Learning to plan with uncertain topological maps

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Webpage: https://edbeeching.github.io/papers/learning_to_plan




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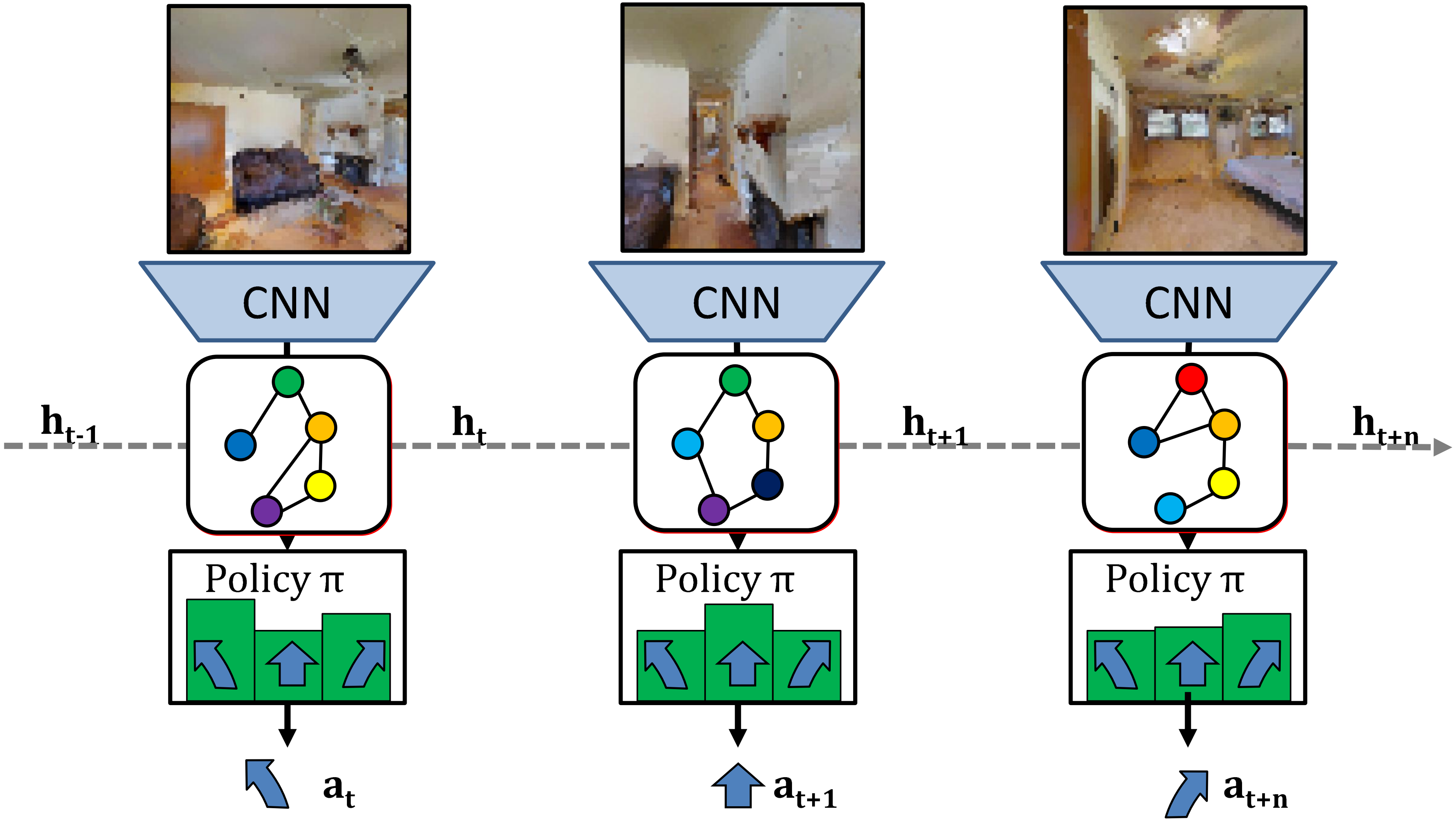
Introduction

- We aim address the problem of planning and control in photorealistic 3D environments Habitat (Savva et al., ICCV 2019)

- This work:
  - Explores the implementation of a neural path planning algorithm
  - To learn to plan in uncertain environments
  - Performs hierarchical planning and control by coupling a high level planner with a low level policy

