Probabilistic Semantic Mapping Using Graph-Structured Sum-Product Networks

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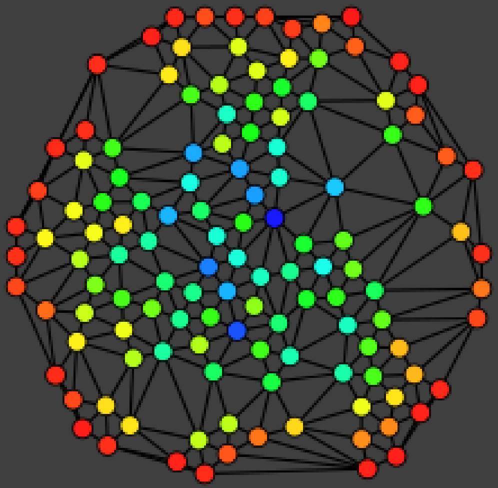
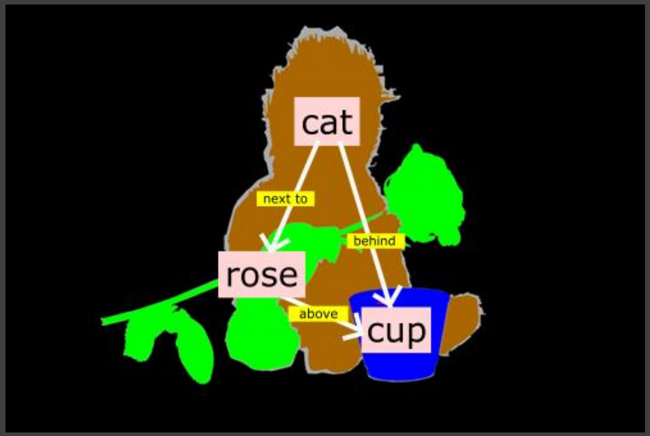
Motivation

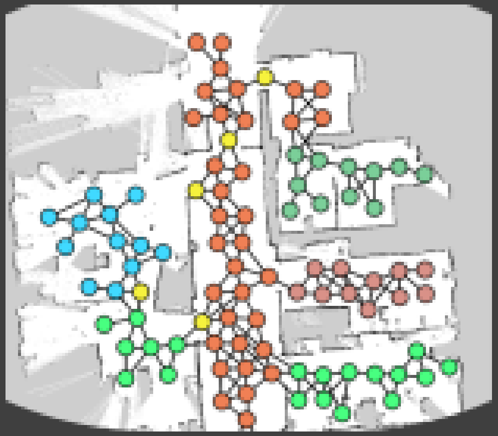
Graph-Structured Data



Social Network Analysis



Computer Vision
(Semantic Segmentation)

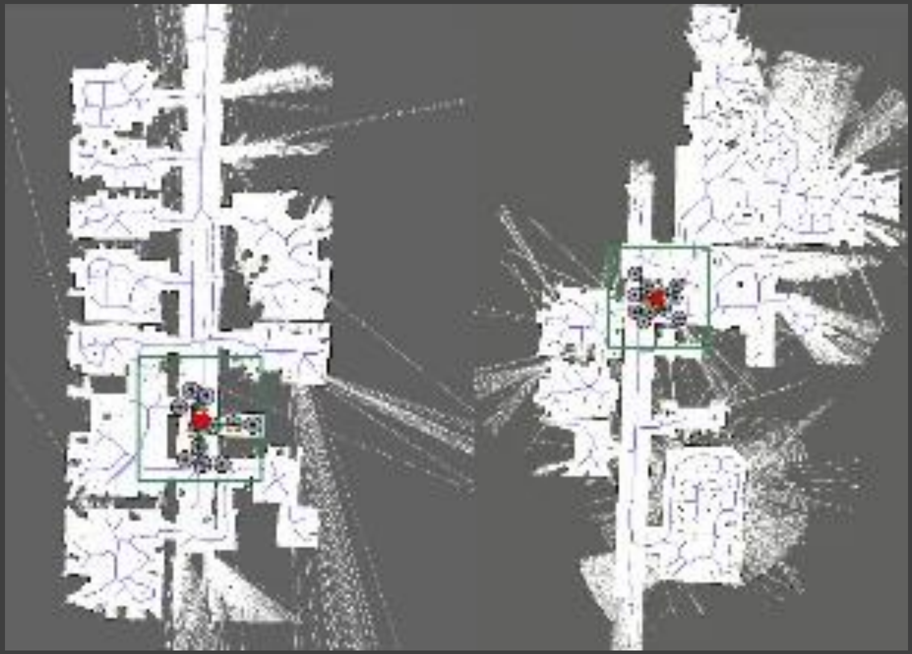


Robotics
(Semantic Maps)

Motivation

Graph-Structured Data

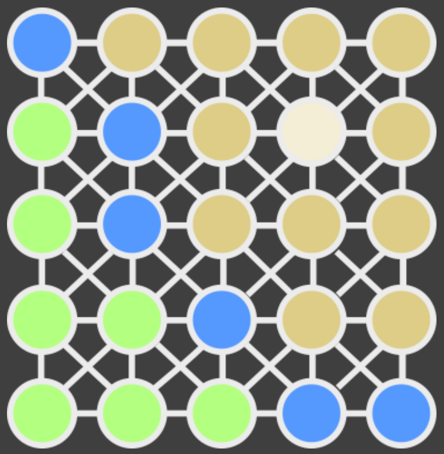
- **Real-world** graph-structured data:
  - Complex
  - Noisy
  - Dynamic
    (with varying size)



Motivation

Traditional Structured-Prediction

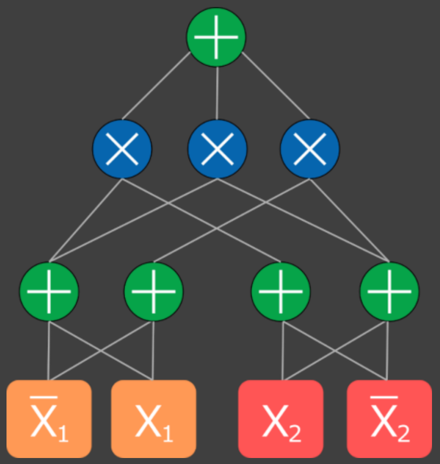
- Inference about graph-structured data
  - **Structured Prediction**



