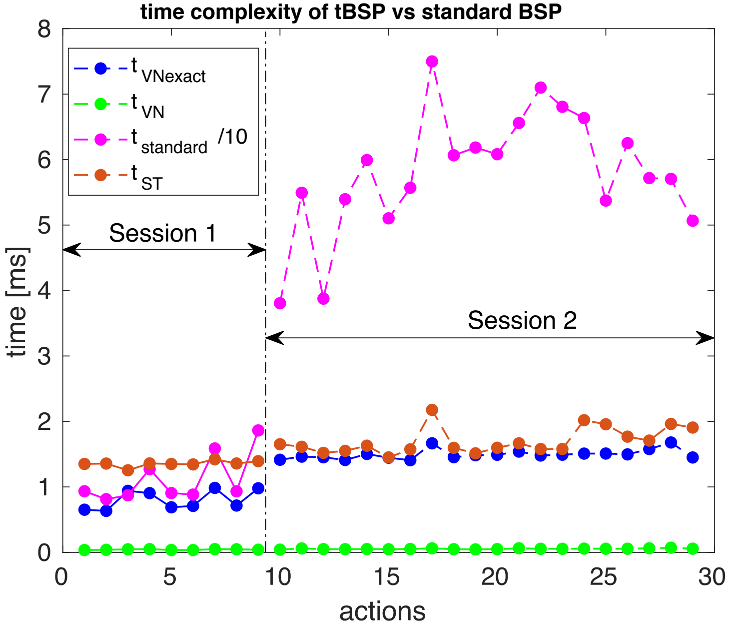
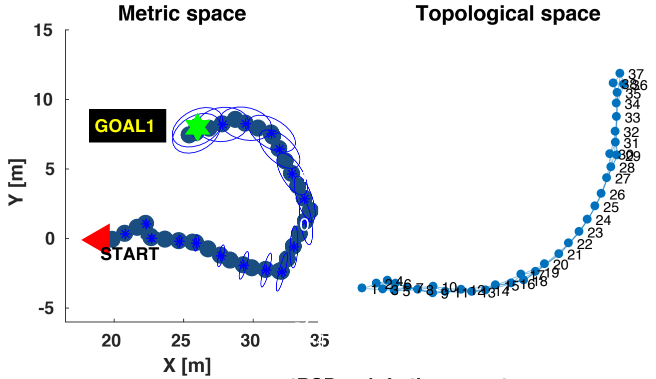
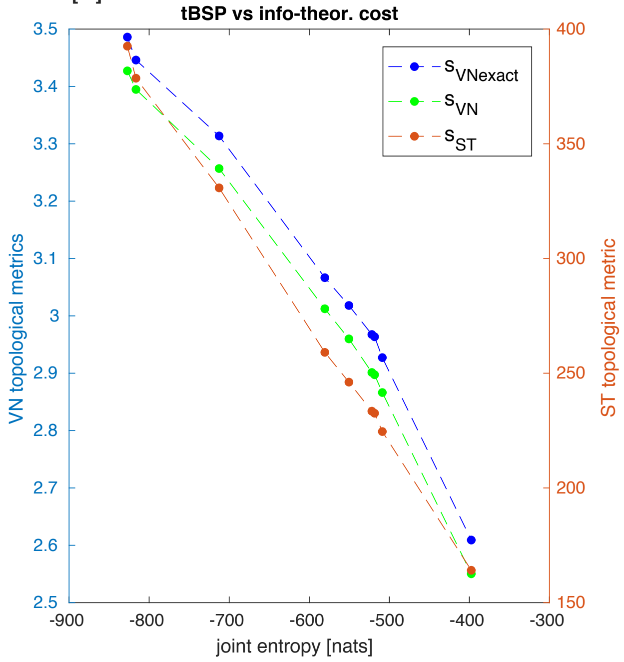
t-BSP: Gazebo Results



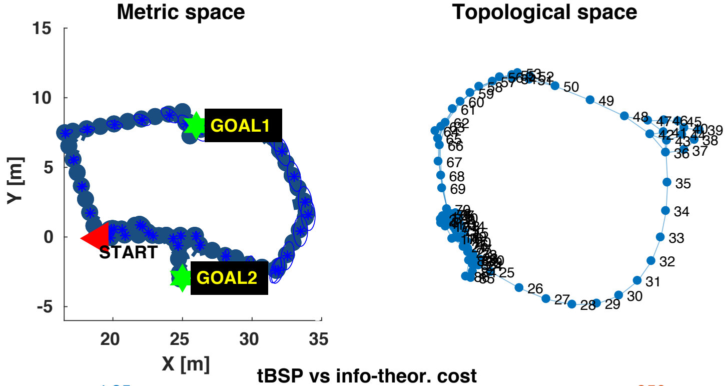


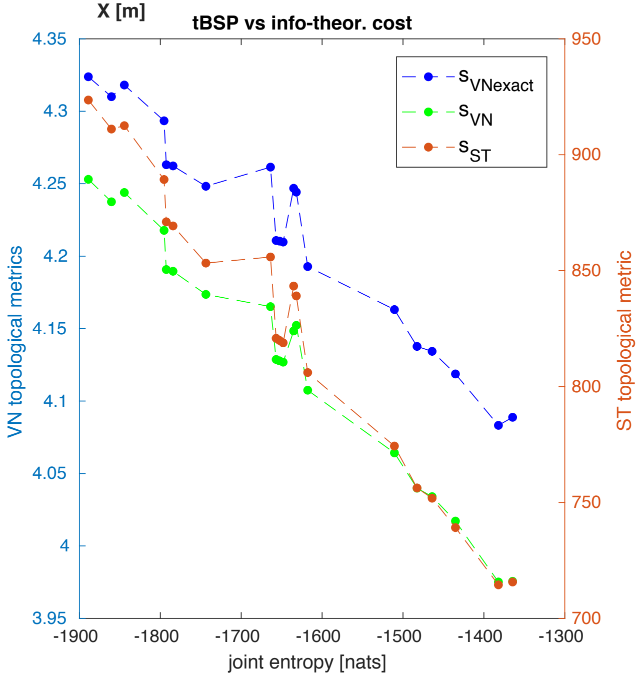
1st planning session (exploration)





2nd planning session (exploitation, loop closures)





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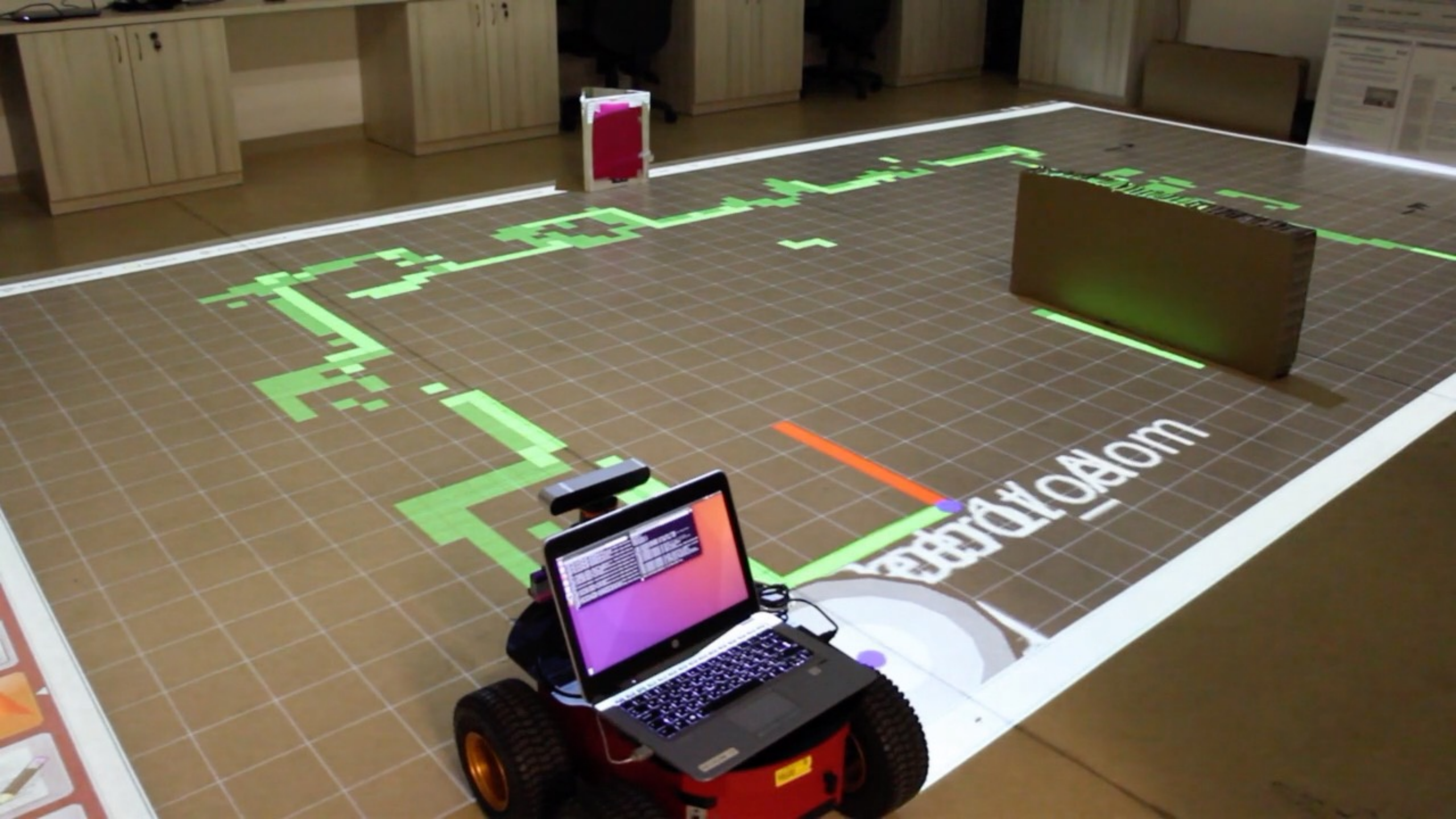
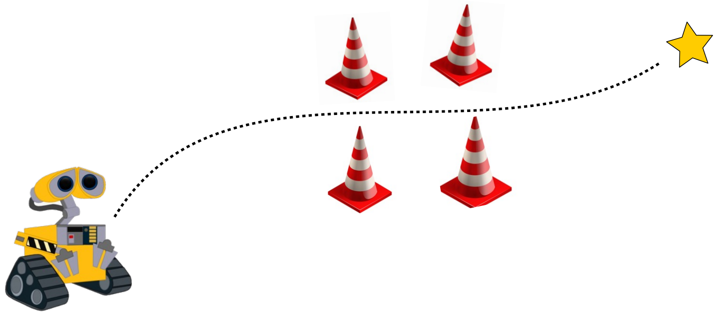
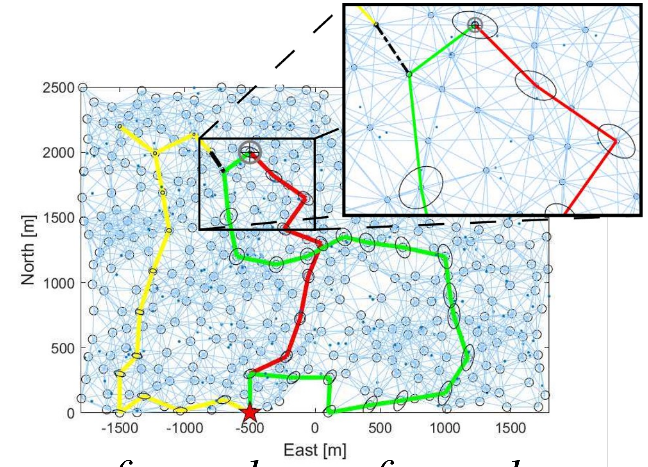


Focused Topological Gaussian Belief Space Planning (ft-BSP)

- **Unfocused** BSP – reduce uncertainty over all variables
- **Focused** BSP – reduce uncertainty over a predefined subset of variables (focused variables)


collision avoidance


focused reconstruction task



focused vs *unfocused*

$$J_{\mathcal{H}}^{F}(\mathcal{U}) = \frac{n^F}{2}\log(2\pi e) - \frac{1}{2}\log\left|\Lambda_{k+L}\right| + \frac{1}{2}\log\left|\Lambda_{k+L}^{U}\right|$$

Expensive!

Topological signatures: S_{WTCD} S_{VND}

M. Shienman, A. Kitanov, and V. Indelman. "Ft-bsp: Focused topological belief space planning." IEEE RA-L’21.

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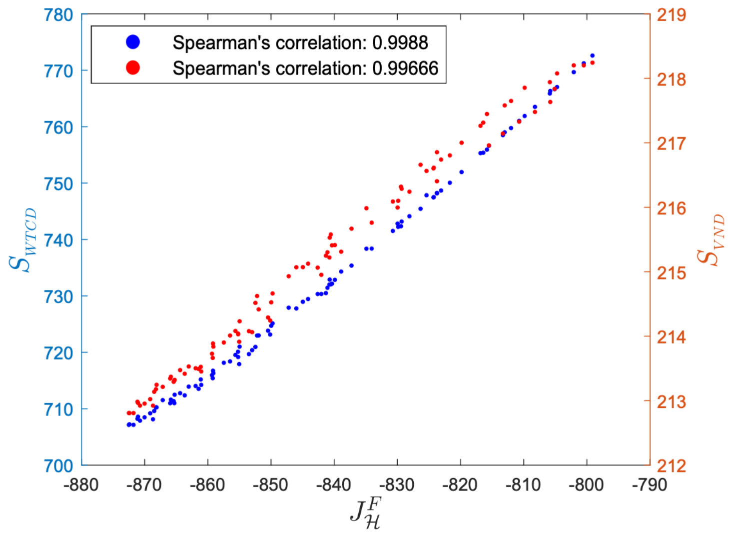
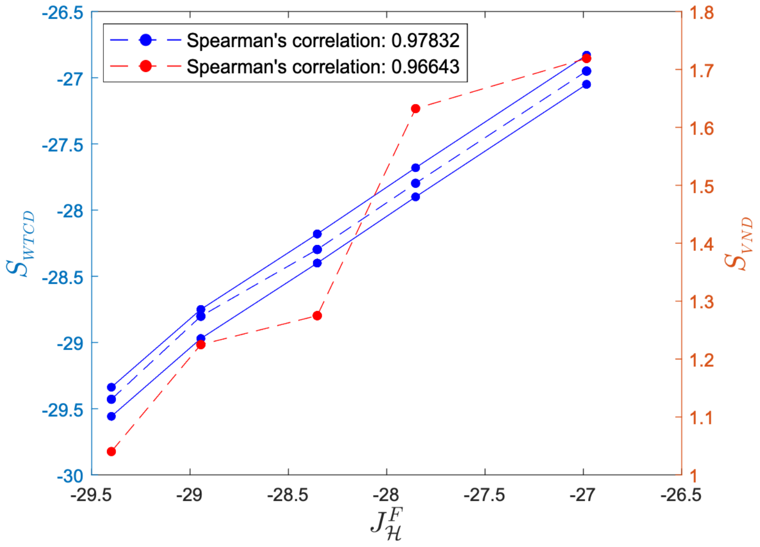


Measurement Selection



Active 2D Pose SLAM

signature	measurement selection	active SLAM
S_{WTCD}	18.88	1.21
S_{VND}	**12.02**	**0.14**
$J^F_{\mathcal{H}}$	146.24	6.34