- Our neural planner:
  - Incorporates visual features in the planning process
  - Exploits regularities in an uncertain graph adjacency matrix
  - Implements an augmented GNN architecture with recurrent updates and a novel gating mechanism

Introduction – Standard recurrent agent

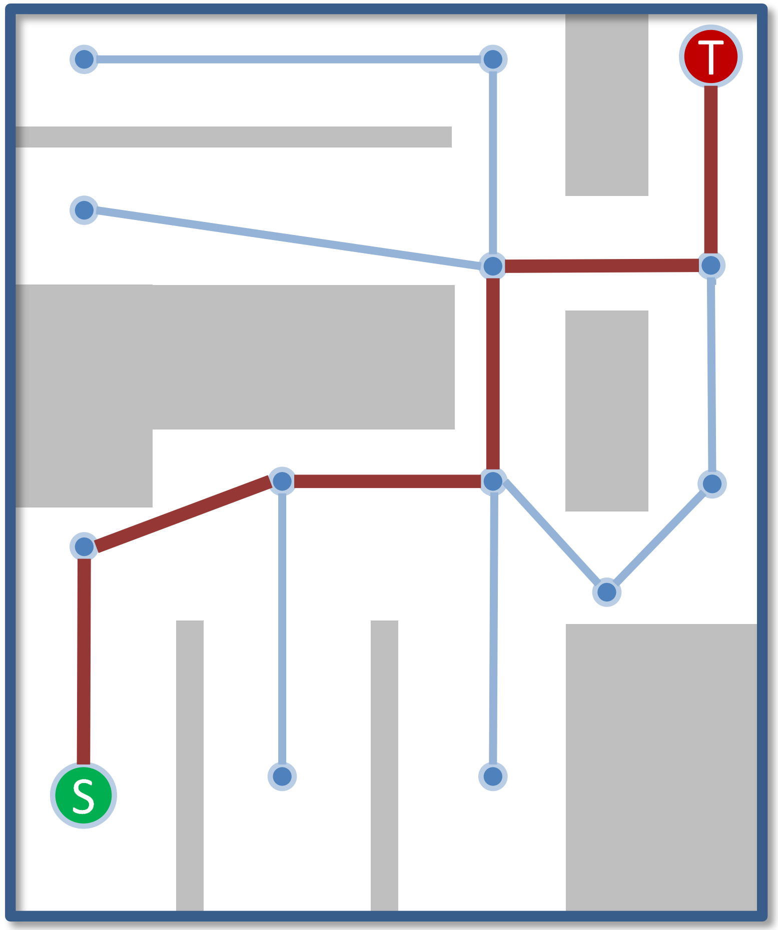


Mirowski et al. ICLR 2017, Jaderburg et al. ICLR 2017, Mirowski et al . ICLR 2018

