Online Simplified Belief Space Planning with Performance Guarantees

Vadim Indelman

TECHNION
Israel Institute of Technology

ANPL
Autonomous Navigation and Perception Lab

Technion Robotics Expo

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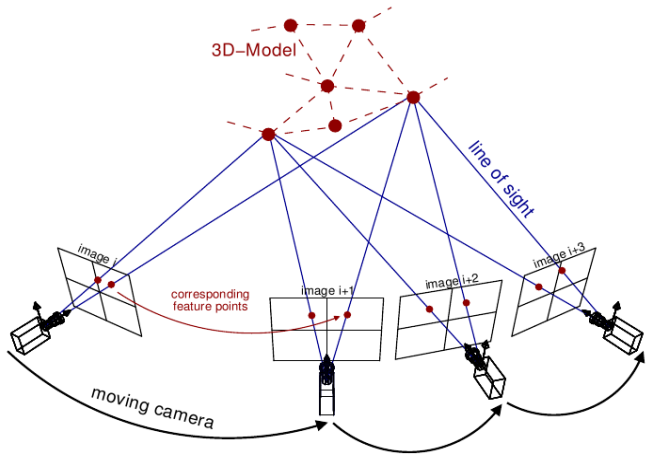
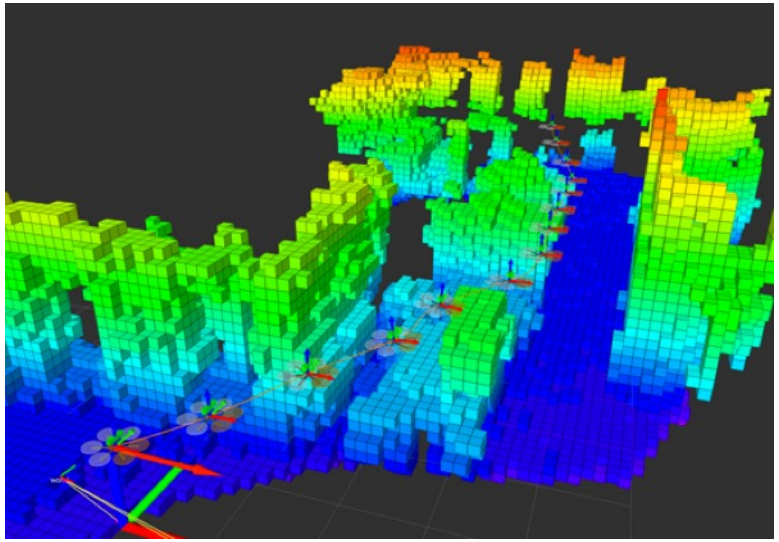
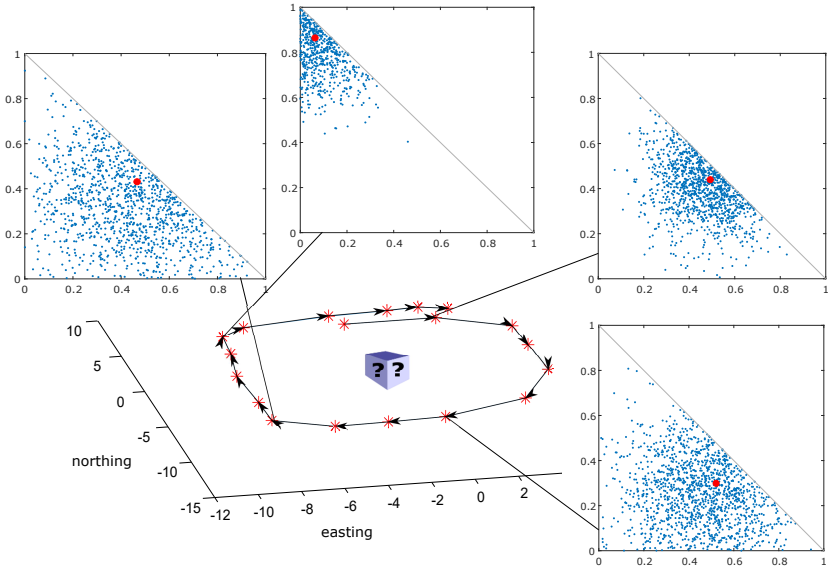
Introduction

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:

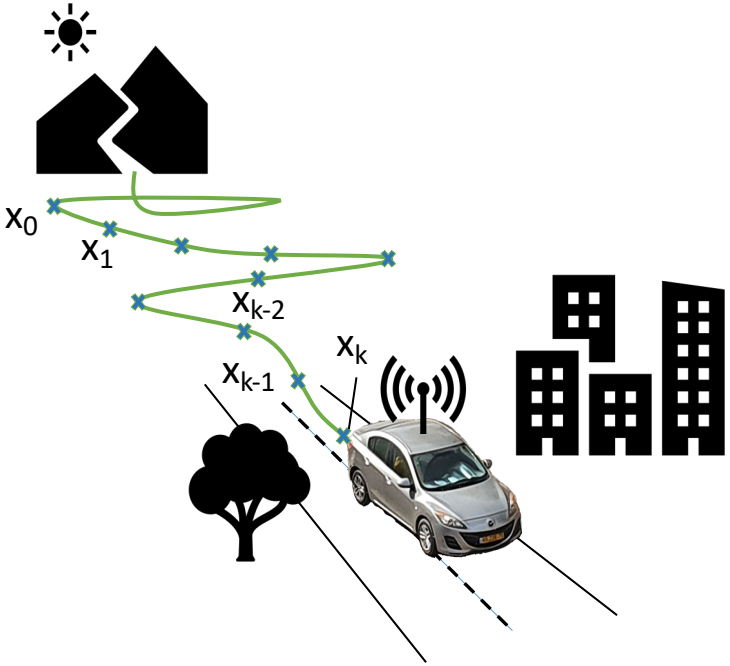
$$b[X_k] \doteq \mathbb{P}(X_k \mid u_{0:k-1}, z_{1:k})$$

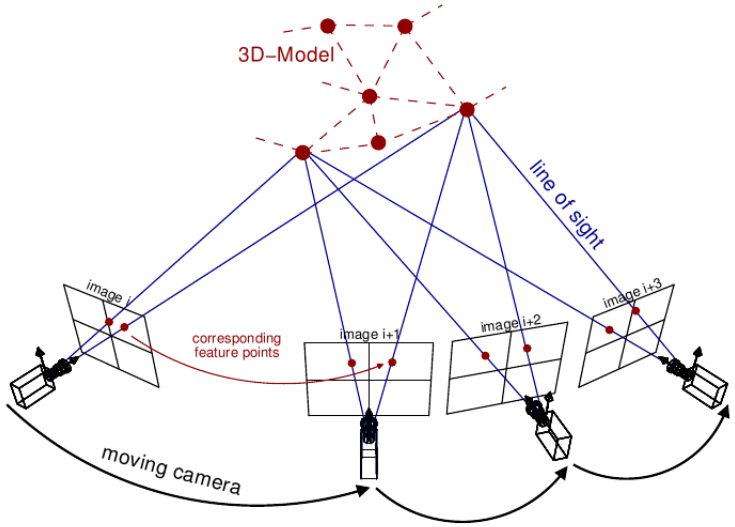
state/variables at time instant k — user controls — observations