Average running time experiments in *ms*

M. Shienman, A. Kitanov, and V. Indelman. "Ft-bsp: Focused topological belief space planning." IEEE RA-L'21.

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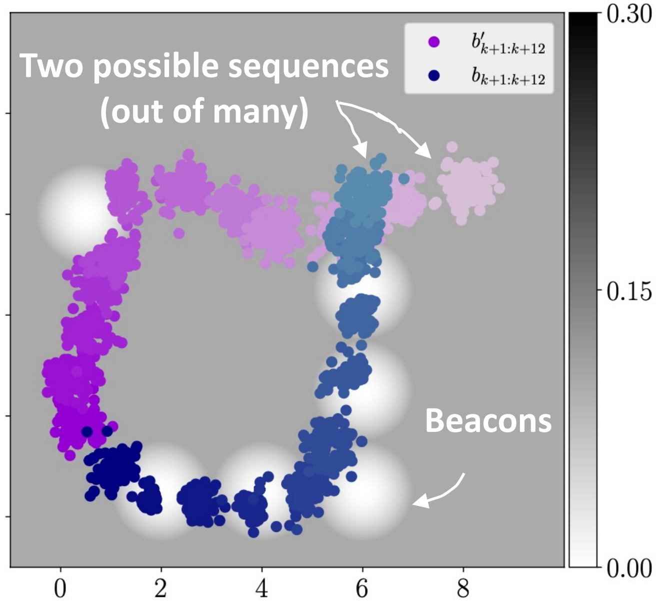
Simplification of POMDPs with Nonparametric Beliefs

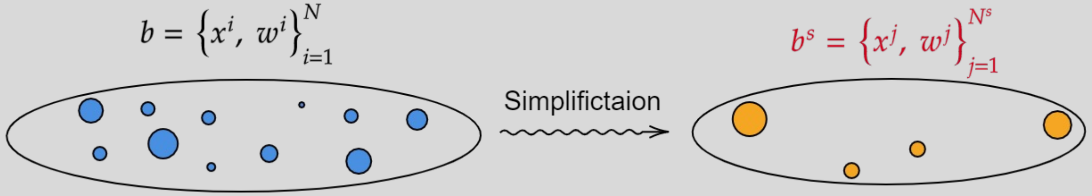
- Value function

$$V_k^{\pi}(b_k) \equiv J_k(b_k, \pi) = \mathbb{E}\{\sum_{l=0}^{L-1} r(b_{k+l}, \pi_{k+l}(b_{k+l})) + r(b_{k+L})\}$$



Simplification:

- Utilize a **subset** of samples for planning
- Information-theoretic reward (entropy)
- Analytical (**cheaper**) bounds over the reward

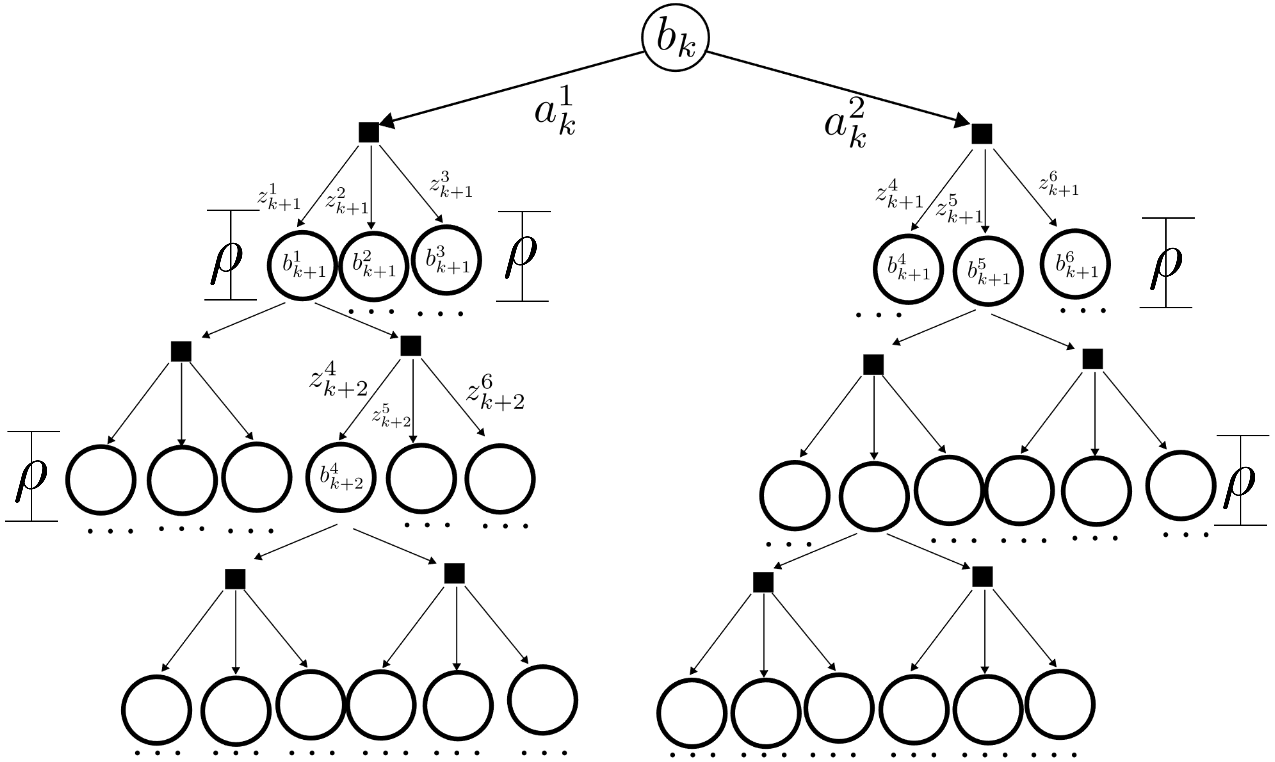


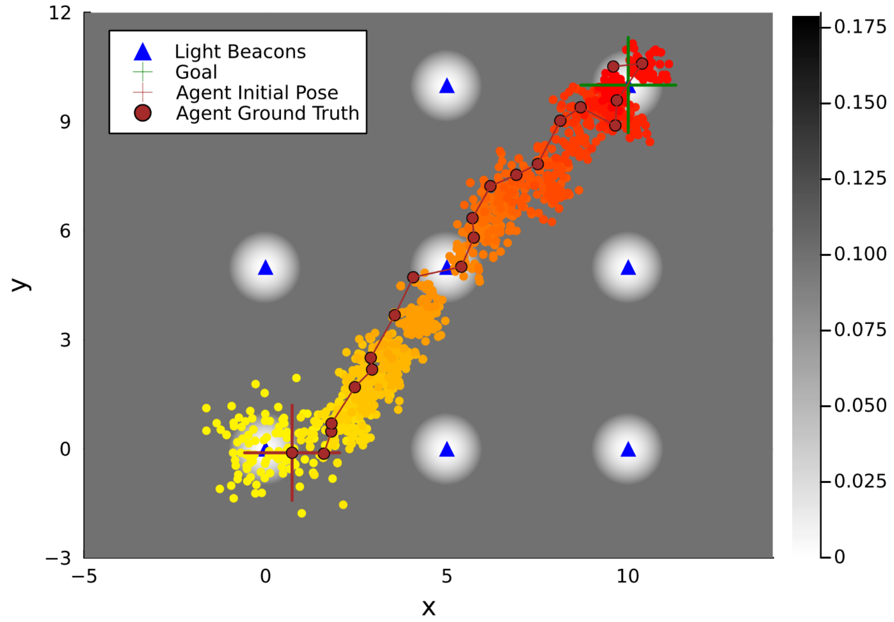
$$lb(b, b^s, a) \leq r(b, a) \leq ub(b, b^s, a)$$

O. Sztyglic and V. Indelman, “Speeding up POMDP Planning via Simplification”, IROS’22.
A. Zhitnikov, O. Sztyglic, and V. Indelman, “No Compromise in Solution Quality: Speeding Up Belief-dependent Continuous POMDPs via Adaptive Multilevel Simplification”, IJRR’24.

Simplification of POMDPs with Nonparametric Beliefs

- **Adaptive multi-level** simplification in a Sparse Sampling setting:





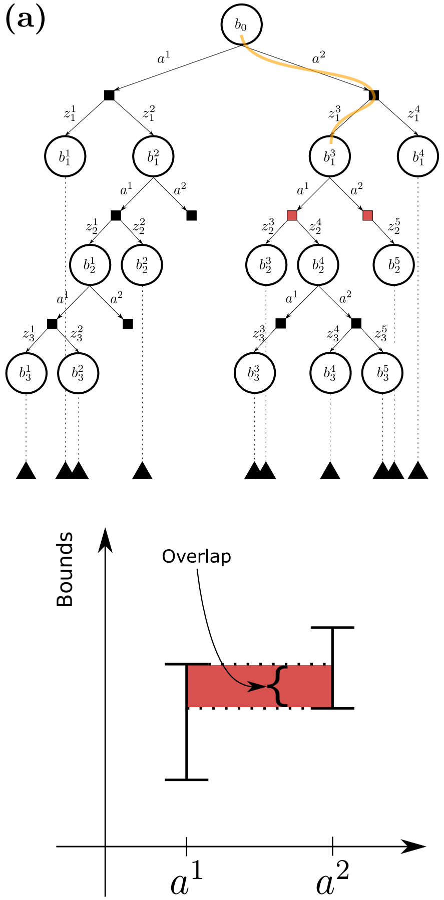
Typical speedup of 20% - 50%,
Same performance!

O. Sztyglic and V. Indelman, “Speeding up POMDP Planning via Simplification”, IROS’22.
A. Zhitnikov, O. Sztyglic, and V. Indelman, “No Compromise in Solution Quality: Speeding Up Belief-dependent Continuous POMDPs via Adaptive Multilevel Simplification”, IJRR’24.

Simplification of POMDPs with Nonparametric Beliefs

- **Adaptive multi-level** simplification in an MCTS setting:

(a)



O. Sztyglic and V. Indelman, “Speeding up POMDP Planning via Simplification”, IROS’22.
A. Zhitnikov, O. Sztyglic, and V. Indelman, “No Compromise in Solution Quality: Speeding Up Belief-dependent Continuous POMDPs via Adaptive Multilevel Simplification”, IJRR’24.

Simplification of Decision-Making Problems

Concept:

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

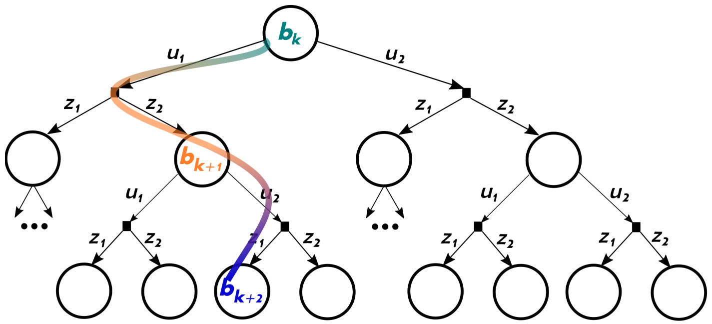
Specific simplifications include:

- 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

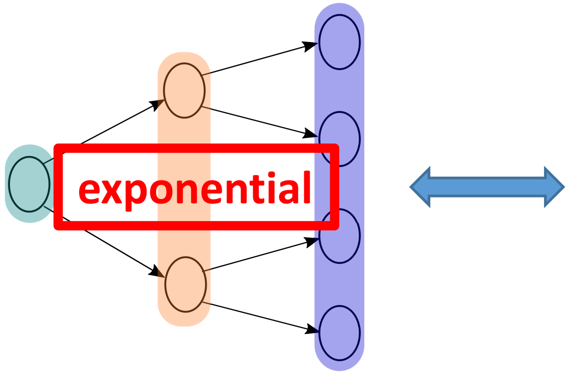
[Indelman RAL'16; Elimelech & Indelman IJRR'22; Sztyglic & Indelman IROS'22, Zhitnikov & Indelman AIJ'22, TRO'24; Shienman & Indelman ICRA'22; Kitanov & Indelman IJRR'24; Zhitnikov et al. IJRR'24, Barenboim & Indelman NIPS'23; Lev-Yehudi, Barenboim & Indelman AAAI'24, Kong & Indelman ISRR 2024]

Simplification of BSP/POMDP with Hybrid Beliefs

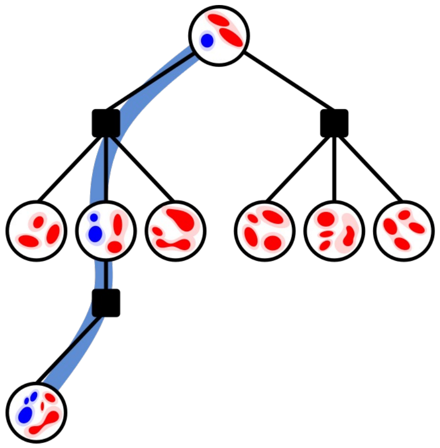
Belief tree



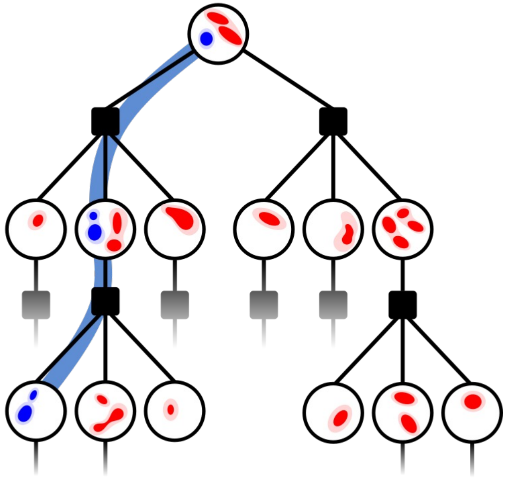
Hypothesis tree



Belief tree with all hypotheses



Belief tree with a subset of hypotheses



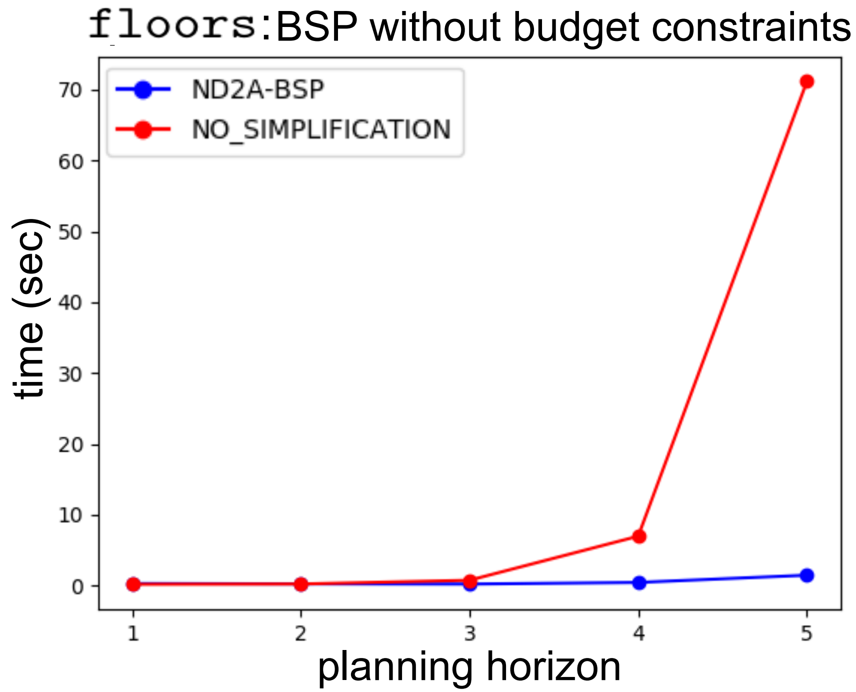
<u>Concept</u>:

