

Learning to select frontiers for large-scale exploration



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Introduction

Vision-Aware Frontier Selection (VAFS) learns to reach goals beyond the explored map. Unlike classical planners like D*, **VAFS learns** the effect of **graph structure** and **visual cues** to estimate each frontier's cost to the goal, then moves toward the cheapest.

Figure 1: Showcase of our method in a challenging off-road planning scenario. The robot needs to reach a goal atop a steep hill (). It finds an easy slope up () and efficiently reaches the goal without backtracking.



Methods: navigation

An agent at node n in known map $\mathcal{M}$ is trying to reach goal node g outside $\mathcal{M}$. At each step, it:

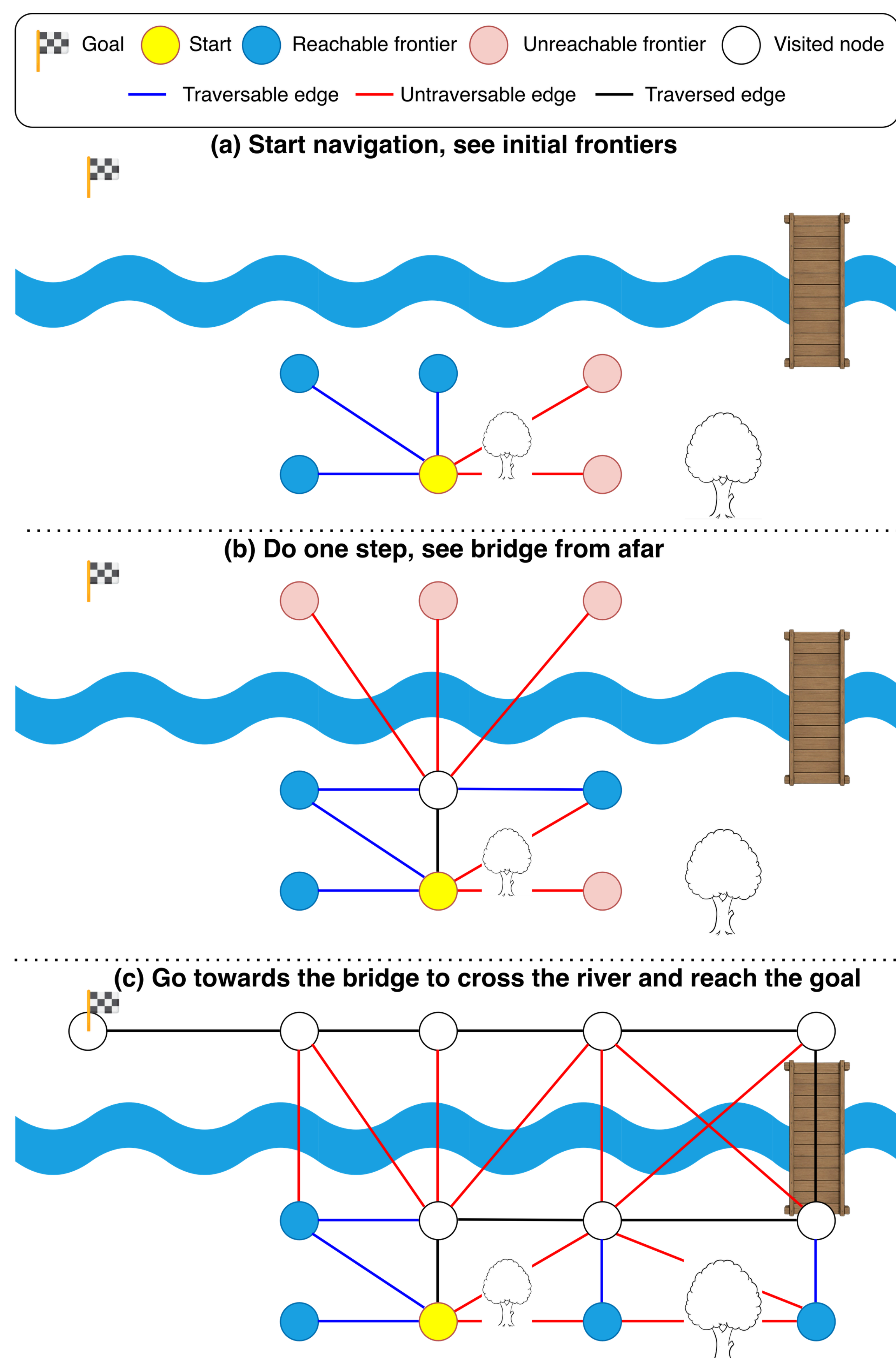
1. Expands $\mathcal{M}$ with new **frontier nodes** neighbouring n
2. Chooses next node n^* in $\mathcal{M}$ according to:

$$n^* = \operatorname{argmin}_{n' \in \mathcal{M}} C(n, n') + V_{\mathcal{M}}(n', g; \theta)$$

$C(n, n')$: shortest-path cost from n to n' in $\mathcal{M}$

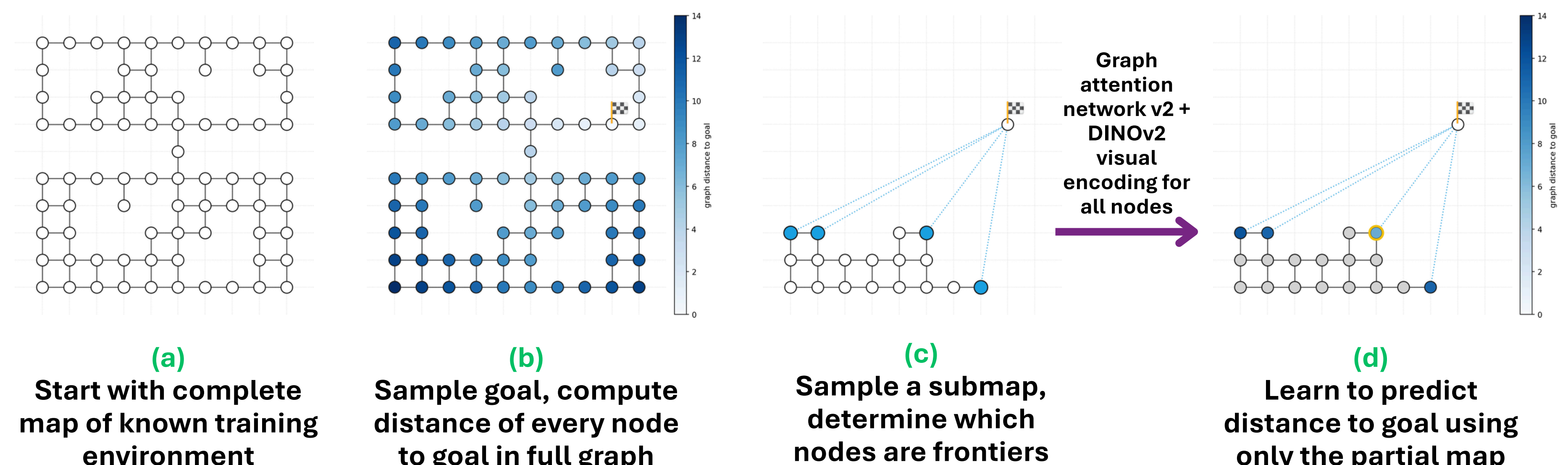
$V_{\mathcal{M}}(n', g; \theta)$: a learned function of estimated cost from n' to g

Figure 2: Method overview



Methods: training

Figure 3: Overview of our training method. We use known, full maps from training environments to train a graph neural network (GNN) to predict which frontier is best.



Experiments & results

- Field experiments:
 - Gault Nature Reserve of McGill University
 - Test platform: Clearpath Husky, RTK-GPS, three OAK-D cameras
 - 32 hours of driving data across varied forest type
 - Trained on real data only
- Simulation, for more controlled validation only (no sim2real):
 - Procedurally generated forest worlds in Minecraft
- Baselines: D*, Bug2 algorithm
- Performance metric: number of steps in the graph before reaching goal
- **We test on environments that were not seen during training**

Figure 4: sample simulation environment used to test our algorithm.

