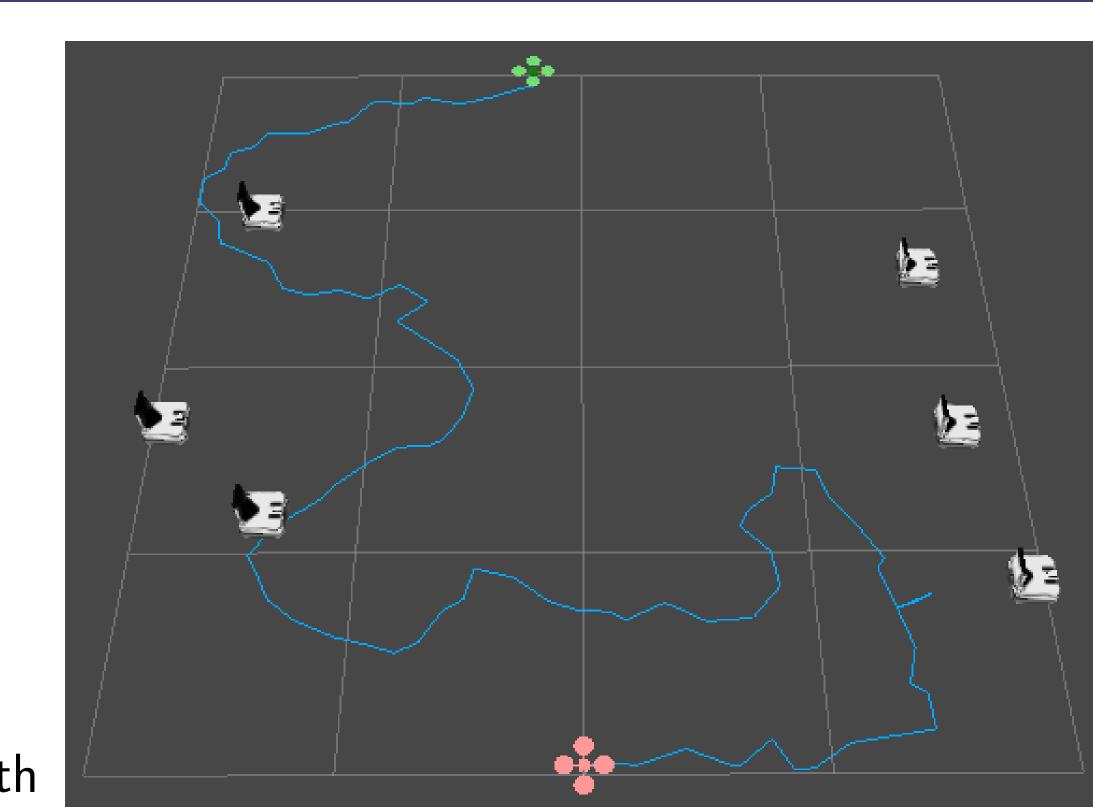
Dodger: Generating Safe Trajectories in Stochastic Dynamic Environments by Leveraging Information about Obstacle Motion

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PROBLEM FORMULATION

- Develop a dynamic obstacle representation that
- accounts for the obstacle's motion
- provides higher costs for paths intersecting their trajectories
- Compute a motion trajectory that:
 reaches the goal region
- avoids collisions with static and dynamic obstacles
- uses imperfect information about obstacle motion to generate a quantitatively safe path