- Example:

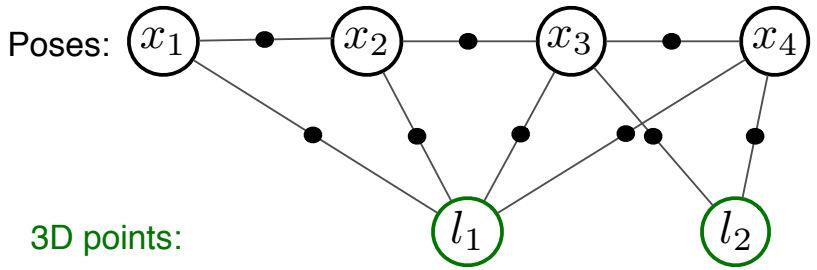
$$X_k \doteq \{x_0, \ldots, x_k, L_k\}$$

Past & current robot states — Landmarks





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



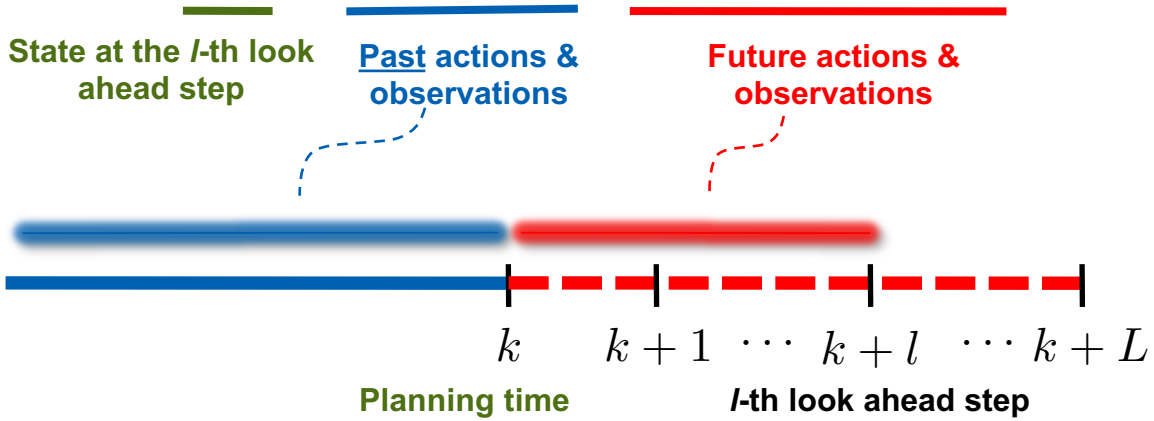
Belief Space Planning (BSP)

- Objective function:

$$J(b[X_k], a) = \mathbb{E}\{\sum_{l=0}^{L-1} r(b[X_{k+l}], a_{k+l}) + r(b[X_{k+L}])\}, \quad a \doteq a_{k:k+L-1} \in \mathcal{A}$$

- Belief at the l-th look-ahead step:

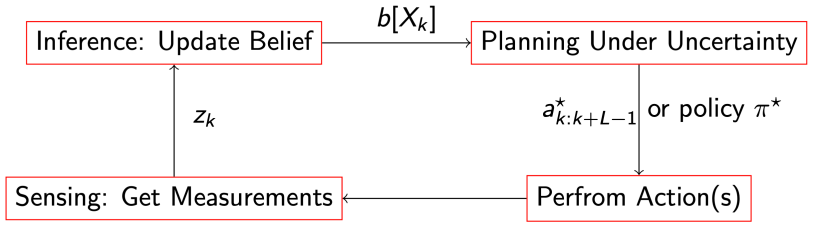
$$b[X_{k+l}] \doteq \mathbb{P}(X_{k+l} \mid u_{0:k-1}, z_{0:k}, u_{k:k+l-1}, z_{k+1:k+l})$$