Introduction – Related works

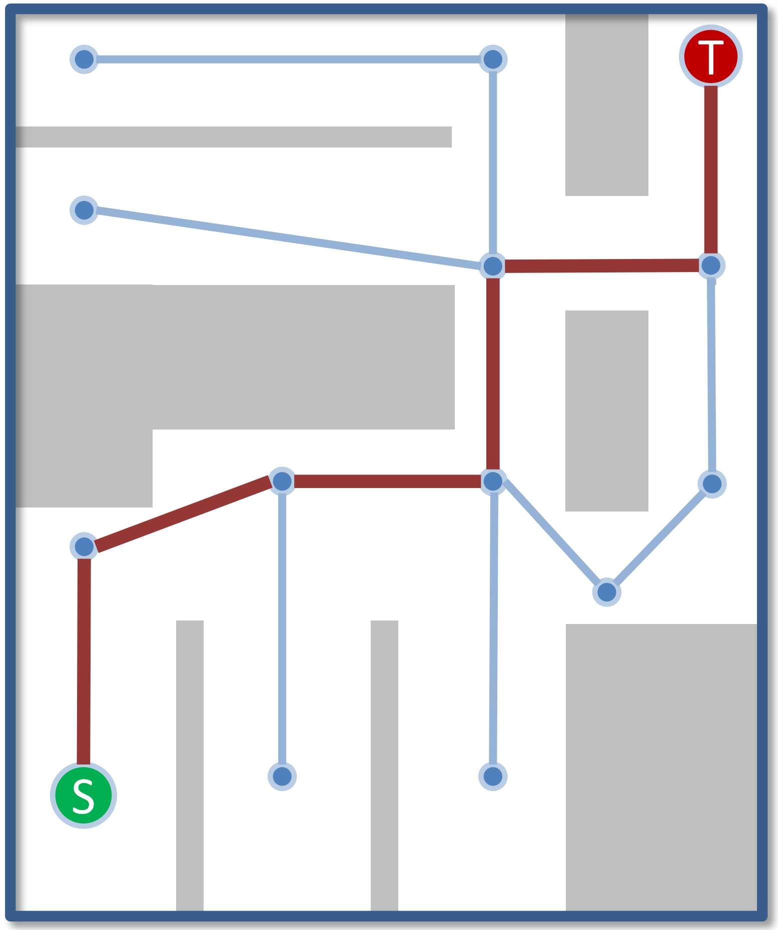
- Related works:
  - Semi-parametric Topological Memory for Navigation (Savinov et al. ICLR 2018)
    - Couples classical planning and learning in the ViZDoom (Kempka et al. CCIG 2016) environment
  - Search on the replay buffer (Eysenbach et al., NeurIPS 2019)
    - Uses values estimates to build a graph
    - Does not generalize to unseen environments
  - Neural Topological SLAM for Visual Navigation (Chaplot et al. CVPR 2020)
    - Combines SLAM with a novel graph based method
    - Relies on classical planning
- This work:
  - Learns a neural approximation of a classical planning algorithm (Bellman-Ford)
  - Demonstrates the method outperforms classical methods on uncertain graphs.