- Traditional structured prediction approaches:
  - Require **fixed** number of variables
  - Require **static** global structure
  - Place strict **constraints** on variable interactions

Graph-Structured **S**um-**P**roduct **N**etworks (GraphSPNs)

Leverages **Sum-Product Networks**



- Guarantee **tractable probabilistic inference**
- Incorporate **probabilistic semantics in structure**
  - **Hierarchical mixture of parts**

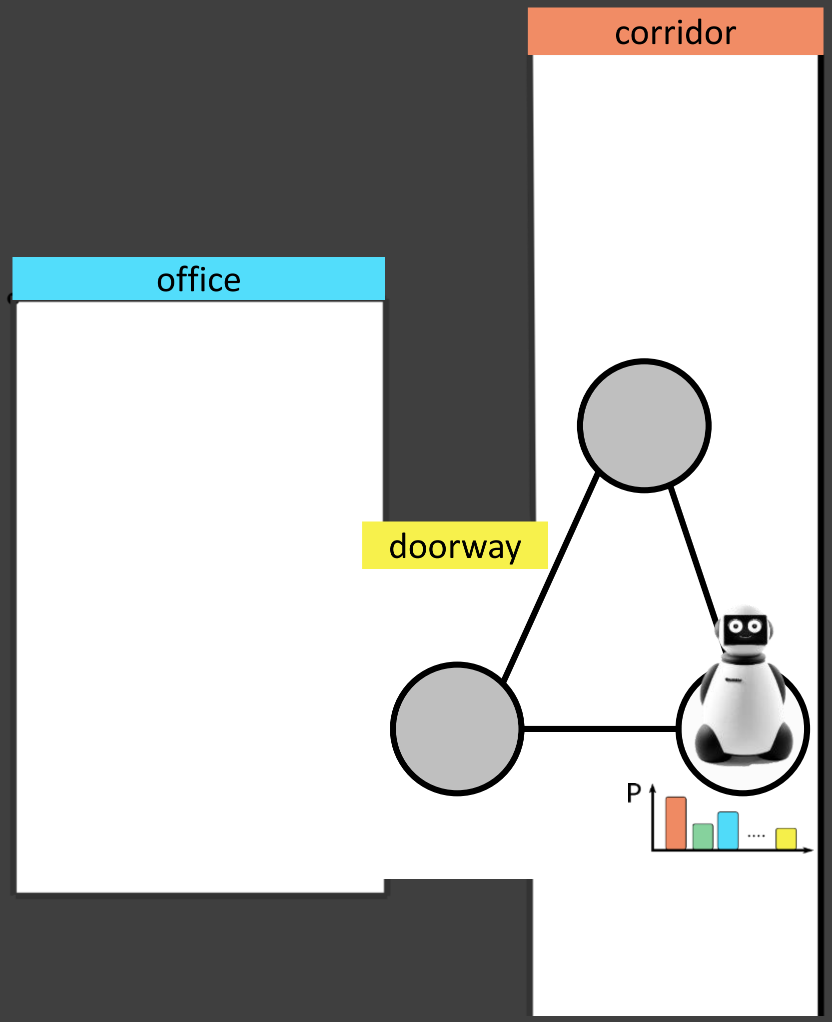
Graph-Structured **S**um-**P**roduct **N**etworks (GraphSPNs)