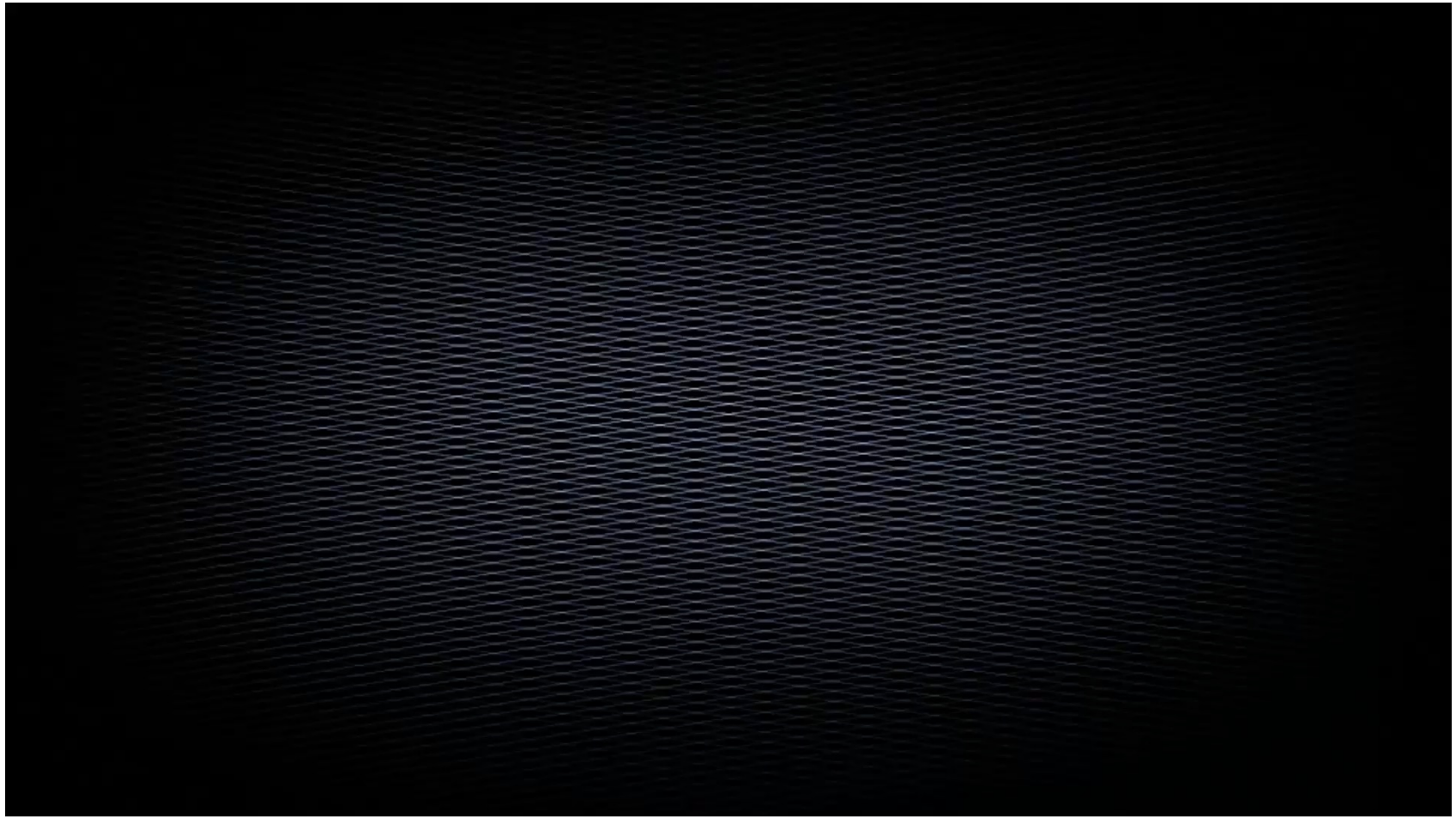


- Examples for reward function $r(b, a)$:
  - Distance to goal (navigate to a goal)
  - Information theoretic reward (reduce uncertainty, exploration)
  - …

Collaborative BSP in Unknown Environments on Quads

Plan-act-sense-infer framework





Belief Space Planning (BSP)

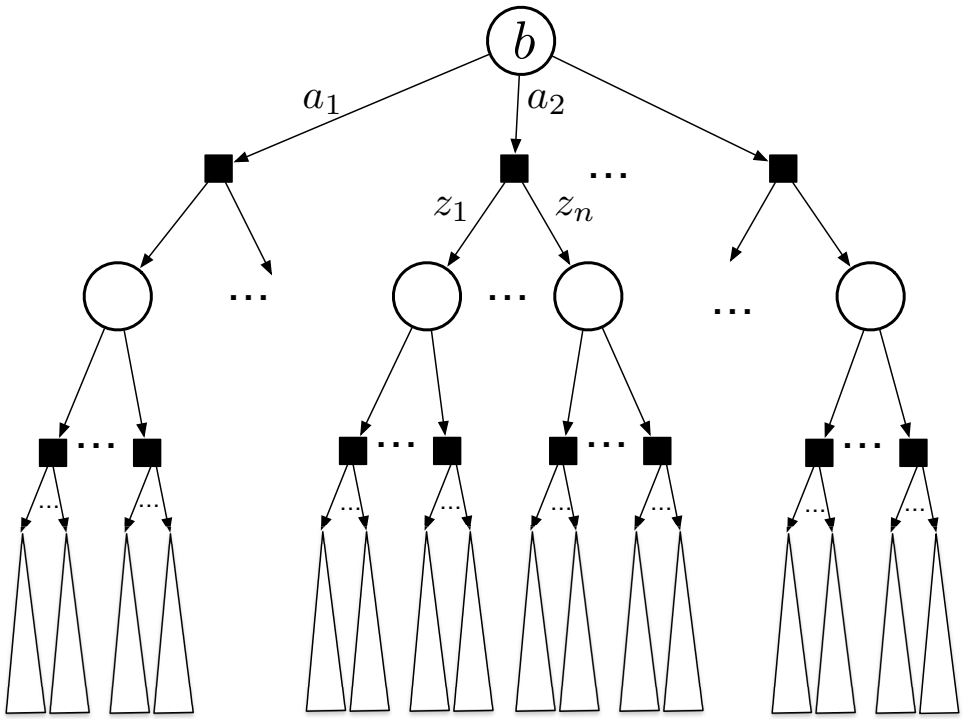
Action sequences:

$$J(b[X_k], a) = \mathbb{E}\{\sum^{L-1} r(b[X_{k+l}], a_{k+l}) + r(b[X_{k+L}])\}, \quad a \doteq a_{k:k+L-1} \in \mathcal{A}$$

Policies:

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

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



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- Finding an optimal solution is generally **computationally intractable**
- **Our focus - want to:**
  - Act autonomously, **online**, while accounting for different sources of uncertainty and ambiguity
  - Reliably operate in **uncertain, perceptually aliased** environments/scenarios
  - Acquire **high-level / semantic** environment understanding
  - Support **belief-dependent** rewards (e.g. information-theoretic)

Simplification of Decision-Making Problems

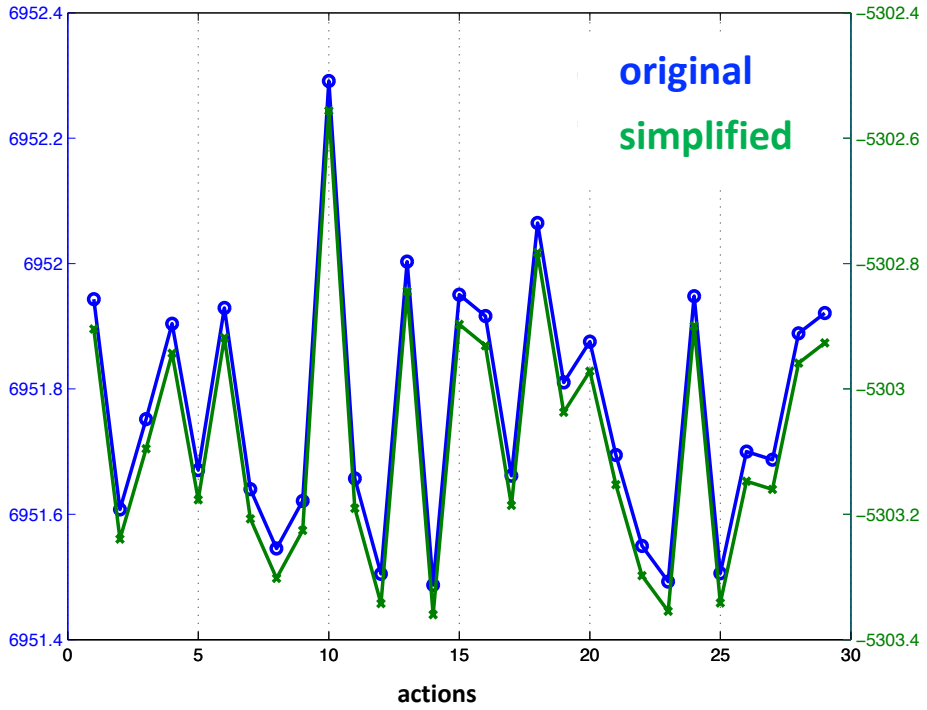
Concept:

- 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]

- **Key observation**: In decision making, only need to sort actions from best to worst
- **Action-consistent** simplification: preserves order between actions w.r.t. original problem

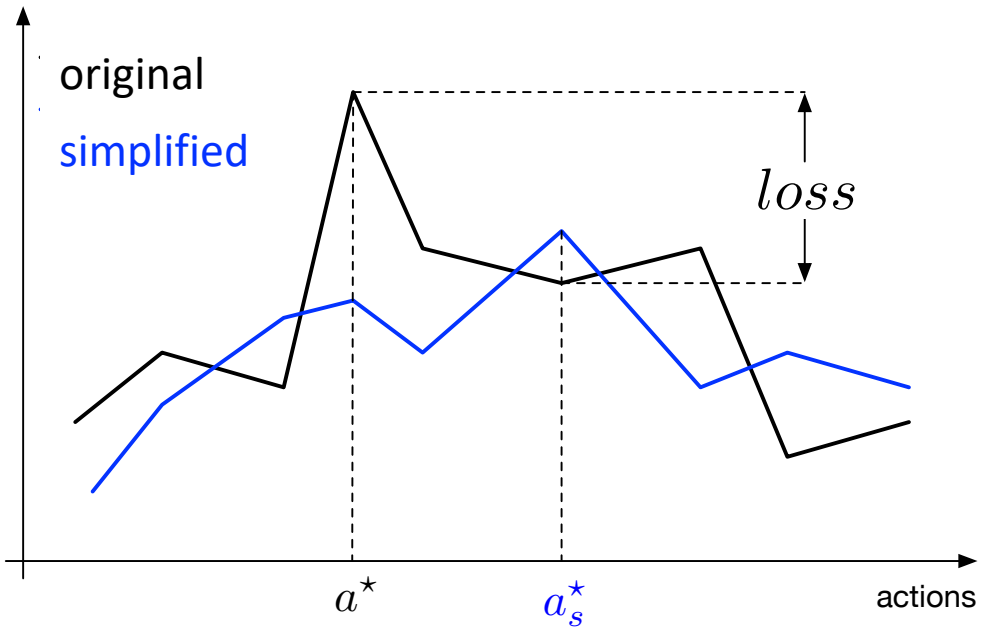


Same optimal action!

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) bounds on $loss$!

Simplification of Decision-Making Problems

Concept:

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

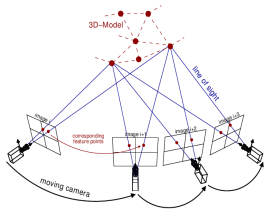
Specific simplifications with performance guarantees developed @ANPL include:

- 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

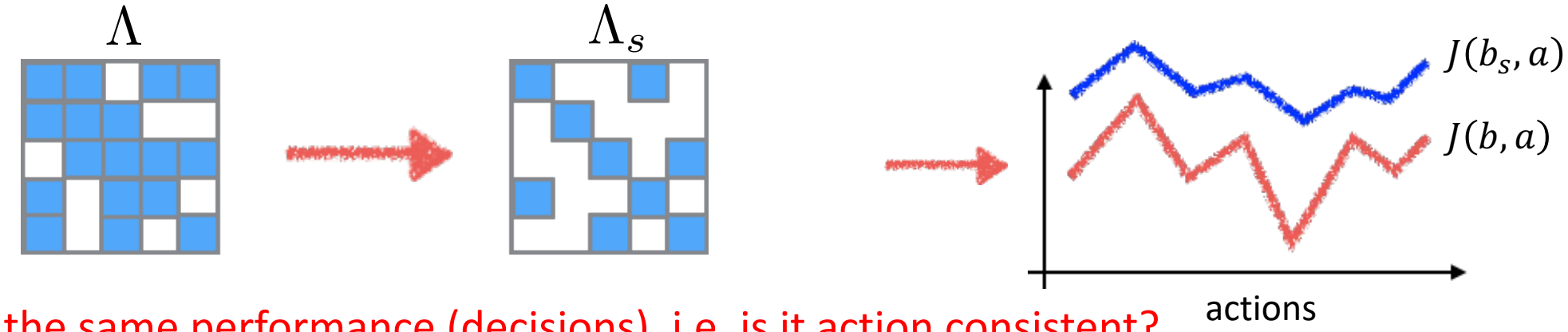
[Indelman RA-L'16][Elimelech and Indelman, IJRR'22]

- 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?