Learning to plan with uncertain topological maps

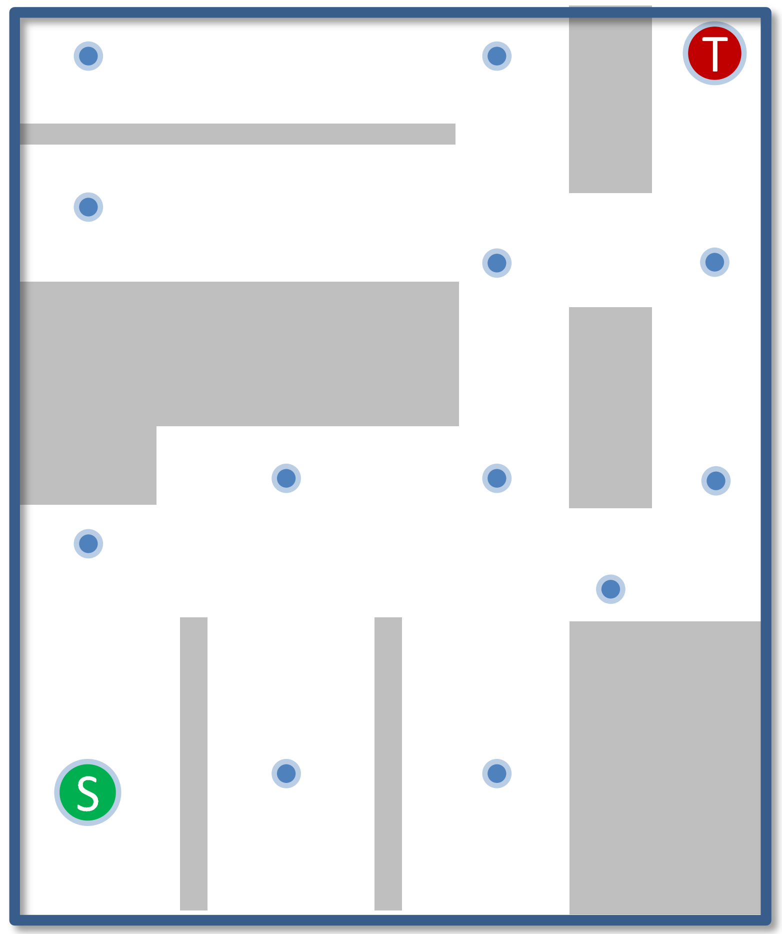


Ground truth

Learning to plan with uncertain topological maps



Ground truth



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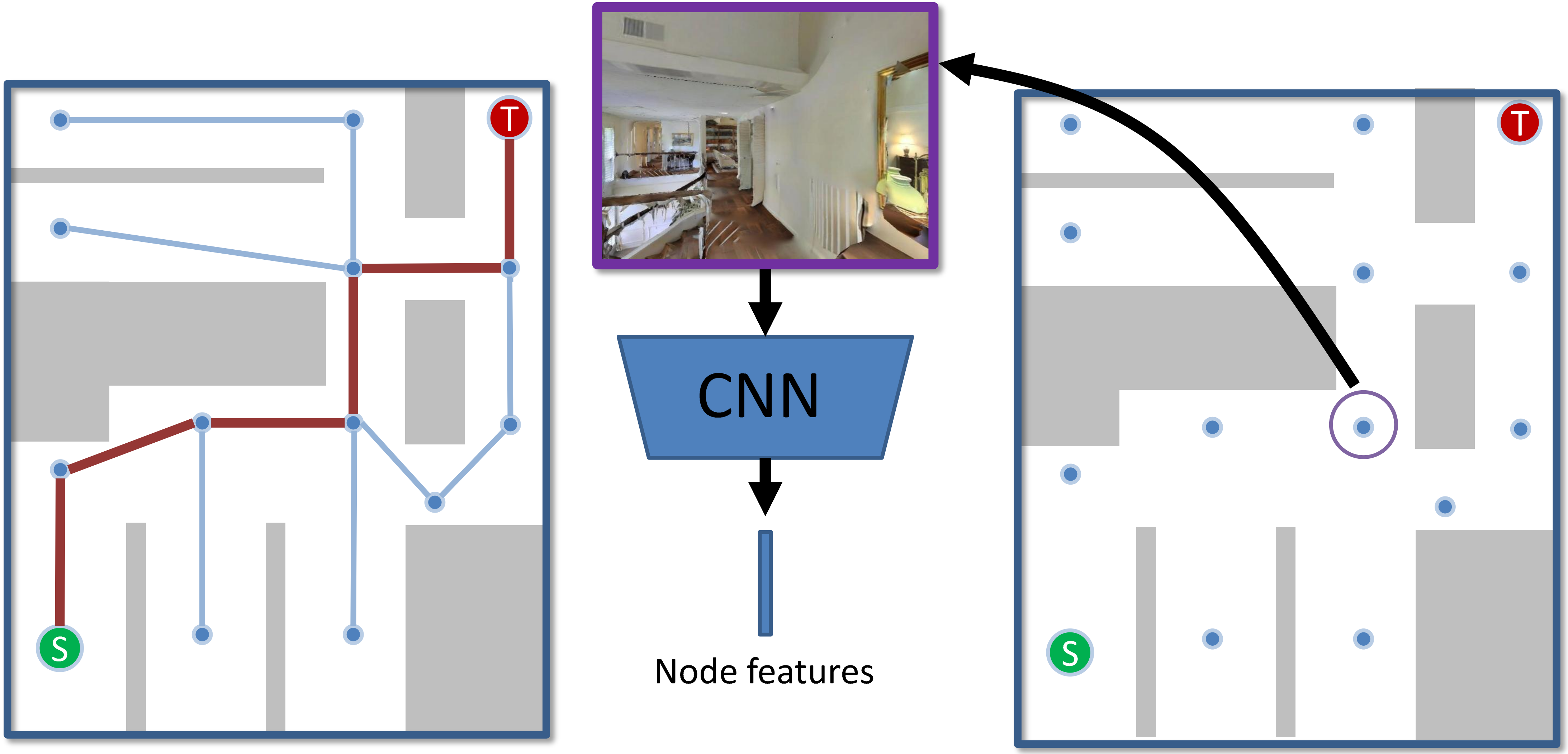