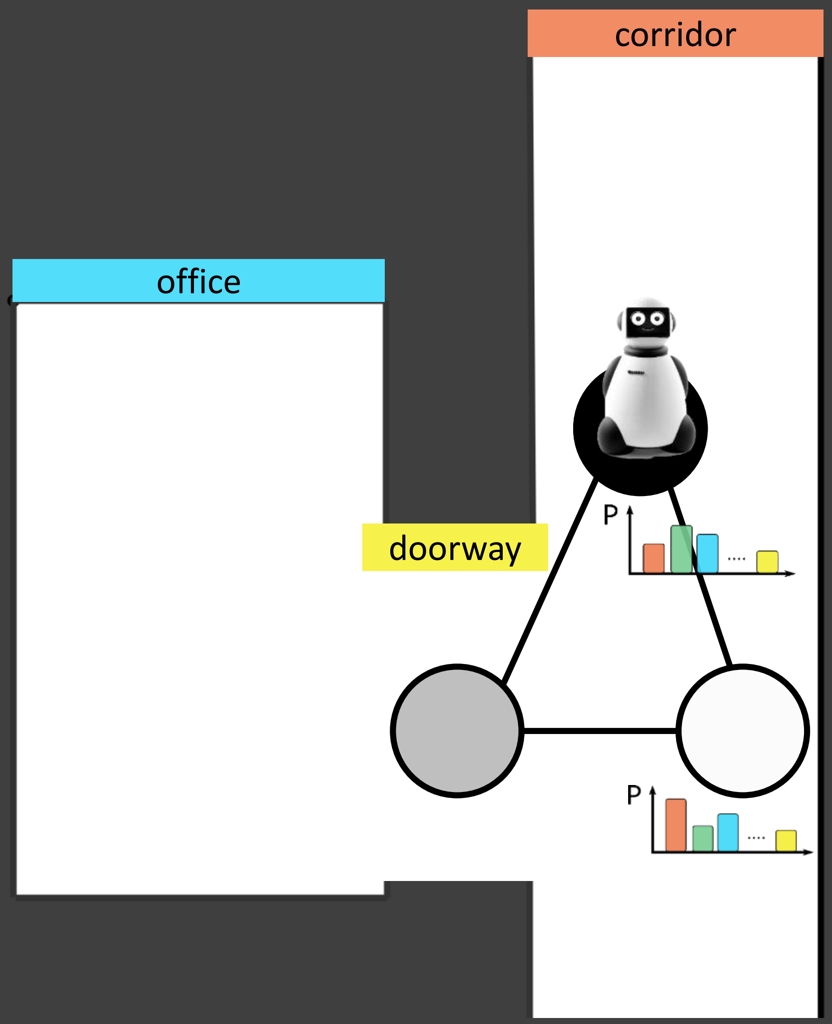
Deep probabilistic model for SP

Complex, noisy variable dependencies

Template models dynamic graphs of varying size

Semantic Mapping Using GraphSPNs


corridor
office
doorway
P


corridor
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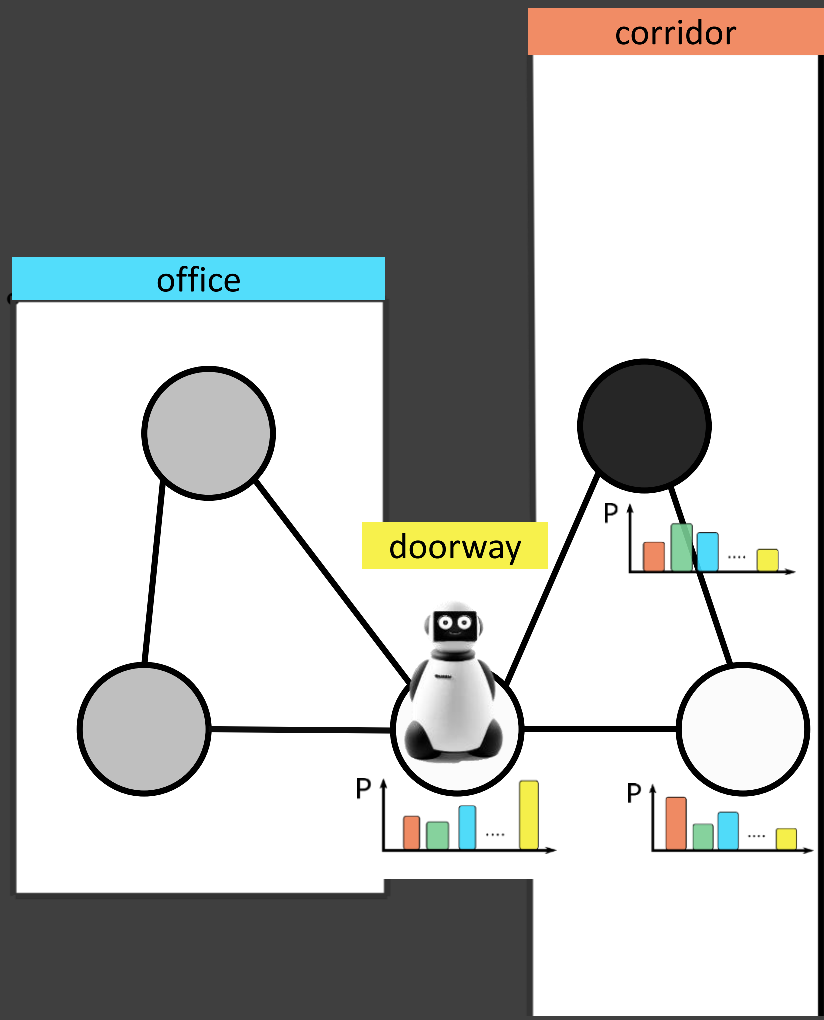
corridor
office
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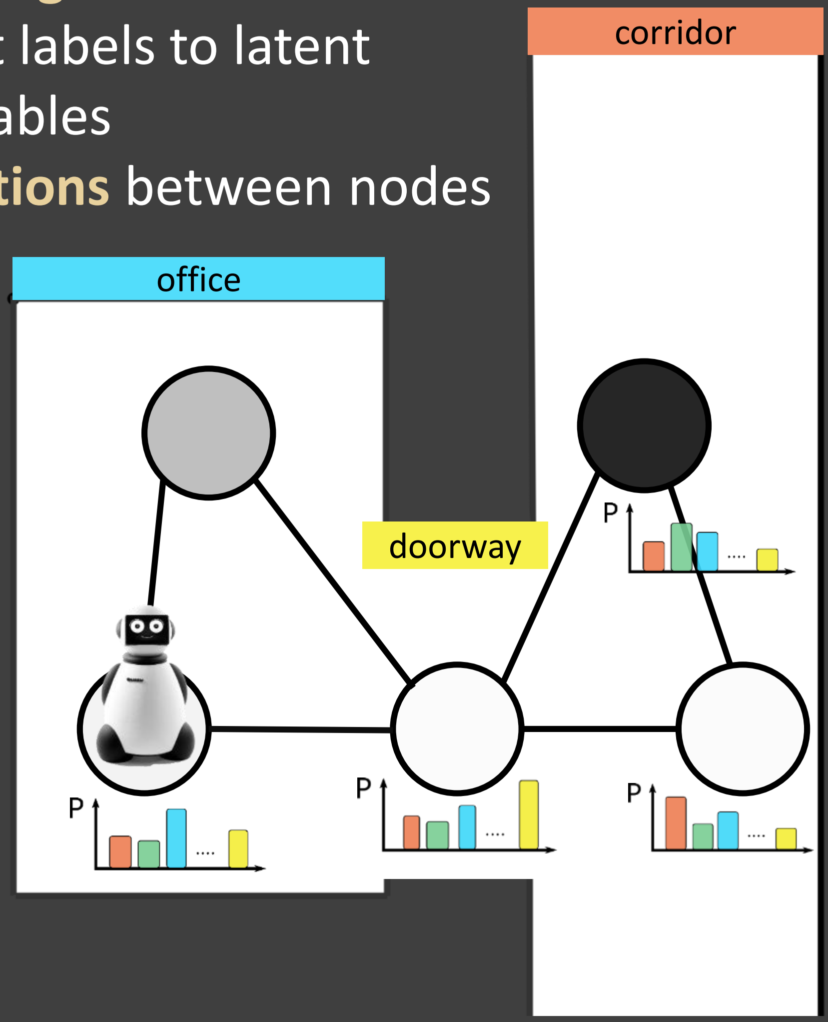
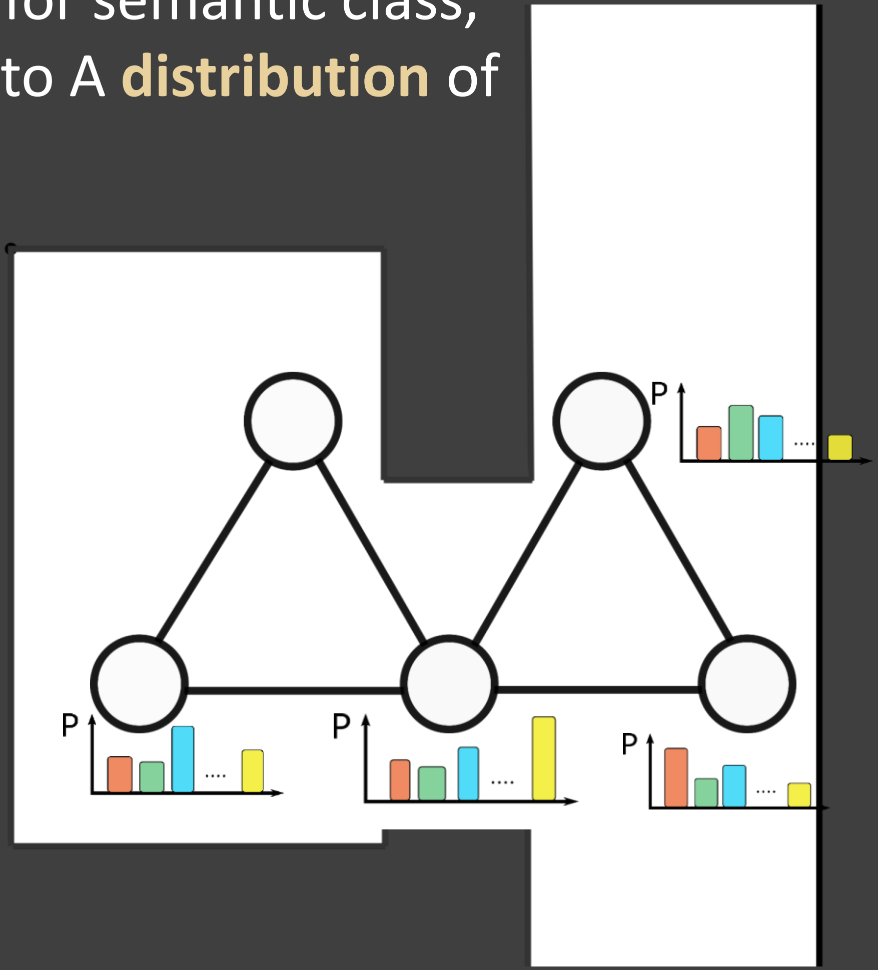
Problem:

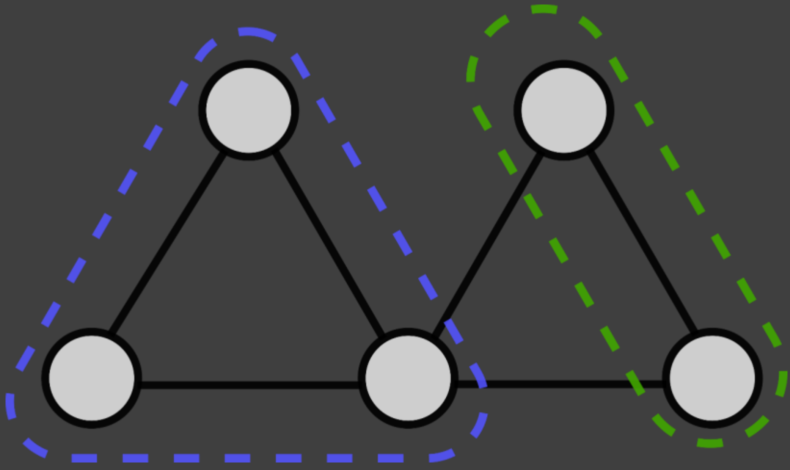
Semantic Mapping:

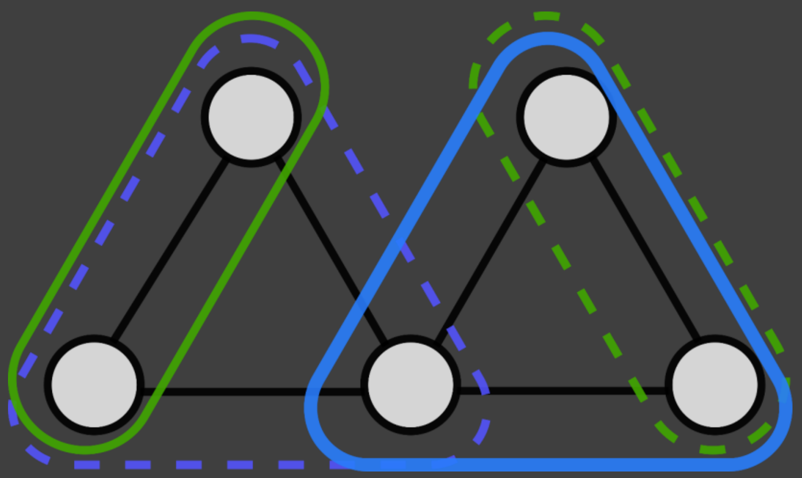
- Assign correct labels to latent semantic variables
- Leverage **relations** between nodes

