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On the Impact of Uncertainty for Path Planning

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Motivation

Path planning on graphs is a key problem for mobile robot navigation. We consider the case in which we are not sure about the traversability of *hidden edges*, which are instead estimated by a probabilistic *binary classifier*. Uncertainty has two sources: inaccuracy of estimator and number of hidden edges. The robot uses a policy — that may account for uncertainty — to navigate from source to target. We are interested in the *impact of uncertainty on the trajectory executed by the robot*. **How important is the classifier quality? How does it affect trajectories generated by different policies?**

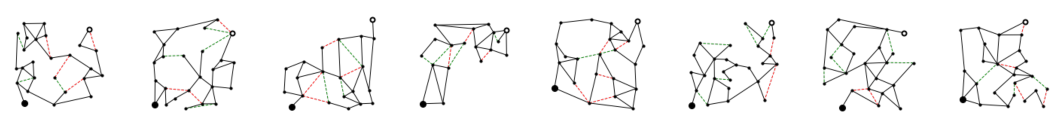
The Canadian Traveller Problem

We analyse the impact of uncertainty on a specific type of path planning problem: the Canadian Traveller Problem (CTP). The CTP searches for the optimal policy to navigate a graph where some edges have unknown traversability: an information that is revealed only *upon arrival at an incident node.* The CTP models scenarios where robots use local sensing to resolve partial information about edges. We design a large simulation campaign on synthetic and real-world maps: millions of **randomly drawn CTP instances** let us model the interplay of policies and uncertainty on the distribution of trajectory costs.

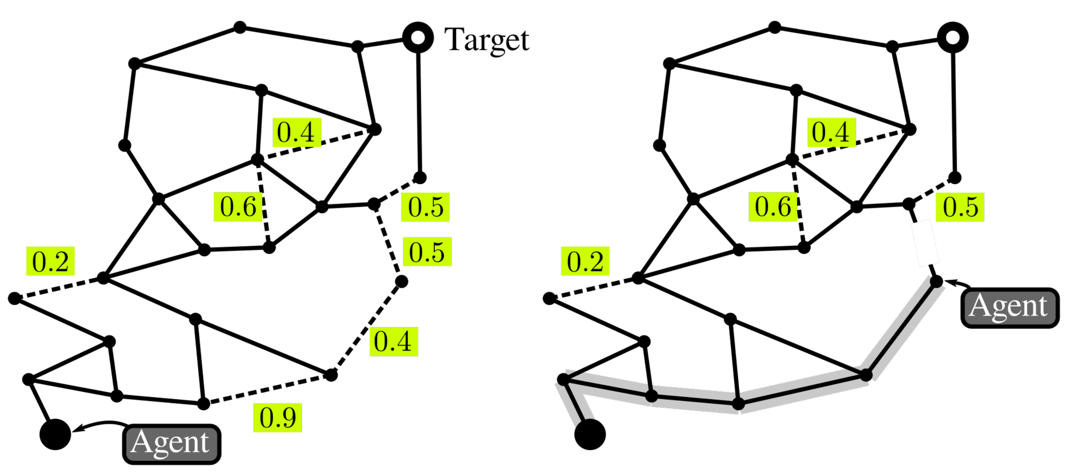
A CTP instance

A CTP instance is given by

a) a graph where some edges are marked as hidden (dashed);
b) source and target nodes;
c) a realization (traversable or not) of the hidden edges, which is unknown to the agent at planning time and only revealed when it passes by an incident node during the execution of the policy;
d) an estimation of traversal probability (yellow) for any hidden edge produced by a classifier of a given quality.



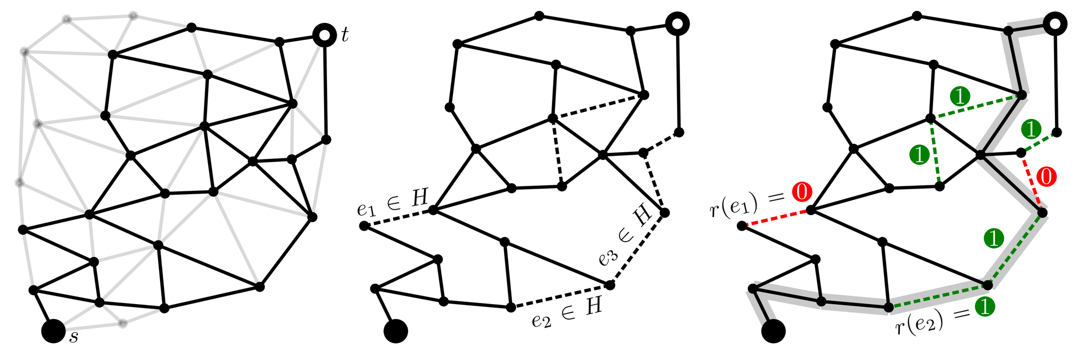
From the available information, the robot computes a policy that it uses to navigate between source and the target; we simulate the robot trajectory (thick, semi-transparent) on the given realization and record its cost.