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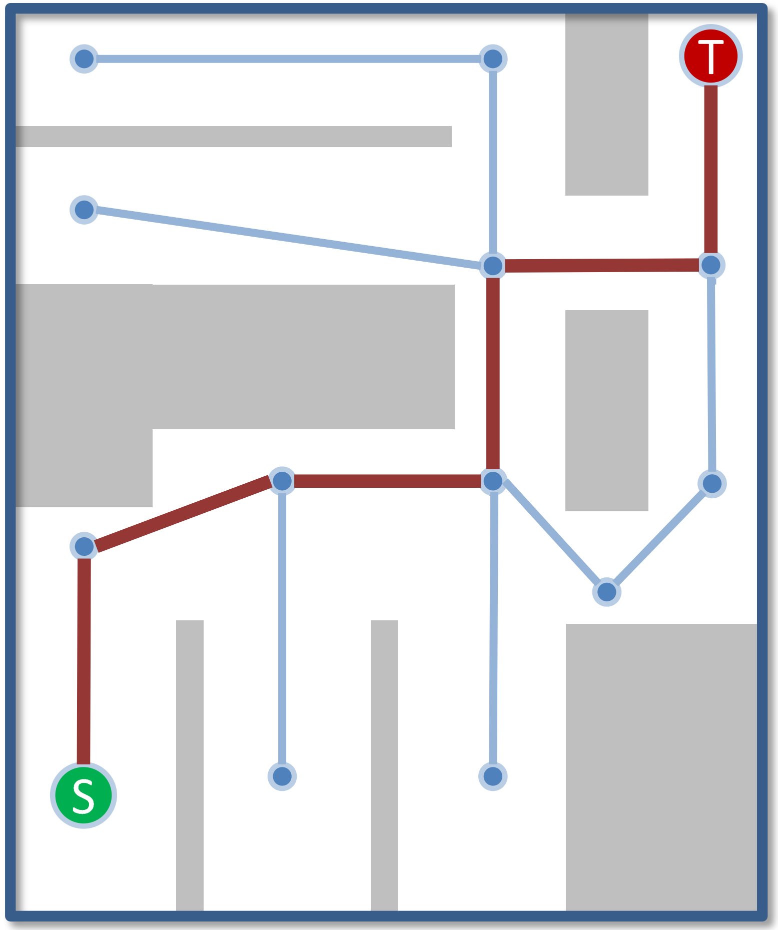
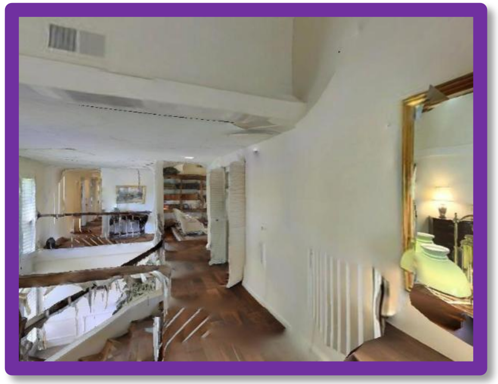
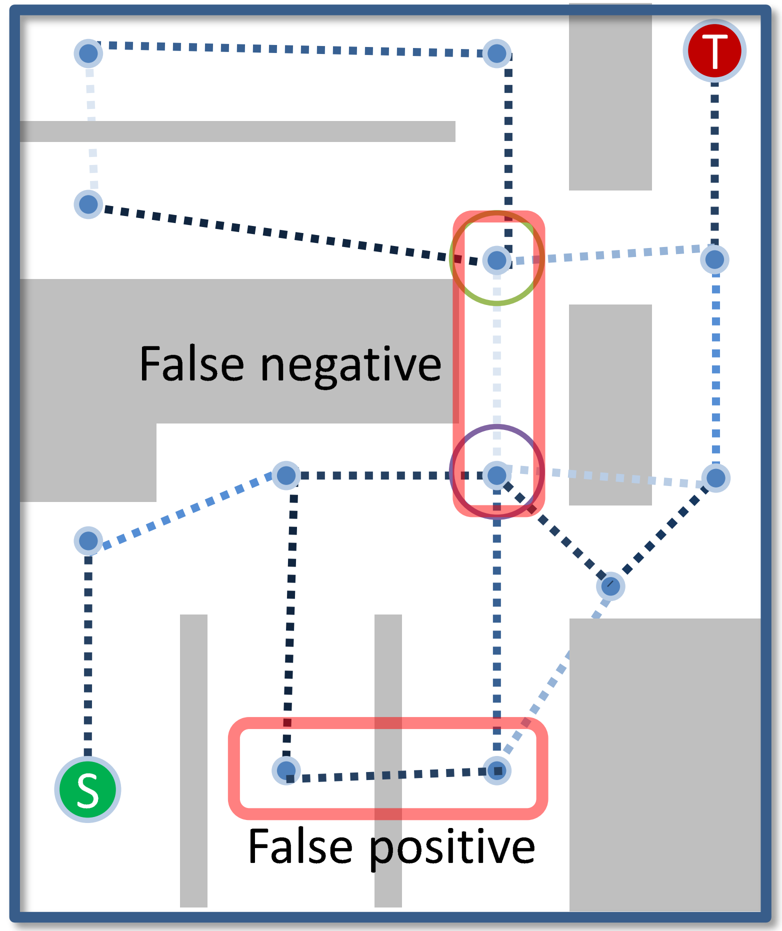


