A Glimpse Into Autonomous Perception and Planning Under Uncertainty

Vadim Indelman

TECHNION
Israel Institute of Technology

ANPL
Autonomous Navigation and Perception Lab

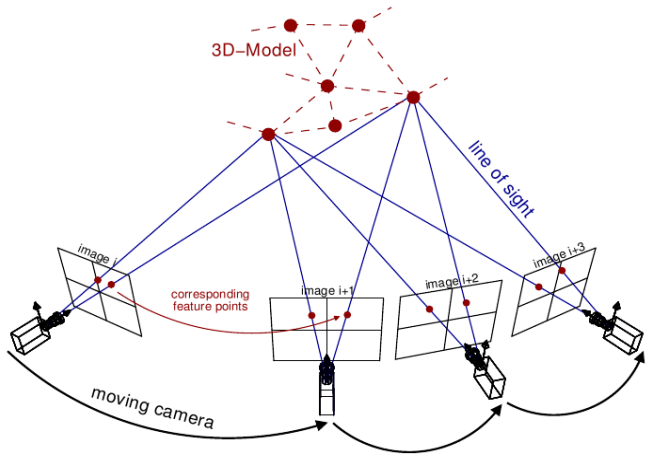
Annual Tech.AI Conference

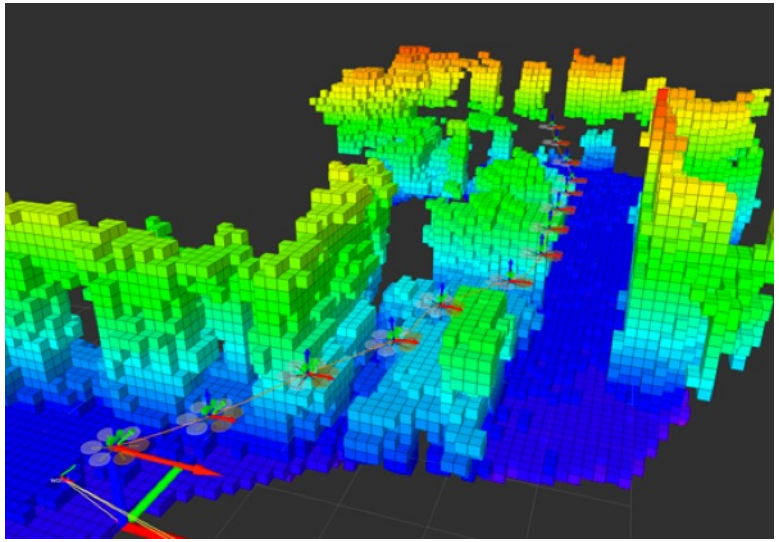
March 17, 2023

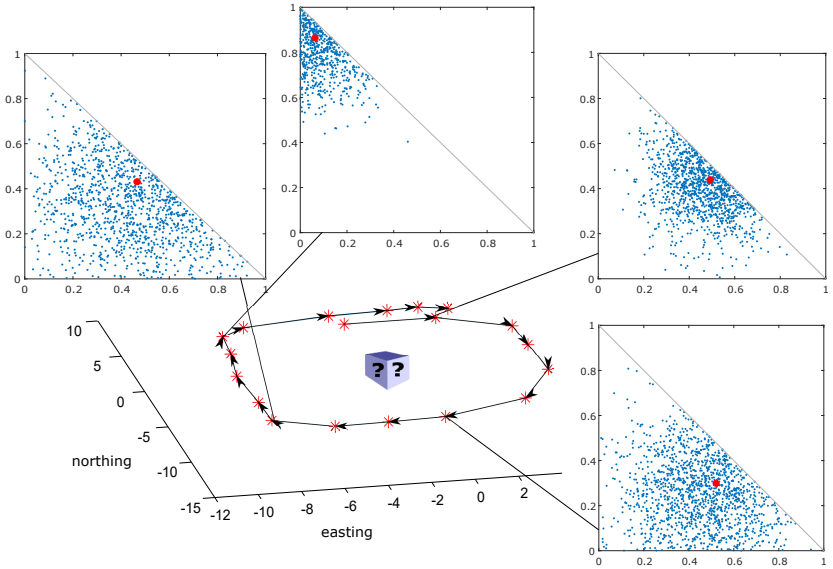
Introduction

Key required capabilities:

- **Perception and Inference**: Where am I? What is the surrounding environment?







Introduction

Key required capabilities:

- **Perception and Inference**: Where am I? What is the surrounding environment?
- **Planning Under Uncertainty**: What should I be doing next?
  - Determine best action(s) to accomplish a task, account for different sources of uncertainty

Perception & Inference ⟷ **Planning Under Uncertainty**

- <u>Related problems</u>: autonomous navigation, active SLAM, informative planning/sensing, etc.

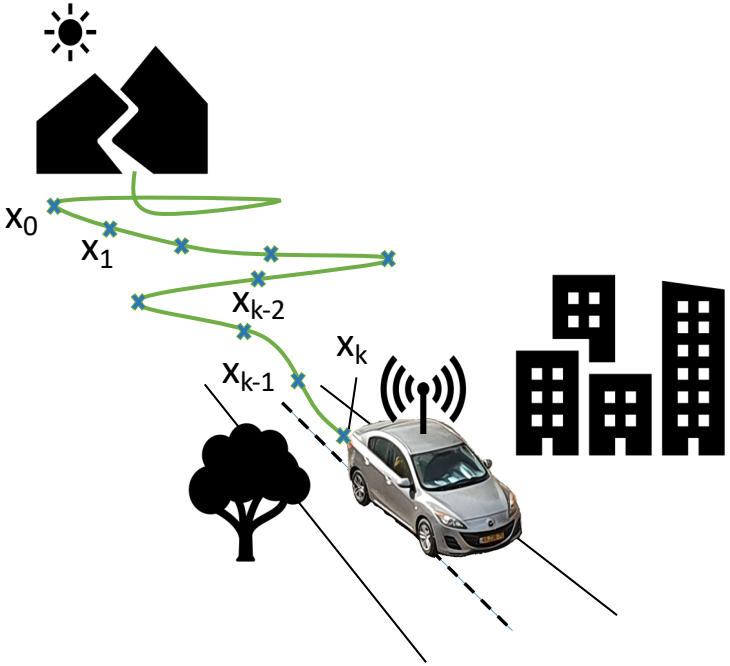
Perception and Inference

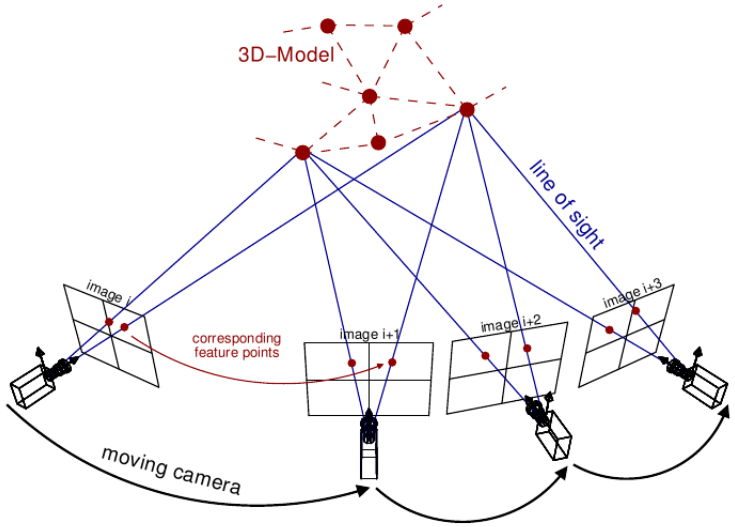
- Posterior belief at time k: $$b_k \triangleq b[X_k] = \mathbb{P}(X_k \mid a_{0:k-1}, z_{1:k})$$

  state/variables at time instant k — actions — observations

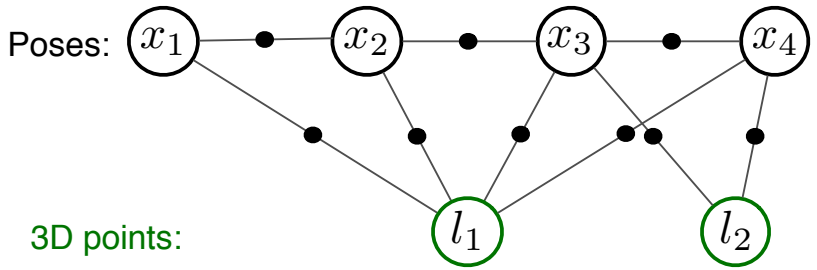
- Example: $$X_k \doteq \{x_0, \ldots, x_k, L_k\}$$

  Past & current robot states — Environment representation, e.g. Landmarks





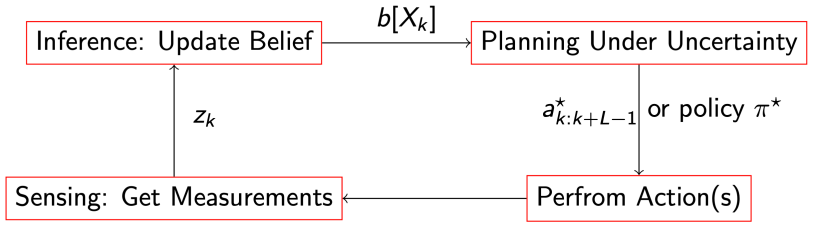
Can be represented with graphical models, e.g. a Factor Graph

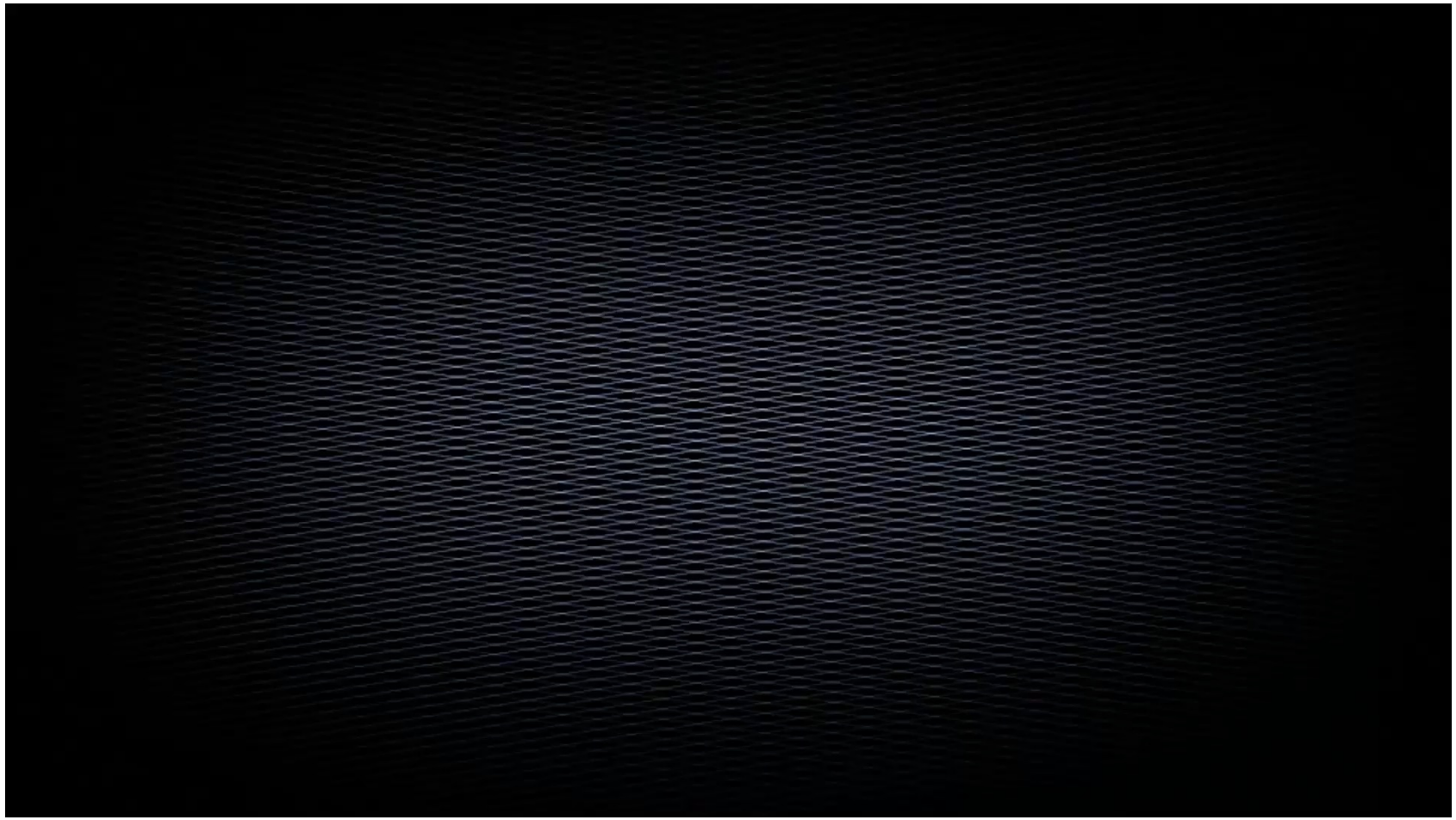


Online Autonomy

Collaborative Inference & Planning in Unknown Environments on Quads

Plan-act-sense-infer framework



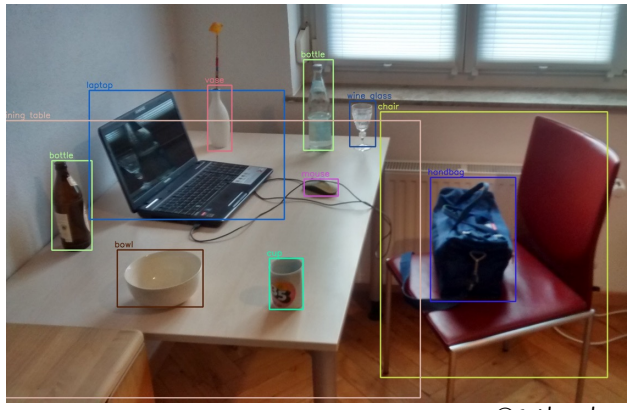


A Glimpse Into Autonomous Perception and Planning Under Uncertainty

- Viewpoint-Dependent Semantic Perception
- Ambiguous Data Association
- Belief Space Planning (BSP)
- Simplification of BSP Problems

Semantic Perception & SLAM

- Geometric mapping is insufficient!
- Need also a <u>reliable</u> high-level understanding of the environment
  - **Semantic** mapping
  - Enabled by advancements in object recognition and classification



© Wikipedia

- Typically, it is assumed semantic observations are **viewpoint independent**
- Often, **per-frame** classification

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?