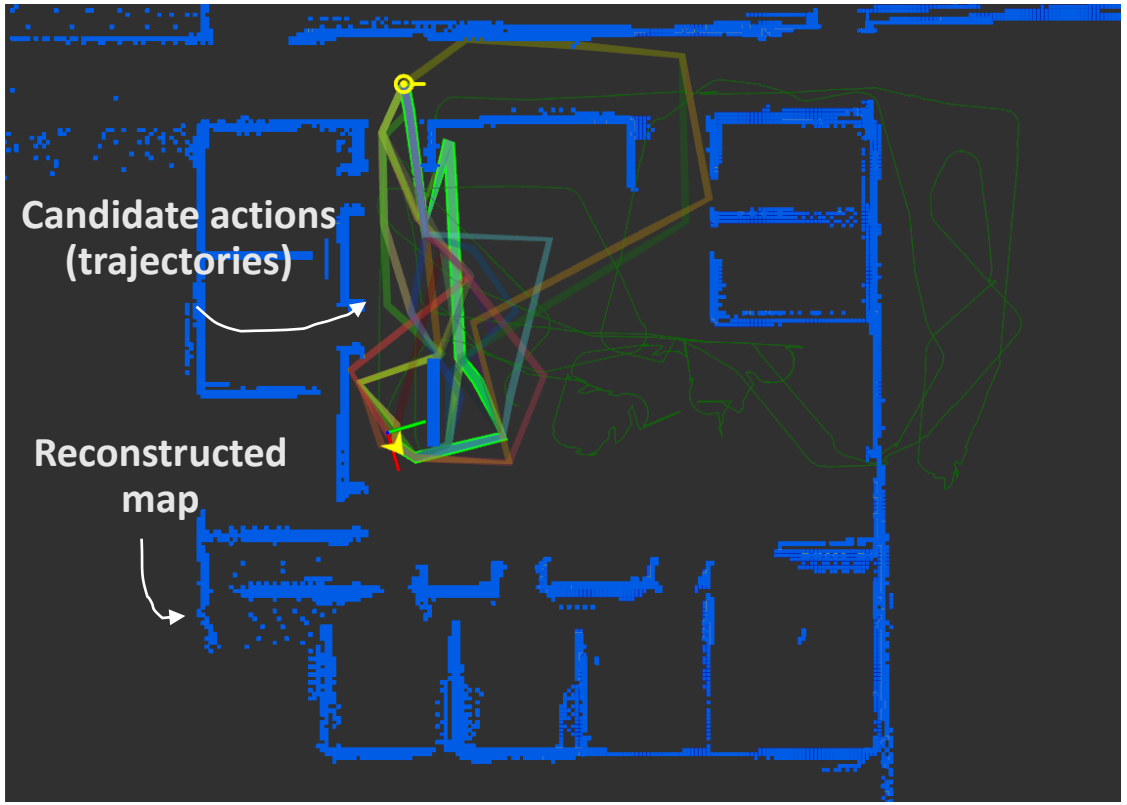
Belief Sparsification for BSP

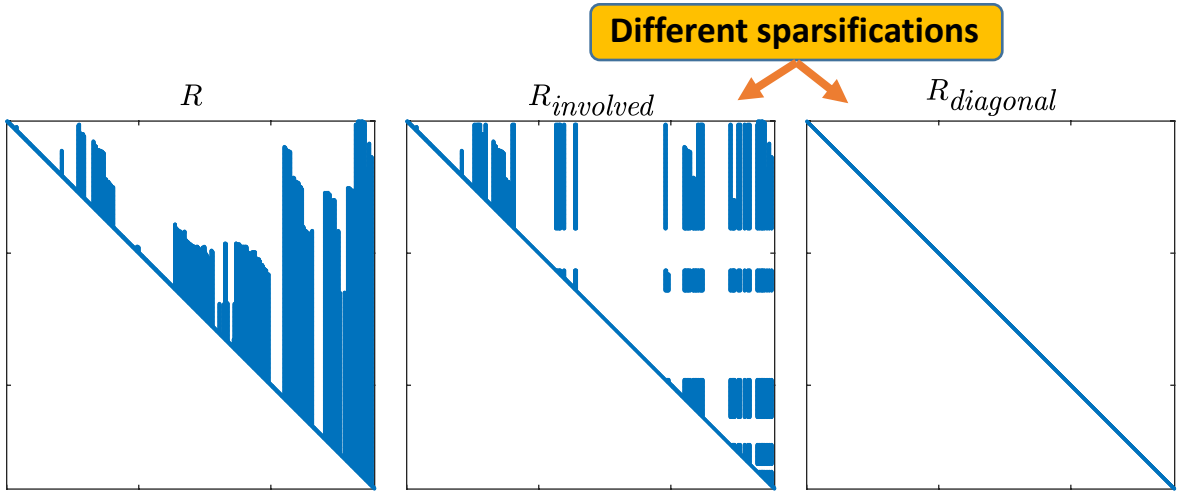
[Elimelech and Indelman, IJRR'22]

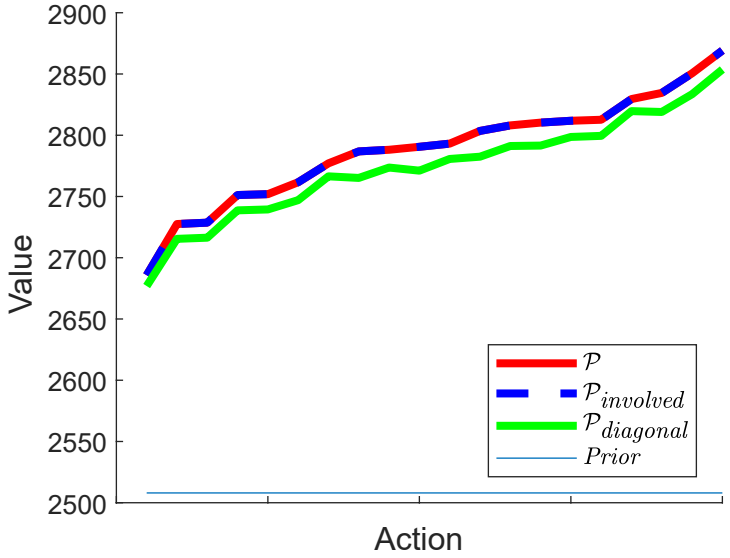
- Agent performs simultaneous localization and mapping
- Maintains a multivariate Gaussian belief

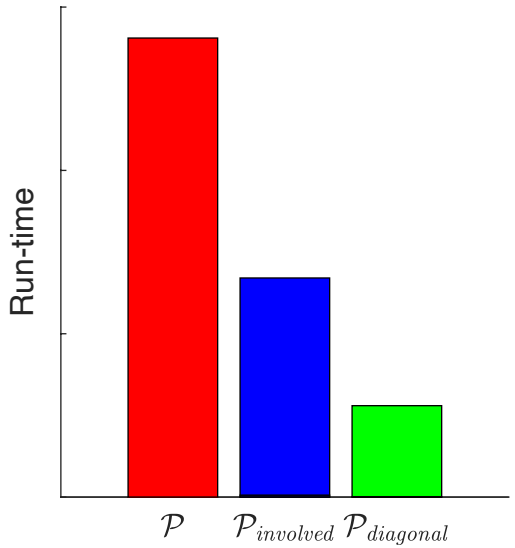
$$b[X] = \mathcal{N}(X^\star, (R^T R)^{-1})$$

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







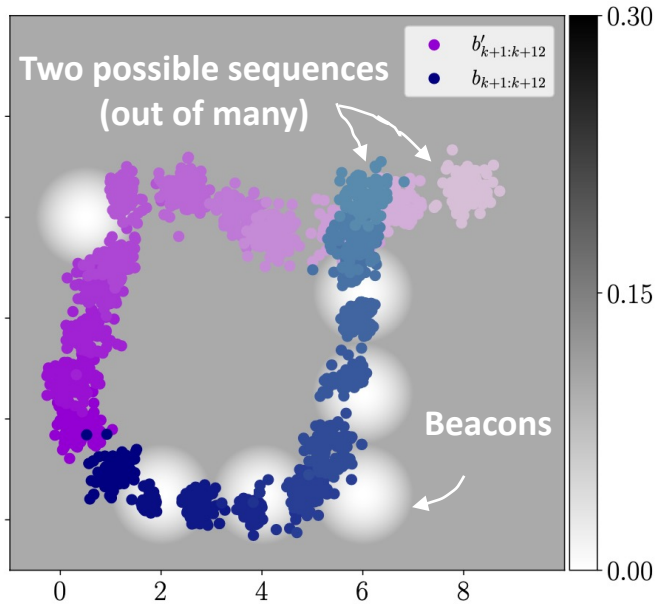


Simplificaiton of BSP with Nonparametric Beliefs

[Sztyglic and Indelman, arXiv'21][Sztyglic, Zhitnikov and Indelman, arXiv'21]