Ground truth





Uncertain graph

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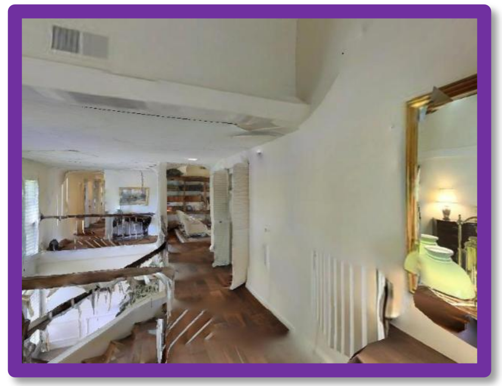
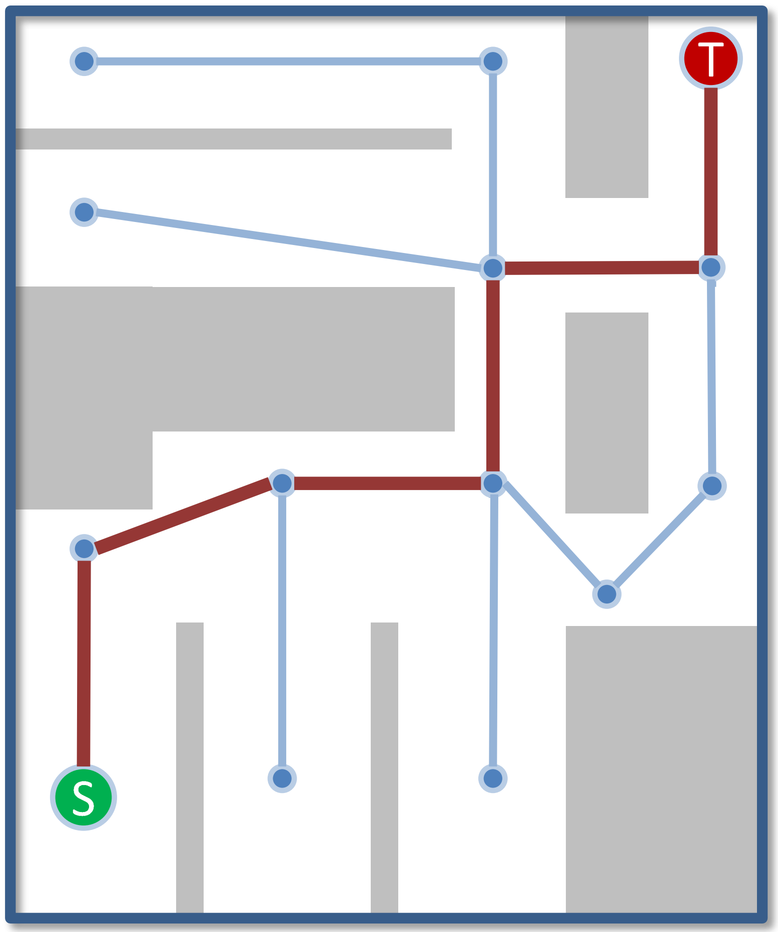
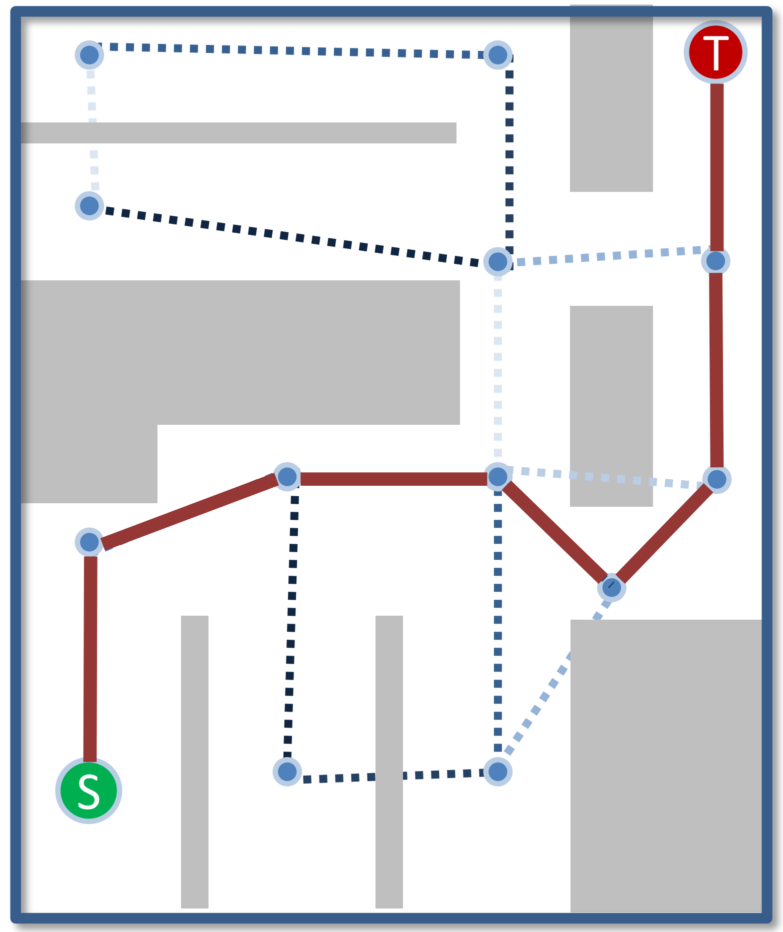