A Viewpoint-Dependent Semantic Observation Model

[Feldman and Indelman, ICRA'18, ARJ'20]

- View-dependent semantic observation model:

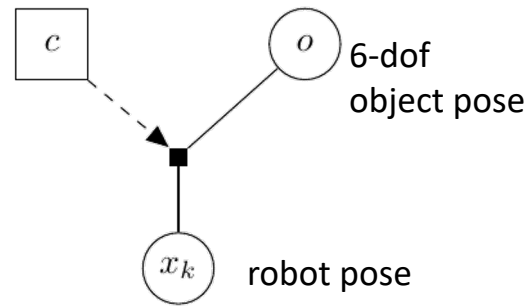
$$\mathbb{P}(z^s \mid c, \mathcal{X}^{rel})$$

semantic observation

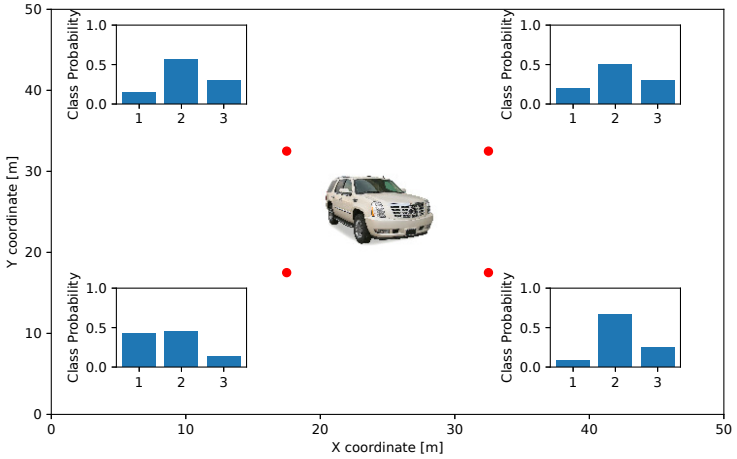
object/scene class

Agent's viewpoint relative to object

semantic factor

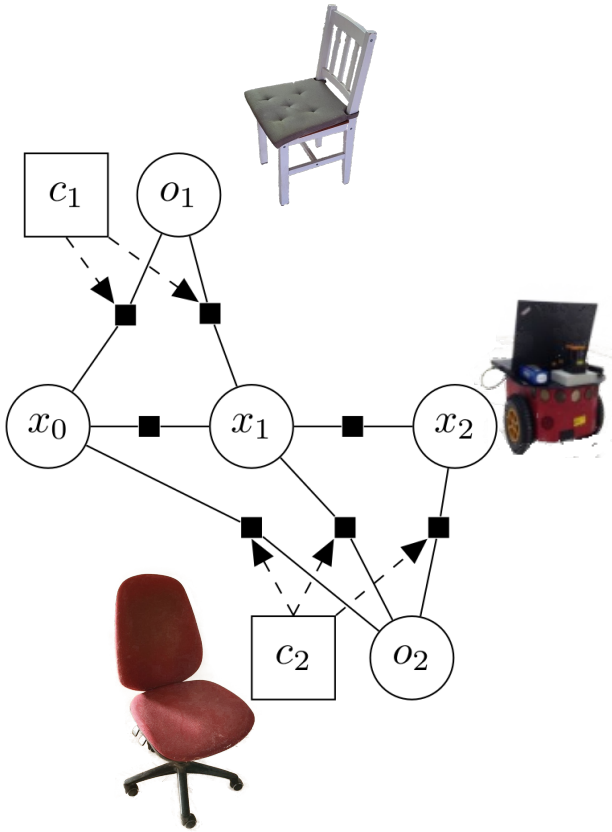


- Generative models
- Couples semantics and geometry



Hybrid Belief

- View-dependent semantic observation model: $\mathbb{P}(z^s \mid c, \mathcal{X}^{rel})$
  - Classes and agent poses are dependent
  - Classes of different objects are dependent



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

robot track

object categories (discrete!)

measurement and control history

$$\mathbb{P}(\mathcal{X}_{0:k}, \mathcal{C}, \mathcal{O} \mid \mathcal{H}_k)$$

objects poses

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

Spatially-Dependent Uncertainty-Aware Classification

[Feldman and Indelman, ICRA'18, ARJ'20]

robot track

object categories (discrete!)

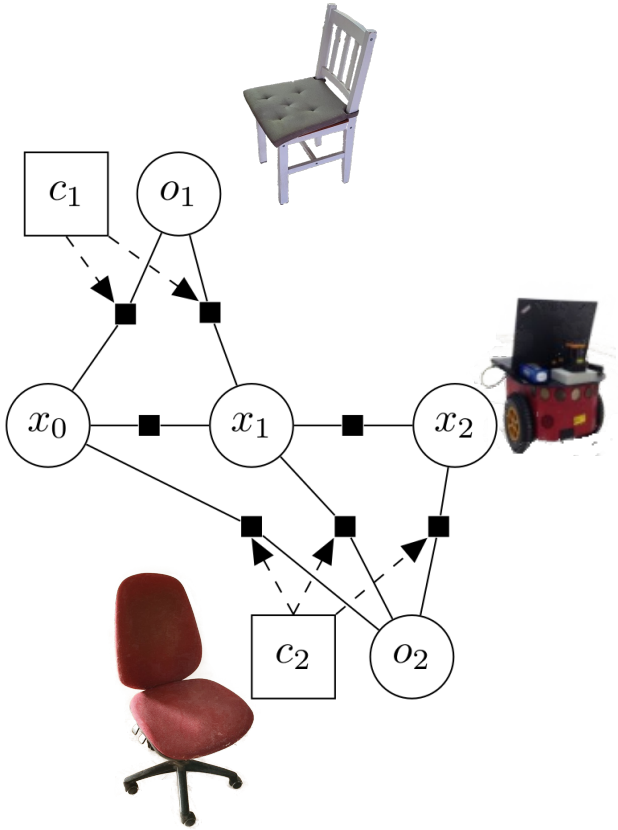
measurement and control history

$$\mathbb{P}(\mathcal{X}_{0:k}, \mathcal{C}, \mathcal{O} \mid \mathcal{H}_k) = \mathbb{P}(\mathcal{X}_{0:k}, \mathcal{O} \mid \mathcal{C}, \mathcal{H}_k)\mathbb{P}(\mathcal{C} \mid \mathcal{H}_k)$$

object geometry

Density over continuous variables conditioned on class hypothesis

hypothesis weight



- Number of hypotheses: #classes^#objects !!
- Pruning hypotheses is essential

Distributed Consistent Multi-Robot Semantic SLAM

[Tchuiev and Indelman, RA-L'20]

Distributed Consistent Multi-Robot Semantic Localization and Mapping

Vladimir Tchuiev and Vadim Indelman

Technion – Israel Institute of Technology

ANPL Autonomous Navigation and Perception Lab

Technion Israel Institute of Technology

A Glimpse Into Autonomous Perception and Planning Under Uncertainty

Viewpoint-Dependent Semantic Perception

Ambiguous Data Association

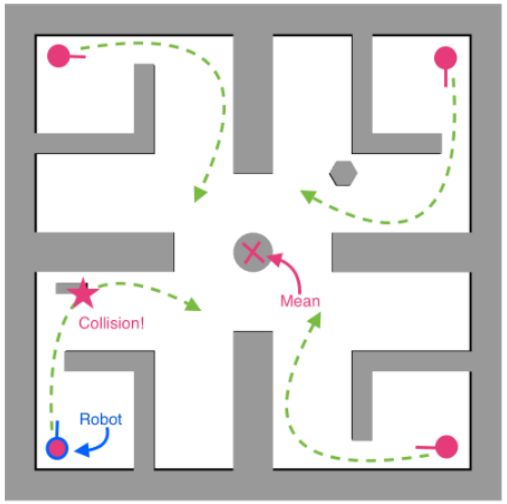
Belief Space Planning (BSP)

Simplification of BSP Problems

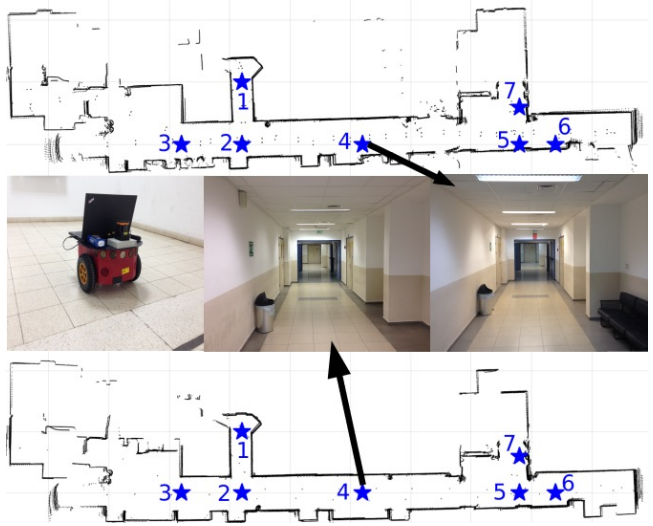
Ambiguous Environments

Angeli et al., TRO'08

Mu et al., IROS'16



Agarwal et al., arXiv 2015



Pathak, Thomas & Indelman, IJRR 2018

Hybrid & Mixture Beliefs

[Pathak, Thomas and Indelman, IJRR'18]

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

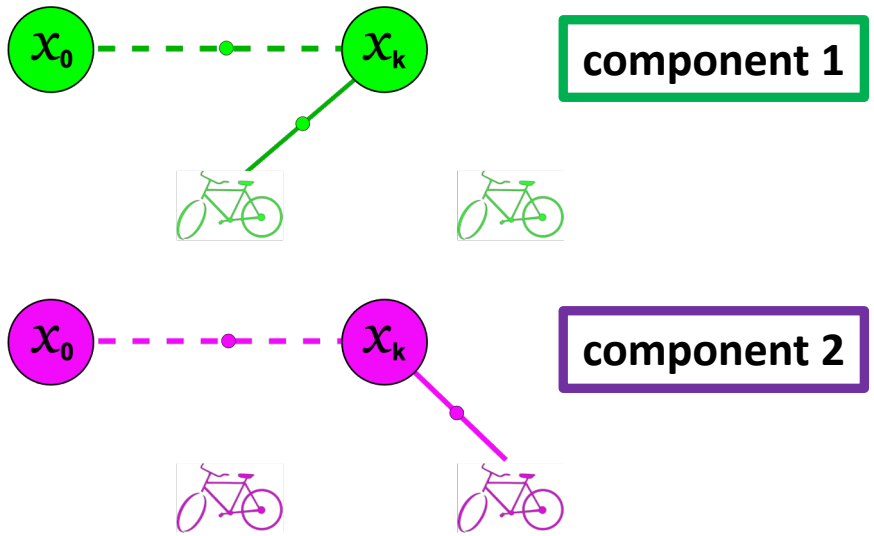
Hybrid & Mixture Beliefs

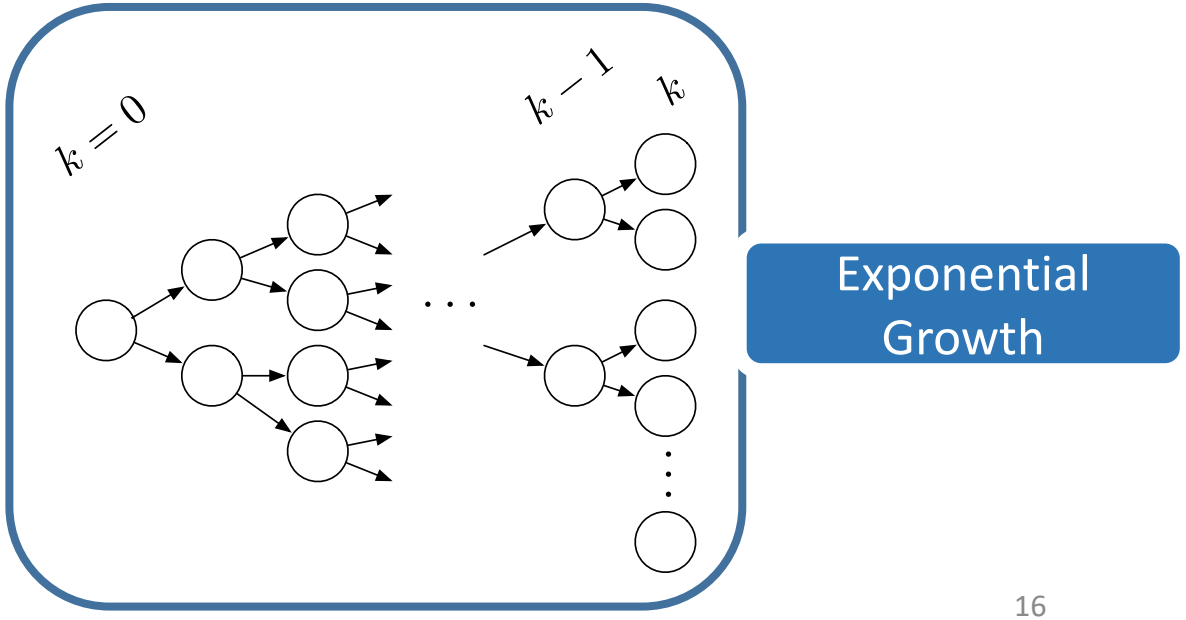
[Pathak, Thomas and Indelman, IJRR'18]