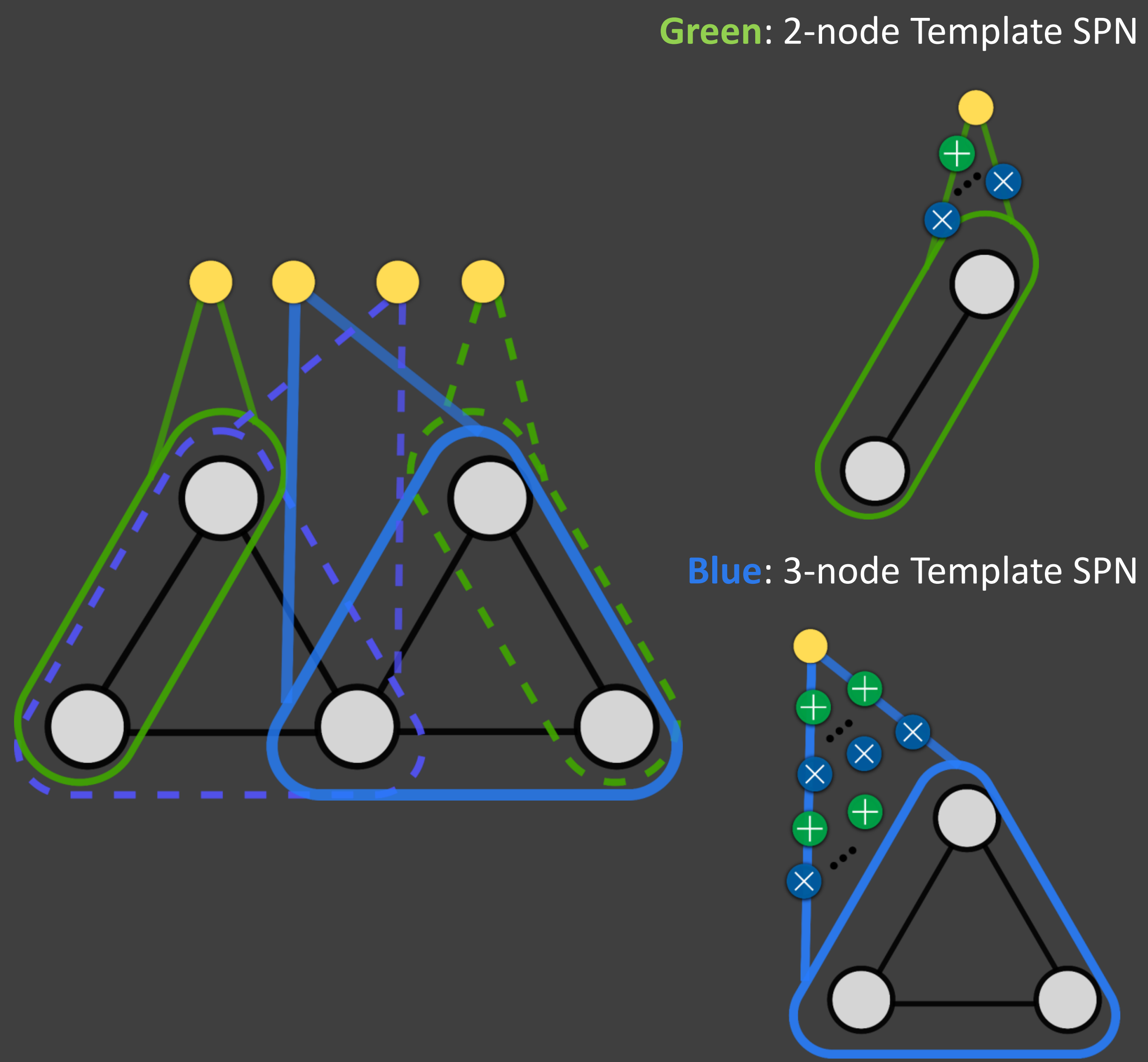


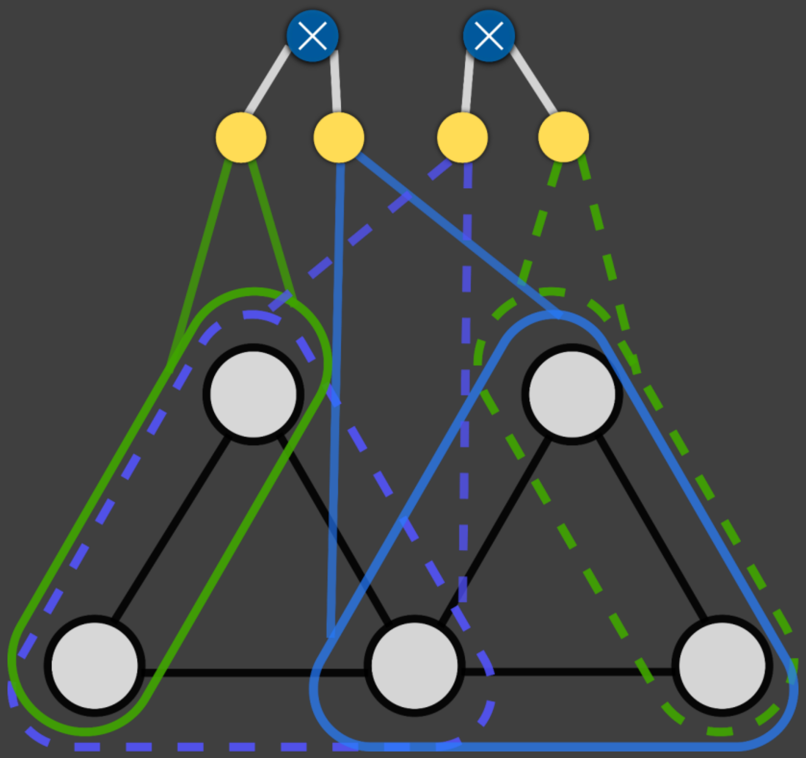
In this example, each node has **one latent variable** for semantic class, Corresponding to A **distribution** of local evidence