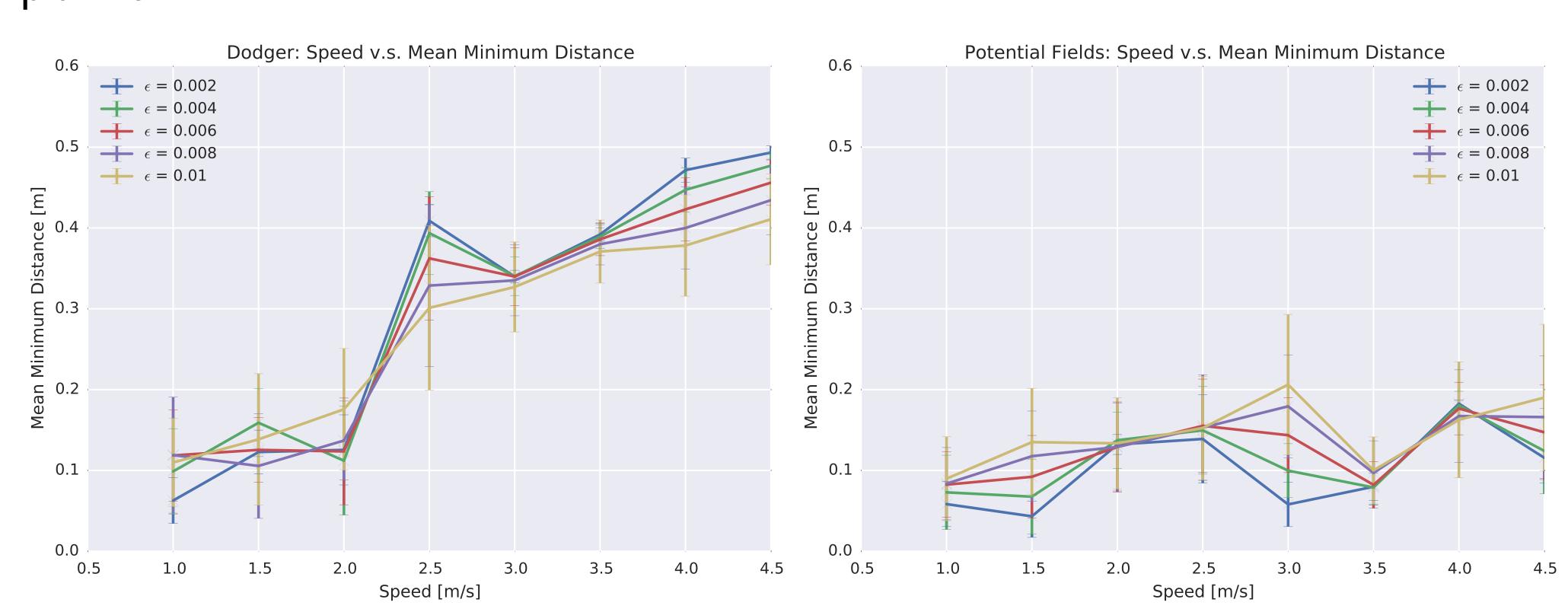


Utilizing information about how the obstacle will move can aid a motion planner to generate paths that will be less likely to lead a robot into a collision