- Have to reason about data association hypotheses within inference and planning
- Hybrid belief over continuous and discrete variables: $\mathbb{P}(X_k, \beta_{0:k} \mid \mathcal{H}_k)$

(e.g. agent state) (e.g. data association hypotheses)

- Belief over agent state is represented by a mixture density (e.g. GMM): $b[X_k] = \sum_i w_k^i b^i[X_k]$





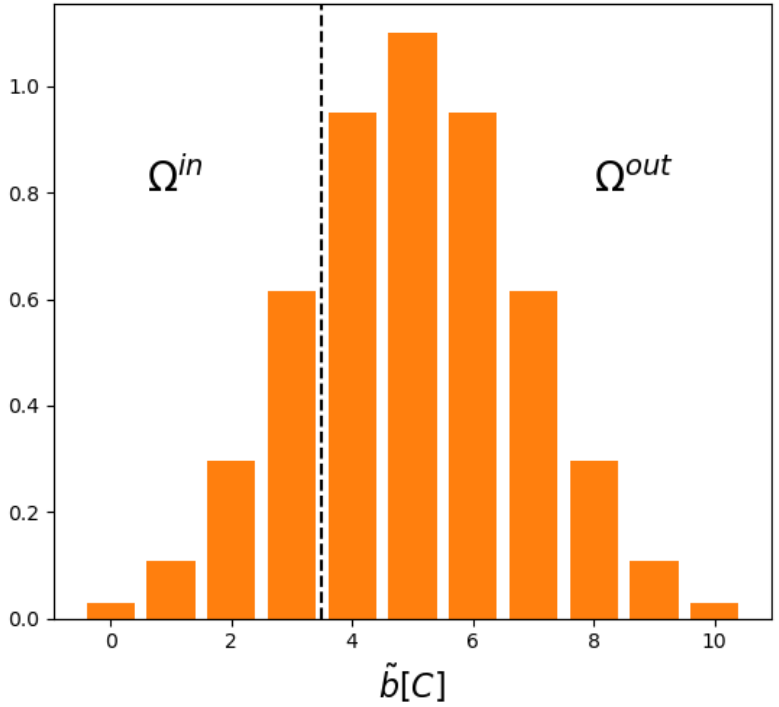
Hypothesis Pruning with Guarantees for Viewpoint-Dependent Semantic SLAM

[Lemberg and Indelman, IROS'22]

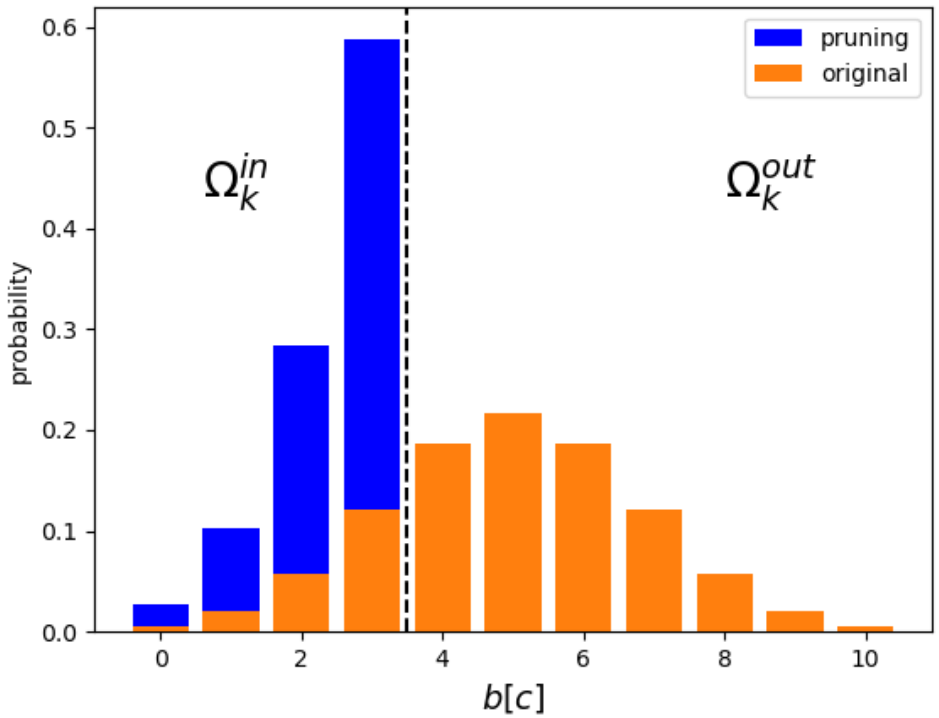
- Number of classification hypotheses is M^N (N: number of objects, M: number of classes)
- Ω^{in} , Ω^{out} : Maintained and pruned hypothesis sets

Issue: After pruning and re-normalization, get **overconfident** hyp. probabilities

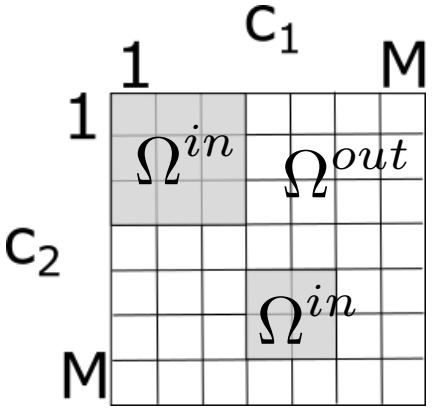
Unnormalized belief



Belief after normalization



For example, for two objects:



Hypothesis Pruning with Guarantees for Viewpoint-Dependent Semantic SLAM

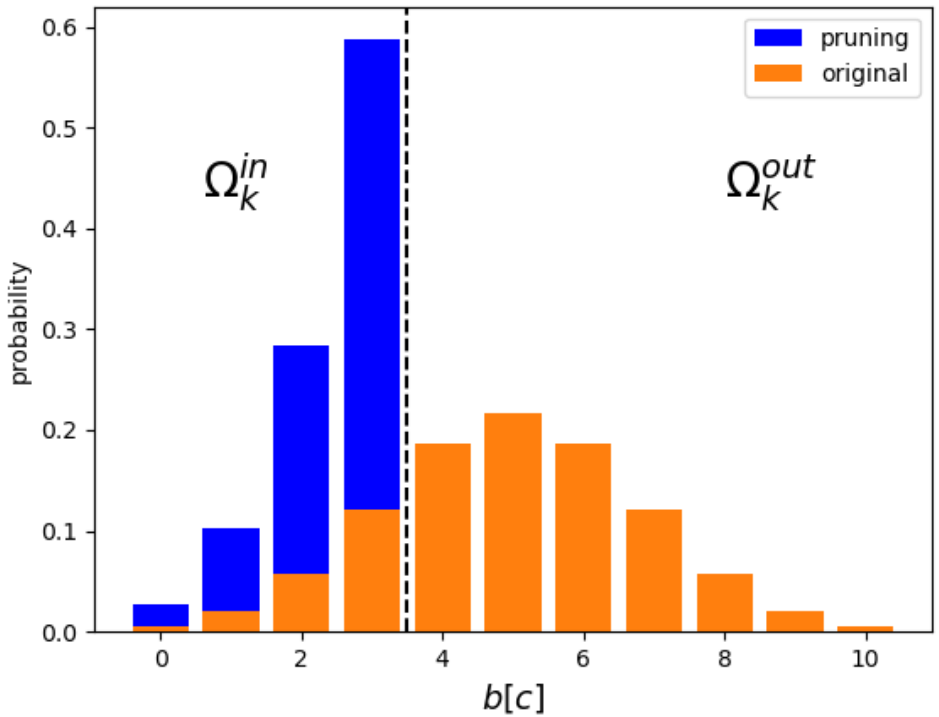
[Lemberg and Indelman, IROS'22]

- Number of classification hypotheses is M^N (N: number of objects, M: number of classes)
- Ω^{in} , Ω^{out} : Maintained and pruned hypothesis sets

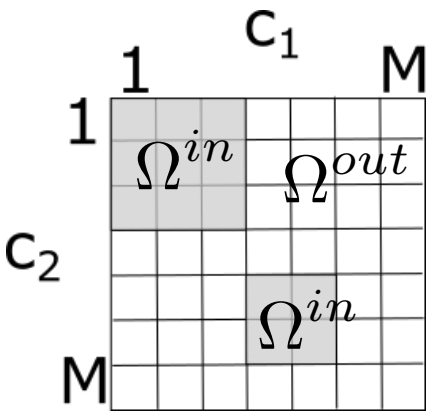
Issue: After pruning and re-normalization, get **overconfident** hyp. probabilities

May lead to dangerous/unsafe decisions!

Belief after normalization



For example, for two objects:



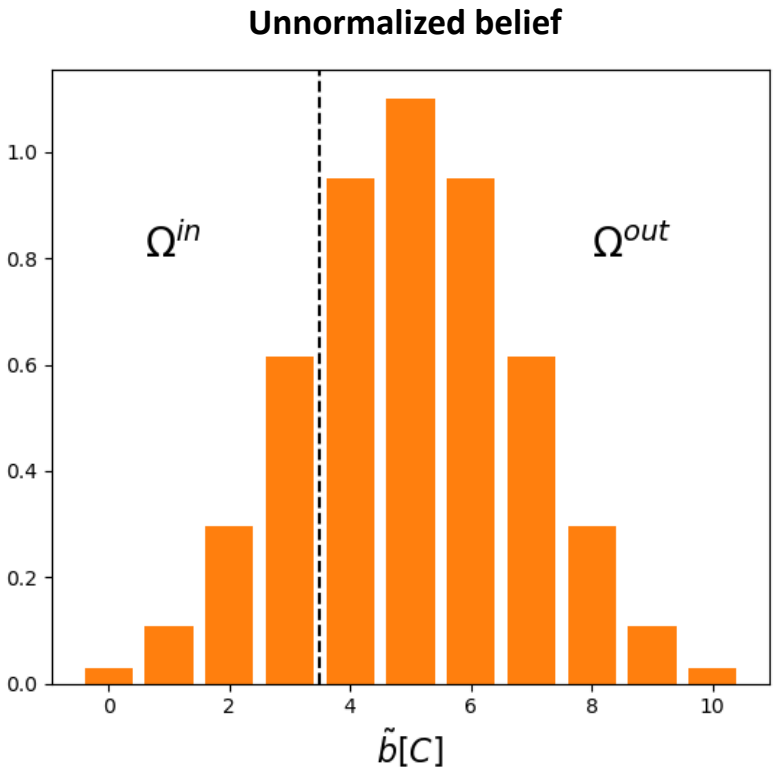
Hypothesis Pruning with Guarantees for Viewpoint-Dependent Semantic SLAM

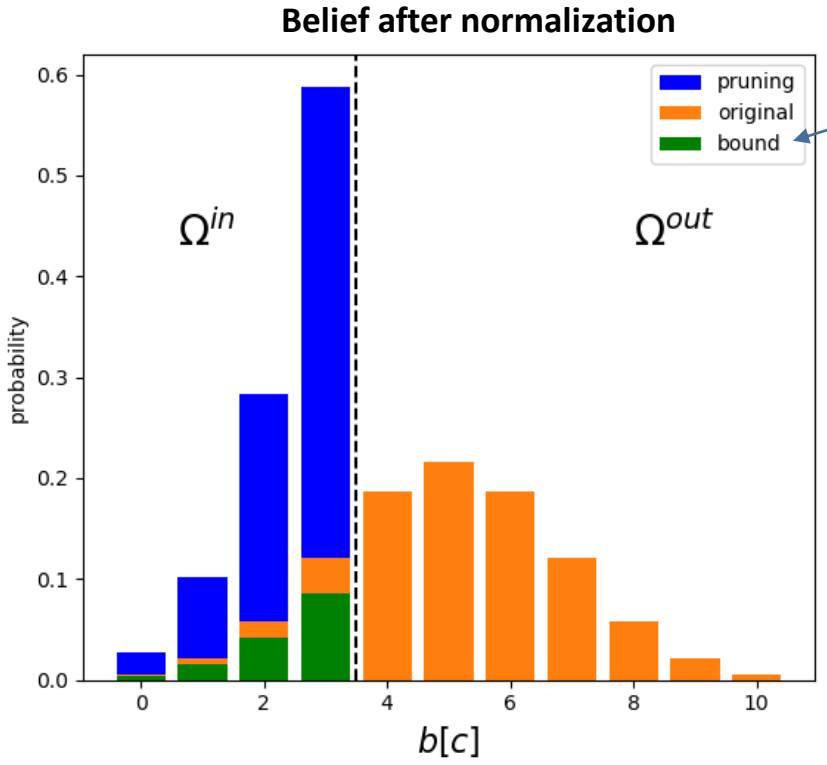
[Lemberg and Indelman, IROS'22]

Issue: after pruning and re-normalization, get **overconfident** hyp. probabilities

- Normalizer is calculated only using the maintained (not-pruned) hypotheses
- **Lower bound** on posterior probabilities of maintained hypotheses (conservative)
  - Provides also indication of (probabilities of) pruned hypotheses

Our contribution





Can we take these concepts to planning?

