CS 294-115 Algorithmic Human-Robot Interaction **Fall 2016**

Lecture 17: Coordination: Infer/Express Intent

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17.1 Coordination

infer intent from partial trajectories
find paths that convey intent

Motivation

Uses for intent inference: collaboration with other agents, detect malignant intent, provide evolutionary advantage: teamwork, reduce communication overhead, detect how to help.

Infer Intent

Assume that a human H starts in a configuration s and moves toward one of several possible goal states g_i, while robot R is observing and wants to infer H's goal. We would like to derive a method of estimating $P(g|\xi_{s-q})$, the probability g is H's goal given a path ξ_{s-q} from the start configuration to some configuration q.

Since $P(\xi_{s-q}|g)$ is easier to compute than $P(g|\xi_{s-q})$, we will employ the method of Bayesian inference.

$$P(g|\xi_{s-q}) = \frac{P(\xi_{s-q}|g)P(g)}{\sum_{g_i} P(\xi_{s-q}|g_i)P(g_i)}.$$

The prior over goals can be uniform in the absence of any other information. The denominator here is called the partition function, and is generally difficult to compute.

Assume that the robot R has observed H and learned the cost function $\mathcal{U}$ (perhaps through inverse reinforcement learning), and that H is noisily optimal. Then applying the maximum entropy principle, $P(\xi_{s-g}) \propto e^{-\mathcal{U}(\xi_{s-g})}$. Since ξ_{s-q} is not the full path $s-g$, we integrate over all possibilities from $q-g$ to get $P(\xi_{s-q}|g)$:

$$P(\xi_{s-q}|g) = \int_{\xi_{q-g}} P(\xi_{s-q}, \xi_{q-g}|g) = \frac{\int_{\xi_{q-g}} P(\xi_{s-q}, \xi_{q-g})}{\int_{\xi_{s-g}} P(\xi_{s-g})}$$

NOTE: This marginalizes the distribution: $P(A) = \int_b P(A,b)db$, where ξ_{s-q} is the A variable, and ξ_{q-g} is the b variable, all conditioned over g_i.

Assuming $\mathcal{U}$ is additive along the path:

$$P(\xi_{s-q}|g) = \frac{\int_{\xi_{q-g}} e^{-\mathcal{U}(\xi_{s-q})-\mathcal{U}(\xi_{q-g})}}{\int_{\xi_{s-g}} e^{-\mathcal{U}(\xi_{s-g})}}$$

Computing the above expression is difficult. In low dimensional spaces, can use softmax value iteration. In high dimensional spaces, Monte Carlo sampling, dimensionality reduction and featurizing can be used.

Another technique is Laplace's method: approximate $\mathcal{U}(\cdot)$ as a quadratic function around (ideally) its minimum, so that $e^{-\mathcal{U}(\cdot)}$ is a Gaussian integral. For example, for paths from s to g, we assume ξ^*_{s-g} as the optimal path from s to g under $\mathcal{U}$, and:

$$\mathcal{U}(\xi) \approx \mathcal{U}(\xi^*_{s-g}) + \frac{1}{2}\|\xi - \xi^*_{s-g}\|^2_{\nabla^2\mathcal{U}}$$

With this approximation:

$$\int_{\xi_{s-g}} e^{-\mathcal{U}(\xi_{s-g})} \approx e^{-\mathcal{U}(\xi^*_{s-g})} \cdot \int_{\xi_{s-g}} e^{-\frac{1}{2}\|\xi_{s-g}-\xi^*_{s-g}\|^2_{\nabla^2\mathcal{U}}}$$

The same approach can be used to approximate the integral over paths from $q-g$ when estimating $P(\xi_{s-q}|g)$. Additionally, in the case where $\mathcal{U}$ is quadratic:

$$P(g|\xi_{s-q}) = \frac{e^{-\mathcal{U}(\xi_{s-q})-\mathcal{U}(\xi^*_{q-g})+\mathcal{U}(\xi^*_{s-g})}}{\sum_{g_i} P(\xi_{s-q}|g_i)P(g_i)} P(g) \propto \frac{e^{-\mathcal{U}(\xi^*_{q-g})}}{e^{-\mathcal{U}(\xi^*_{s-g})}} P(g)$$

Notice here that $e^{-\mathcal{U}(\xi_{s-q})}$ cancels out from top and bottom. This is a product of the Markov assumption in formulating the problem, although this assumption may be faulty. The proportionality constant is based on the evaluation of the Hessian component.

The intuition for this formulation: We assign probabilistic weight based on the optimal path frmo $q-g_i$ $\xi^*_{q-g_i}$ compared to the optimal path from $s-g_i$, and compared to the optimal paths to the other goals from the start.

Express Intent

The goal now is for R to find paths from which H can infer the end goal. The robot R models H as doing Bayesian inference as explained in the previous section [assumption backed up by papers next class]. Therefore, the robot needs to solve the following optimization problem

$$\max_{\xi} \int P(g|\xi_{s-\xi(t)})dt$$

with g being the actual robot goal. This has the form of Euler-Lagrange: $\int F(t, \xi(t), \dot{xi}(t))$, and can be solved similarly to before. Notice the best trajectory would be to place the robot immediately at the desired goal. In the case that this is not possible, however, exaggerated actions will increase the distance to other optimal goals more than they perturb from the optimal path to $g^{(R)}$, making it easier to understand intent.