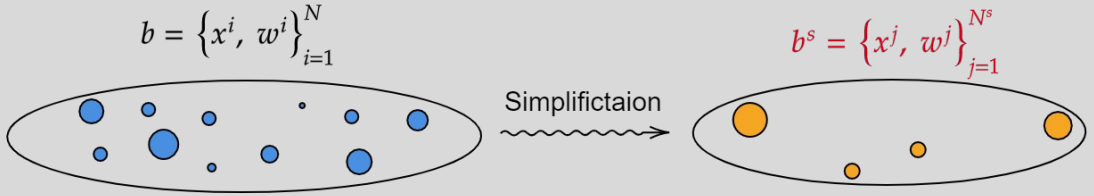
- BSP with nonparametric beliefs represented via samples

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



Simplification:

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

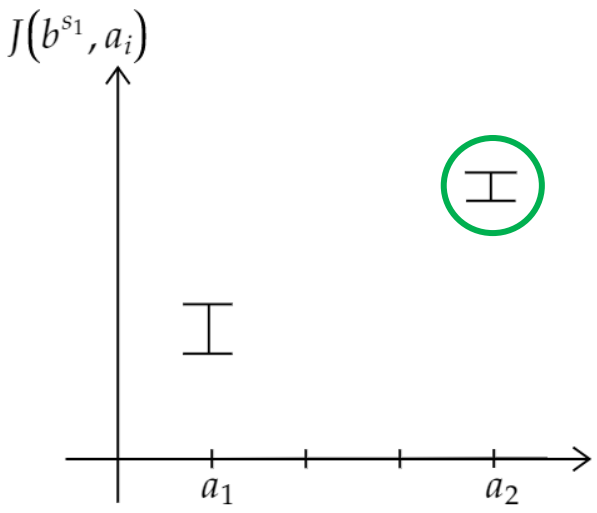


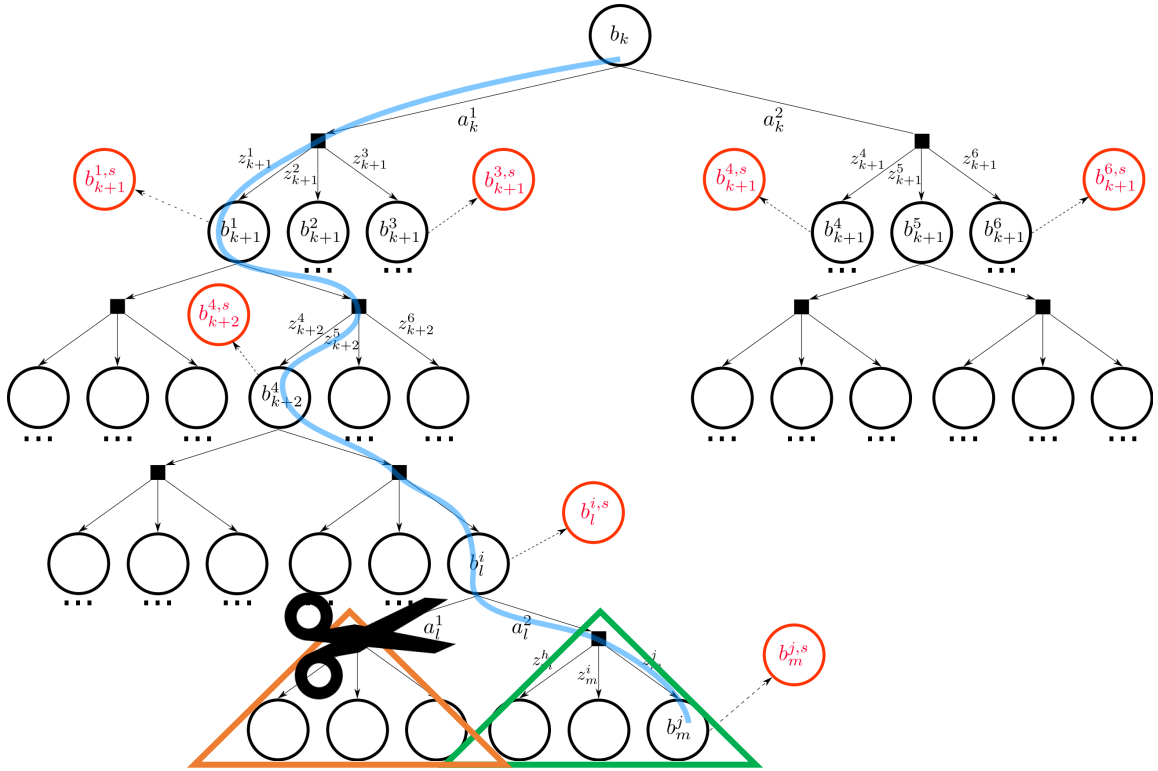
$$lb(b,b^s,a) \leq r(b,a) \leq ub(b,b^s,a)$$

Simplificaiton of BSP with Nonparametric Beliefs

[Sztyglic and Indelman, arXiv'21][Sztyglic, Zhitnikov and Indelman, arXiv'21]