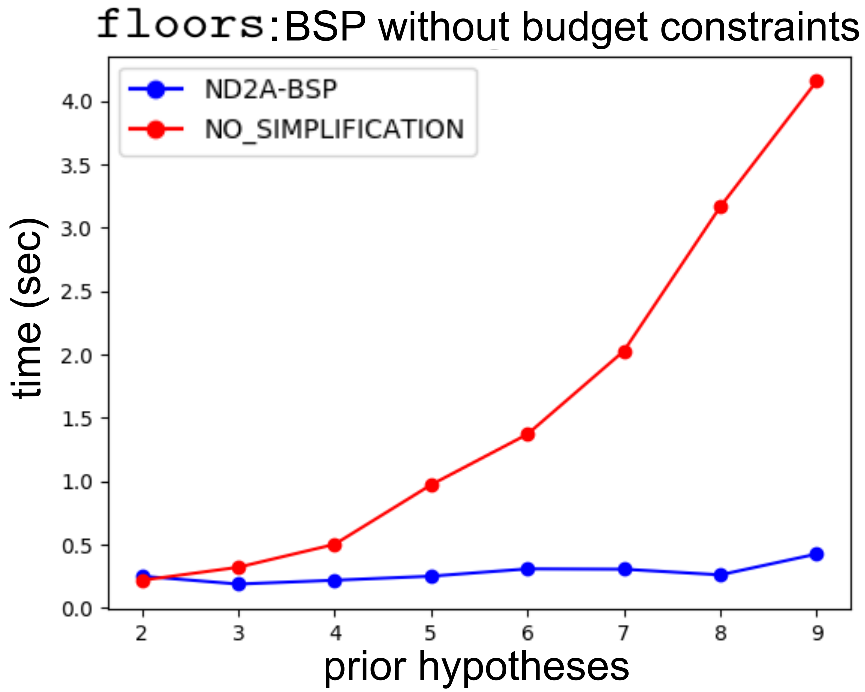
- Instead, utilize only a **subset** of hypotheses
- Derive reward bounds, given planning task (reward)
  - Disambiguate between hypotheses
  - Navigate to a goal
  - ..

$$\mathcal{LB}(b_k, \pi) \leq V^{\pi}(b_k) \leq \mathcal{UB}(b_k, \pi)$$

M. Shienman and V. Indelman, "D2A-BSP: Distilled Data Association Belief Space Planning with Performance Guarantees Under Budget Constraints," ICRA'22, **Outstanding Paper Award Finalist**.
M. Shienman and V. Indelman, "Nonmyopic Distilled Data Association Belief Space Planning Under Budget Constraints," ISRR'22.
M. Barenboim, M. Shienman, and V. Indelman, "Monte Carlo Planning in Hybrid Belief POMDPs," IEEE RA-L'23.
M. Barenboim, I. Lev-Yehudi, and V. Indelman, "Data Association Aware POMDP Planning with Hypothesis Pruning Performance Guarantees," IEEE RA-L'23.

Simplification of BSP/POMDP with Hybrid Beliefs





- Significant speed-up in planning
- Same planning performance is **<u>guaranteed</u>** (no overlap between bounds)

M. Shienman and V. Indelman, "D2A-BSP: Distilled Data Association Belief Space Planning with Performance Guarantees Under Budget Constraints," ICRA'22, **Outstanding Paper Award Finalist**.
M. Shienman and V. Indelman, "Nonmyopic Distilled Data Association Belief Space Planning Under Budget Constraints," ISRR'22.

Simplification of BSP/POMDP with Hybrid Beliefs

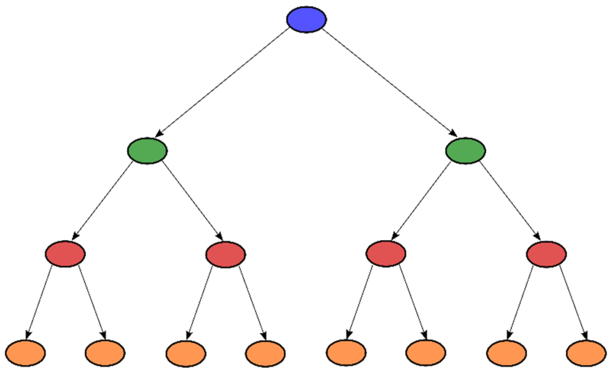
- Derived a deterministic bound to relate the full set of hypotheses to a subset thereof,

Corollary

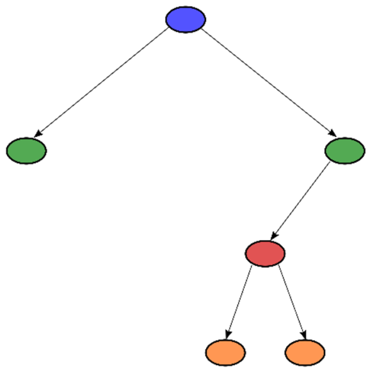
For any policy π, and selection of hypotheses set $\{\beta^i_{0:\mathcal{T}}\}_{i=0}^{|\mathcal{B}|}$ the following holds,

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

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

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[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]

POMDPs with Deterministic Guarantees

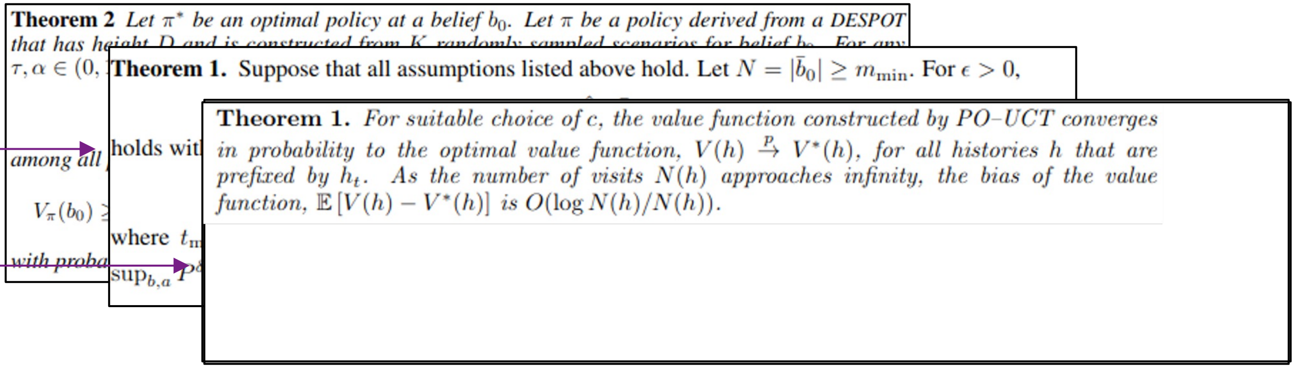
SOTA sampling based approaches come with probabilistic theoretical guarantees

DESPOT

AdaOPS

POMCP

…



Theorem 2 *Let π^* be an optimal policy at a belief b_0. Let π be a policy derived from a DESPOT*

Theorem 1. Suppose that all assumptions listed above hold. Let $N = |\bar{b}_0| \geq m_{\min}$. For $\epsilon > 0$,

Theorem 1. *For suitable choice of c, the value function constructed by PO–UCT converges in probability to the optimal value function, $V(h) \xrightarrow{p} V^*(h)$, for all histories h that are prefixed by h_t. As the number of visits $N(h)$ approaches infinity, the bias of the value function, $\mathbb{E}[V(h) - V^*(h)]$ is $O(\log N(h)/N(h))$.*

Can we get deterministic guarantees?

We show that deterministic guarantees are indeed possible!

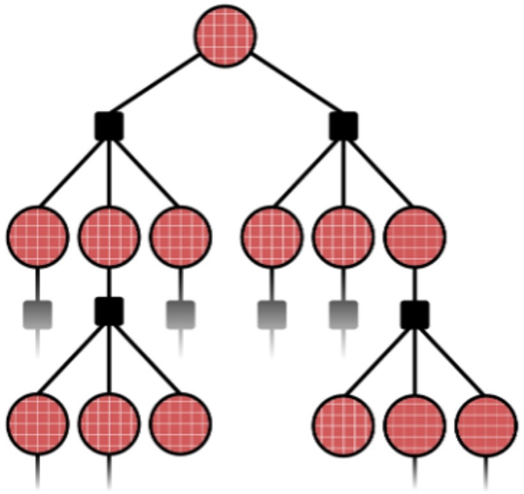
M. Barenboim and V. Indelman, “Online POMDP Planning with Anytime Deterministic Guarantees,” NeurIPS’23.

Online POMDP Planning with Anytime Deterministic Guarantees

Concept:

Instead of solving the original POMDP, consider a simplified version of that POMDP.

$$\mathcal{M} \longrightarrow \bar{\mathcal{M}}$$



Derive a mathematical relationship between the solution of the simplified, and the theoretical POMDP.

$$V(b) \quad ? \quad \bar{V}(b)$$

M. Barenboim and V. Indelman, “Online POMDP Planning with Anytime Deterministic Guarantees,” NeurIPS’23.

Online POMDP Planning with Anytime Deterministic Guarantees

- Given a POMDP: $\mathcal{M} = \langle \mathcal{X}, \mathcal{Z}, \mathcal{A}, b_0, \mathcal{P}_T, \mathcal{P}_Z, \rho, \gamma \rangle$
- Define a **simplified** POMDP,

$$\bar{\mathcal{M}} = \langle \underbrace{\bar{\mathcal{X}}, \bar{\mathcal{Z}}}, \mathcal{A}, \underbrace{\bar{b}_0, \bar{\mathcal{P}}_T, \bar{\mathcal{P}}_Z}, \rho, \gamma \rangle$$

$$\bar{\mathcal{X}}(H_t) \subset \mathcal{X}$$
$$\bar{\mathcal{Z}}(H_t) \subset \mathcal{Z}$$

$$\bar{b}_0(x) \triangleq \begin{cases} b_0(x) & , x \in \bar{\mathcal{X}}_0 \\ 0 & , otherwise \end{cases}$$

$$\bar{\mathbb{P}}(x_{t+1} \mid x_t, a_t) \triangleq \begin{cases} \mathbb{P}(x_{t+1} \mid x_t, a_t) & , x_{t+1} \in \bar{\mathcal{X}}(H_{t+1}^-) \\ 0 & , otherwise \end{cases}$$

$$\bar{\mathbb{P}}(z_t \mid x_t) \triangleq \begin{cases} \mathbb{P}(z_t \mid x_t) & , z_t \in \bar{\mathcal{Z}}(H_t) \\ 0 & , otherwise \end{cases}$$

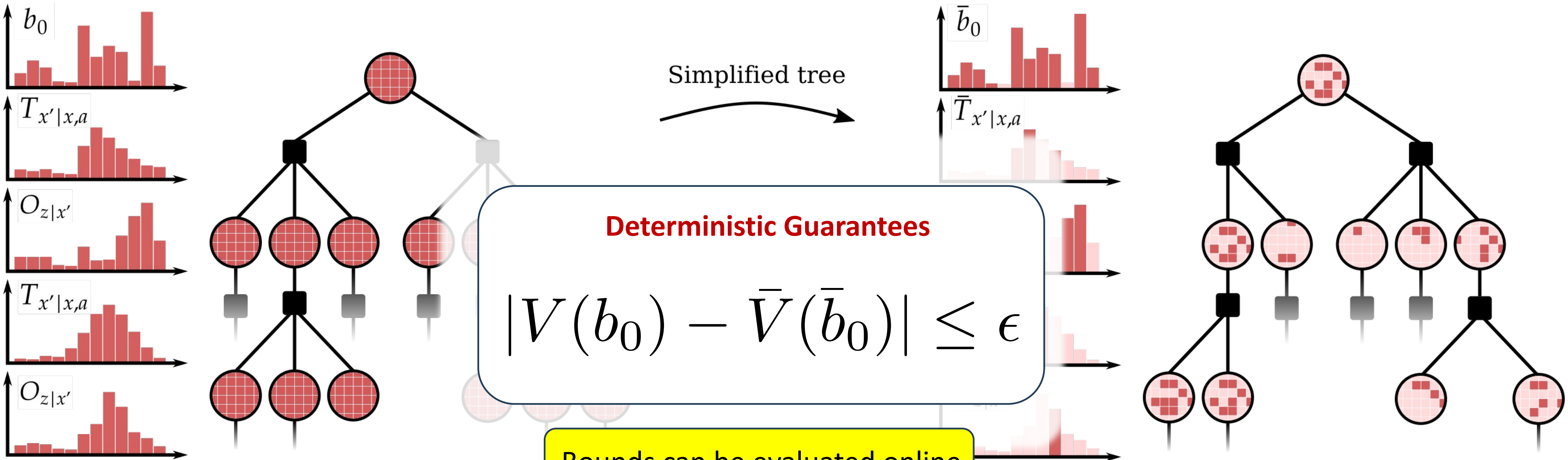
- Simplified value function

$$\bar{V}^{\pi}(\bar{b}_t) \triangleq r(\bar{b}_t, \pi_t) + \bar{\mathbb{E}}_{z_{t+1:\mathcal{T}}}\left[\bar{V}^{\pi}(\bar{b}_{t+1})\right]$$

M. Barenboim and V. Indelman, "Online POMDP Planning with Anytime Deterministic Guarantees," NeurIPS'23.

Online POMDP Planning with Anytime Deterministic Guarantees

- Deterministic guarantees (assuming discrete spaces)



Deterministic Guarantees

$$|V(b_0) - \bar{V}(\bar{b}_0)| \leq \epsilon$$

Bounds can be evaluated online

M. Barenboim and V. Indelman, “Online POMDP Planning with Anytime Deterministic Guarantees,” NeurIPS’23.

Online POMDP Planning with Anytime Deterministic Guarantees

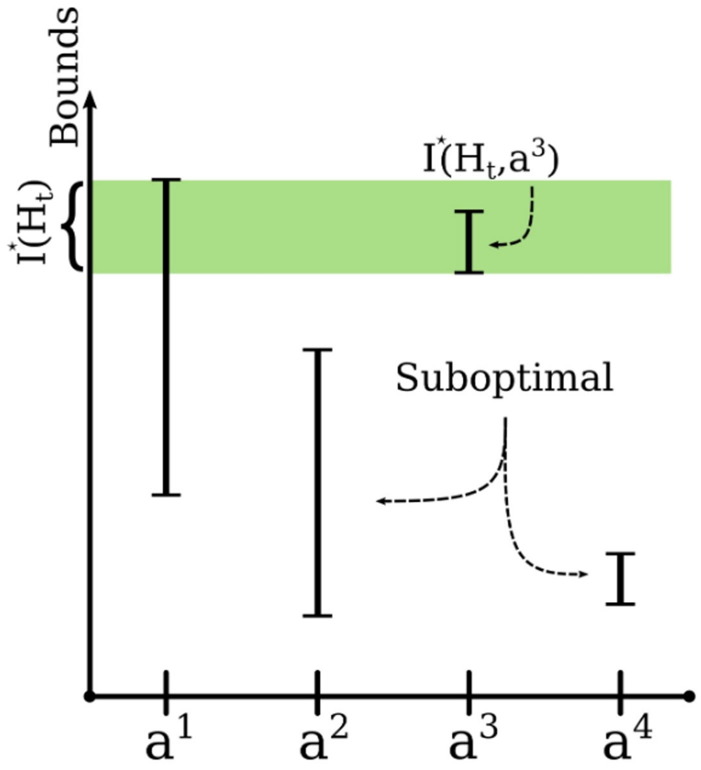
Importantly, the bounds can be calculated during planning.

