LHMP2020

2nd Workshop on Long-term Human Motion Prediction

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Exploration/Exploitation in Path Planning Using Probability Propagation *

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$$f(s_1,a_1) = \pi(s_1,a_1);$$

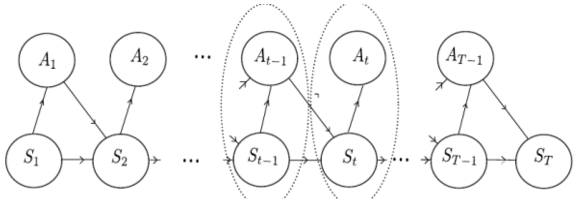
$$f(s_t,a_t) = \sum_{a_{t-1}} p(a_t|s_t,a_{t-1}) \sum_{s_{t-1}} p(s_t|s_{t-1}a_{t-1}) f(s_{t-1},a_{t-1}) \qquad t=2:T$$

$$f(s_T) = \sum_{a_{T-1}} \sum_{s_{T-1}} p(s_T|s_{T-1},a_{T-1}) f(s_{T-1},a_{T-1});$$

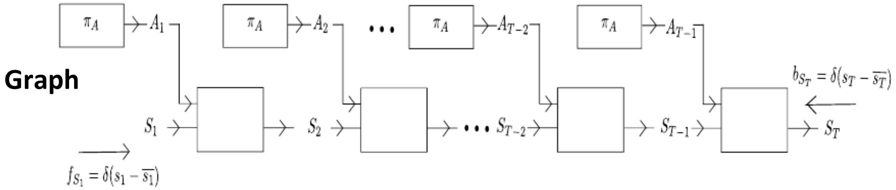
$$b(s_{T-1},a_{T-1}) \propto \sum_{s_T} p(s_T|s_{T-1}a_{T-1}) b(s_T);$$

$$b(s_{t-1},a_{t-1}) \propto \sum_{a_t} p(a_t|s_t,a_{t-1}) \sum_{s_t} p(s_t|s_{t-1}a_{t-1}) b(s_t,a_t) \qquad t=T-1:2$$