A Glimpse Into Autonomous Perception and Planning Under Uncertainty

Viewpoint-Dependent Semantic Perception

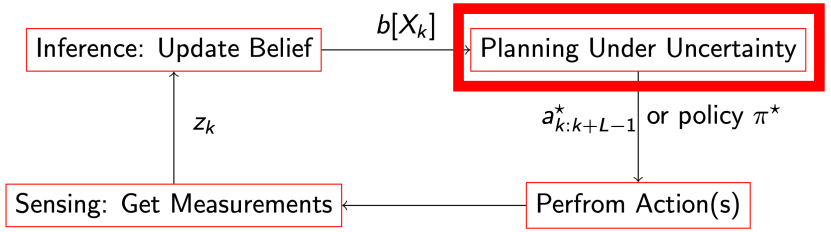
Ambiguous Data Association

Belief Space Planning (BSP)

Simplification of BSP Problems

Belief Space Planning (BSP)

Plan-act-sense-infer framework

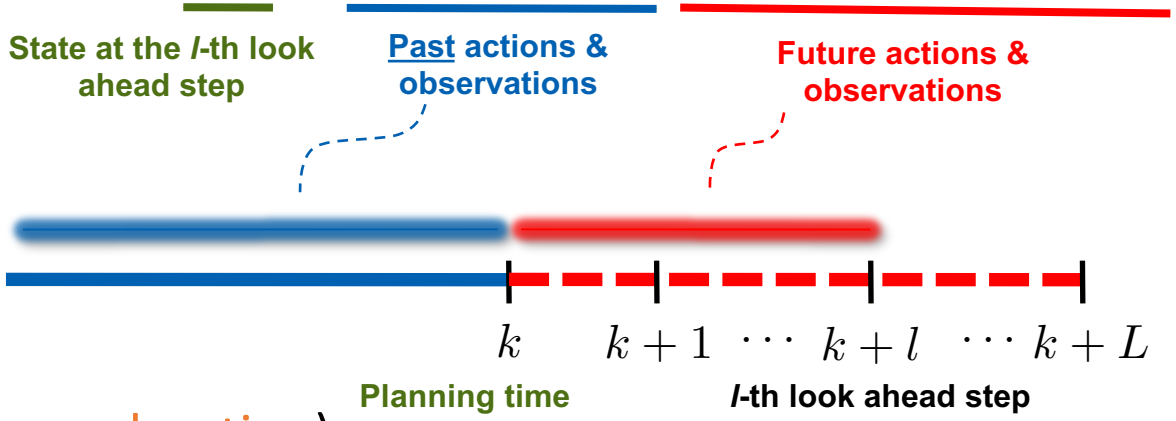


Belief Space Planning (BSP)

- Objective/Value function, planning horizon of L time steps:

Action sequences: $$J(b_k, a) = \mathbb{E}[\sum_{\ell=0}^{L-1} r(b_{k+\ell}, a_{k+\ell}) + r(b_{k+L})] \quad , \quad a \triangleq a_{k:k+L-1}$$

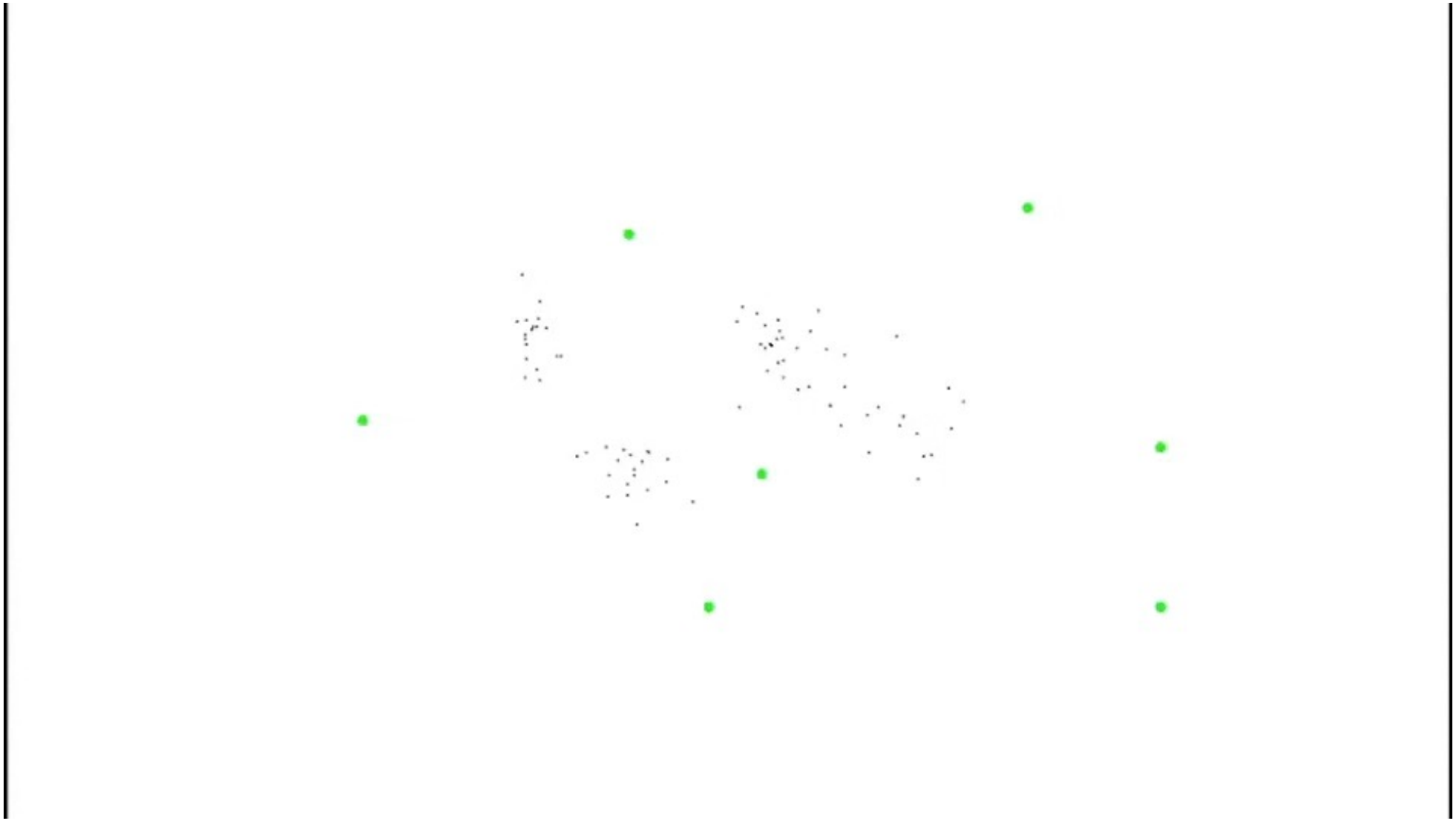
- Belief at the ℓ-th look-ahead step: $b_{k+\ell} \triangleq b[X_{k+\ell}] = \mathbb{P}(X_{k+\ell} \mid a_{0:k-1}, z_{0:k}, a_{k:k+\ell-1}, z_{k+1:k+\ell})$



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

Belief Space Planning (BSP)

[Indelman, Carlone, Dellaert IJRR'15]

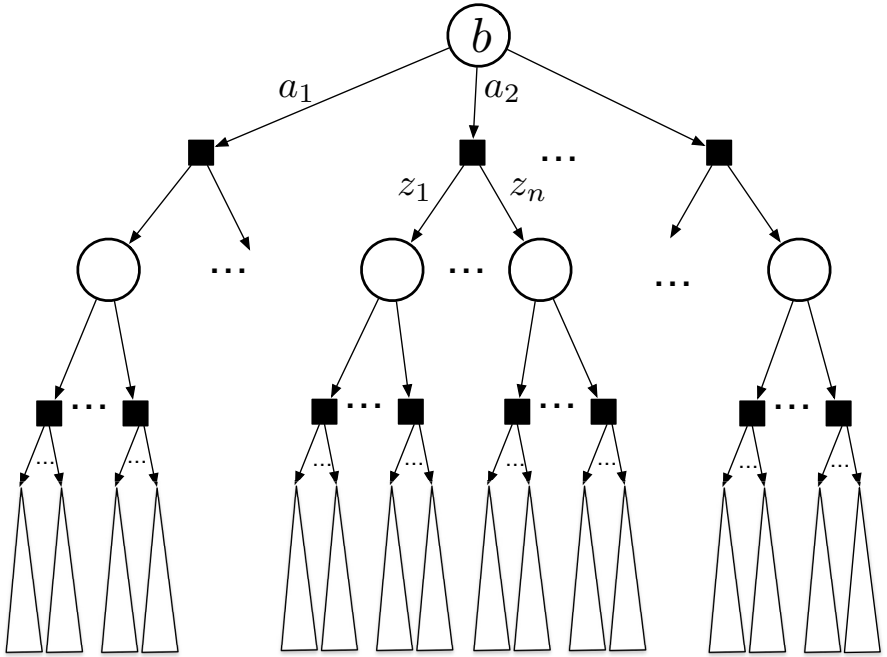


Belief Space Planning (BSP)

Action sequences: $$J(b_k, a) = \mathbb{E}[\sum_{\ell=0}^{L-1} r(b_{k+\ell}, a_{k+\ell}) + r(b_{k+L})] \quad , \quad a \triangleq a_{k:k+L-1}$$

Policies: $$V^{\pi}(b_k) = \mathbb{E}[\sum_{\ell=0}^{L-1} r(b_{k+\ell}, \pi_{k+\ell}(b_{k+\ell})) + r(b_{k+L})] \quad , \quad \pi \triangleq \pi_{k:k+L-1}$$

- Finding an optimal solution is generally **computationally intractable**



A Glimpse Into Autonomous Perception and Planning Under Uncertainty

Viewpoint-Dependent Semantic Perception

Ambiguous Data Association

Belief Space Planning (BSP)

Simplification of BSP Problems

Simplification of Decision-Making Problems

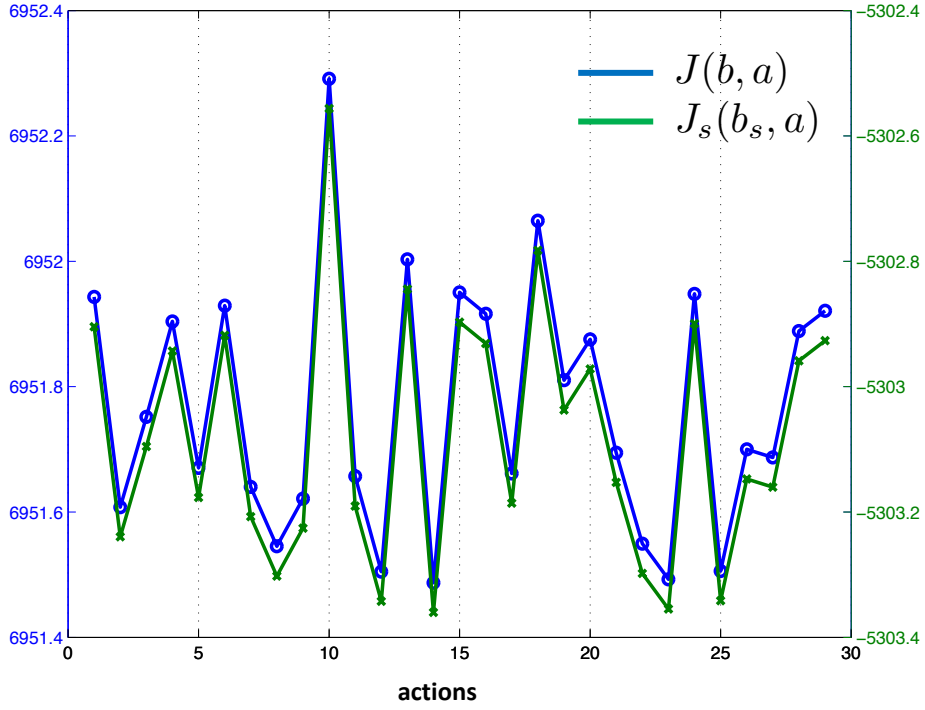
Concept:

- Identify and solve a **simplified computationally-easier** decision-making problem
- Provide performance guarantees – how can we measure simplification quality?