How can we use them?

- **Pruning of sub-optimal branches**
  → Made possible by the deterministic guarantees
- **Stopping criteria for the planning phase**
  → Made possible by the deterministic guarantees
- **Finding the optimal solution in finite time**
  → Without recovering the theoretical tree

Deterministic Guarantees

$$\left|V(b_0) - \bar{V}(\bar{b}_0)\right| \leq \epsilon$$

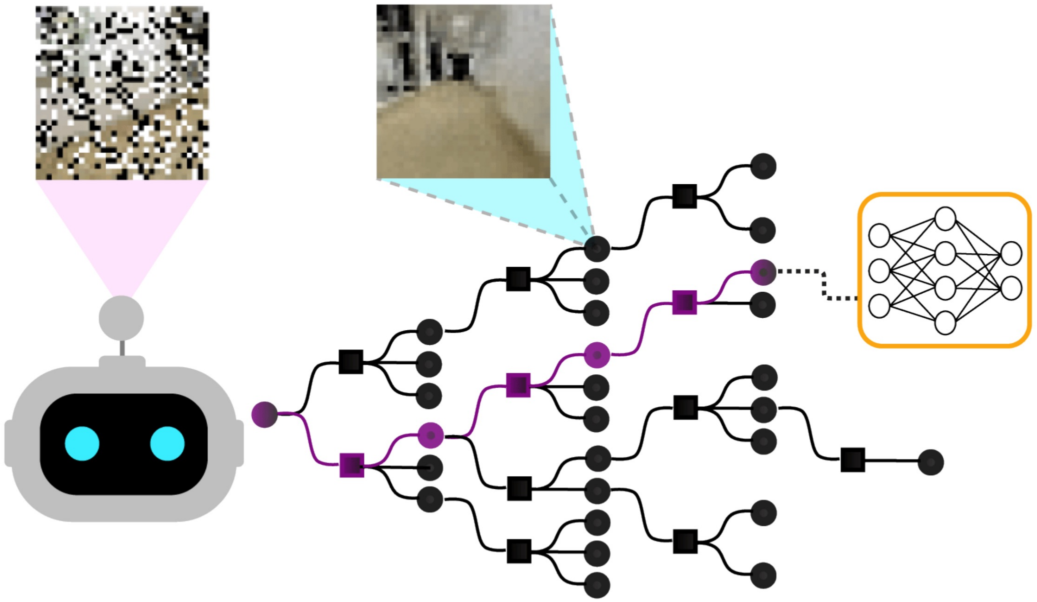


M. Barenboim and V. Indelman, "Online POMDP Planning with Anytime Deterministic Guarantees," NeurIPS'23.

Simplifying Complex Observation Models with Probabilistic Guarantees

Visual POMDP planning

- Visual observations are complex to model in planning[1,2]
- Learned observation models are (often) impractical for solving POMDPs in real time



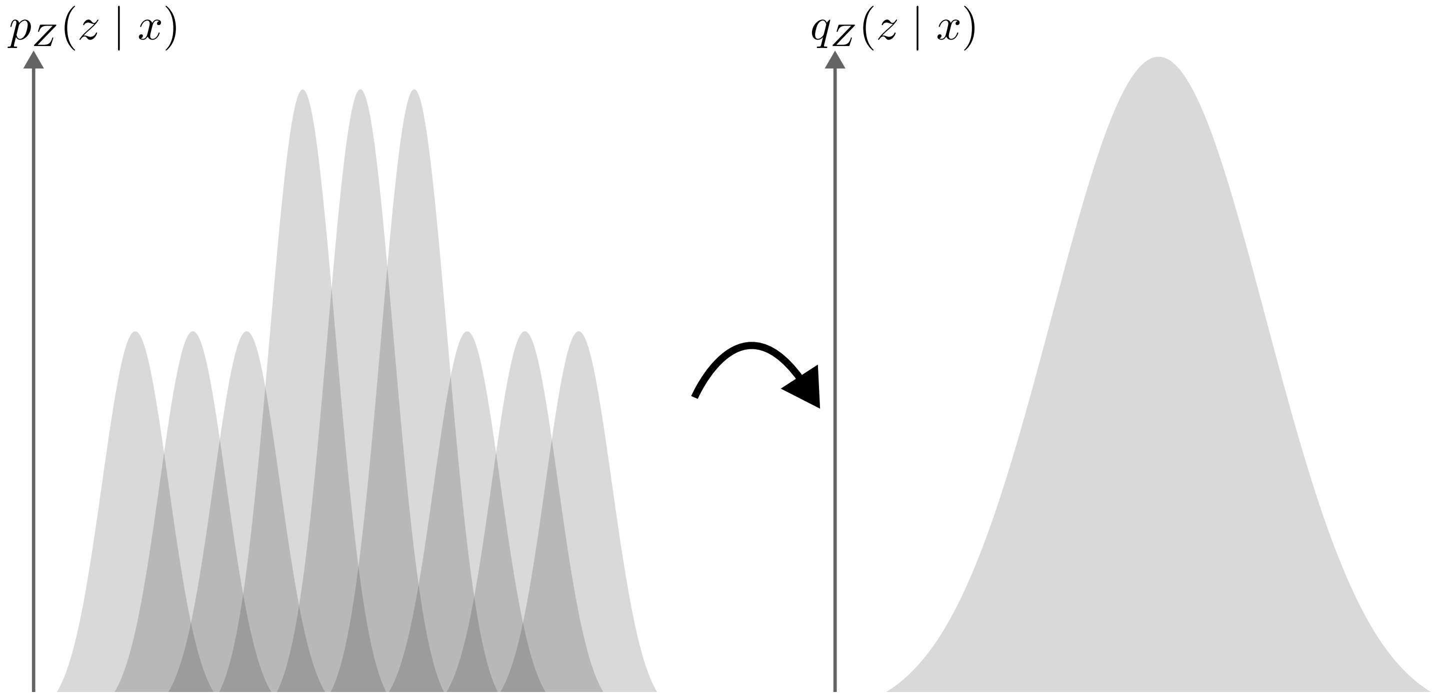
Can we simplify the learned models?
What is the impact on planning performance?

[1]Wang et al., "DualSMC: Tunneling Differentiable Filtering and Planning under Continuous POMDPs".
[2]Deglurkar et al., "Compositional Learning-based Planning for Vision POMDPs".

I. Lev-Yehudi, M. Barenboim, and V. Indelman, "Simplifying Complex Observation Models in Continuous POMDP Planning with Probabilistic Guarantees and Practice," AAAI'24.

Simplifying Complex Observation Models with Probabilistic Guarantees

- We replace the (learned) observation model p_Z with a cheaper model q_Z
  - Simpler GMM, Shallower Neural Network, etc.
  - Example:



Simplified models

$p_\theta(z \mid x)$

Original, **expensive**

$q_\phi(z \mid x)$

Simplified, **cheap**

I. Lev-Yehudi, M. Barenboim, and V. Indelman, "Simplifying Complex Observation Models in Continuous POMDP Planning with Probabilistic Guarantees and Practice," AAAI'24.

Simplifying Complex Observation Models with Probabilistic Guarantees

- We replace the (learned) observation model p_Z with a cheaper model q_Z
- Simplified action-value function: $Q^{q_Z}_{\mathbf{P}}$

Corollary 3

For arbitrary $\varepsilon, \delta > 0$ *there exists a number of particles for which*

$$|\underline{Q^{p_Z}_{\mathbf{P}}(b_t, a)} - \underline{\hat{Q}^{q_Z}_{\mathbf{M_P}}(\bar{b}_t, a)}| \leq \hat{\Phi}_{\mathbf{M_P}}(\bar{b}_t, a) + \varepsilon$$

with probability of at least $1 - \delta$ *for any guaranteed planner*

Theoretical Q function of the POMDP, with **original** models

Estimator of the Q function of a **particle-belief** POMDP, with **simplified** models

	Theoretical Values	PB-MDP	Planner
Original Model	$Q^{p_Z}_{\mathbf{P}}$	$Q^{p_Z}_{\mathbf{M_P}}$	$\hat{Q}^{p_Z}_{\mathbf{M_P}}$
Simplified Model	$Q^{q_Z}_{\mathbf{P}}$	$Q^{q_Z}_{\mathbf{M_P}}$	$\hat{Q}^{q_Z}_{\mathbf{M_P}}$

- Importance sampling
- Separate calculations to offline/online

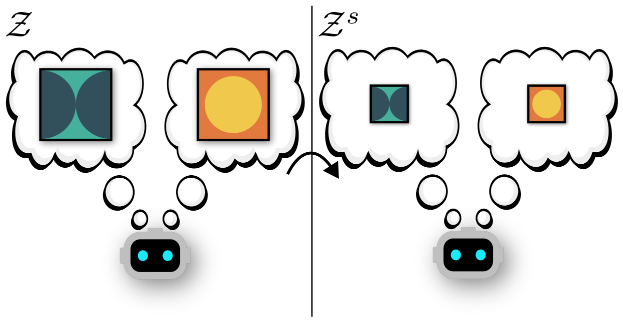
I. Lev-Yehudi, M. Barenboim, and V. Indelman, “Simplifying Complex Observation Models in Continuous POMDP Planning with Probabilistic Guarantees and Practice,” AAAI’24.

Simplified POMDP Planning with an Alternative Observation Space

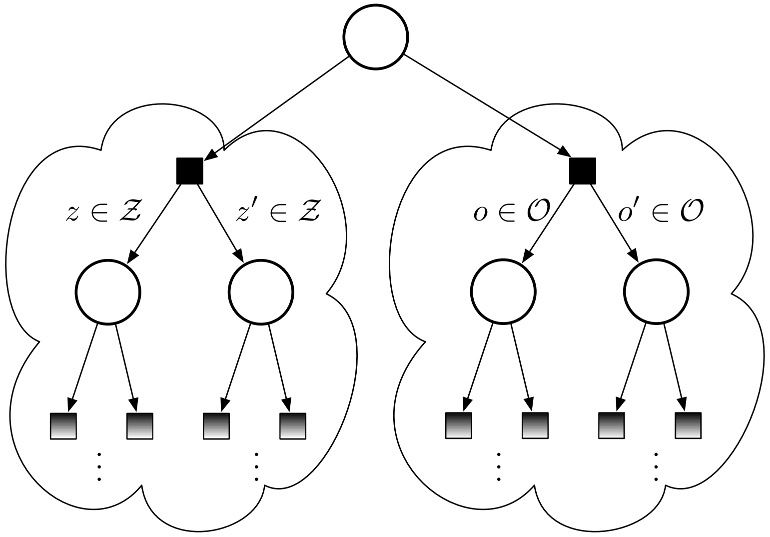
- Switch to an alternative observation space and model

Model Definition

POMDP tuple: $\langle \mathcal{X}, \mathcal{A}, \mathcal{Z}, \mathbb{P}_T, \mathbb{P}_Z, b_k, r \rangle \rightarrow \langle \mathcal{X}, \mathcal{A}, \mathcal{O}, \mathbb{P}_T, \mathbb{P}_O, b_k, r \rangle$



- Only at certain levels and branches of the tree



original observation space and model

alternative observation space and simplified model

D. Kong and V. Indelman, "Simplified Belief Space Planning with an Alternative Observation Space and Formal Performance Guarantees," ISRR'24.

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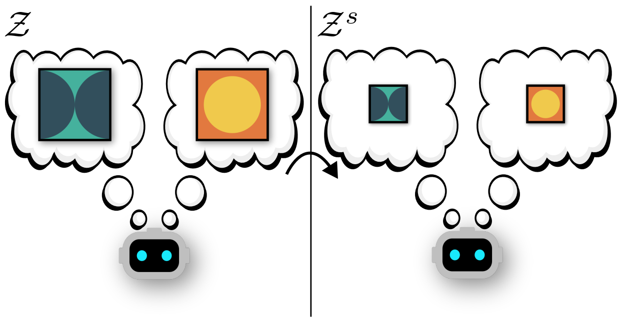

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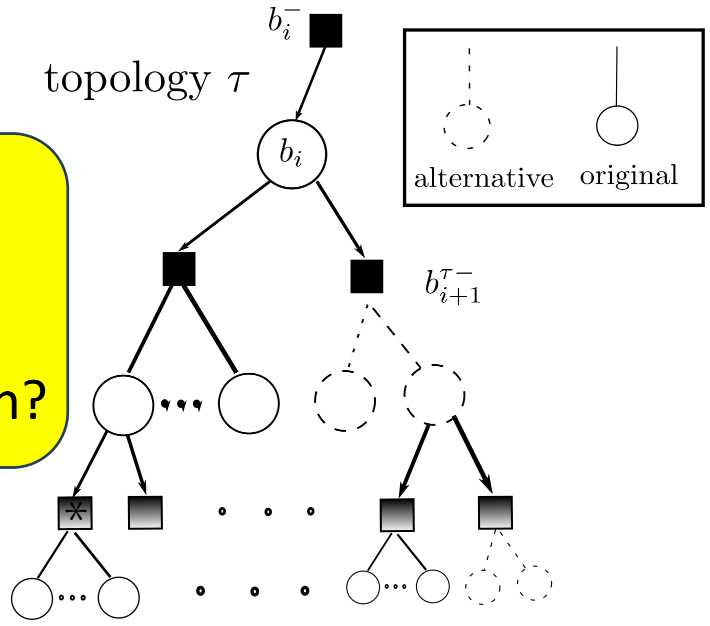

Main questions addressed:

- How to decide online where to simplify in belief tree?
- How to provide formal performance guarantees?
- How to adaptively transition between the different levels of simplification?

D. Kong and V. Indelman, "Simplified Belief Space Planning with an Alternative Observation Space and Formal Performance Guarantees," ISRR'24.