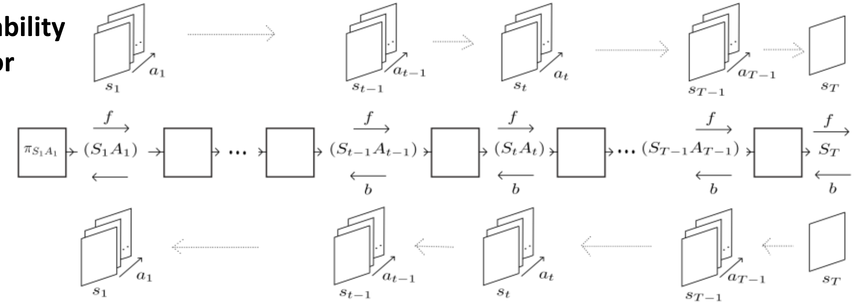
Bayesian Graph



Factor Graph



Probability Tensor Flow



Pure Diffusion

Goal

Start

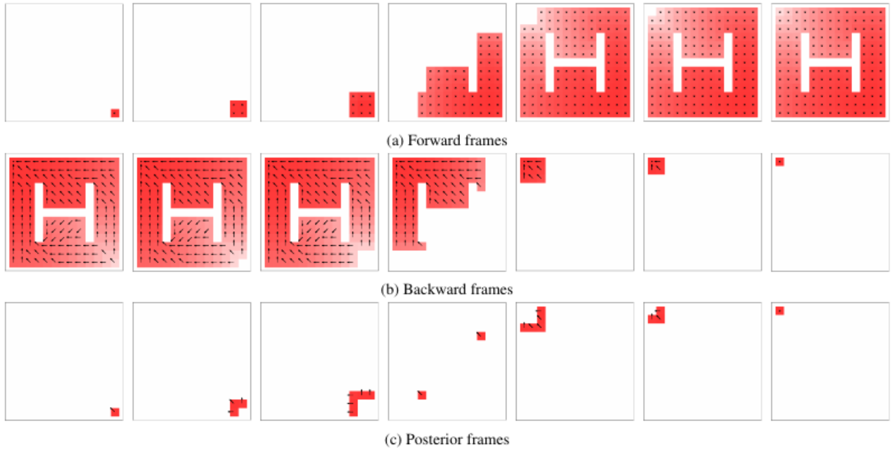
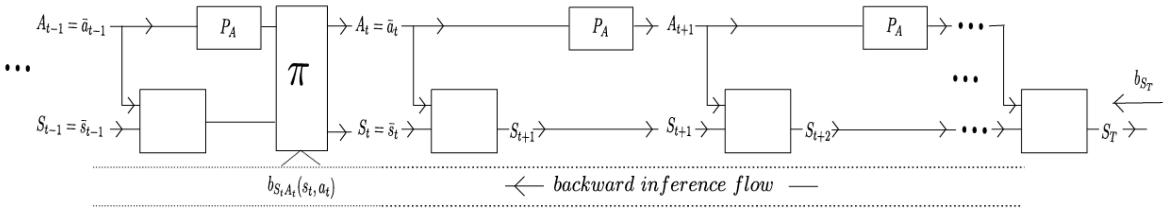


Fig. 2: Flows. From left to right, the snaps are taken at time $t=1, t=2, t=3, t=10, t=18, t=19, t=T=20$

Introducing control using the backward flow



Known MAP and Goal

G-algorithm Outline:

(a) Initialize state (goal) at time $t = T$ with $b_{S_T}(s_t) = \delta(s - \overline{g})$;

(b) Compute the complete backward flow using the last two equations in (4) from $t = T$ to $t = 2$;

(c) Initialize the state and action (start) at time $t = 1$ with $f_{S_1 A_1}(s_1, a_1) = \delta(s_1 - \overline{s}, a_1 - \bar{a})$;

(d) Set $t \leftarrow t + 1$ and compute the forward distribution $f_{S_t A_t}(s_t, a_t)$ using the second equation in (4);

(e) Compute the posterior distribution:

$p_{S_t A_t}(s_t, a_t) \propto f_{S_t A_t}(s_t, a_t) b_{S_t A_t}(s_t, a_t)$;

(f) Set $(S_t, A_t) = (\bar{s}_t, \bar{a}_t) = \text{argmax } p_{S_t A_t}(s_t, a_t)$

(g) Replace forward distribution as:

$f_{S_t A_t}(s_t, a_t) = \delta(s_t = \bar{s}_t, a_t = \bar{a}_t)$

(h) Back to (d) for the next time step.

The algorithm essentially maximizes the likelihood in a greedy fashion. The solution is reached much like in the Viterbi algorithm (poor man's Viterbi) in a large-dimensional space. Therefore, if the time horizon is set to minimum time, the solution is optimal.

Extended to multiple agents:

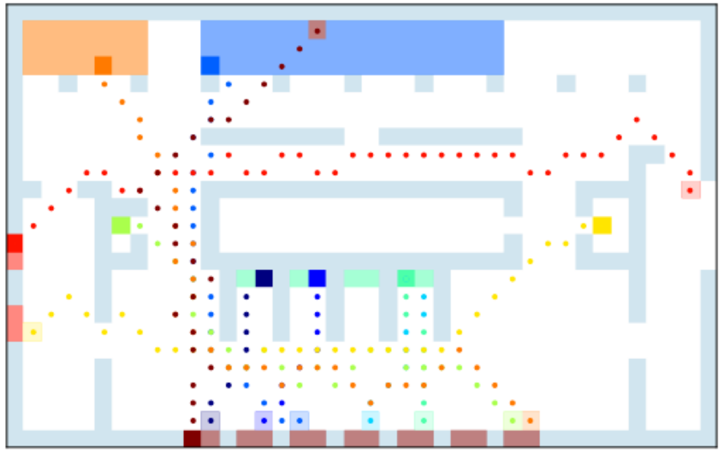


Figure 1. **Agents move in a train station-like environment from their starting positions to their goals**

[13] Francesco A.N. Palmieri, Krishna R. Pattipati, Giovanni Fioretti, Giovanni Di Gennaro, and Amedeo Buonanno, "Path Planning Using Probability Tensor Flow," *arXiv:2003.02774*, sub. for journal publication, II review, 2020.