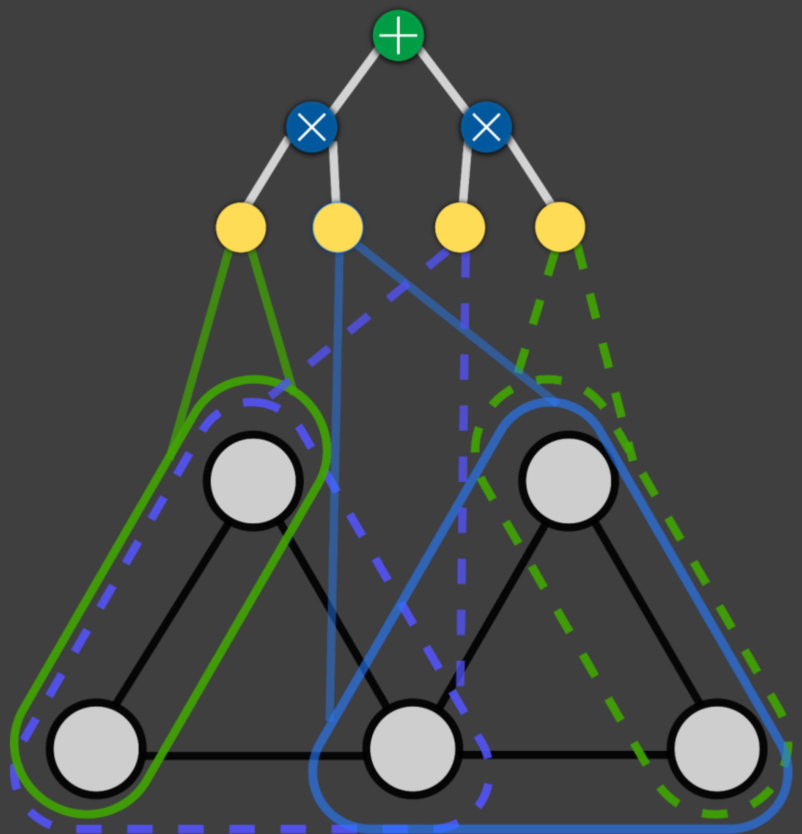


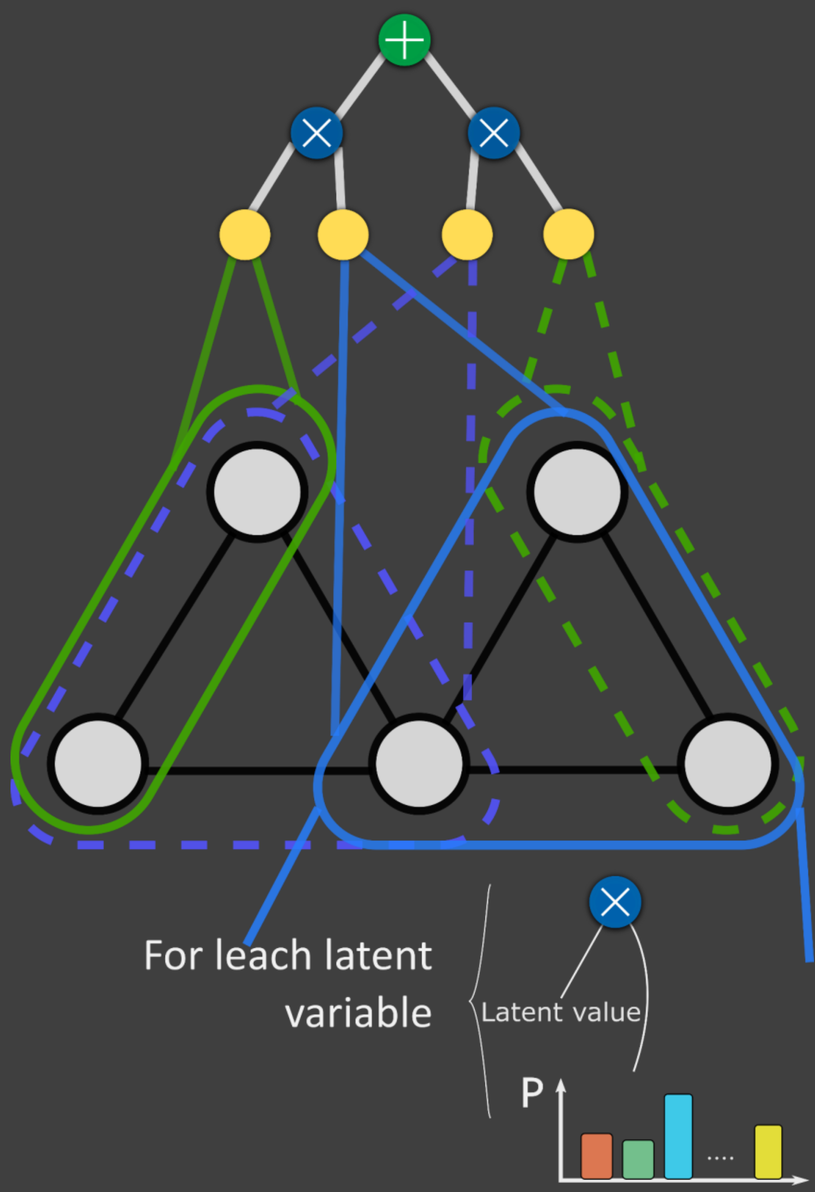





Green: 2-node Template SPN
Blue: 3-node Template SPN



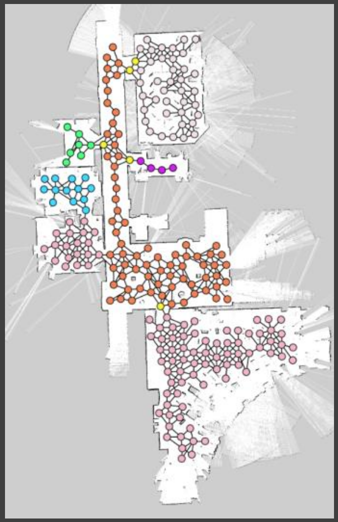
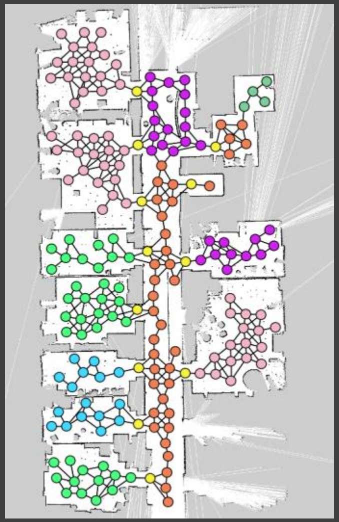



For leach latent
variable
Latent value
P
....