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Partitioning of a Multivariate Observation Space

- Value function: $$V^{\pi}(b_k) = R(b_k, \pi_k(b_k)) + \underset{z_{k+1:k+\ell}}{\mathbb{E}}\left[\sum_{i=k+1}^{k+\ell} R(b_i, \pi_i(b_i))\right]$$
- Belief-dependent reward: entropy

$$R(b, \pi(b)) \triangleq -\mathcal{H}(X) \equiv \mathbb{E}_{X\sim b}\left(\log b[X]\right)$$

- The expected reward at each *i*th look-ahead step:

$$\underset{Z_{k+1:i}}{\mathbb{E}}[R(b_i, a_{i-1})] = -\mathcal{H}(X_i | Z_{k+1:i})$$

- Future observations are drawn from the distribution $\mathbb{P}(Z_{k+1:i} \mid b_k, \pi)$

T. Yotam and V. Indelman, "Measurement Simplification in ρ-POMDP with Performance Guarantees," IEEE T-RO'24.

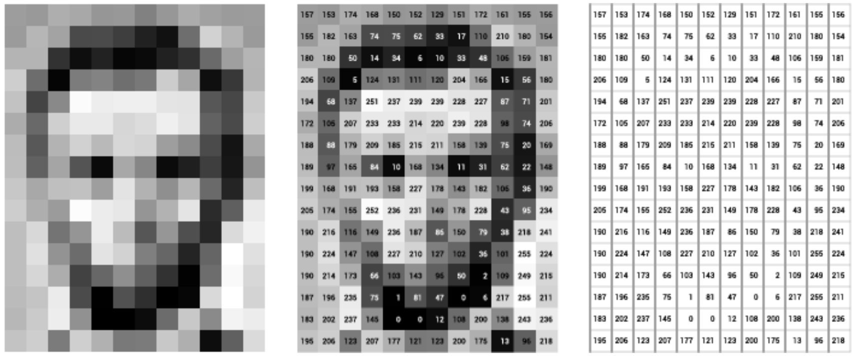
Partitioning of a Multivariate Observation Space

- Consider a multivariate random variable $Z \in \mathcal{Z}$, that represents future observations:

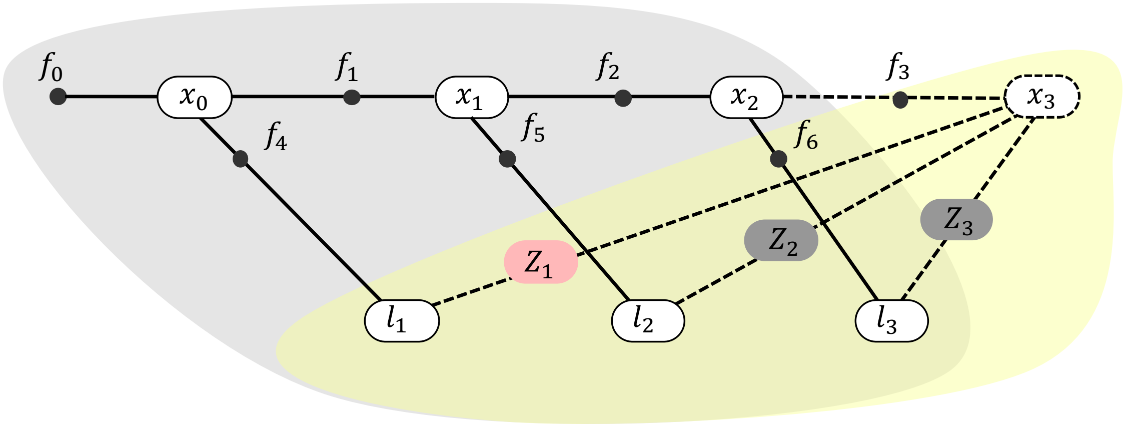
$$Z = (Z^1, Z^2, \ldots, Z^m)$$

- Examples:

Raw measurement of an image sensor



Factor graph



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Partitioning of a Multivariate Observation Space

- Consider a multivariate random variable $Z \in \mathcal{Z}$, that represents future observations:

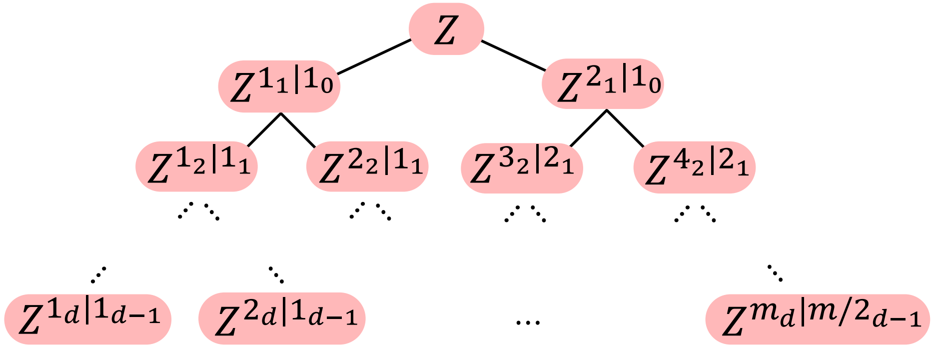
$$Z = (Z^1, Z^2, \ldots, Z^m)$$

- We can partition $Z \in \mathcal{Z}$ into different subsets/components, e.g.

$$Z^s = \{Z^1, Z^2, \ldots, Z^n\}$$
$$Z^{\bar{s}} = \{Z^{n+1}, Z^{n+2}, \ldots, Z^m\}$$

$$Z = Z^s \cup Z^{\bar{s}}$$

- Hierarchical Partitioning:

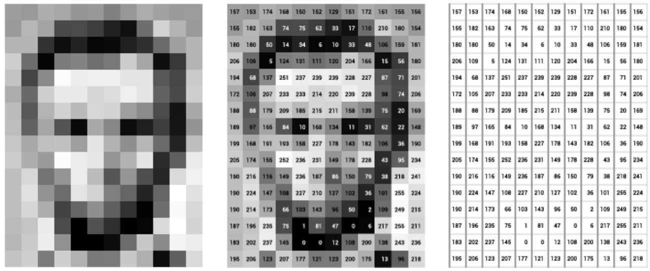


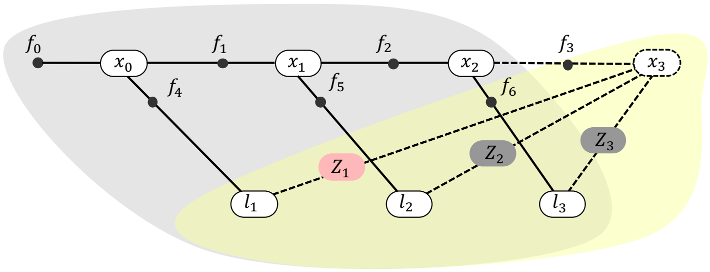
T. Yotam and V. Indelman, “Measurement Simplification in ρ-POMDP with Performance Guarantees,” IEEE T-RO’24.

Partitioning of a Multivariate Observation Space

But why is this a good idea?

- Apply partitioning to a raw image measurement of size 20x20 binary pixels
- Consider all of the different permutations for each pixel, 2^{400} in total
- If we partition $Z^{s} \triangleq \{Z^{x,y} \mid y \leq 10\}$ and $Z^{\bar{s}} \triangleq \{Z^{x,y} \mid y > 10\}$
  - Need to consider 2^{200} permutations for each
  - Overall, 2^{201} vs $2^{\wedge 400}$ permutations





T. Yotam and V. Indelman, “Measurement Simplification in ρ-POMDP with Performance Guarantees,” IEEE T-RO’24.

Partitioning of a Multivariate Observation Space

Lemma 2

Given two sets of expected measurements $(Z^s, Z^{\bar{s}})$*, the conditional Entropy can be factorized as*

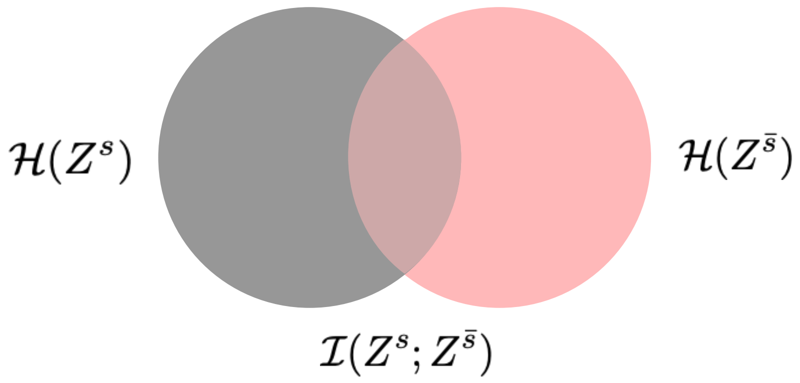
$$\mathcal{H}(X|Z) = \mathcal{H}(Z^s|X) + \mathcal{H}(Z^{\bar{s}}|X) - \mathcal{H}(Z^s, Z^{\bar{s}}) + \mathcal{H}(X)$$

$$\mathcal{LB} \leq \mathcal{H}(X|Z) \leq \mathcal{UB}$$

$$\mathcal{LB} \triangleq \mathcal{H}(Z^s \mid X) + \mathcal{H}(Z^{\bar{s}}|X) - \mathcal{H}(Z^s) - \mathcal{H}(Z^{\bar{s}}) + \mathcal{H}(X)$$

$$\mathcal{UB} \triangleq \mathcal{H}(Z^s|X) + \mathcal{H}(X) - \mathcal{H}(Z^s)$$

$$\mathcal{H}(Z^s, Z^{\bar{s}}) = \mathcal{H}(Z^s) + \mathcal{H}(Z^{\bar{s}}) - \mathcal{I}(Z^s; Z^{\bar{s}})$$



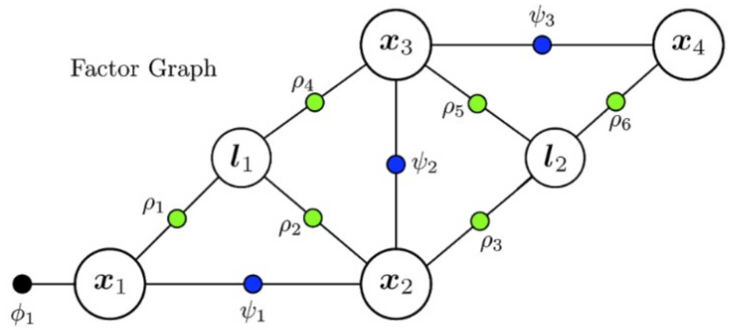
T. Yotam and V. Indelman, "Measurement Simplification in ρ-POMDP with Performance Guarantees," IEEE T-RO'24.

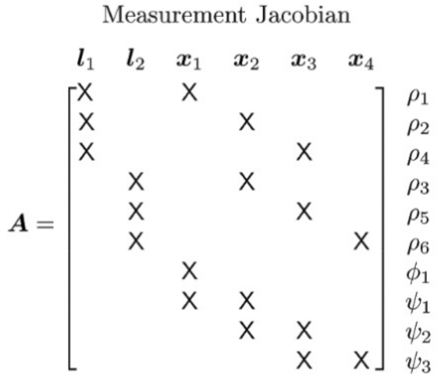
Partitioning of a Multivariate Observation Space

<u>Multivariate **Gaussian** Belief</u>

- Posterior information matrix:

$$\Lambda_i = \Lambda_k^{\text{Aug}} + A_i^T A_i$$





- Prior work[1,2] - application of the matrix determinant lemma:

$$\text{entropy} \;\propto\; \left|\Lambda_k + A^T \cdot A\right| = \left|\Lambda_k\right| \cdot \left|I_m + A \cdot \Sigma_k \cdot A^T\right|$$

posterior info matrix

For information gain:

$$\ln \frac{|\Lambda_k + A^T A|}{|\Lambda_k|} = \ln |I_m + A \cdot \Sigma_k \cdot A^T| = \ln |I_m + {}^I A \cdot \Sigma_k^{M,{}^I X} \cdot ({}^I A)^T|$$

One-time calculations for all candidate actions
Recover entries only for the involved variables in any of the actions

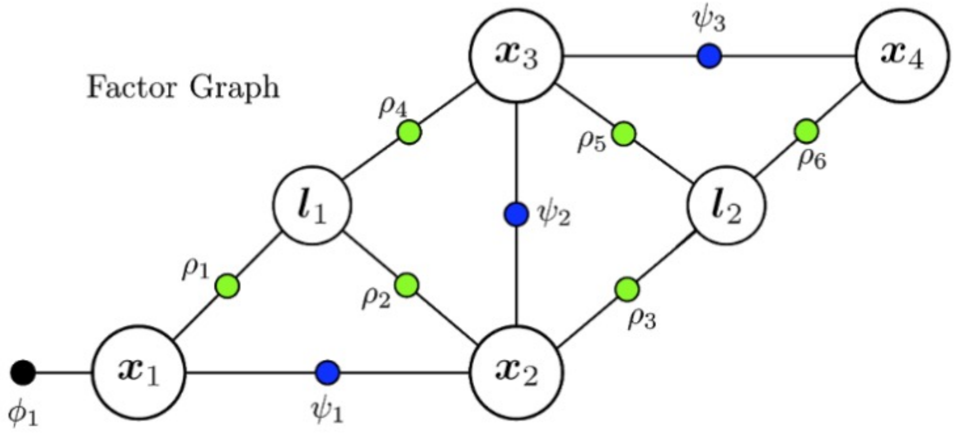
[1]D. Kopitkov and V. Indelman, "No belief propagation required: belief space planning in high-dimensional state spaces via factor graphs, the matrix determinant lemma, and re-use of calculation", IJRR'17.
[2]D. Kopitkov and V. Indelman, "General-purpose incremental covariance update and efficient belief space planning via a factor-graph propagation action tree", IJRR'19.

Partitioning of a Multivariate Observation Space

Partitioning of a Gaussian Belief

$$\Lambda_i = \Lambda_k^{\text{Aug}} + A_i^T A_i$$

Factor Graph

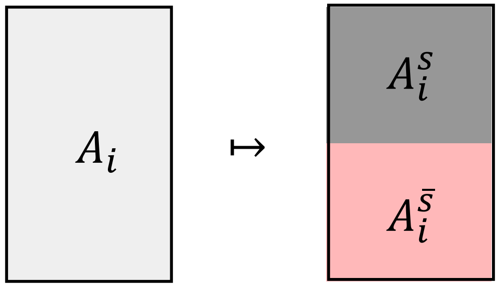


Measurement Jacobian

$$\mathbf{A} = \begin{array}{c} \begin{array}{cccccc} \boldsymbol{l}_1 & \boldsymbol{l}_2 & \boldsymbol{x}_1 & \boldsymbol{x}_2 & \boldsymbol{x}_3 & \boldsymbol{x}_4 \end{array} \\ \begin{bmatrix} X & & X & & & \\ X & & & X & & \\ X & & & & X & \\ & X & & X & & \\ & X & & & X & \\ & X & & & & X \\ & & X & & & \\ & & X & X & & \\ & & & X & X & \\ & & & & X & X \end{bmatrix} \end{array} \begin{array}{c} \rho_1 \\ \rho_2 \\ \rho_4 \\ \rho_3 \\ \rho_5 \\ \rho_6 \\ \phi_1 \\ \psi_1 \\ \psi_2 \\ \psi_3 \end{array}$$

Observation partitioning corresponds to splitting the Jacobian into blocks

$$Z_i \mapsto (Z_i^s, Z_i^{\bar{s}})$$



Bounds[1]:

$$\mathcal{LB} = C - \frac{1}{2} \underset{Z_{k+1:i}}{\mathbb{E}} \left[\ln \frac{f\left(\Lambda_k^{\text{Aug}-}, A_i^s\right) \cdot f\left(\Lambda_k^{\text{Aug}-}, A_i^{\bar{s}}\right)}{|\Lambda_k^{\text{Aug}-}|}\right]$$

$$\mathcal{UB} = C - \frac{1}{2} \underset{Z_{k+1:i}}{\mathbb{E}} \left[\ln f\left(\Lambda_k^{\text{Aug}-}, A_i^s\right)\right],$$

$$f(\Lambda, A) \triangleq |\Lambda + A^T A|$$

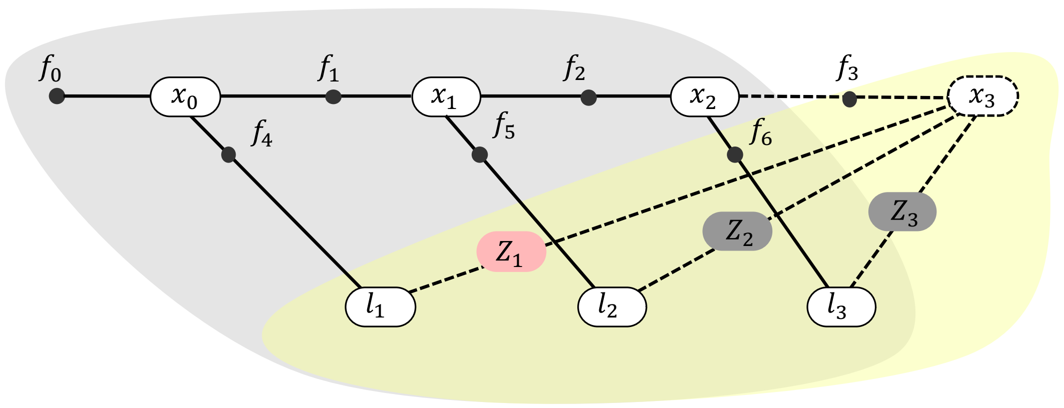
Reduced complexity wrt rAMDL[2]:

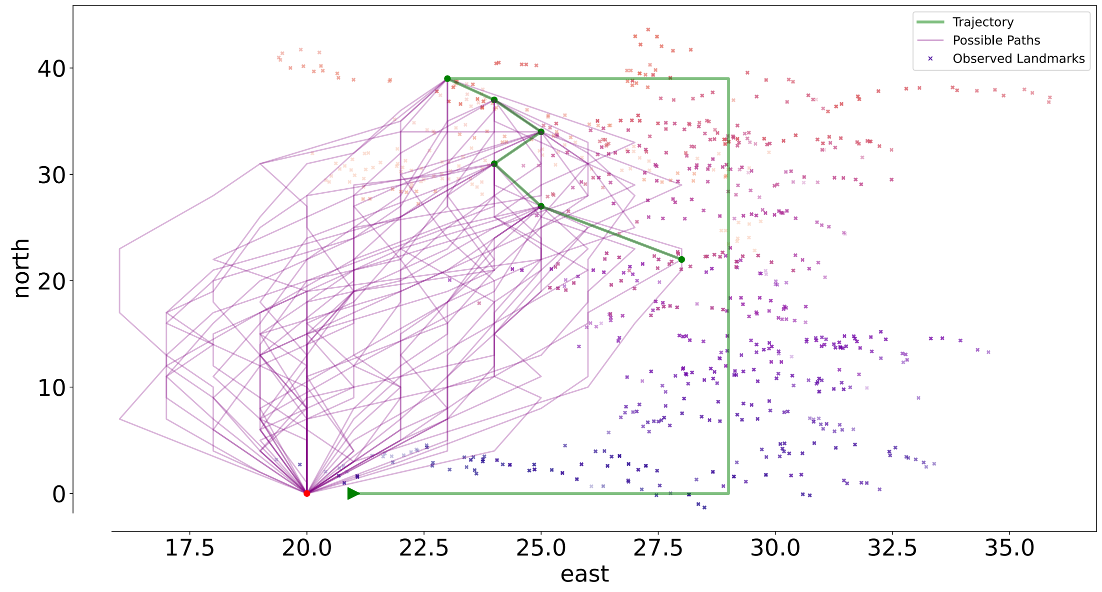
$$O\left(\frac{m^3}{4}\right) \text{ vs } O(m^3)$$

[1] T. Yotam and V. Indelman, "Measurement Simplification in ρ-POMDP with Performance Guarantees," IEEE T-RO'24.
[2] D. Kopitkov and V. Indelman, "No Belief Propagation Required: Belief Space Planning in High-Dimensional State Spaces via Factor Graphs, Matrix Determinant Lemma and Re-use of Calculation," IJRR'17.
[2] D. Kopitkov and V. Indelman, "General-purpose incremental covariance update and efficient belief space planning via a factor-graph propagation action tree", IJRR'19.

Partitioning of a Multivariate Observation Space

Application to Active SLAM





# Paths	# Factors	RP	rAMDL[2]	MP (ours)[1]
100	2956	No	11.521 ± 0.537	$\mathbf{6.888 \pm 0.155}$
100	2956	Yes	24.636 ± 1.381	$\mathbf{11.758 \pm 0.372}$
100	5904	Yes	84.376 ± 14.458	$\mathbf{32.069 \pm 4.913}$

Table: Total planning time in seconds (lower is better)

[1]T. Yotam and V. Indelman, “Measurement Simplification in ρ-POMDP with Performance Guarantees,” IEEE T-RO’24.
[2]D. Kopitkov and V. Indelman, “No Belief Propagation Required: Belief Space Planning in High-Dimensional State Spaces via Factor Graphs, Matrix Determinant Lemma and Re-use of Calculation,” IJRR’17.
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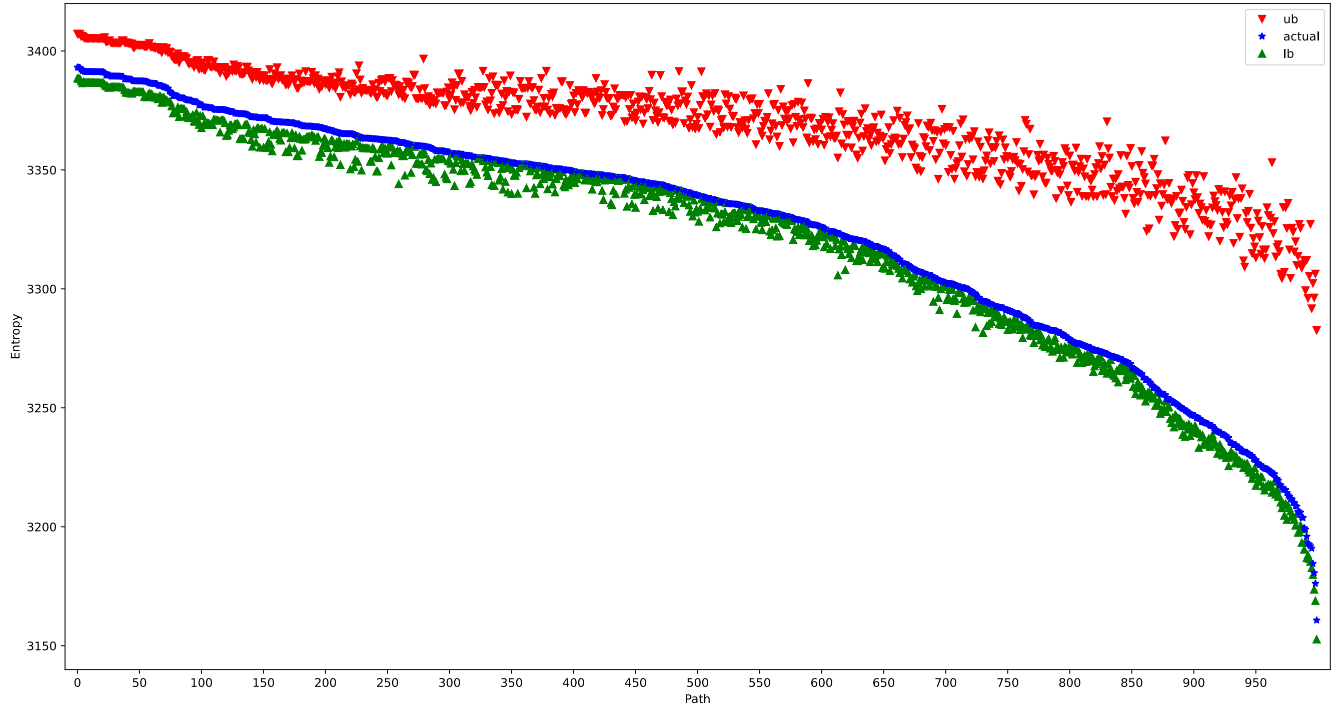

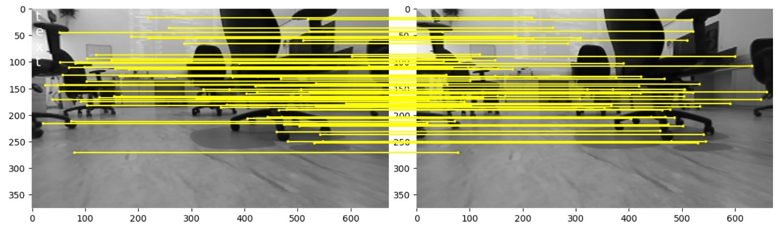

Method	time [sec]
MP (ours)[1]	$\mathbf{585.507 \pm 27.153}$
rAMDL[2]	802.545 ± 25.651
iSAM2[3]	1764.835 ± 26.521

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[1]T. Yotam and V. Indelman, “Measurement Simplification in ρ-POMDP with Performance Guarantees,” IEEE T-RO’24.
[2]D. Kopitkov and V. Indelman, “No Belief Propagation Required: Belief Space Planning in High-Dimensional State Spaces via Factor Graphs, Matrix Determinant Lemma and Re-use of Calculation,” IJRR’17.
[2]D. Kopitkov and V. Indelman, “General-purpose incremental covariance update and efficient belief space planning via a factor-graph propagation action tree”, IJRR’19.
[3]M. Kaess, et al., "iSAM2: Incremental smoothing and mapping using the Bayes tree," IJRR’12.

Simplification of Decision-Making Problems

Concept:

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

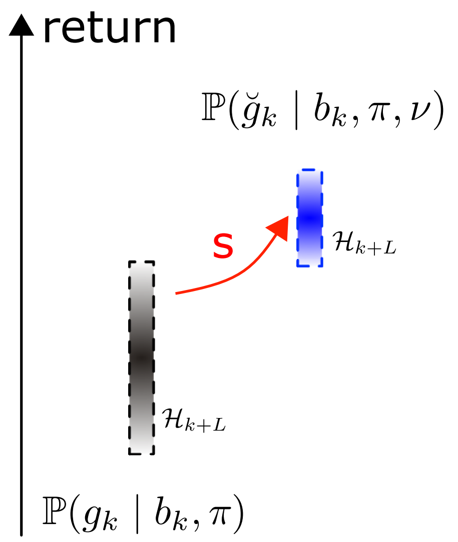
Specific simplifications include:

- 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]

Simplification of Risk Averse POMDP Planning

- Impact of simplification on **distribution** over returns/rewards
- Simplified **risk aware** decision making with belief-dependent rewards



$$g_k = f_{g_k}(\rho_{k+1:k+L})$$

S simplification

original

simplified

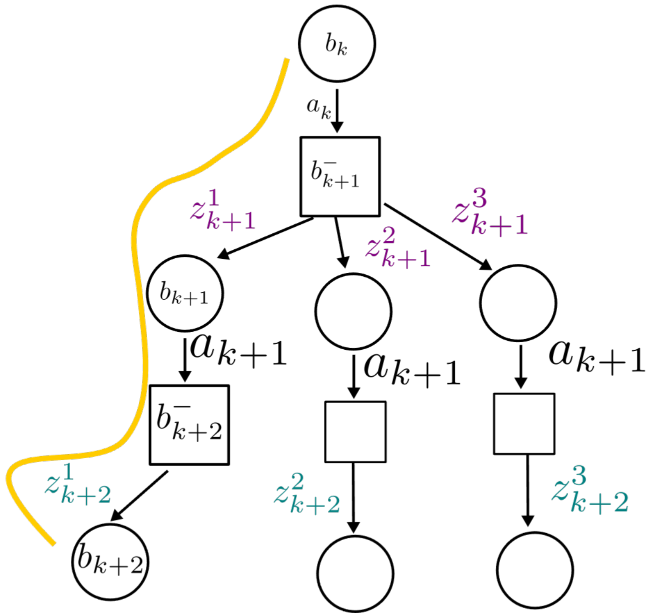
$$V^{\pi}(b_k) = \varphi\Big(\mathbb{P}(\rho_{k+1:k+L} | b_k, \pi_{k:k+L-1}), g_k\Big)$$

Y. Pariente and V. Indelman, "Simplification of Risk Averse POMDPs with Performance Guarantees,", arXiv'24.
A. Zhitnikov and V. Indelman, "Simplified Risk Aware Decision Making with Belief Dependent Rewards in Partially Observable Domains," Artificial Intelligence, 2022.

Probabilistically Constrained Belief Space Planning

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

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



<u>Information gain</u>[1]:

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

<u>Safety</u>[2]:

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

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

Agenda

Experience Reuse in POMDP Planning

POMDP Planning with Hybrid Beliefs

Simplification of POMDP with Formal Guarantees

Multi-agent POMDP Planning with Inconsistent Beliefs

Simplification of Decision-Making Problems

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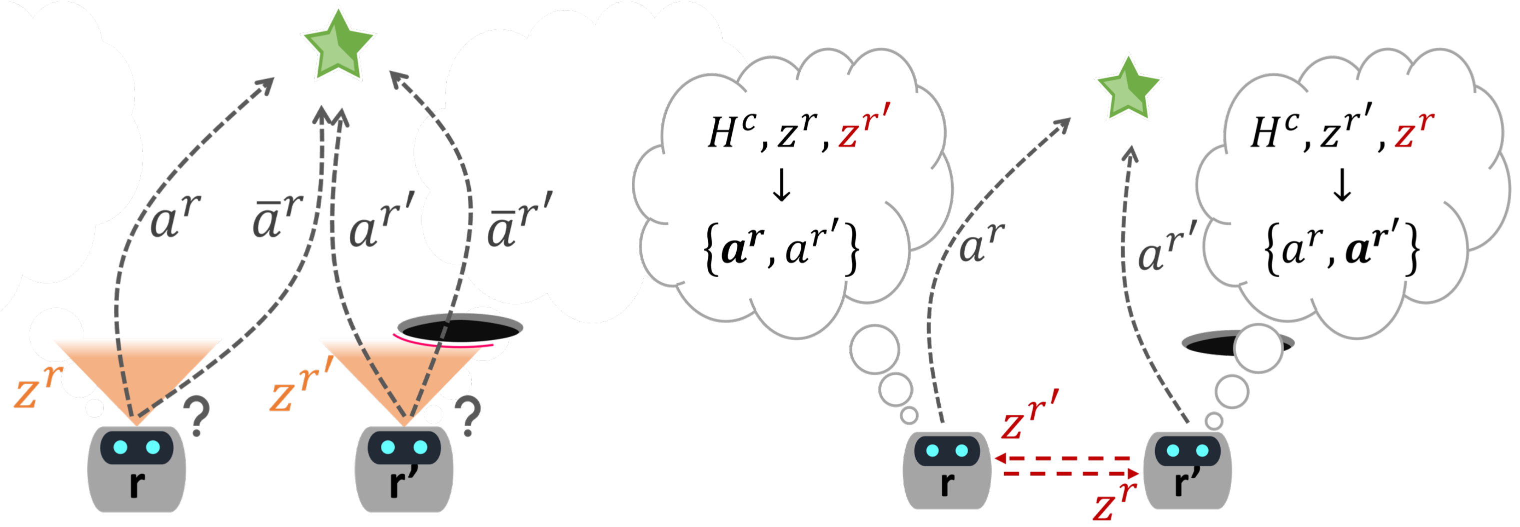
Multi-Robot Belief Space Planning

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

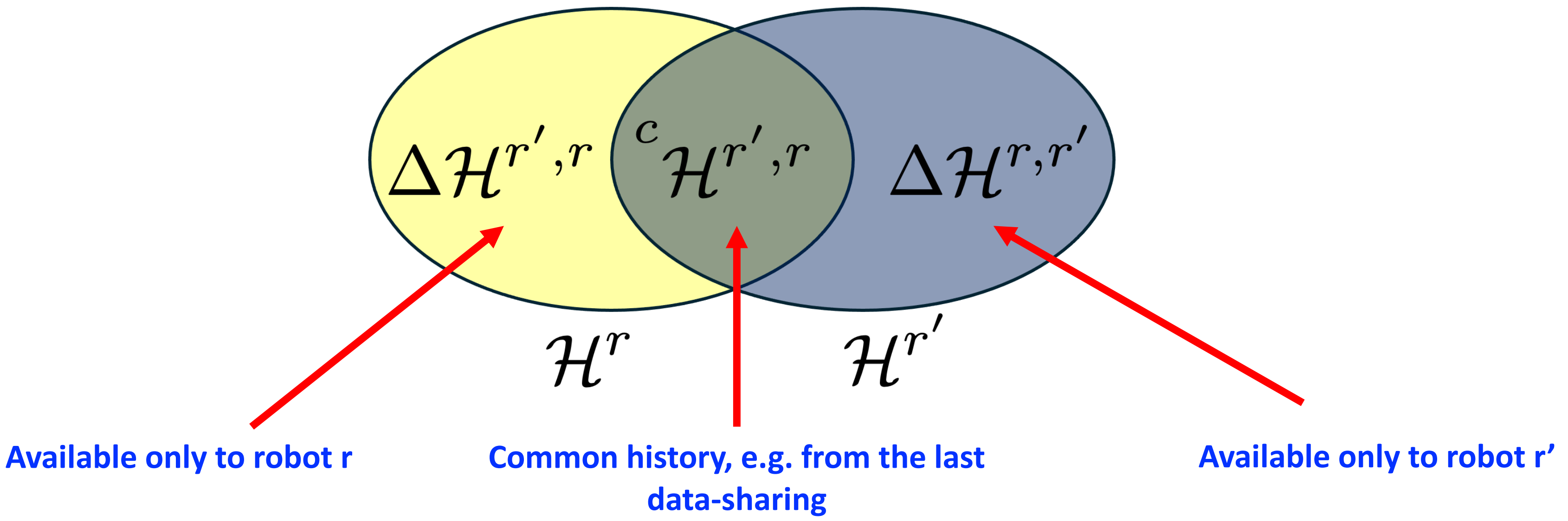


Multi-Robot Cooperative BSP with Inconsistent Beliefs

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

- Histories & beliefs of the robots may **differ** 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.