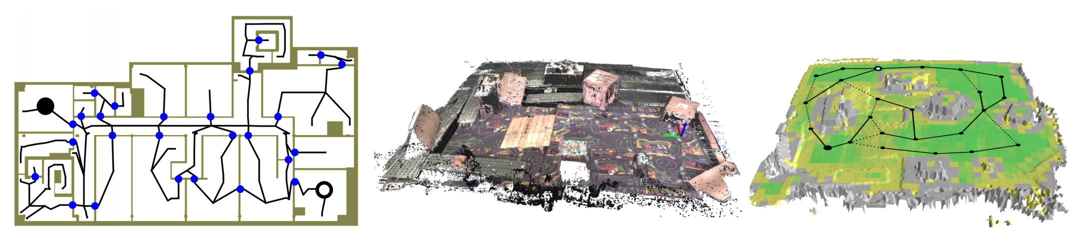
The maps

We experiment with two kind of maps: random planar graphs and real-world maps.

Random graphs are built from the Delaunay triangulation of random points by randomly deleting a fraction of the edges (light grey). Then, N hidden edges (dashed) are randomly picked to produce interesting planning instances; their realization (red/green) is randomly drawn from a Bernoulli(0.5) distribution. Start and target nodes are in the bottom-left and top-right corners, and are always connected.

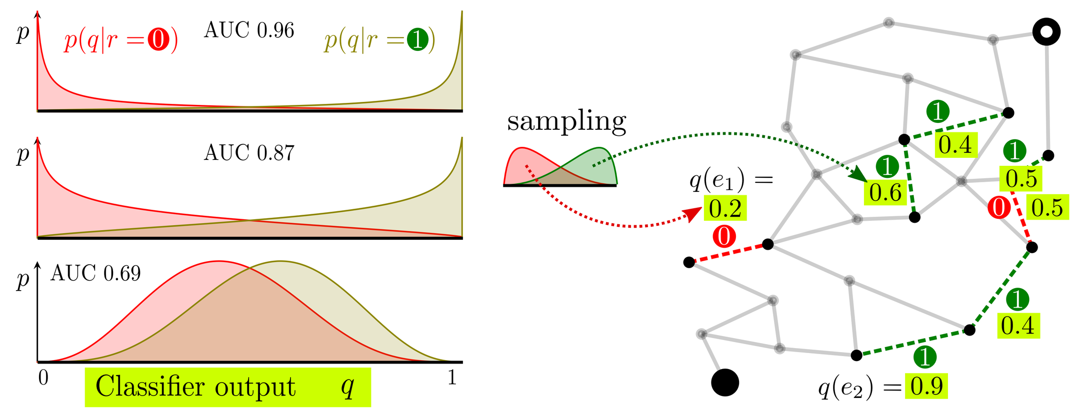


Two real-world maps represent different scenarios: the navigation graph derived from the floor plan a *real indoor building*, where a robot is unsure if doors are open; and a sparse navigation graph derived from the *elevation map of rough terrain*, where the robot is unsure to be able to traverse certain patches.



The estimators

We model the outputs of calibrated traversability estimators of different quality as a one parameter (AUC) family of Beta distributions. For each instance (graph and realization), we randomly sample estimations of a given quality (yellow labels) from the model distributions.



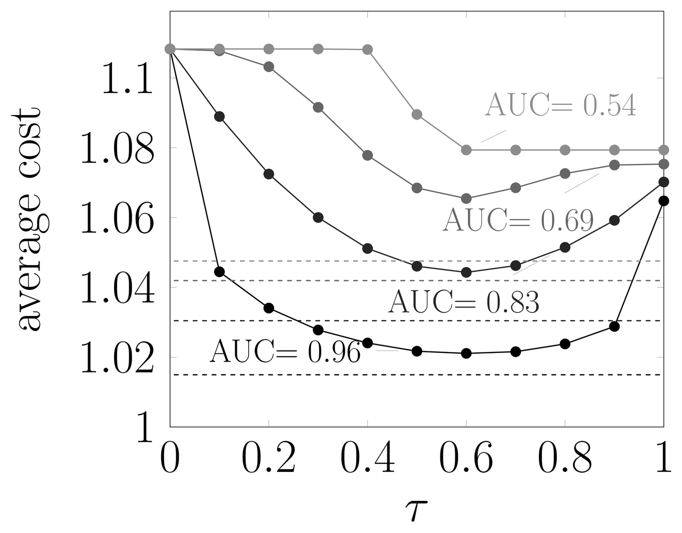
The policies

We compare the optimal policy π_{opt} with a family of heuristic policies $\pi(\tau)$, $\tau \in [0, 1]$. **The optimal policy** is the policy that minimizes the *expected cost*: in a given state, it accounts for the cost and likelihood of all possible realizations; it is computed in $O(3^N)$ time using Value Iteration. **The moderately pessimistic policies** are much cheaper ($O(N \log N)$): they assume that only hidden edges with an estimated traversal probability lower than τ are in fact not traversable: $\pi(0)$ is very optimistic while $\pi(1)$ is very pessimistic.