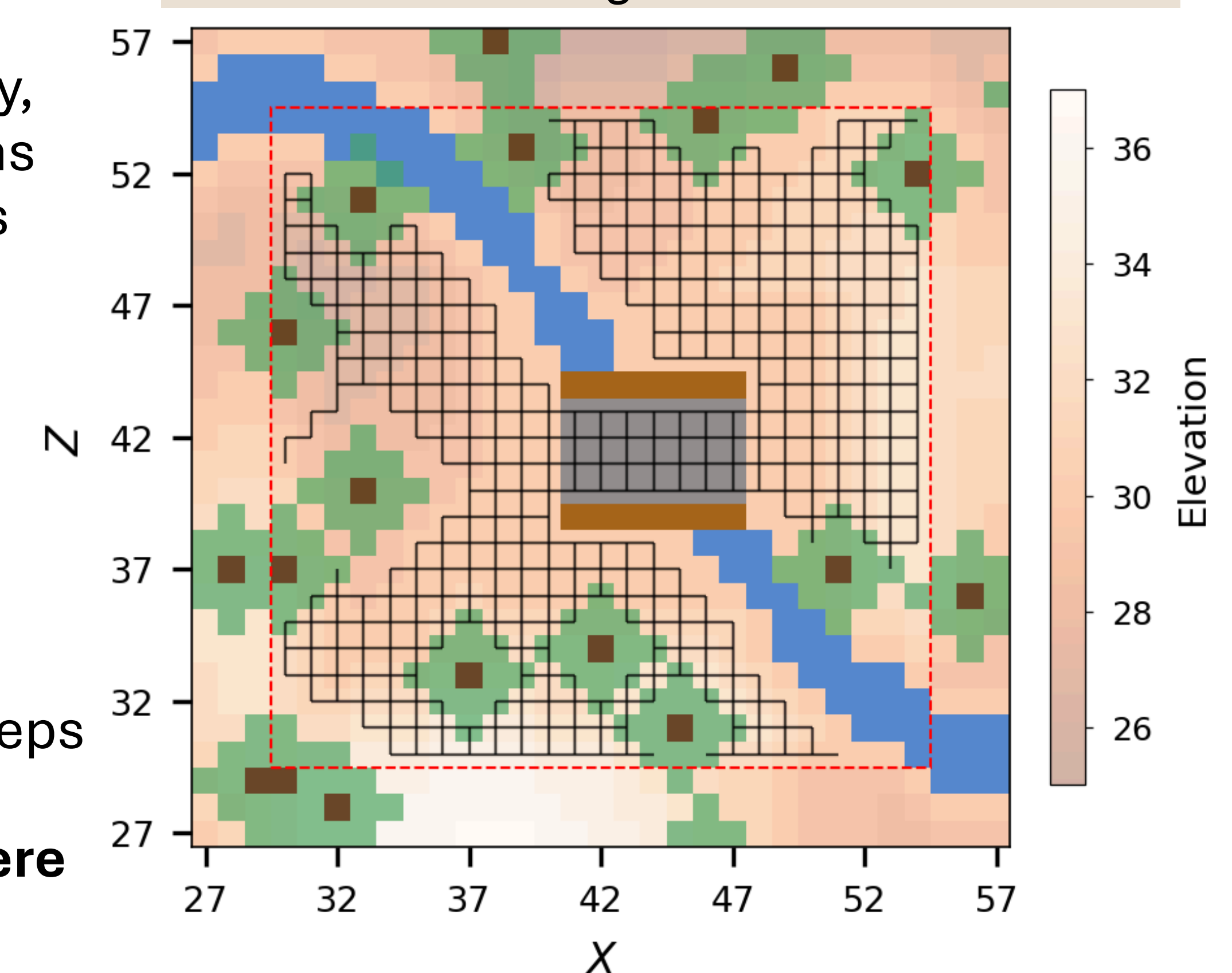
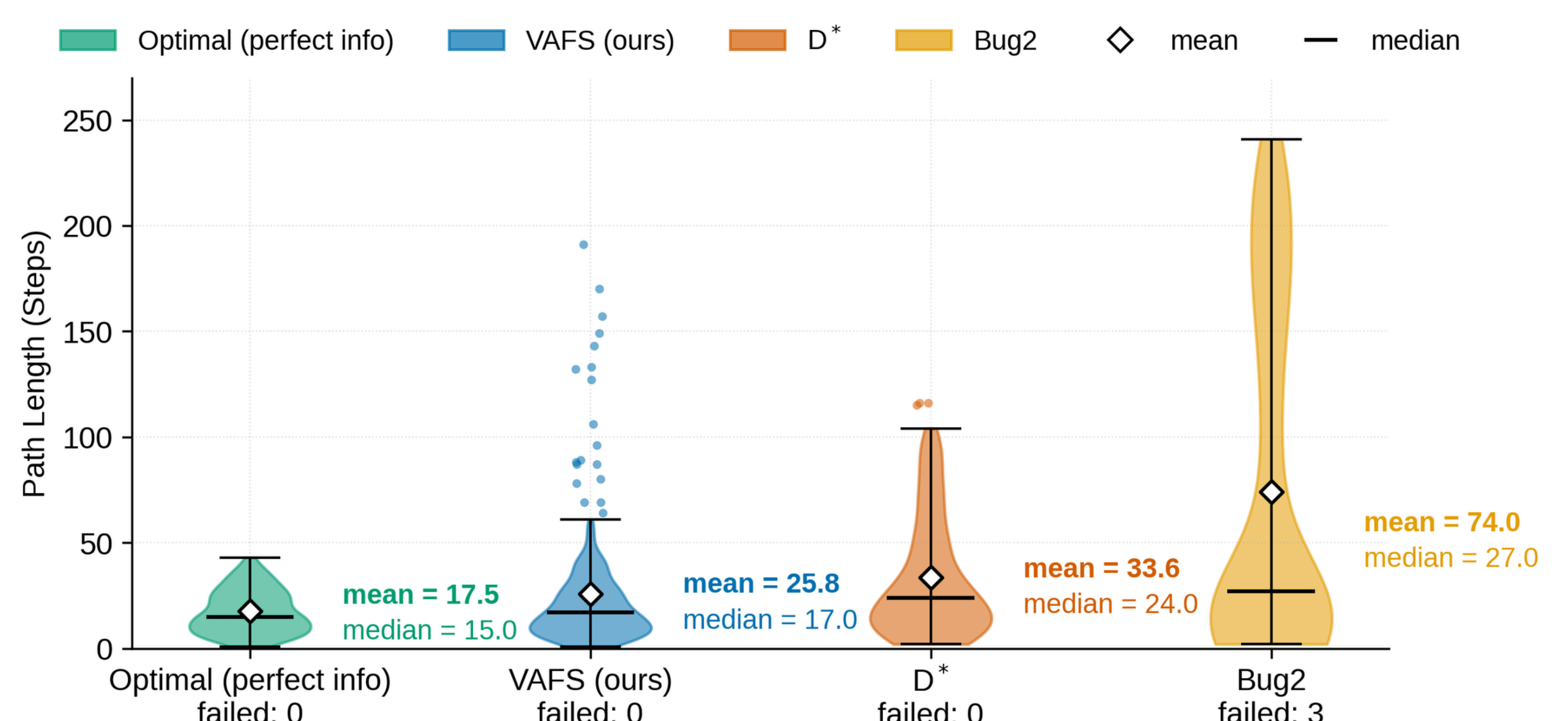


Figure 5: Our Clearpath Husky test robot exploring an unknown environment in Quebec. Here, it needs to reason about the hill being too steep and find an alternate path.

Figure 6: Results for our simulation experiments. We randomly sample a start and goal 250 times across 10 different test maps. **We can see our method is outperforming D* and closing the gap towards optimality.**



Conclusion

Our method, VAFS, can leverage vision to predict which frontier is more promising to reach a goal, using a graph neural network which generalizes to unknown environments. We beat D* in thorough simulation experiments across different terrain, and validated the method on real forest data in challenging conditions.