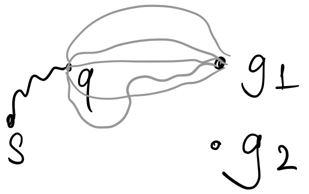
Inferring Intent

ξ_{S-Q}



$P(g_i \mid \xi_{S-Q})$

$\hat{g} = \arg\max_{g_i} P(g_i \mid \xi_{S-Q})$

WHY?

Bayesian Inference! Easier to reason about $P(\xi_{S-Q} \mid g)$

↳ assume that H is approx optimal like in MaxEnt IRL

$$P(\xi_{S-G} \mid g) = \frac{e^{-U(\xi_{S-G})}}{\int_{\bar{\xi}_{S-G}} e^{-U(\bar{\xi}_{S-G})}}$$

$$P(g_i \mid \xi_{S-Q}) = \frac{P(\xi_{S-Q} \mid g_i)\, P(g_i)}{\sum_g P(\xi_{S-Q} \mid g)\, P(g)}$$

$$P(\xi_{S-Q} \mid g) = \int_{\bar{\xi}_{Q-G}} P(\xi_{S-Q}\, \bar{\xi}_{Q-G} \mid g)$$

$$= \int_{\xi_{Q-G}} \frac{e^{-U(\xi_{S-Q}\, \bar{\xi}_{Q-G} \mid g)}}{\int_{\bar{\xi}_{S-G}} e^{-U(\bar{\xi}_{S-G})}}$$

$$= e^{-U(\xi_{S-Q})} \cdot \frac{\int \dots}{\int \dots}$$

$\int_{\bar{\xi}_{Q-G}} e^{-U(\bar{\xi}_{Q-G})}$

$\int_{\bar{\xi}_{S-G}} e^{-U(\bar{\xi}_{S-G})}$

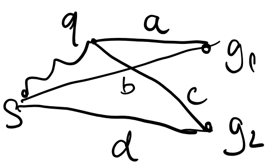
approximate integral via Laplace

$$U[\xi] \approx \underbrace{U[\xi^*]}_{\text{constant}} + \underbrace{\nabla U^T (\xi - \xi^*)}_{0} + \underbrace{\tfrac{1}{2}\|\xi - \xi^*\|^2_{\nabla^2 U}}_{} \to \text{Gaussian Integral}$$

$$P(\xi_{S-q}|g) = e^{-\mathcal{U}(\xi_{S-q})}\ \frac{e^{-\mathcal{U}(\xi^*_{q-g})}\int_{\bar\xi_{q-g}} e^{-\frac{1}{2}\|\bar\xi_{q-g}-\xi^*_{q-g}\|^2_{\nabla^2\mathcal{U}}}}{e^{-\mathcal{U}(\xi^*_{S-g})}\int_{\bar\xi_{S-g}} e^{-\frac{1}{2}\|\bar\xi_{S-g}-\xi^*_{S-g}\|^2_{\nabla^2\mathcal{U}}}}$$

even easier: approximate via $e^{-\mathcal{U}(\xi^*)}$

$$P(g_1|\xi_{S-q}) = \frac{e^{-\mathcal{U}(\xi_{S-q})}\cdot e^{-\mathcal{U}(\xi^*_{q-g_1})+\mathcal{U}(\xi^*_{S-g_1})}P(g_1)}{e^{-\mathcal{U}(\xi_{S-q})}\sum_g\left(e^{-\mathcal{U}(\xi^*_{q-g})+\mathcal{U}(\xi^*_{S-g})}\right)P(g)}$$



$$P(g_1|\xi_{S-q}) = \frac{\cancel{e^{-\mathcal{U}(\xi_{S-q})}}\cdot\frac{e^{-a}}{e^{-b}}}{\cancel{e^{-\mathcal{U}(\xi_{S-q})}}\left(\frac{e^{-a}}{e^{-b}}+\frac{e^{-c}}{e^{-d}}\right)}$$

Expressing Intent

- switch H and R: now H is computing $P(g|\overbrace{\xi_{S-q}}^{\text{R traj}})$
- R wants H to put high prob on g^*

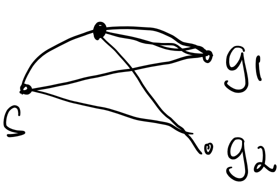
LIS: $\max_\xi \int P(g^*|\xi_{S-\xi(t)})\,dt$.

$\max_g P(g|\xi)$ — intent inference (norm. over g; search over g)

$\max_\xi P(\xi|g)$ — predictability (norm over ξ; search over ξ)

$\max_\xi P(g|\xi)$ — legibility (norm over g; search over ξ)

normalization matters!
⇒ ≠ $\max_\xi P(\xi|g)$
even with uniform prior



optimizing $\mathcal{L}$: gradient descent

$$\nabla_\xi \mathcal{L}(t) = \frac{\partial F}{\partial \xi(t)} - \frac{d}{dt}\cancel{\frac{\partial F}{\partial \xi'(t)}}$$

Let $J_g(q) = \min_{\xi_{q-g}} U(\xi_{q-g})$ — optimal cost to go

$$F(t, \underbrace{\xi(t)}_{q}, \cancel{\xi'(t)}) = \frac{e^{-J_{g^*}(q) + J_{g^*}(S)}}{\sum_g e^{-J_g(q) + J_g(S)}} \begin{matrix} = l \\ \\ = h \end{matrix}$$

assume uniform prior

$$\frac{\partial F}{\partial q} = \frac{l'h - h'l}{h^2} \qquad l' = e^{-J_{g^*}(q) + J_{g^*}(S)} \cdot (-\nabla_q J_{g^*})$$

grad of value function

$$h' = \sum_g e^{-J_g(q) + J_g(S)} (-\nabla_q J_g)$$

for every goal

$$\left.\begin{aligned} l'h &= e^{()} \sum_g e^{()} (-\nabla_q J_{g^*}) \\ h'l &= e^{()} \sum_g e^{()} (-\nabla_q J_g) \end{aligned}\right\} \Rightarrow$$

gradient points in direction $\sum_g \left(\nabla_q J_g e^{()} - \nabla_q J_{g^*} e^{()} \right)$

decrease cost to go to g^*

increase cost to go to others

exaggerates to the left for goal on the east