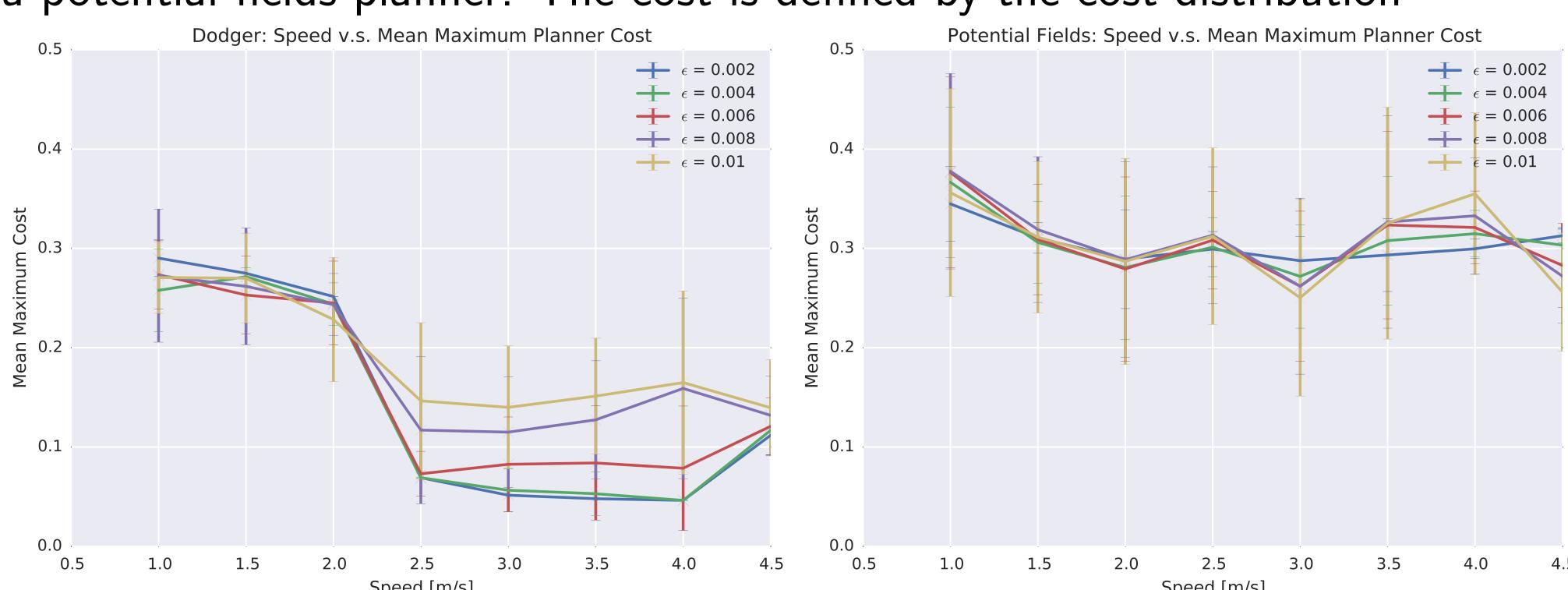
However, perfect information about the motion of obstacles is almost always not readily available or easy to compute since they may veer off their predicted trajectory

EXPERIMENTAL RESULTS

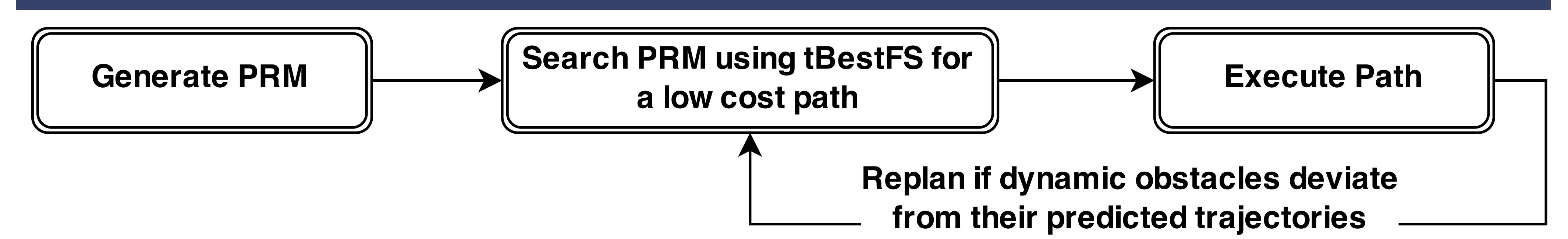
Average minimum distance to any obstacle compared to a potential fields planner



Maximum cost incurred by the robot along the paths generated by Dodger and a potential fields planner. The cost is defined by the cost distribution