Experiments

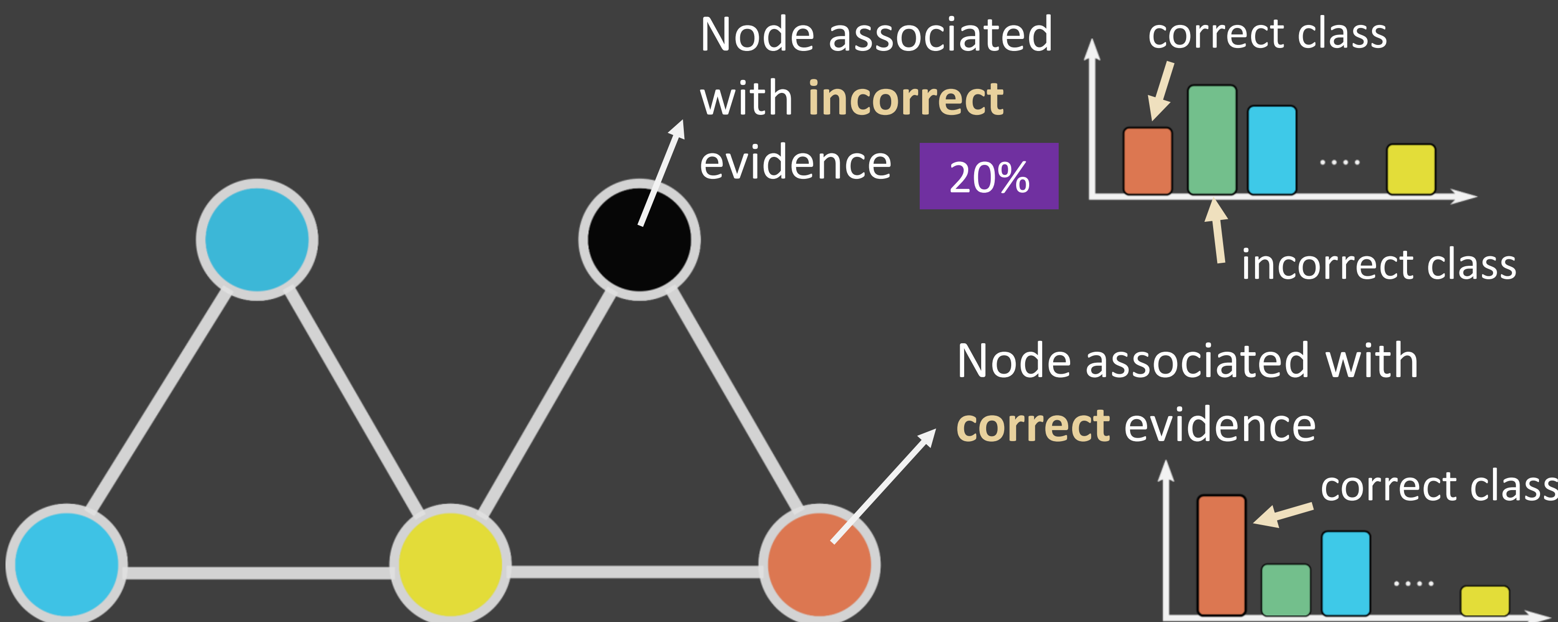
Dataset

- **99** topological graphs on 11 floors of 3 buildings in different cities.
  - **Trained** template SPNs **on graphs from 2 buildings**
  - **Tested** inference over full graphs **on the other building**