No knowledge of the map and limited visibility

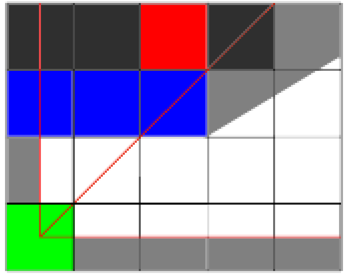


Figure 2. Agent's viewing geometry. The agent (green) looks at 315° (counterclockwise angles) with 90° viewing aperture. Because of the presence of the obstacles (blue), the goal (red) is not visible. The black areas are the invisible regions. We assume that a partially visible cell is visible (gray).

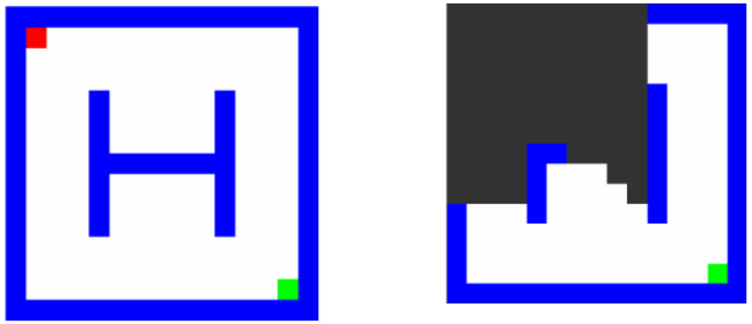
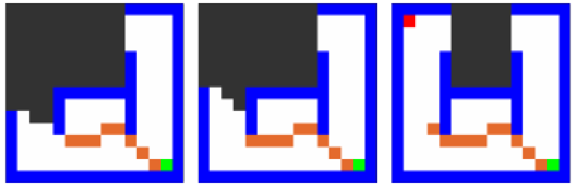
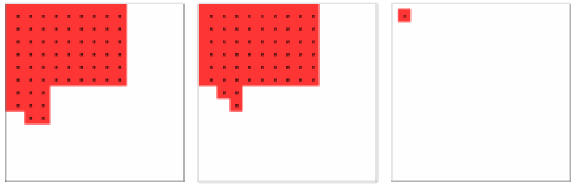


Fig. 10: Limited visibility. The black zone represents the area of the map the agent doesn't know yet.

The unknown map becomes a distributed goal



(a) Exploration frames



(b) Goals exploration frames

Fig. 11: Exploration. The frames show the position of the agent and the known area at $t = 10$, $t = 11$ and $t = 12$.

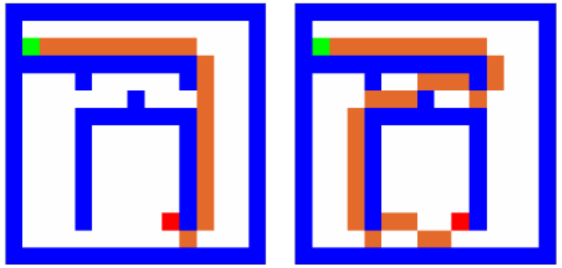
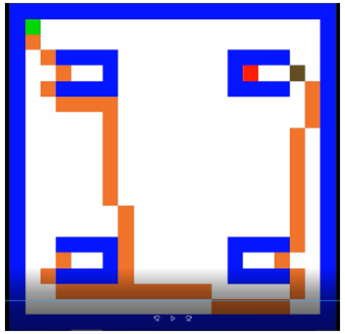
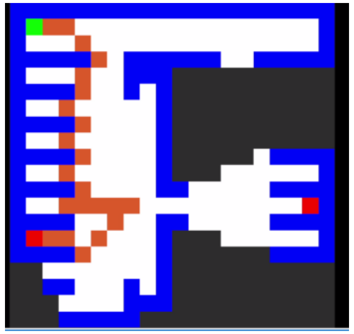


Figure 4. Paths obtained with a fully known map (left) and after exploration due to limited view (right)

Animations



Hidden target



Parking lot

Films available at the poster session, or on our website
https://www.mlsptlab-unicampania.it/research/topics/path-modeling.html