APPROACH



1. Dynamic Obstacle Representation

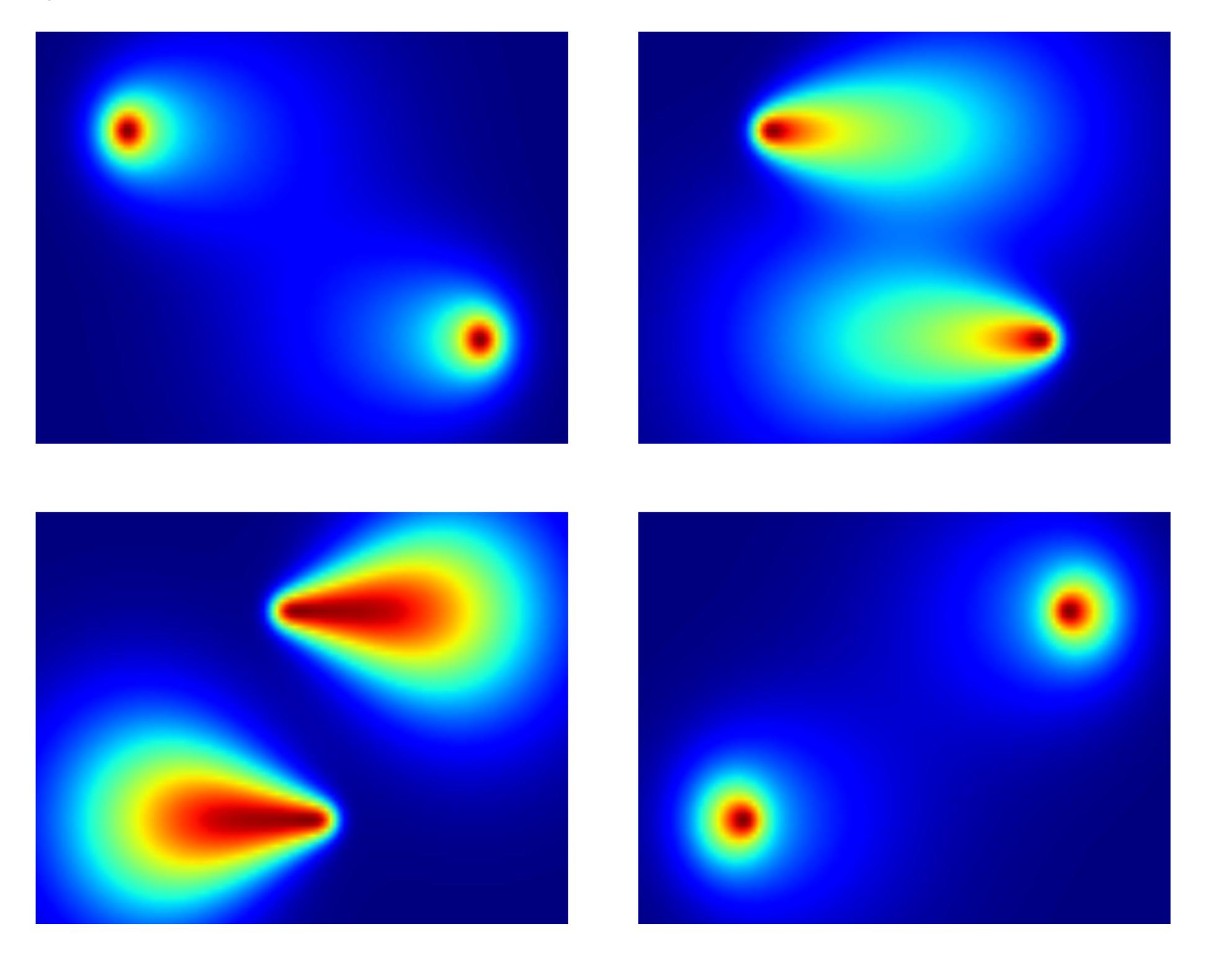
A dynamic obstacle is represented by five variables:

- I is the initial configuration of the obstacle,
- ullet is a function, $\zeta:\mathbb{R}^+ o\mathbb{R}^2$, representing the velocity of the obstacle
- ullet is used to define a random variable $ho \sim \mathcal{U}(-\epsilon,\epsilon)$
- $ullet \xi$ is the last known configuration of the obstacle used for extrapolation
- ullet T is the time at which ξ was recorded

The cost distribution for a single dynamic obstacle used as a heuristic for planning is:

$$P_a(x,y,t_0,t_m) = \frac{1}{t_m} \cdot \int_{t_0}^{t_m} \mathcal{N}(\zeta_a(t),\alpha \cdot (t-t_0)^2 + \beta,x,y) \cdot (t_m-t+1)^{\gamma} dt$$