Simplification of Decision-Making Problems

[Indelman RA-L'16][Elimelech and Indelman, IJRR'22]

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

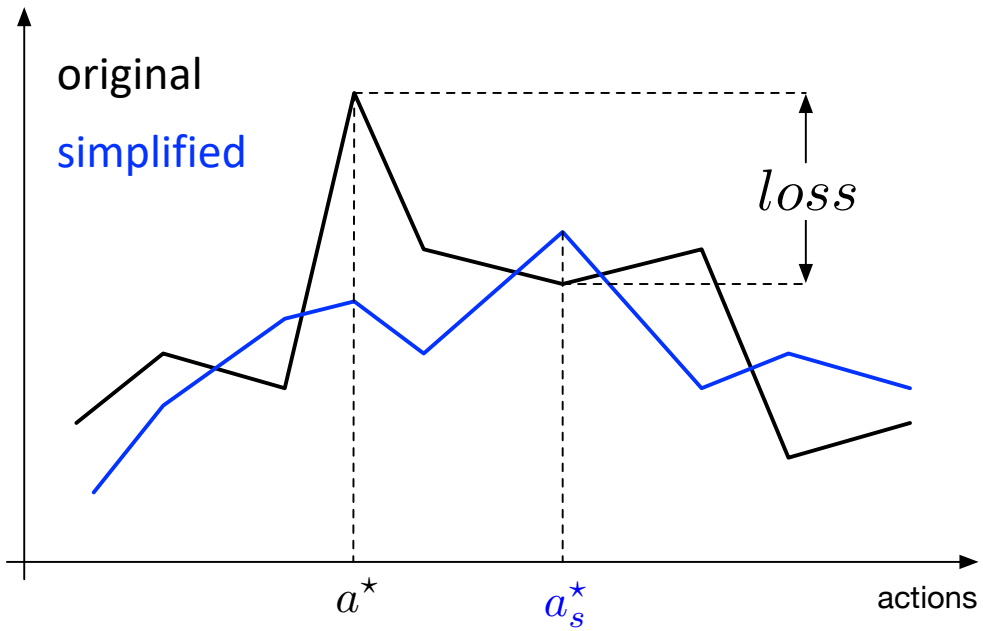


Same optimal action!

Simplification of Decision-Making Problems

[Elimelech and Indelman, IJRR'22]

- Action consistency cannot be always guaranteed



Original problem:

$$a^* \doteq \underset{a \in \mathcal{A}}{\operatorname{argmax}}\, J(b, a)$$

Simplified problem:

$$a_s^* \doteq \underset{a \in \mathcal{A}}{\operatorname{argmax}}\, J_s(b_s, a)$$

- To provide performance guarantees, need **tight (& computationally cheap) bounds** on the loss/regret!

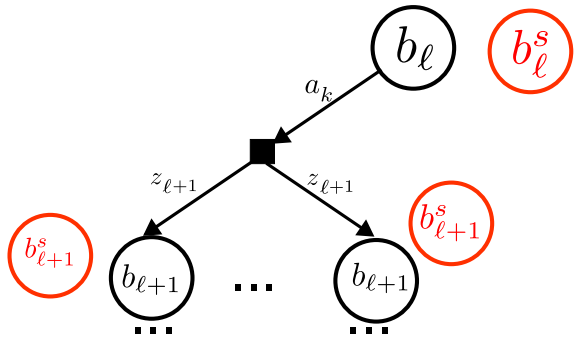
Simplification of BSP Problems

[Elimelech and Indelman, IJRR'22][Sztyglic and Indelman, IROS'22][Zhitnikov, Sztyglic and Indelman, arXiv'21]

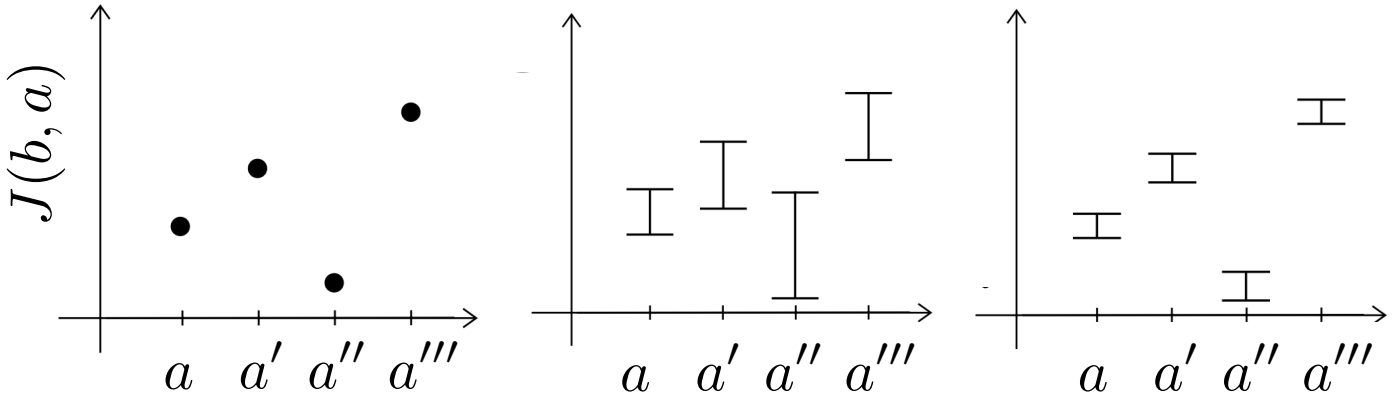
- For example, reward bounds based on a simplified version of the belief:

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

computationally cheaper



- Reward bounds induce bounds on the objective/value function



Simplification of Decision-Making Problems

Concept:

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

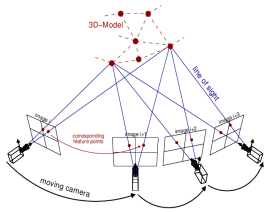
Specific simplifications with performance guarantees developed @ANPL include:

- Gaussian belief over a high dim. state:
  - (i) Sparsification
  - (ii) Topological signature
- Nonparametric belief represented by a set of samples:
  - (i) Utilize a subset of samples (deterministic/stochastic bounds);
  - (ii) Resort to an abstract observation model
- Mixture/hybrid belief: utilize a subset of hypotheses

Belief Sparsification for BSP

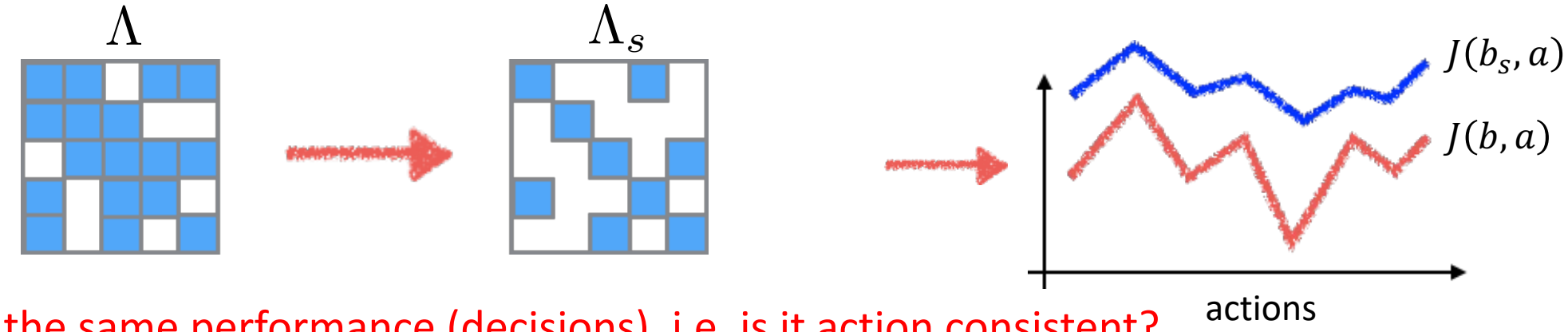
[Indelman RA-L'16][Elimelech and Indelman, IJRR'22]

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



<u>Setting</u>:

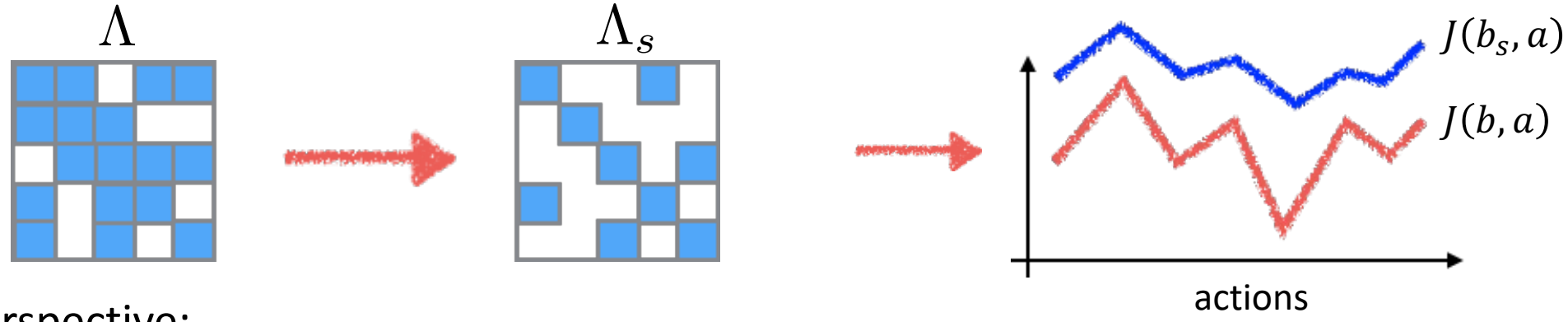
- Gaussian belief over high dim. state $X \in \mathbb{R}^n$: $b[X] = \mathcal{N}(X^\star, \Lambda^{-1}) = \mathcal{N}(X^\star, (R^T R)^{-1})$
- Information-theoretic reward (entropy): $H[X] = \frac{1}{2}\log((2\pi e)^n |\Lambda|^{-1})$



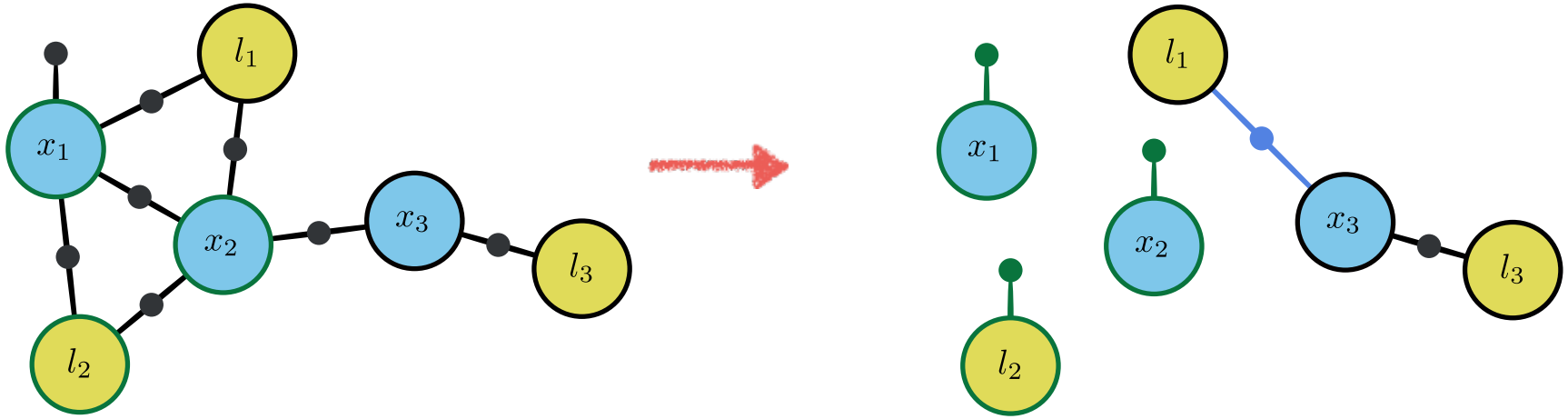
- Do we get the same performance (decisions), i.e. is it action consistent?