Selected results on random graphs

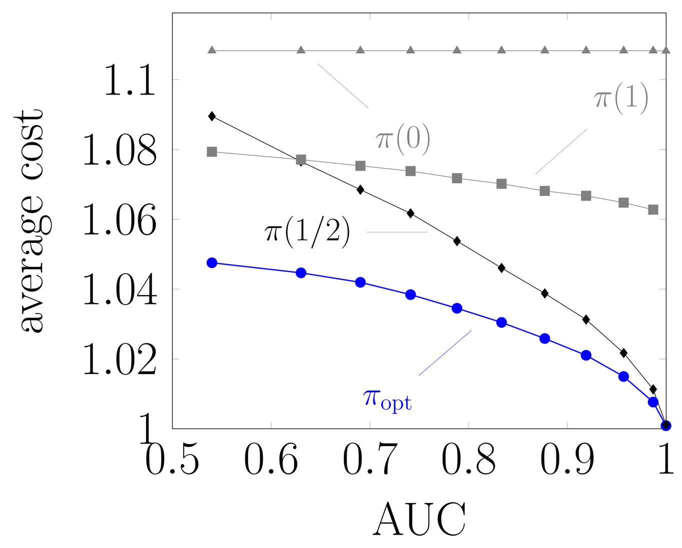
The heuristics

Lower estimation quality blurs the difference among the heuristics (dashed line is π_{opt}). Especially for good quality classifiers, it is better to be just moderately pessimistic ($\tau \approx 0.6$).



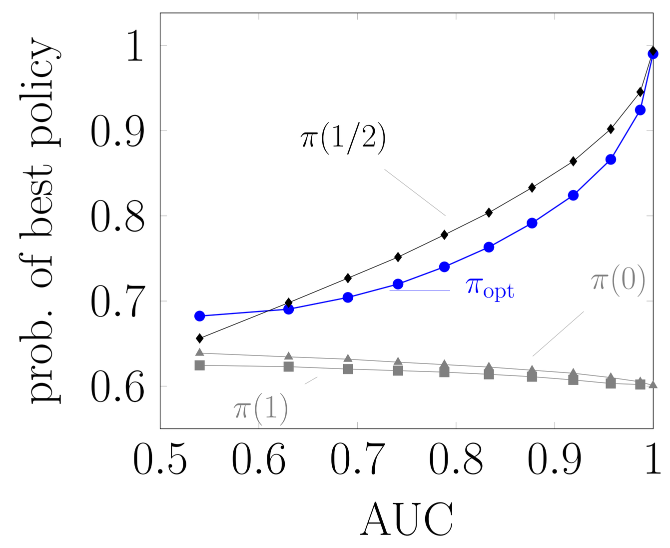
The estimation quality

Lower estimation quality makes the planning problem harder. The gap between the heuristics and the optimal policy grows monotonically as the estimation quality decreases.



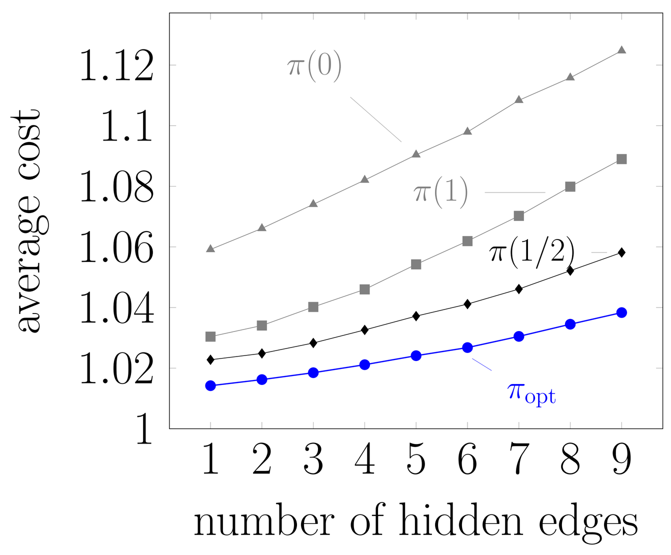
Average vs median case

The optimal policy performs better in average and worst cases, but performs worse in the median case. The best heuristics incur sometimes in very large costs that penalizes their mean performance.



Hidden edges

The relative performance of the policies remain similar with increasing number of hidden edges. The average gaps are small but may be large on particular maps. Here AUC=0.83.



Do you want to know more?

This poster, the code to replicate the experiments, and all the results are available at
`https://github.com/jeguzzi/resilience`

Acknowledgement

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