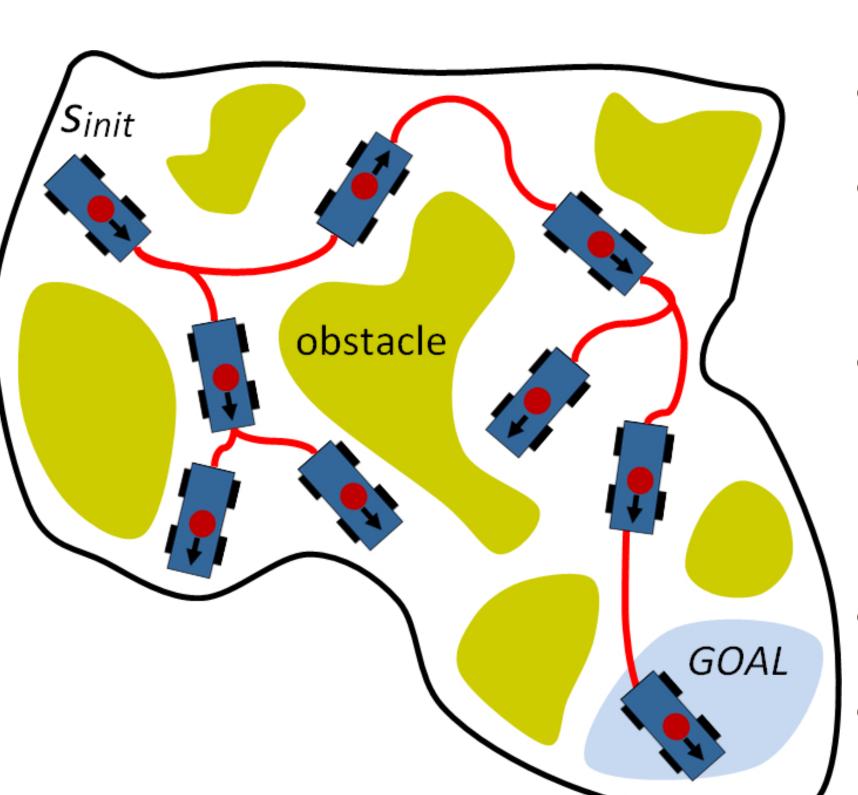
Where $[t_0, t_m]$ defines the interval for which the cost distribution is evaluated on. This serves to represent the likelihood of an obstacle moving to an (x, y) location between for a time t such that $t_0 \le t \le t_m$



2. Generating the Probabilistic Roadmap (PRM)

- constructed over the configuration space of the robot
- used to guide the expansion of the temporal graph search

3. Motion Tree



- defined as $\mathcal{T} = (V_{\mathcal{T}}, E_{\mathcal{T}})$
- each vertex $v \in V_{\mathcal{T}}$ associated with a collision-free state
- each edge $(v_i, v_j) \in E_T$ associated with a collision free and dynamically feasible trajectory from v_i to v_j
- rooted at the initial state
- expanded by adding new vertices and edges

4. Grouping of Tree Vertices

ullet roadmap configuration $c \in V_{RM}$ acts as Voronoi site containing tree vertices that have c as their closest roadmap configuration

 $\operatorname{group}_{\mathcal{T},c} = \{s : s \in \mathcal{T} \land c = \operatorname{NearestCfgRM}(s)\}$

motion tree partitioned into different groups

$$\operatorname{groups}_{\mathcal{T}} = \{\operatorname{group}_{\mathcal{T},c} : c \in V_{RM} \land |\operatorname{group}_{\mathcal{T},c}| > 0\}$$

5. Selecting a Tree Group for Expansion

select group with maximum weight

weight(group_{$$\mathcal{T},c$$}) = $\alpha^{\text{NrSel(group}_{\mathcal{T},c)}}/\text{hcost}(c)$

- promote expansions from groups with low heuristic costs
- apply selection penalty with $0 < \alpha < 1$ after each selection to avoid overexploration or becoming stuck

6. Expanding the Tree from the Selected Group

- promote expansions along shortest path from c to goal \Rightarrow select a target configuration c_{target} at random from this path
- promote expansions along new directions \Rightarrow select a target configuration c_{target} at random from the entire configuration space
- select vertex v in groups $_{\mathcal{T},c}$ closest to c_{target}
- ullet apply controller to generate trajectory from v toward $c_{
 m target}$