Belief Sparsification for BSP

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



- Graphical models perspective:



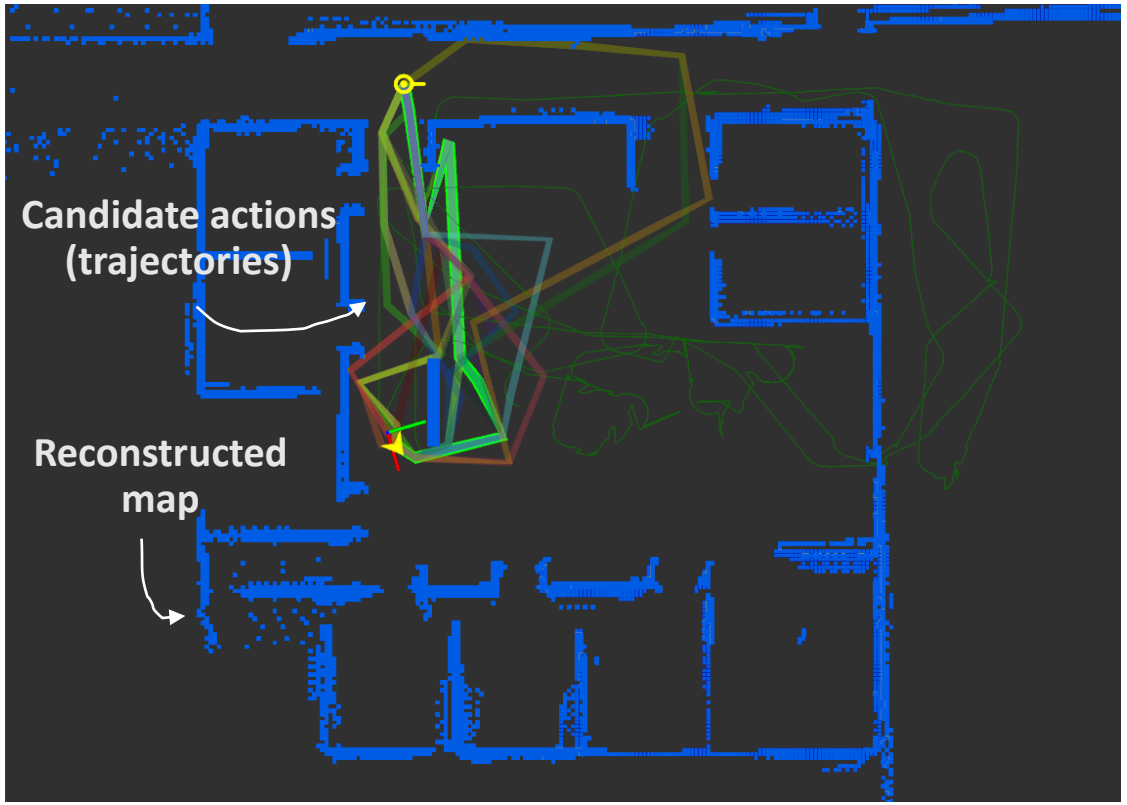
Belief Sparsification for BSP

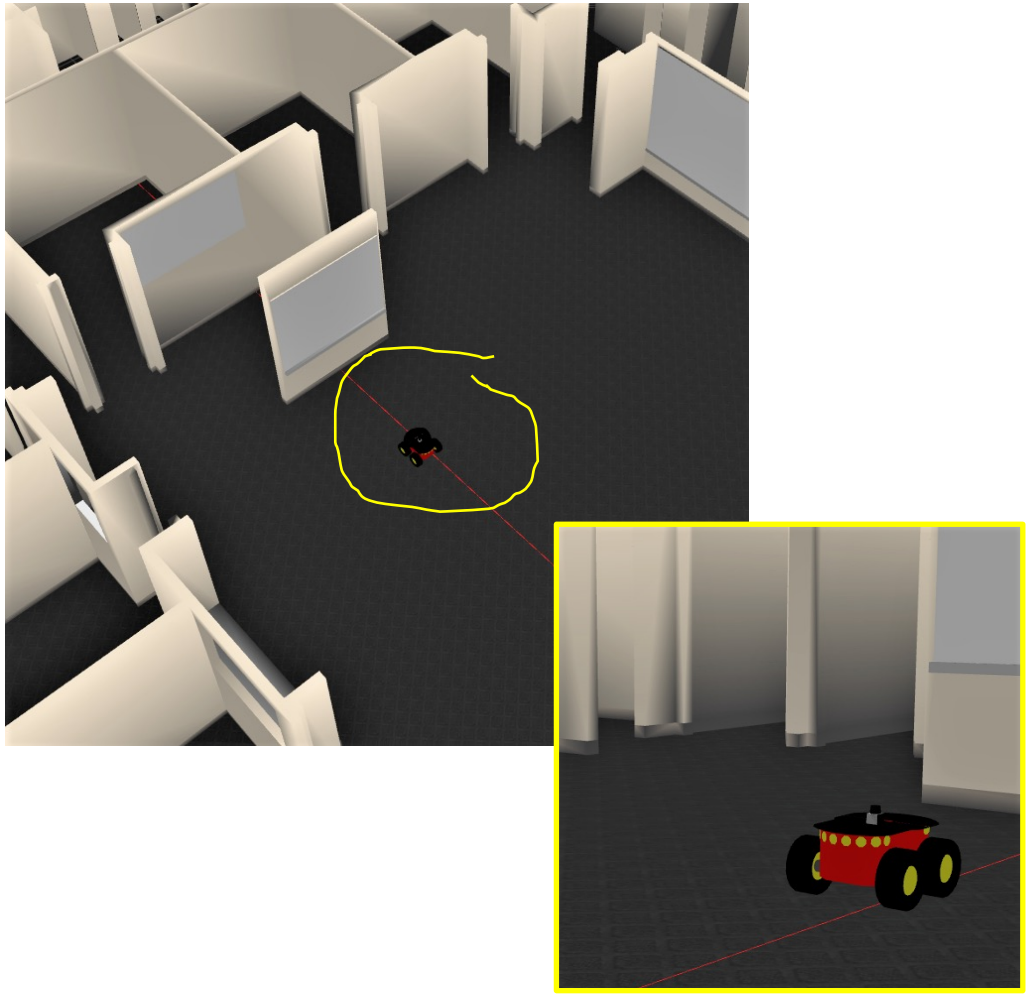
[Elimelech and Indelman, IJRR'22]

- 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**





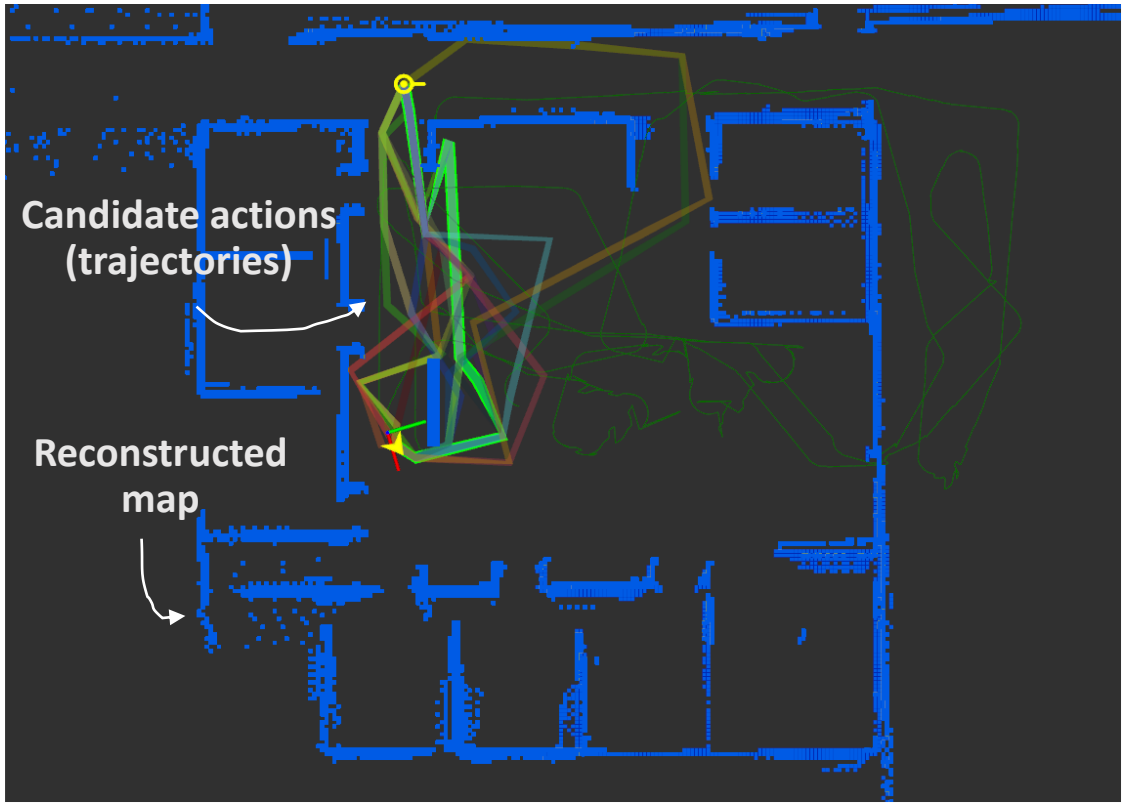
Belief Sparsification for BSP

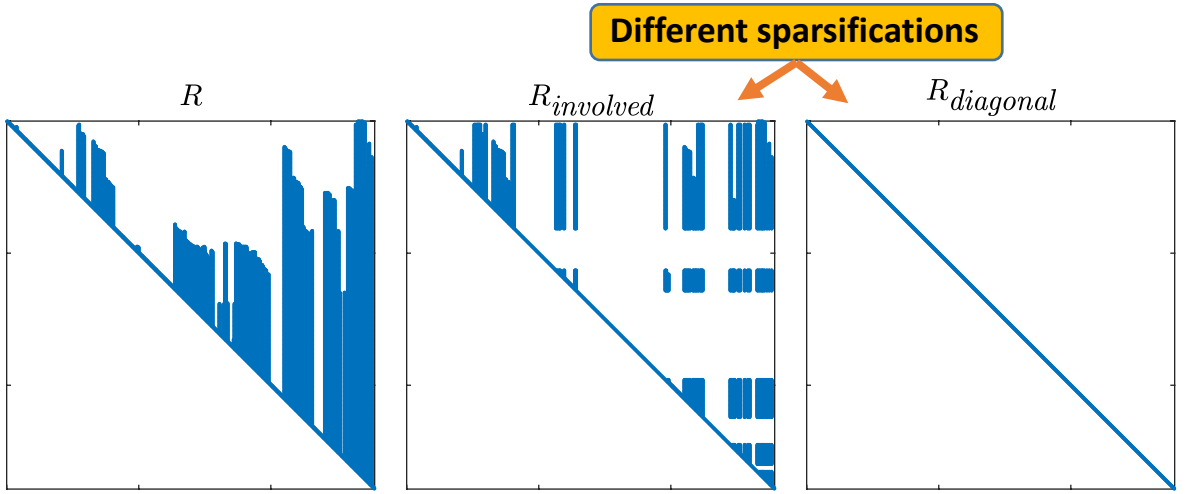
[Elimelech and Indelman, IJRR'22]

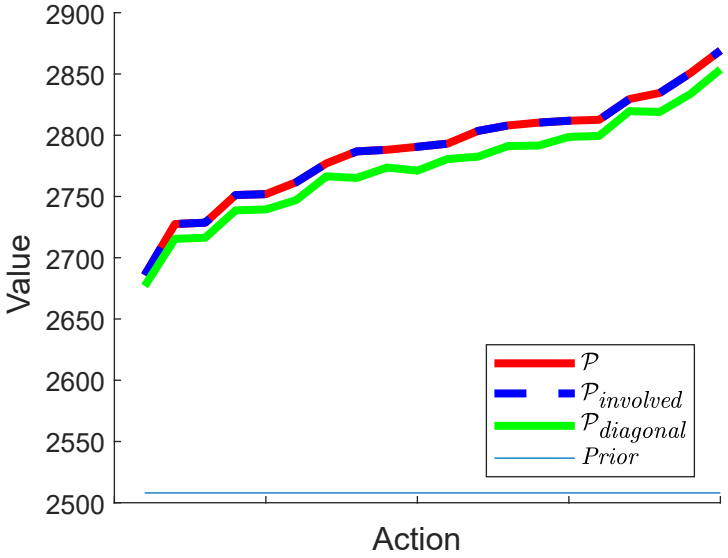
- Agent performs simultaneous localization and mapping
- Maintains a multivariate Gaussian belief

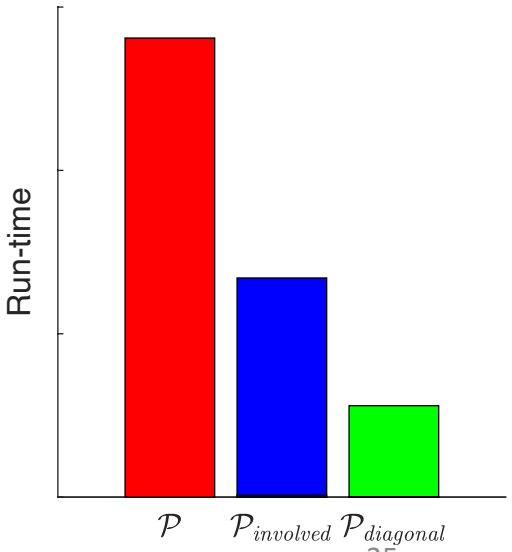
$$b[X] = \mathcal{N}(X^\star, (R^T R)^{-1})$$