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- Decentralized POMDP tuple from the perspective of robot r:

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

- Objective function:

$$J(b_k^r, a_{k+}) = \underset{z_{k+1:k+L}}{\mathbb{E}} \left[\sum_{l=0}^{L-1} \rho(b_{k+l}^r, a_{k+l}) + \rho(b_{k+L}^r) \right]$$

T. Kundu, M. Rafaeli, and V. Indelman, "Multi-Robot Communication-Aware Cooperative Belief Space Planning with Inconsistent Beliefs: An Action-Consistent Approach," IROS'24.
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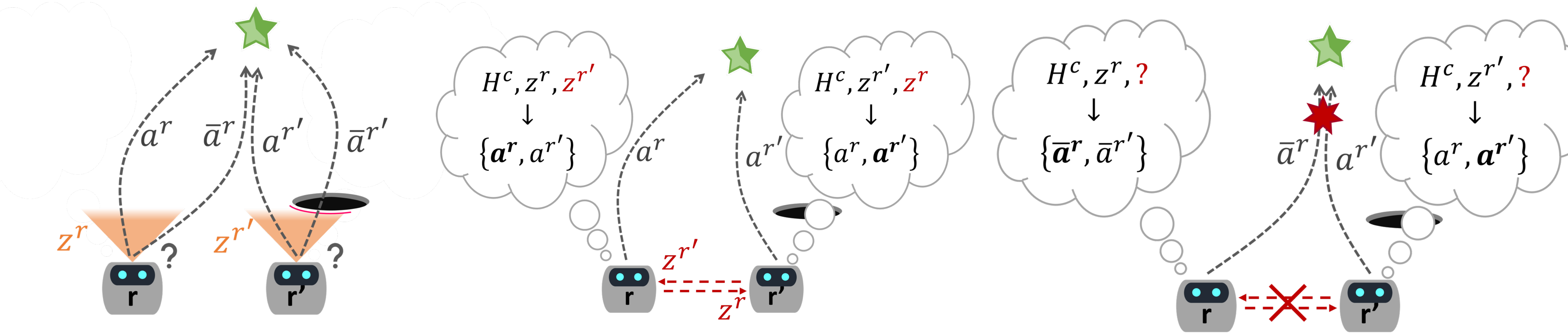
- **Can lead to a lack of coordination and unsafe and sub-optimal actions**



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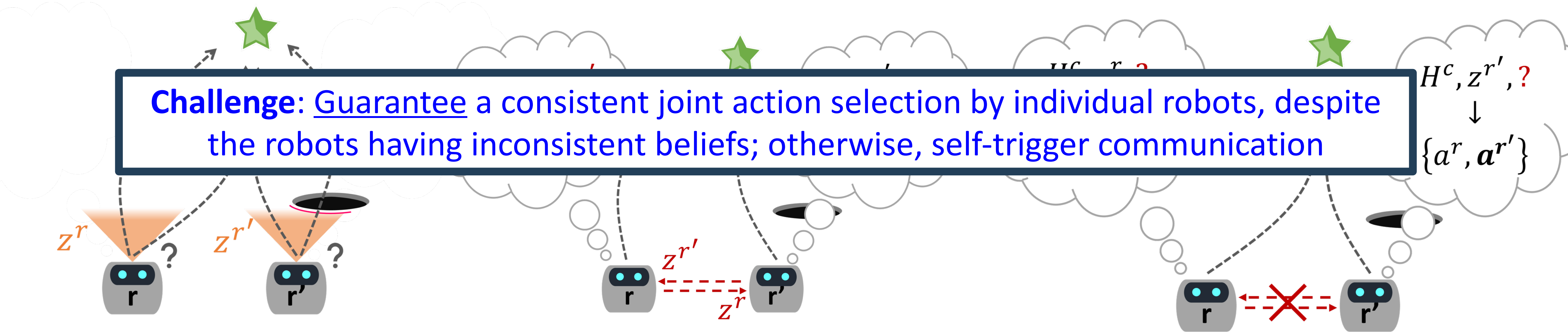
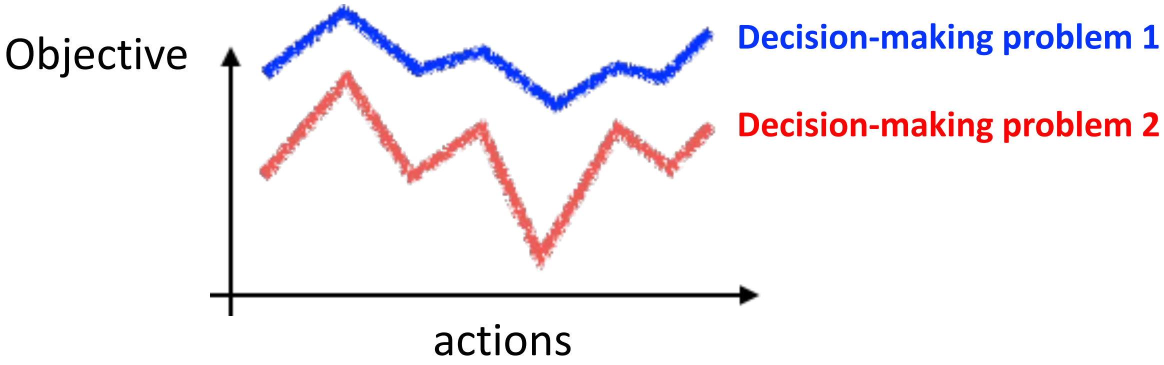


Challenge: Guarantee a consistent joint action selection by individual robots, despite the robots having inconsistent beliefs; otherwise, self-trigger communication

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.

Action Consistency

- If two decision-making problems have the **same action preference**, this implies both have the **same best action regardless of the actual objective/value function values**



- **Key idea**: to guarantee consistent multi-robot decision-making, each robot
  - reasons about its own and other robots' action preferences while accounting for the **missing information** between the robots
  - checks if for all these realizations, we get the same best joint action

V. Indelman, "No Correlations Involved: Decision Making Under Uncertainty in a Conservative Sparse Information Space," IEEE RA-L'16.
K. Elimelech and V. Indelman, "Simplified decision making in the belief space using belief sparsification," IJRR'22.
A. Kitanov and V. Indelman, "Topological Belief Space Planning for Active SLAM with Pairwise Gaussian Potentials and Performance Guarantees," IJRR'24.

Decentralized Verification of Multi-Robot Action Consistency (MR-AC)

- From the perspective of robot r, MR-AC holds if the selected joint actions are the same based on:

  1. Its local information
  2. What it perceives about the reasoning of the other robot r'
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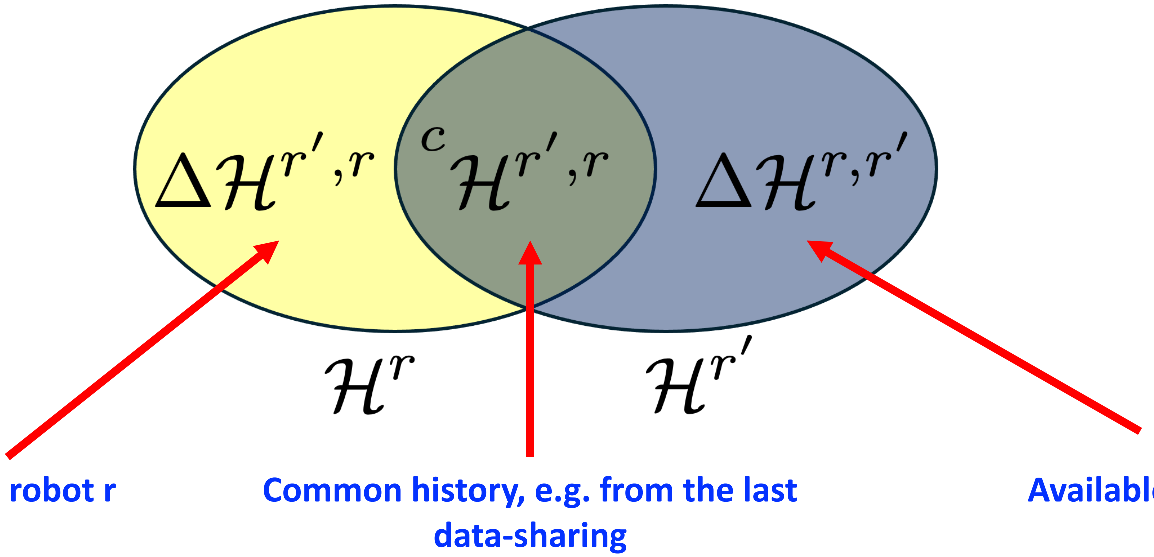

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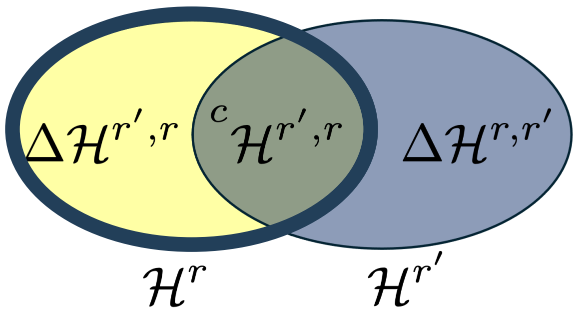
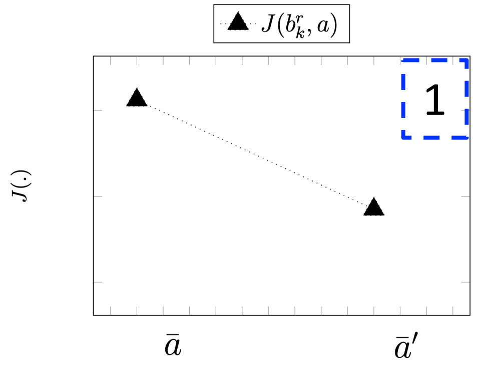


Toy example for $|\mathcal{A}| = |\mathcal{Z}| = 2$:



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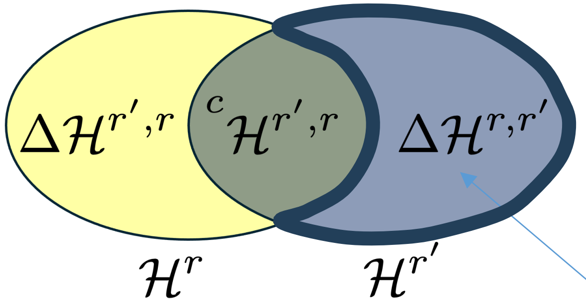

Robot r reasons about possible values of this data

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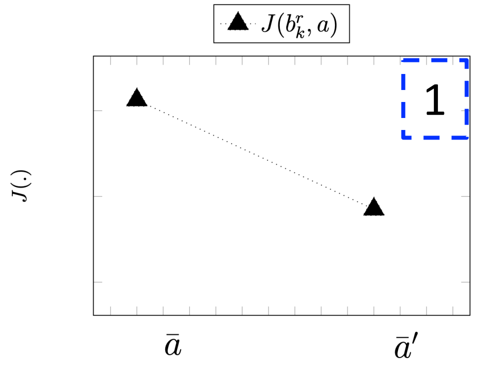

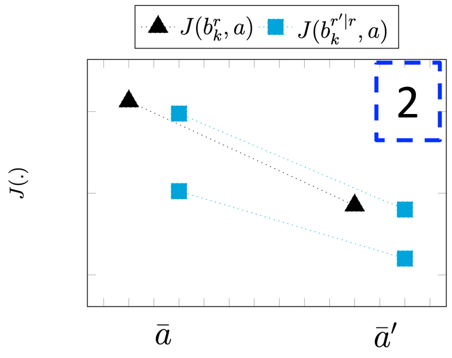

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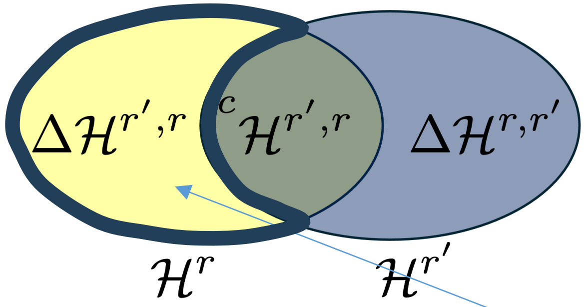

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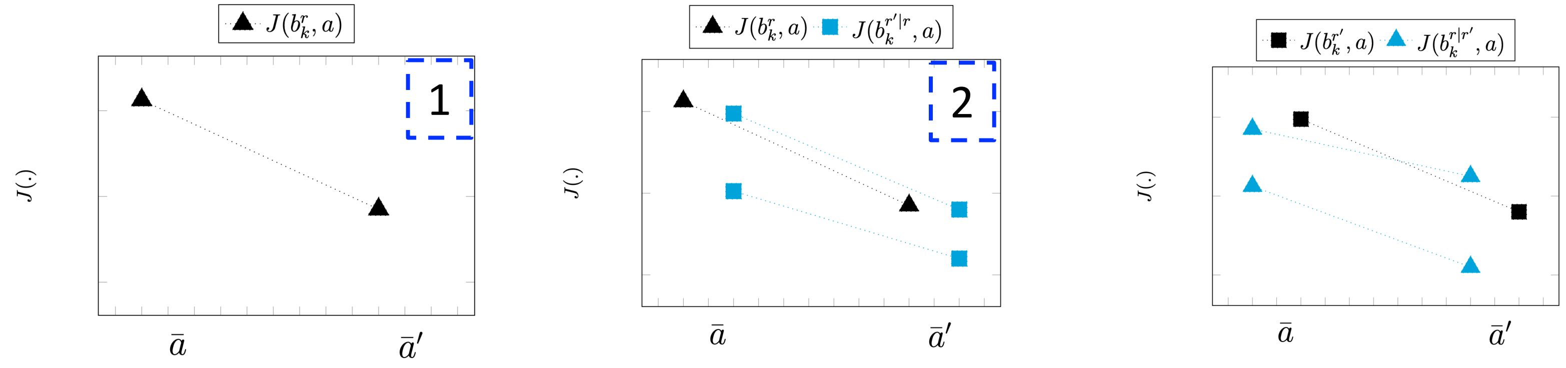