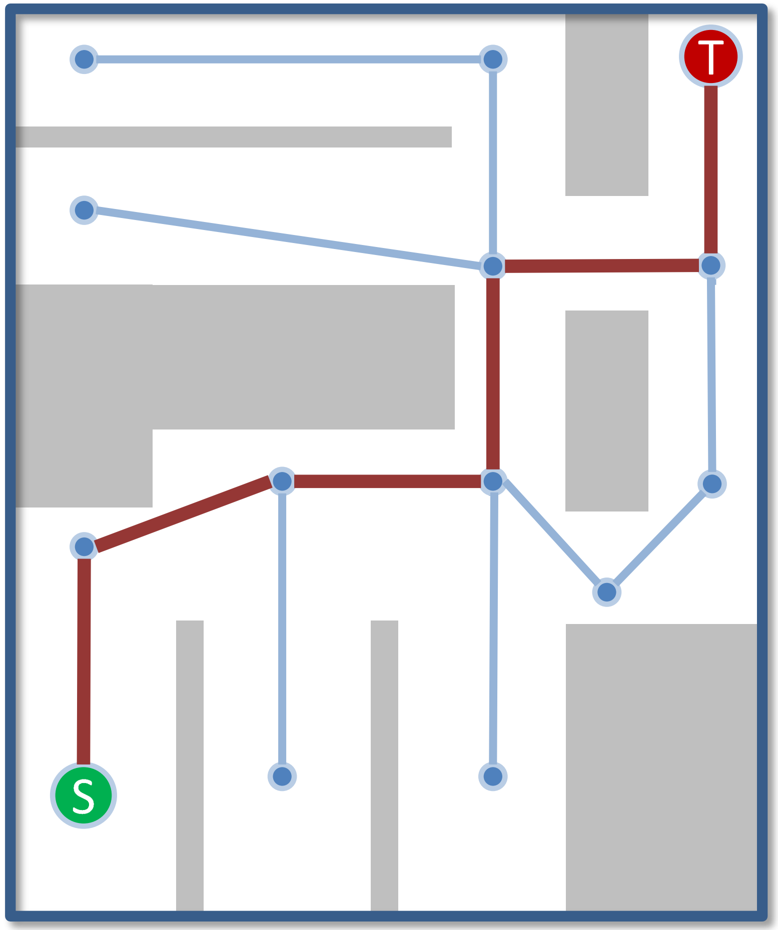
Ground truth

Classical planning:
- **Binary connectivity**
- **Cannot exploit visual information**