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

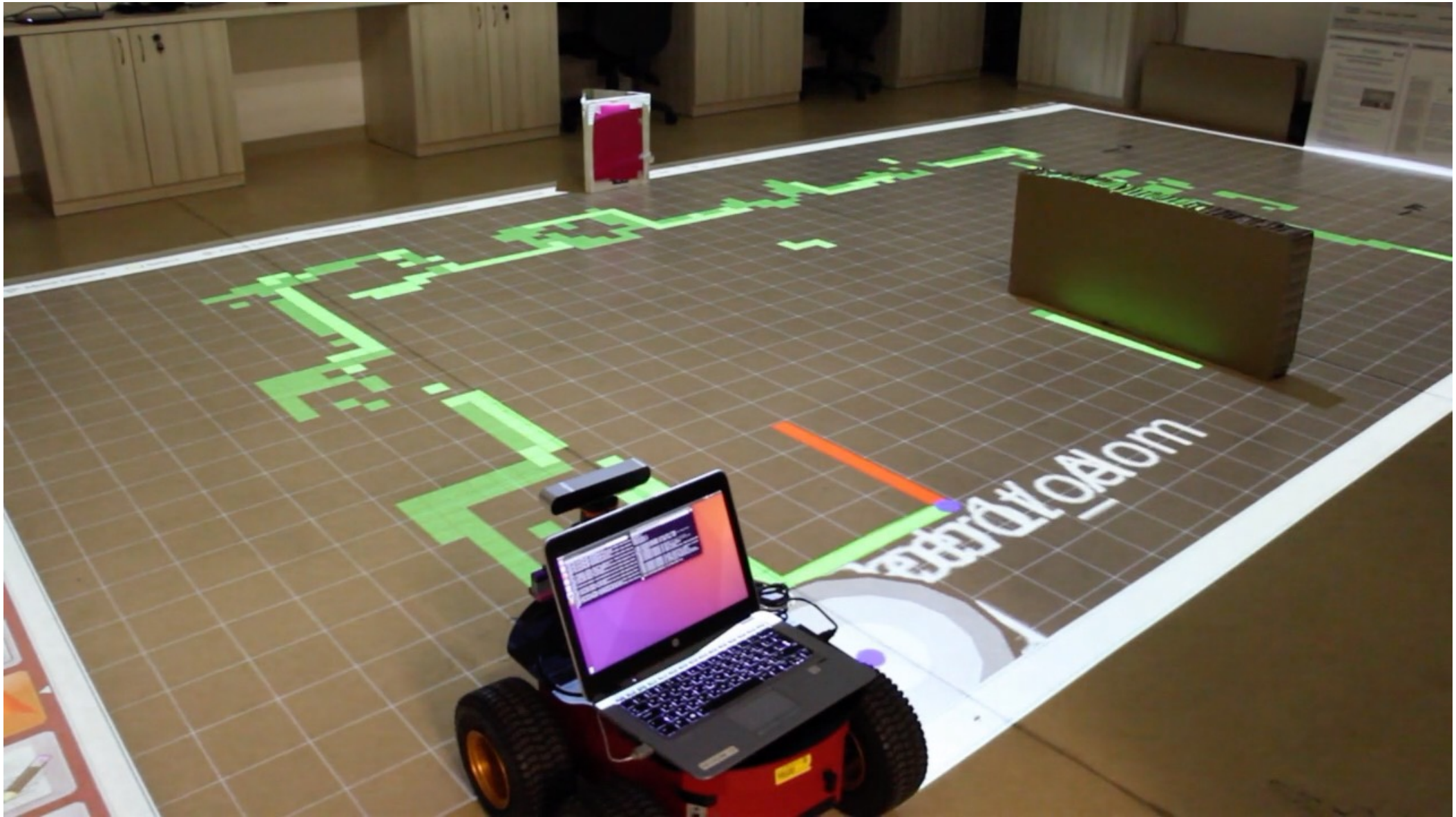








Real World Experiment



Simplification of Decision-Making Problems

Concept:

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

Specific simplifications with performance guarantees developed @ANPL include:

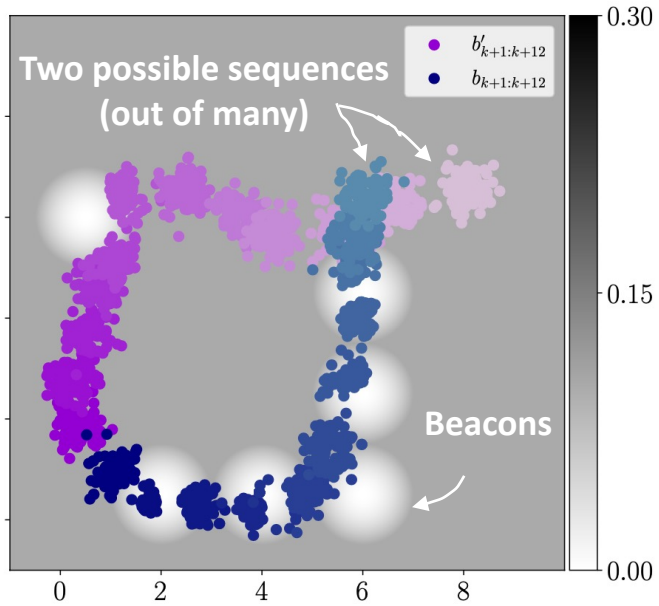
- Gaussian belief over a high dim. state:
  - (i) Sparsification
  - (ii) Topological signature
- Nonparametric belief represented by a set of samples:
  - (i) Utilize a subset of samples (deterministic/stochastic bounds);
  - (ii) Resort to an abstract observation model
- Mixture/hybrid belief: utilize a subset of hypotheses

Simplification of BSP with Nonparametric Beliefs

[Sztyglic and Indelman, IROS'22][Zhitnikov, Sztyglic and Indelman, arXiv'21] [Zhitnikov and Indelman, AI'22]

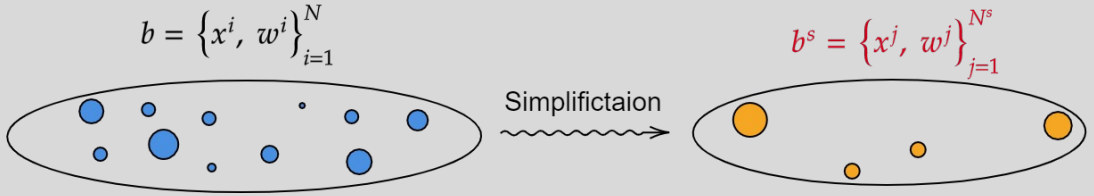
- BSP with nonparametric beliefs represented via samples

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



Simplification:

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



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

Simplification of BSP with Nonparametric Beliefs

[Sztyglic and Indelman, IROS'22][Zhitnikov, Sztyglic and Indelman, arXiv'21] [Zhitnikov and Indelman, AI'22]

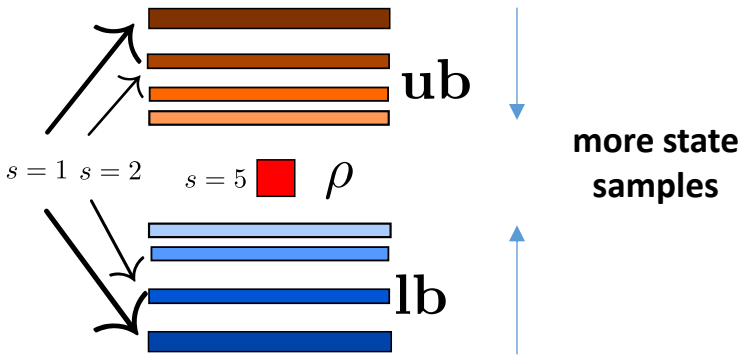
- Reward bounds induce bounds on the objective/value function

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

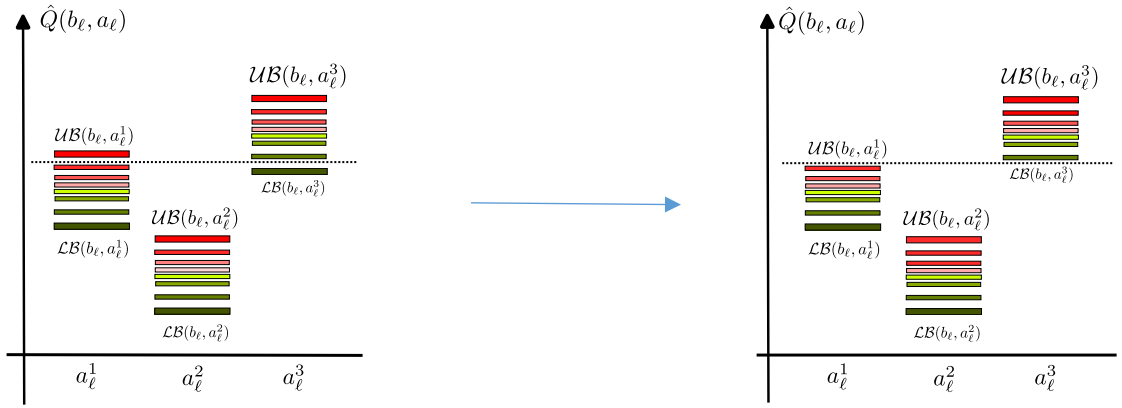
$$\mathcal{LB}(b_k, \pi) \leq V^\pi(b_k) \leq \mathcal{UB}(b_k, \pi)$$

- If bounds do not overlap - prune sub-optimal branches traversing the tree
- Else – **tighten** the bounds by **adapting** simplification level with calculation re-use
  - i.e. **take more** particles to represent the simplified belief(s)

Multi-level simplification:



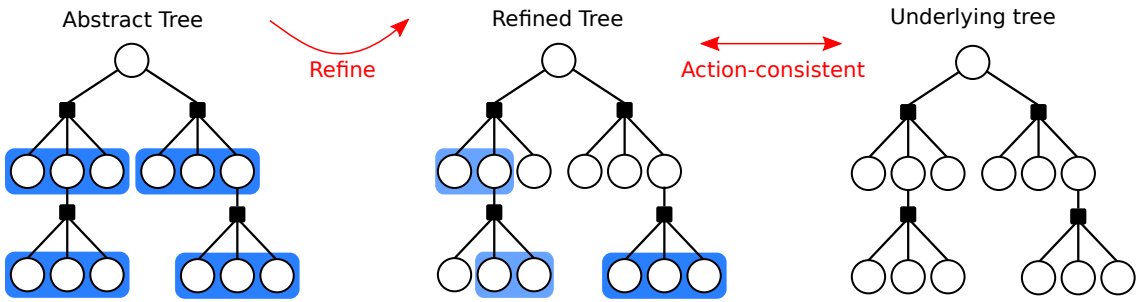
Adapt bounds until there is no overlap (wrt best action)



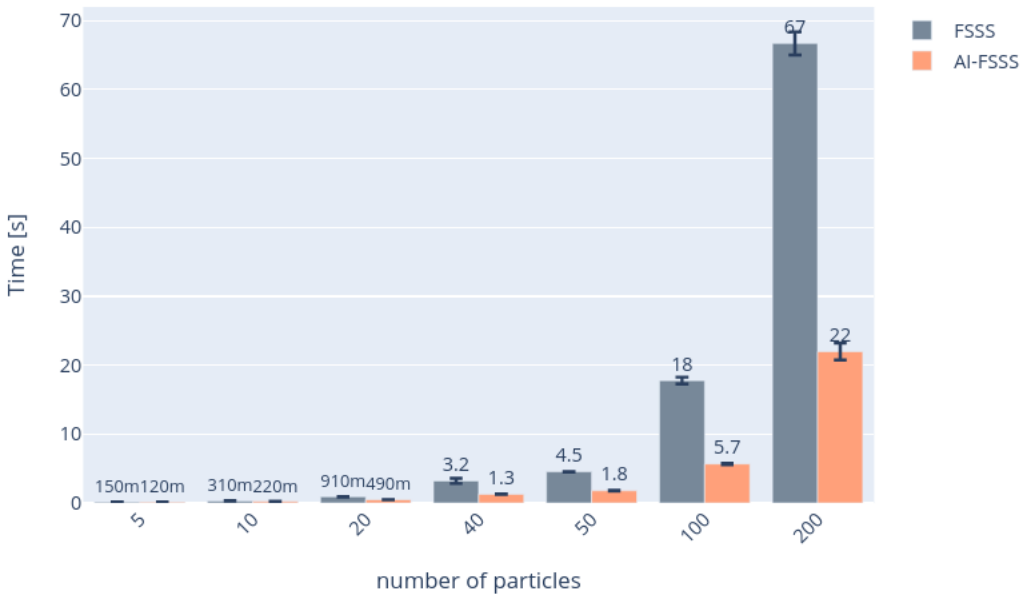
Adaptive Information Belief Space Planning

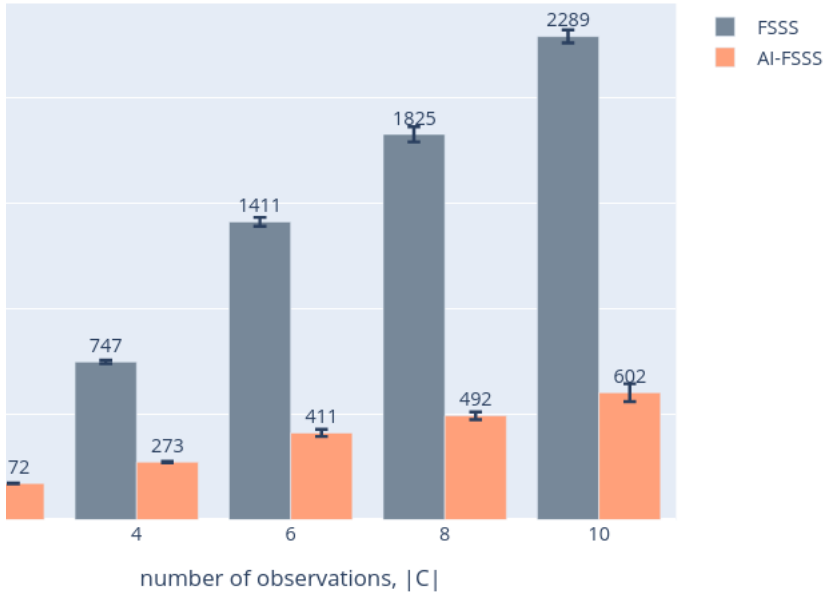
[Barenboim and Indelman, IJCAI'22]

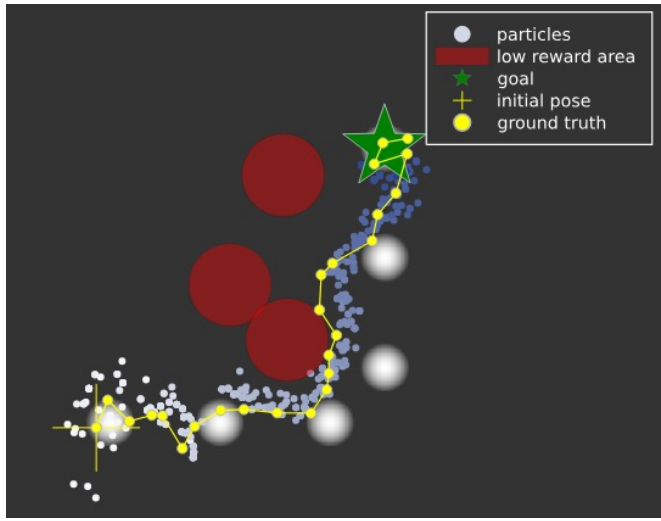
- Adaptive aggregation scheme via an abstract observation model