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

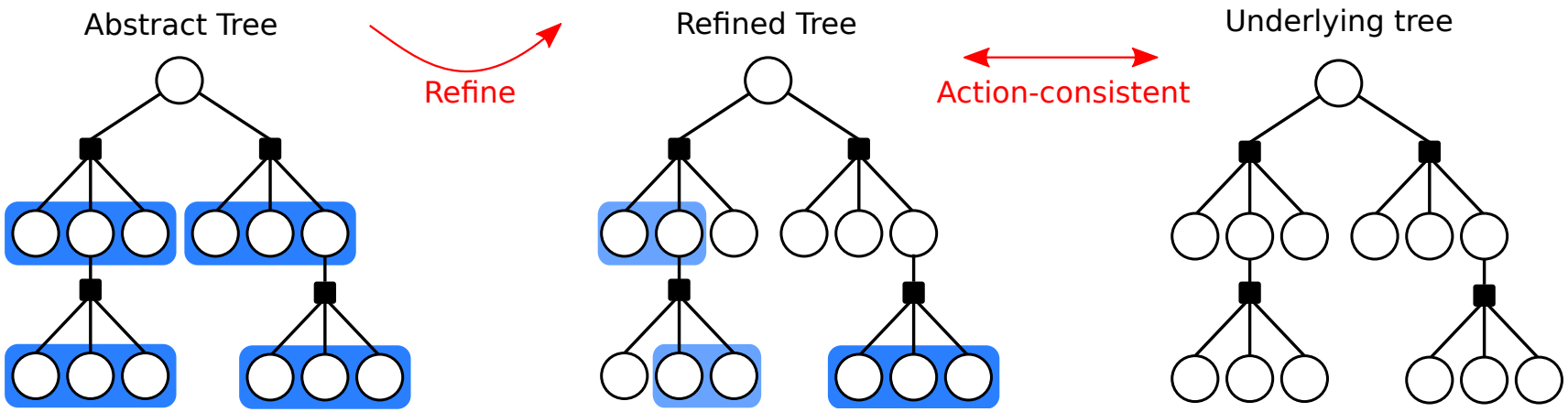


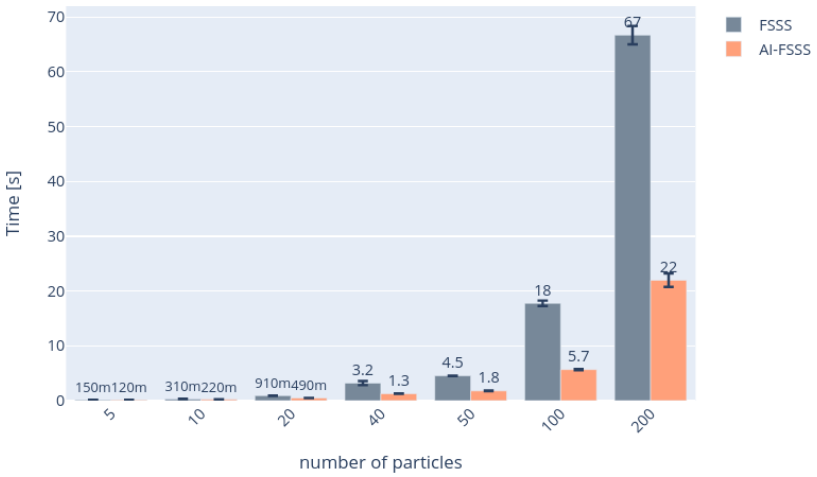


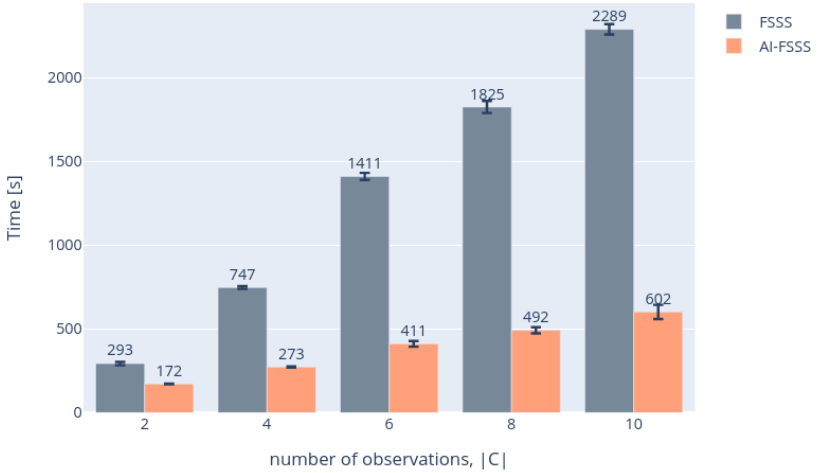
Adaptive Information Belief Space Planning

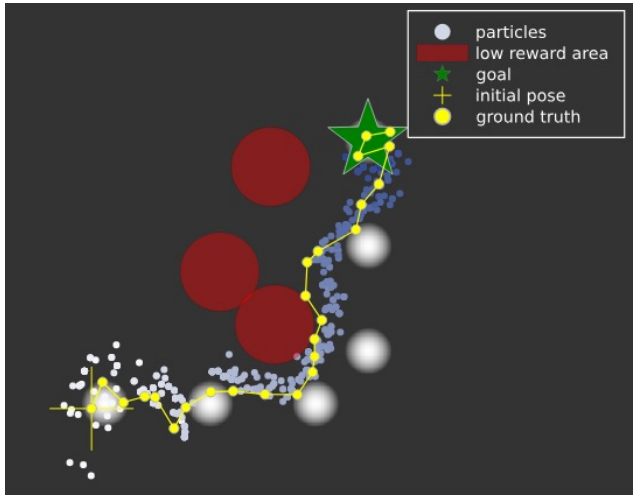
[Barenboim and Indelman, IJCAI'22]