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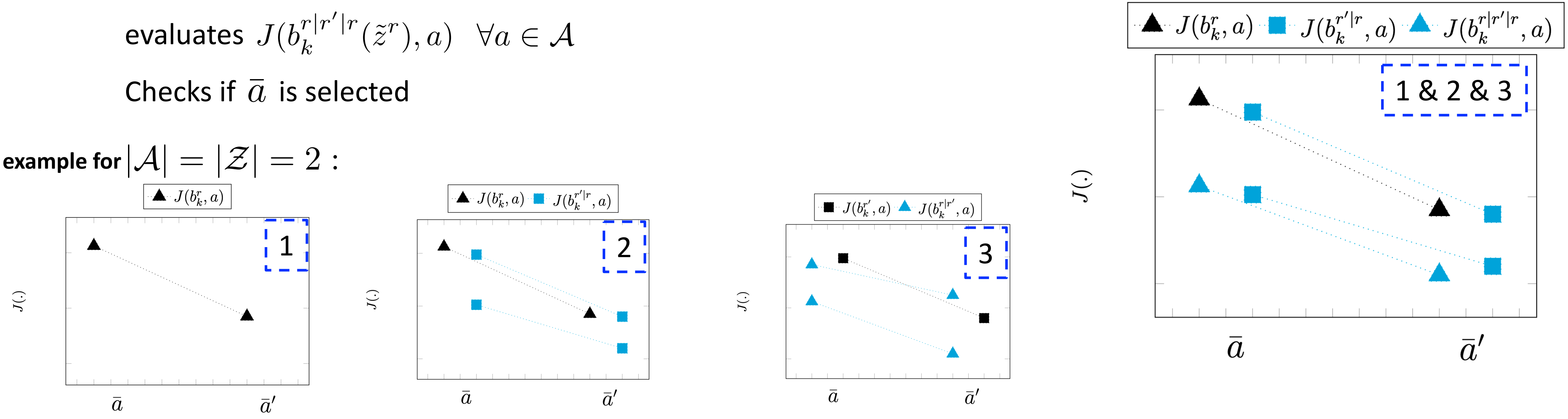
For each possible observation of r’, $\tilde{z}^r \in \Delta\mathcal{Z}_k^{r',r}$, robot r

constructs a plausible belief of robot r’: $b_k^{r|r'|r}(\tilde{z}^r) \triangleq \mathbb{P}(x_k \mid {}^c\mathcal{H}_k^{r',r}, \tilde{z}^r)$

evaluates $J(b_k^{r|r'|r}(\tilde{z}^r), a) \quad \forall a \in \mathcal{A}$

Checks if $\bar{a}$ is selected

Toy example for $|\mathcal{A}| = |\mathcal{Z}| = 2$:



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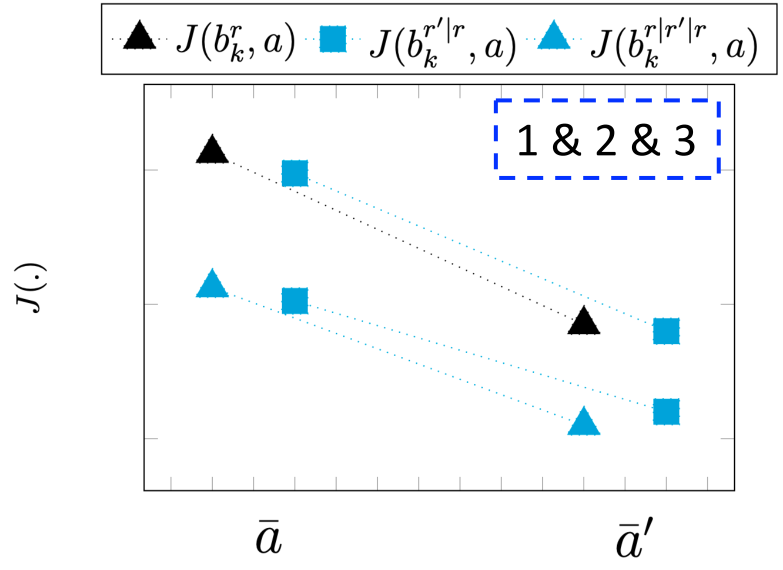


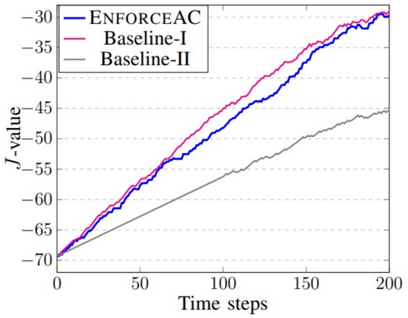
- Same best action in all cases?
  - **Yes**: MR-AC is **guaranteed** to be satisfied
    - Robots are **guaranteed** to choose the same joint action
    - **No further data sharing** is needed!
  - **No**: self-trigger communication, share some data, repeat Steps 1-3

T. Kundu, M. Rafaeli, and V. Indelman, "Multi-Robot Communication-Aware Cooperative Belief Space Planning with Inconsistent Beliefs: An Action-Consistent Approach," IROS'24.

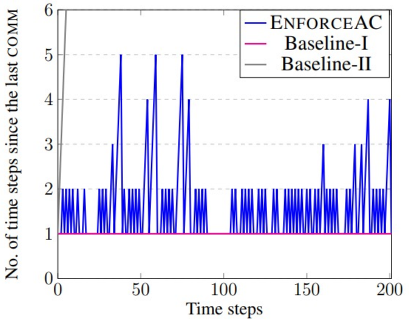
T. Kundu, M. Rafaeli, A. Gulyaev, and V. Indelman, "Action-Consistent Decentralized Belief Space Planning with Inconsistent Beliefs and Limited Data Sharing: Framework and Simplification Algorithms with Formal Guarantees," arXiv'25.

Simulation Results (Search & Rescue Scenario)

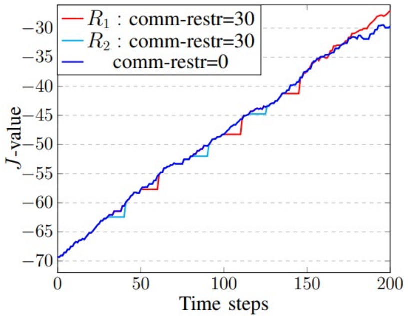
- EnforceAC: our approach
- Baseline I: always communicate all data
- Baseline II: never communicate



(a) *comm-restr* = 0



(b) *comm-restr* = 0



(c) *comm-restr* = 30

NOT-AC (ACTION INCONSISTENCY), COMMS AND TIME FOR $E = 200$.

Input	Algorithm	Not-AC	COMM	Time
comm-restr = 0	Baseline-II	181	0	1.3s
Motion prim. = 4	Baseline-I	0	400	1.3s
MaxEntropy-Init	ENFORCEAC	0	238	12.4s
comm-restr = 0	Baseline-II	185	0	1.3s
Motion prim. = 4	Baseline-I	0	400	1.4s
Entropy-Init	ENFORCEAC	0	268	8.7s
comm-restr = 0	Baseline-II	194	0	3.6s
Motion prim. = 8	Baseline-I	0	400	3.5s
MaxEntropy-Init	ENFORCEAC	0	248	36.4s
comm-restr = 0	Baseline-II	188	0	3.6s
Motion prim. = 8	Baseline-I	0	400	3.6s
Entropy-Init	ENFORCEAC	0	278	31.1s
comm-restr = 20	Baseline-II	194	0	3.3s
Motion prim. = 8	Baseline-I	14	360	4.3s
MaxEntropy-Init	ENFORCEAC	13	224	94.9s
comm-restr = 20	Baseline-II	188	0	3.2s
Motion prim. = 8	Baseline-I	14	360	3.6s
Entropy-Init	ENFORCEAC	10	251	31.2s
comm-restr = 30	Baseline-II	188	0	3.4s
Motion prim. = 8	Baseline-I	22	340	4.0s
MaxEntropy-Init	ENFORCEAC	20	238	46.9s

T. Kundu, M. Rafaeli, and V. Indelman, “Multi-Robot Communication-Aware Cooperative Belief Space Planning with Inconsistent Beliefs: An Action-Consistent Approach,” IROS’24.

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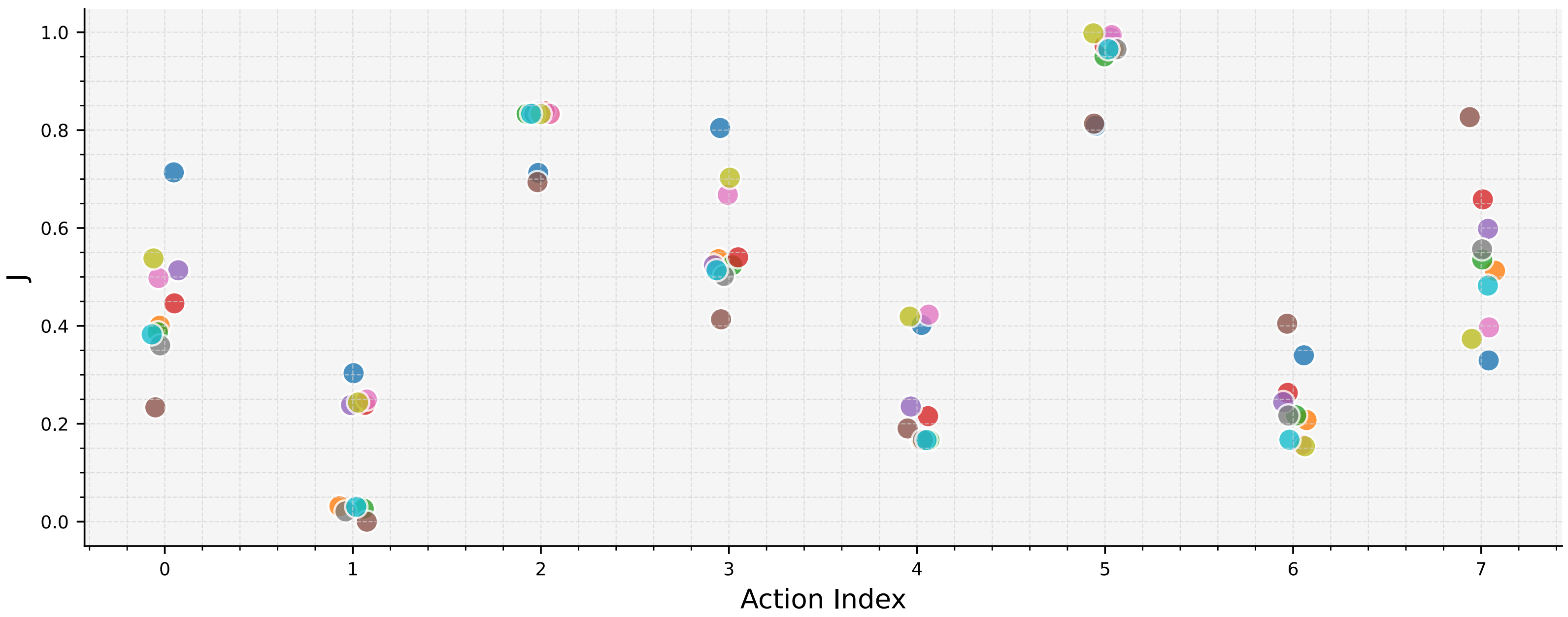
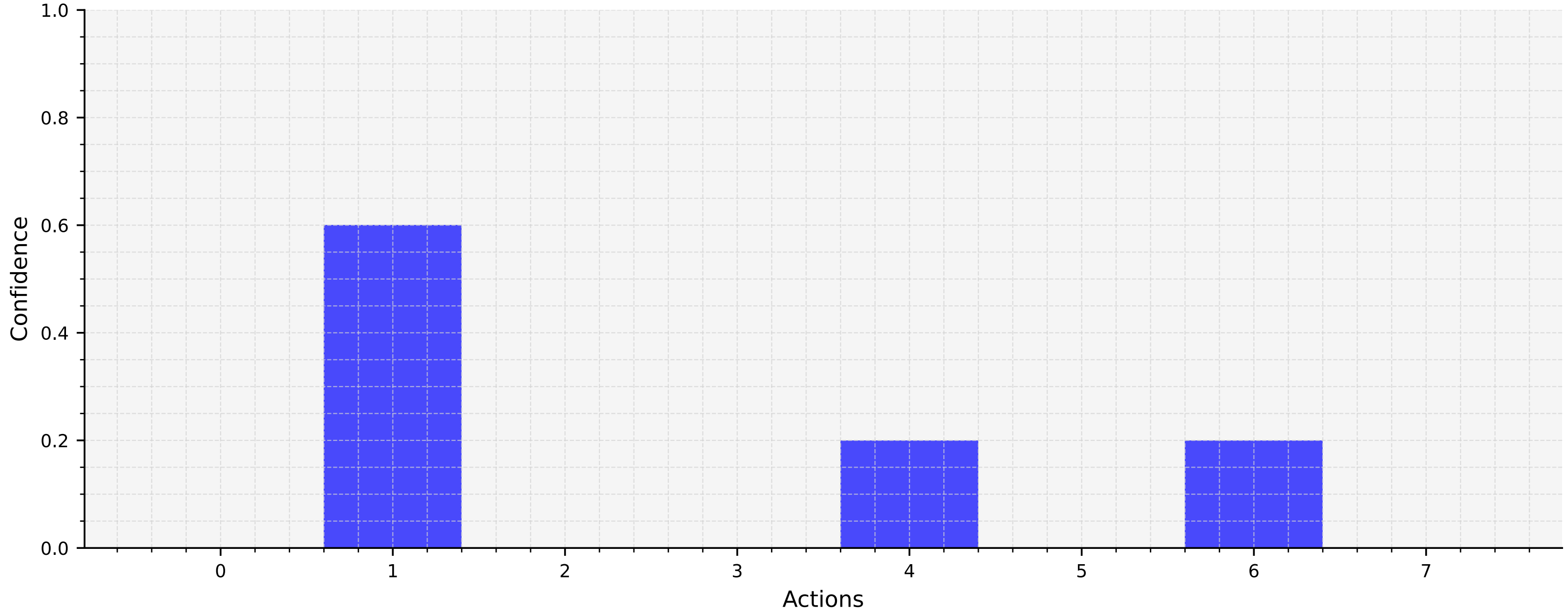
Probabilistic MRAC

Step 2:
Sampled measurement realizations



MRAC probability for each action



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Probabilistic MRAC

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Agenda

Towards Scalable Online Decision Making Under Uncertainty in Partially Observable Environments

- Experience Reuse in POMDP Planning
- POMDP Planning with Hybrid Beliefs
- Simplification of POMDP with Formal Guarantees
- Multi-agent POMDP Planning with Inconsistent Beliefs

Thank You

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ANPL Autonomous Navigation and Perception Lab

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