- **Significant planning speedup, same planning performance!**



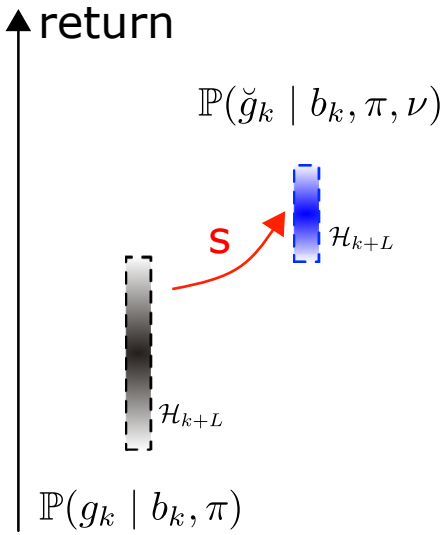




Distributional Perspective

[Zhitnikov and Indelman, AI'22]

- 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

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

Simplification of Decision-Making Problems

Concept:

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

Specific simplifications with performance guarantees developed @ANPL include:

- Gaussian belief over a high dim. state:
  - (i) Sparsification
  - (ii) Topological signature
- Nonparametric belief represented by a set of samples:
  - (i) Utilize a subset of samples (deterministic/stochastic bounds);
  - (ii) Resort to an abstract observation model
- Mixture/hybrid belief: utilize a subset of hypotheses

BSP/POMDP with Hybrid & Mixture Beliefs

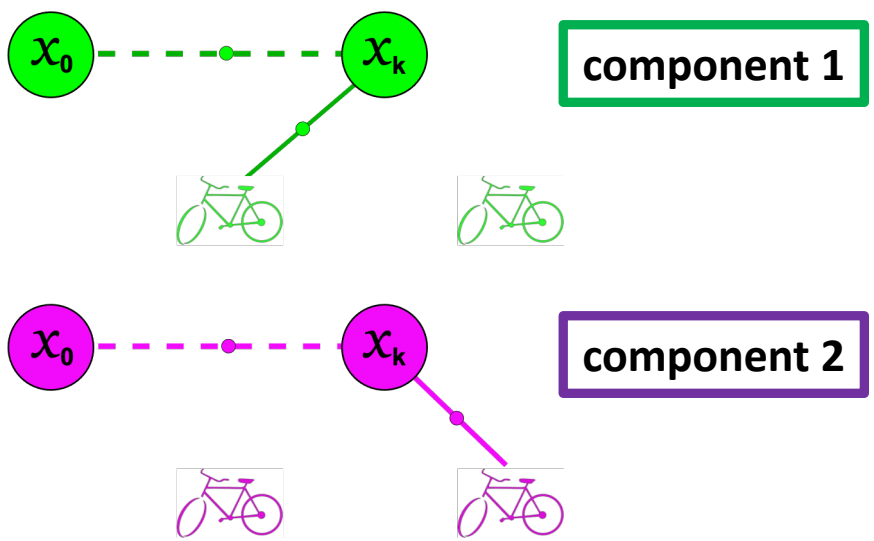
[Pathak, Thomas and Indelman, IJRR'18]

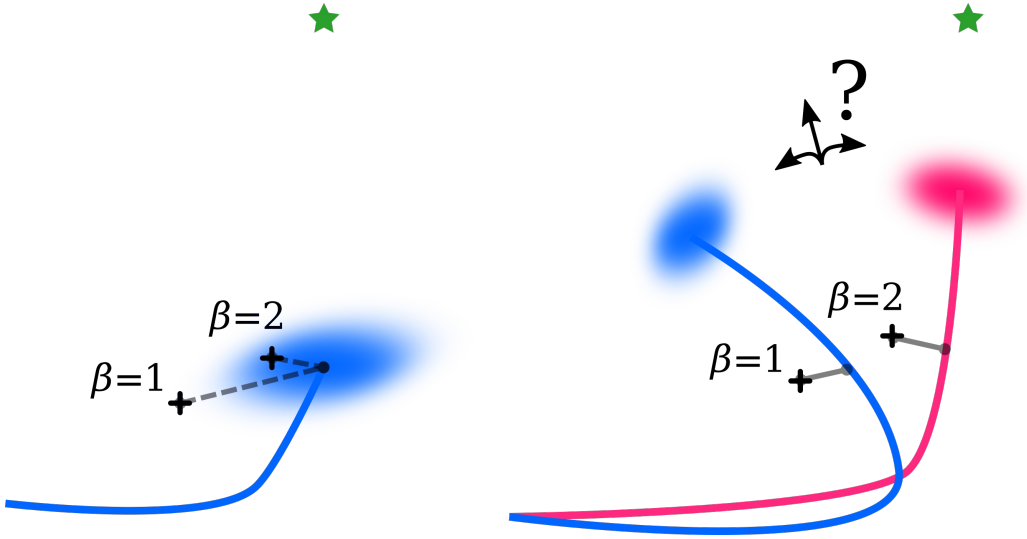
- Reason about hypotheses within inference and planning
- Hybrid belief over continuous and discrete variables: $\mathbb{P}(X_k, \beta_{0:k} \mid \mathcal{H}_k)$

(e.g. agent state) (e.g. data association & classification hypotheses)

- Belief over agent state is represented by a mixture density (e.g. GMM): $b[X_k] = \sum_i w_k^i b^i[X_k]$

- Example: data association hypotheses:

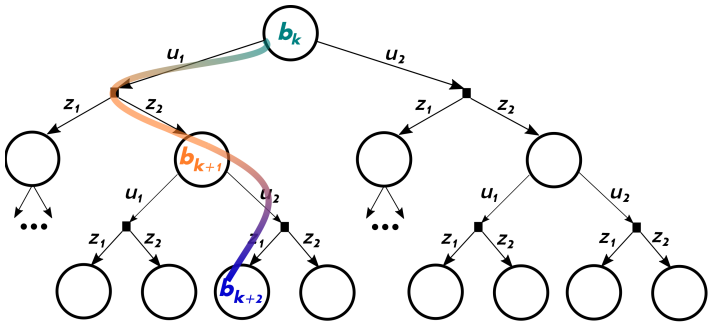




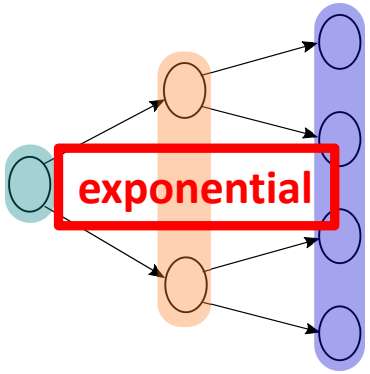
Simplification of BSP/POMDP with Hybrid Beliefs

[Shienman and Indelman, ICRA'22, Outstanding Paper Award Finalist; ISRR'22][Barenboim, Shienman and Indelman, arXiv'22] [Barenboim, Lev-Yehudi and Indelman, arXiv'23]

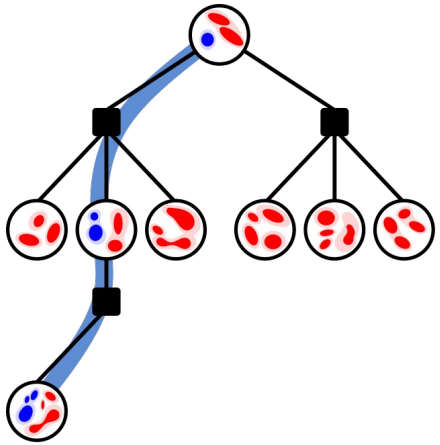
Belief tree



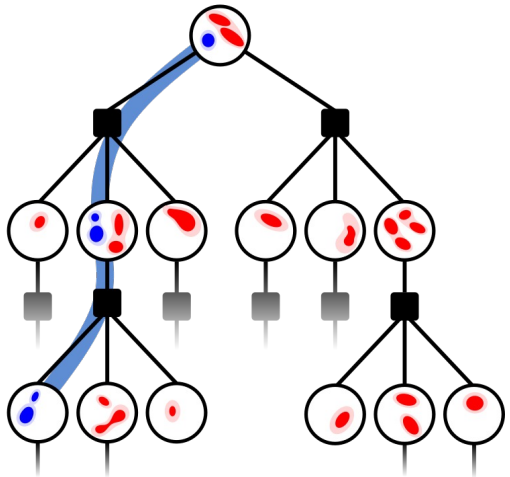
Hypothesis tree



Belief tree with **all** hypotheses



Belief tree with a **subset** of hypotheses



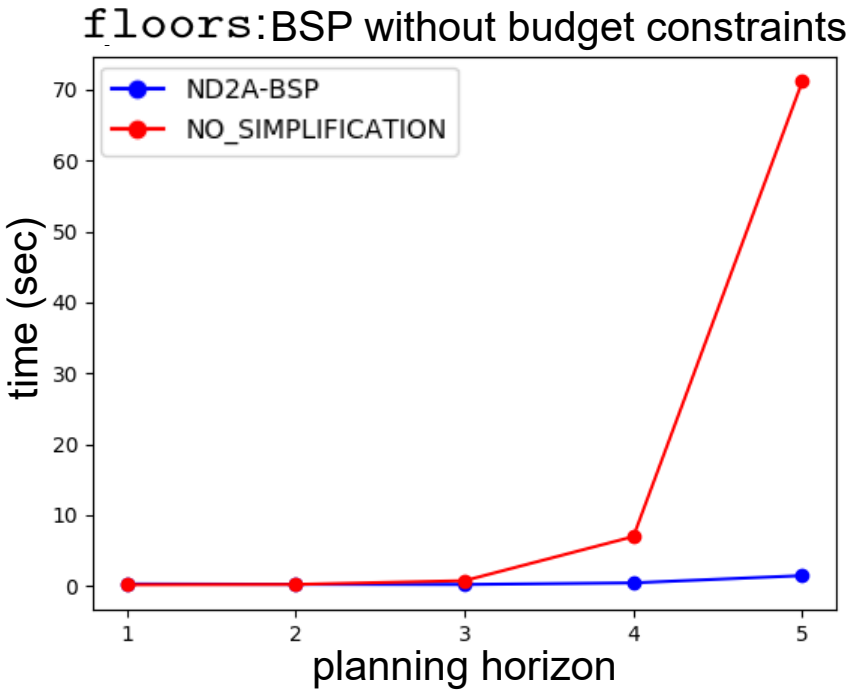
Concept:

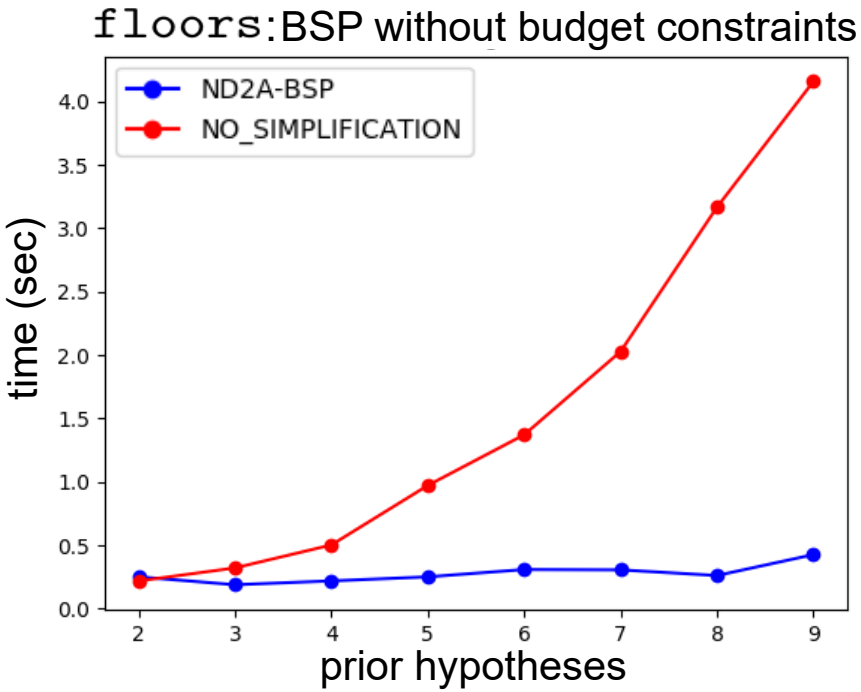
- Instead, utilize only a **subset** of hypotheses
- Derive reward bounds, given planning task (reward)
  - Disambiguate between hypotheses
  - Navigate to a goal
  - ..

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

Simplification of BSP/POMDP with Hybrid Beliefs

[Shienman and Indelman, ICRA'22, Outstanding Paper Award Finalist; ISRR'22][Barenboim, Shienman and Indelman, arXiv'22] [Barenboim, Lev-Yehudi and Indelman, arXiv'23]





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

A Glimpse Into Autonomous Perception and Planning Under Uncertainty

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

Viewpoint-Dependent Semantic Perception

Ambiguous Data Association

Belief Space Planning (BSP)

Simplification of BSP Problems

A Glimpse Into Autonomous Perception and Planning Under Uncertainty

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