- Adaptive aggregation scheme via an abstract observation model





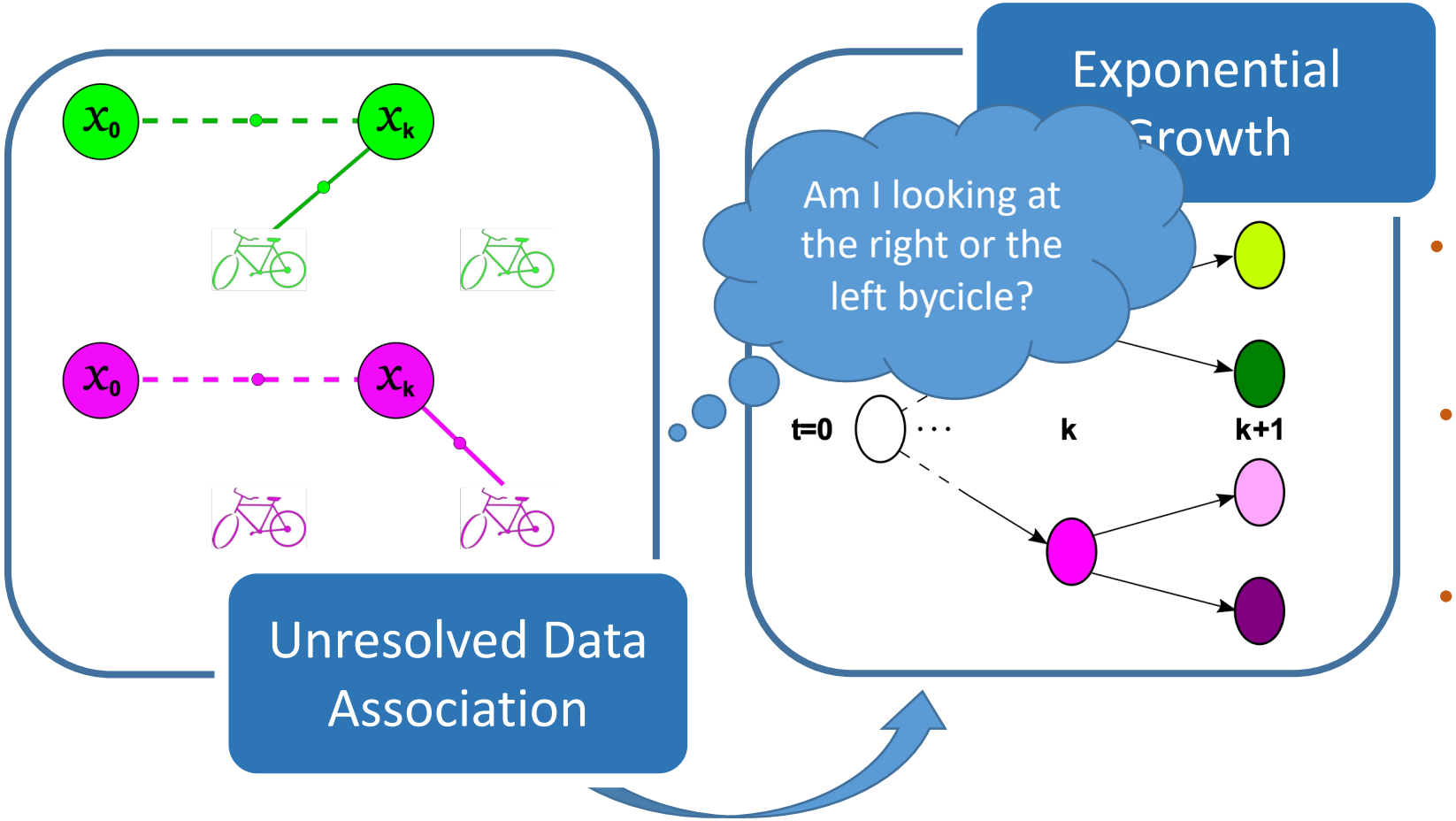




D2A-BSP: Distilled Data Association Belief Space Planning with Performance Guarantees Under Budget Constraints

[Shienman and Indelman, ICRA'22, Outstanding Paper Award Finalist]

Consider ambiguous/aliased environments



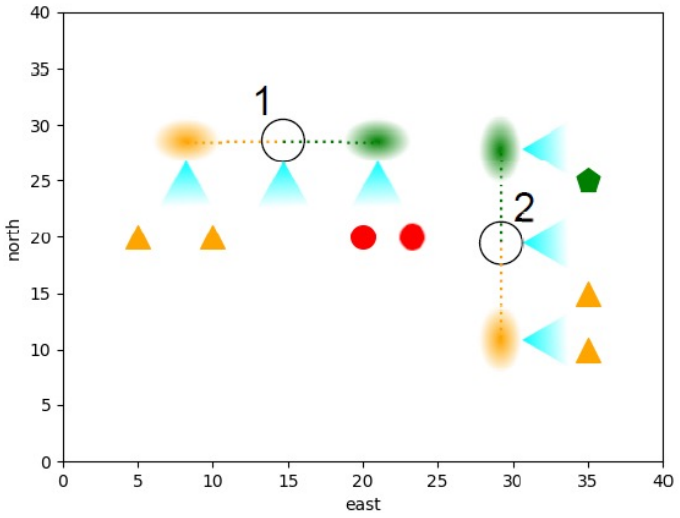
- Goal: plan to **disambiguate** between hypotheses under budget constraints
- Simplification: Utilize only a **distilled subset** of hypotheses
- Provide performance guarantees

D2A-BSP: Distilled Data Association Belief Space Planning with Performance Guarantees Under Budget Constraints

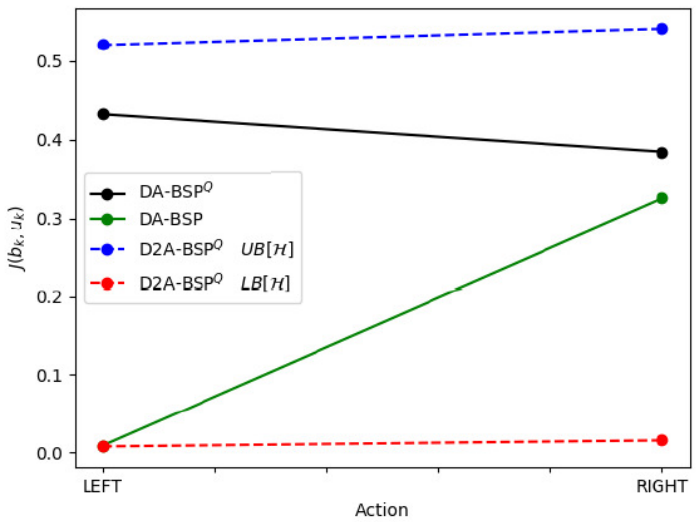
[Shienman and Indelman, ICRA'22, Outstanding Paper Award Finalist]

Goal Disambiguate between hypotheses under budget constraints

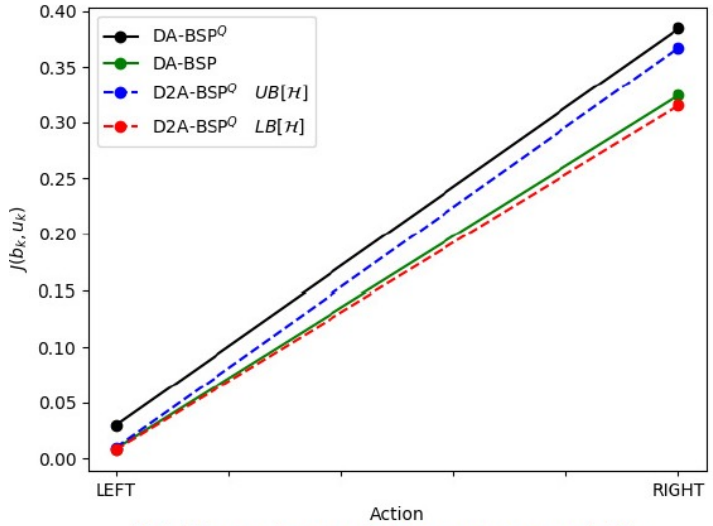
D2A-BSP A novel planning approach that utilizes only a **distilled subset** of hypotheses with performance guarantees



(a) BSP with 2 prior hypotheses



(b) Planning using component #1



(c) Planning using component #2

Conclusions

- **Online Simplified Belief Space Planning with Performance Guarantees**
  - Identify and solve a simplified computationally-easier decision-making problem
  - Provide performance guarantees (via deterministic/stochastic bounds)

→ Yields significant speed-up in planning with no (or bounded) loss in performance

- See additional research directions on ANPL website!

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