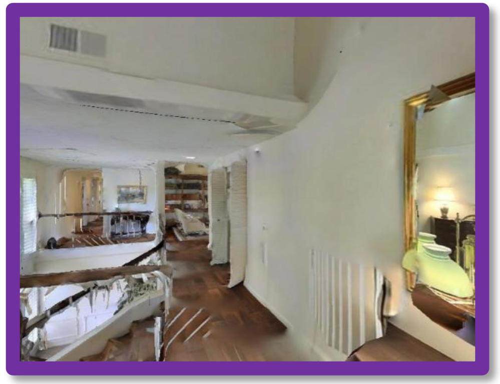


Uncertain graph

Learning to plan with uncertain topological maps

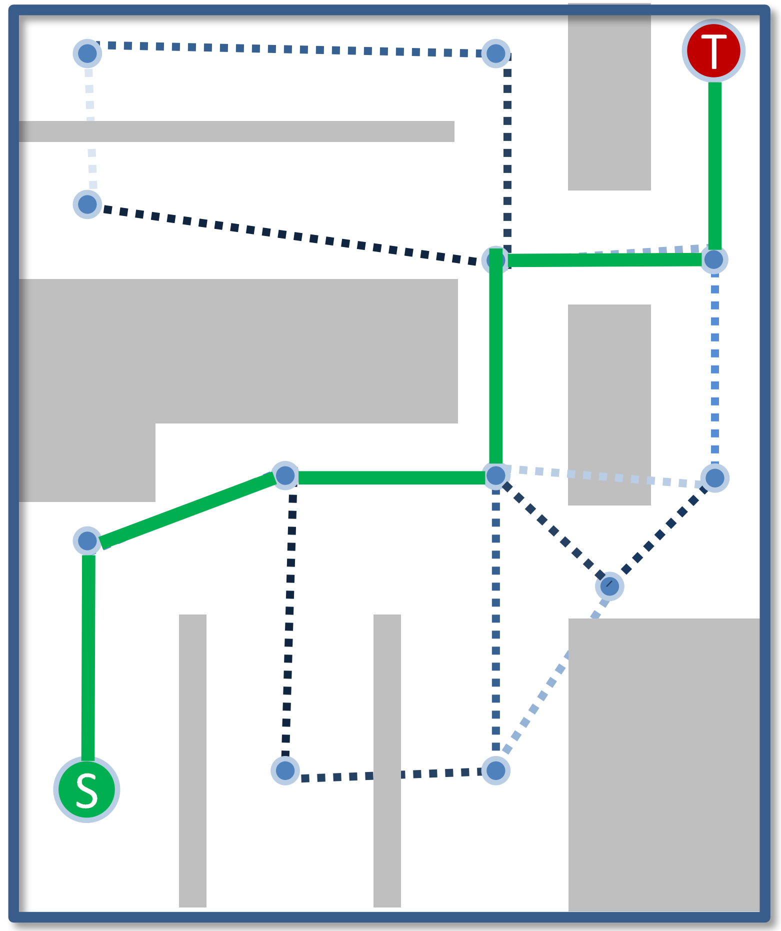


Ground truth



Classical planning:
- **Binary connectivity**
- **Cannot exploit visual information**

Neural planning:
- **Exploits uncertain connectivity**
- **Uses visual features**
- **Learn from regularities in the graph structure**



Uncertain graph

Graph generation

- Graphs were generated by training:
  - an exploratory policy trained to maximize coverage (Chen et al. ICLR 2019)
  - a parameterized function $f(\boldsymbol{o}_1, \boldsymbol{o}_2, \boldsymbol{h}_t)$ that predicts whether there is line of sight connectivity between two observations.

- Dataset generation:
  - Each graph contains 32 nodes
  - 72,000,000 training examples
  - 16,000,000 test examples

Training

- Treat planning as a classification problem
- During training: ground truth optimal paths are available
- For each node, perform an n-class classification of the next node on the optimal path to the target
- Each node, i, contains a feature embedding $\boldsymbol{x}_i = [\boldsymbol{v}_i, \boldsymbol{e}_i, t_i, \boldsymbol{d}_i, \boldsymbol{s}_i]$

  Where:

  $\boldsymbol{v}_i$: visual features

  $\boldsymbol{e}_i$: edge connection probabilities

  t_i: boolean value indicating if the node is the target

  $\boldsymbol{d}_i$: distances from node i to all other nodes

  $\boldsymbol{s}_i$: one hot vector identifying the node

Inductive bias

- Inspiration – Classical path planning algorithms
  - Dijkstra’s algorithm:
    - Contains priority queue which is not differentiable
  - Bellman Ford:
    - Iterates over neighbors
    - Passes messages
    - Updates bounds
    - Potential for a neural approximation with an augmented GNN