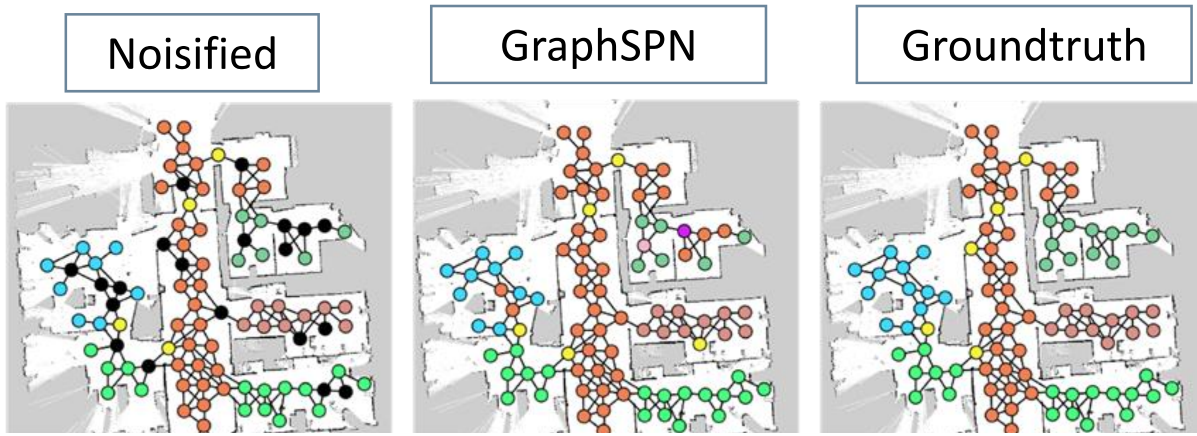



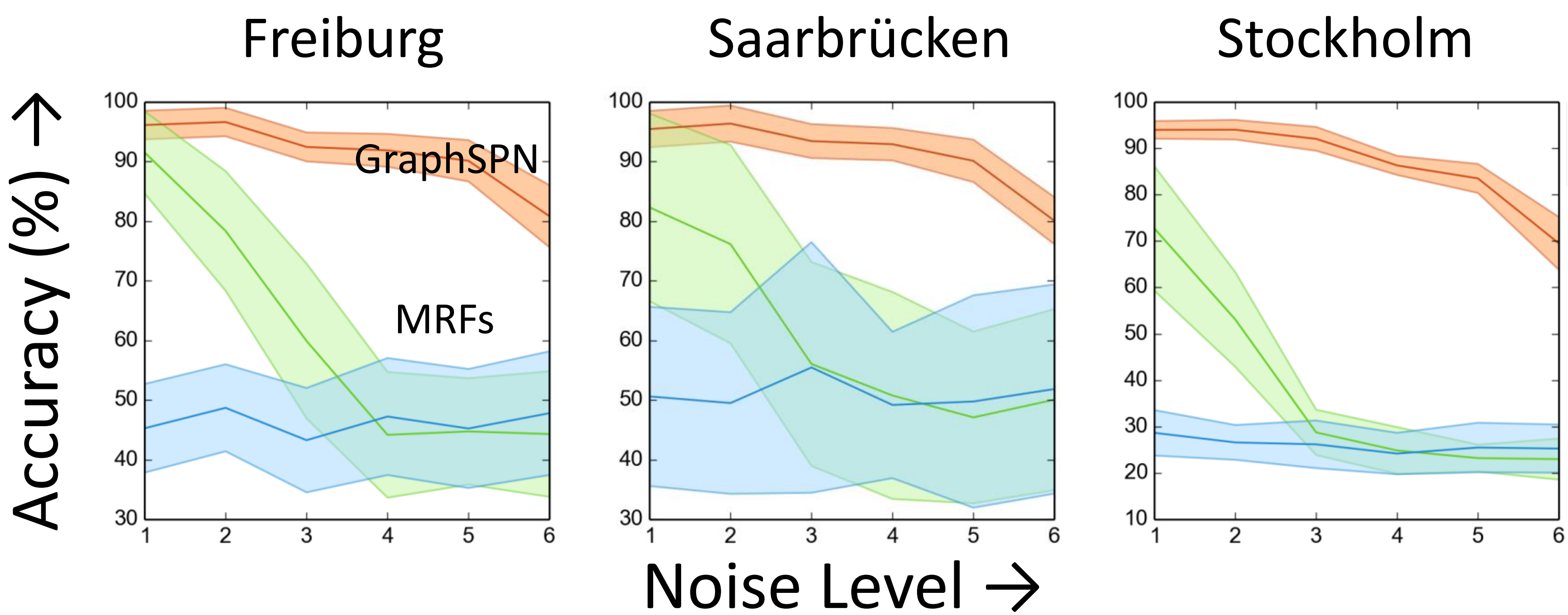

Experiment 1

Disambiguate Noisy Semantic Info



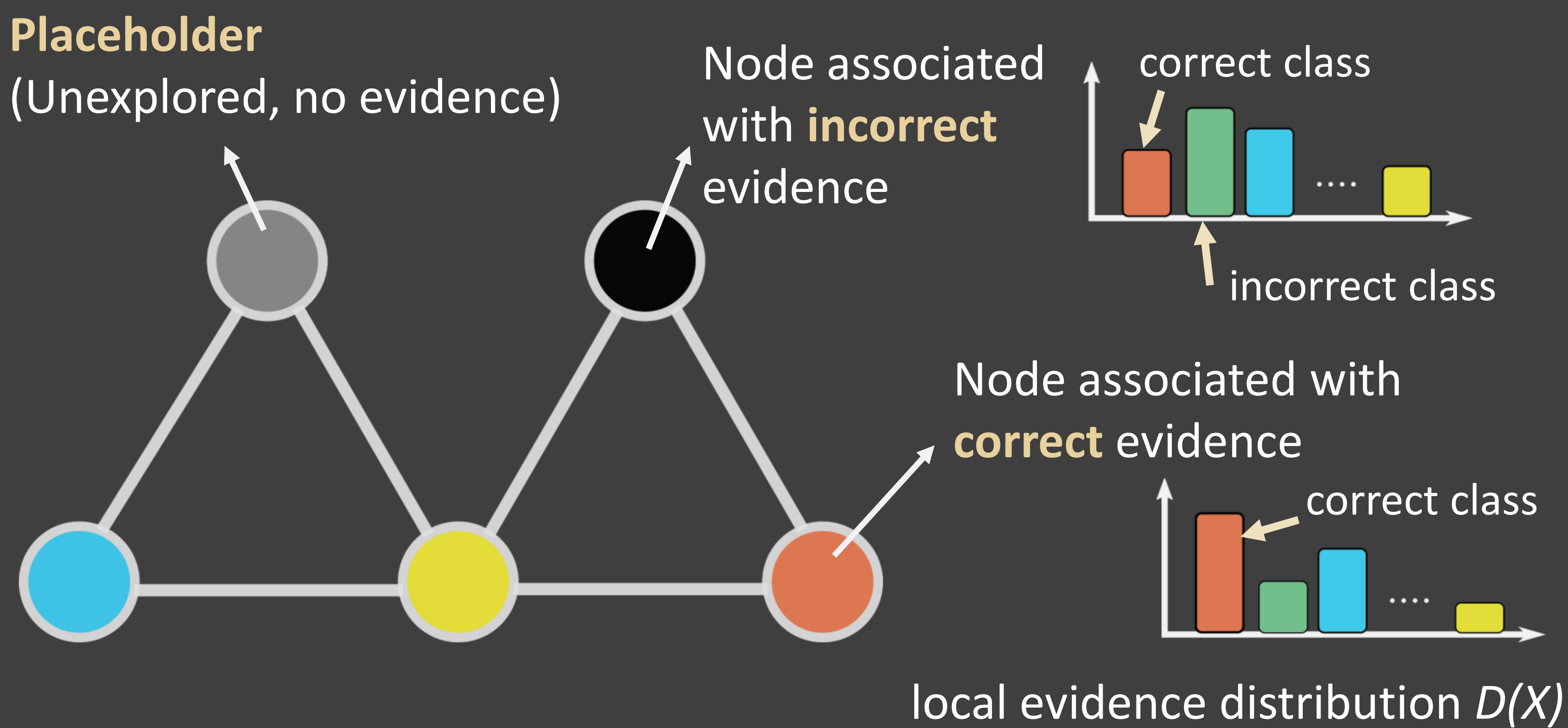
Results


Noisified
GraphSPN
Groundtruth

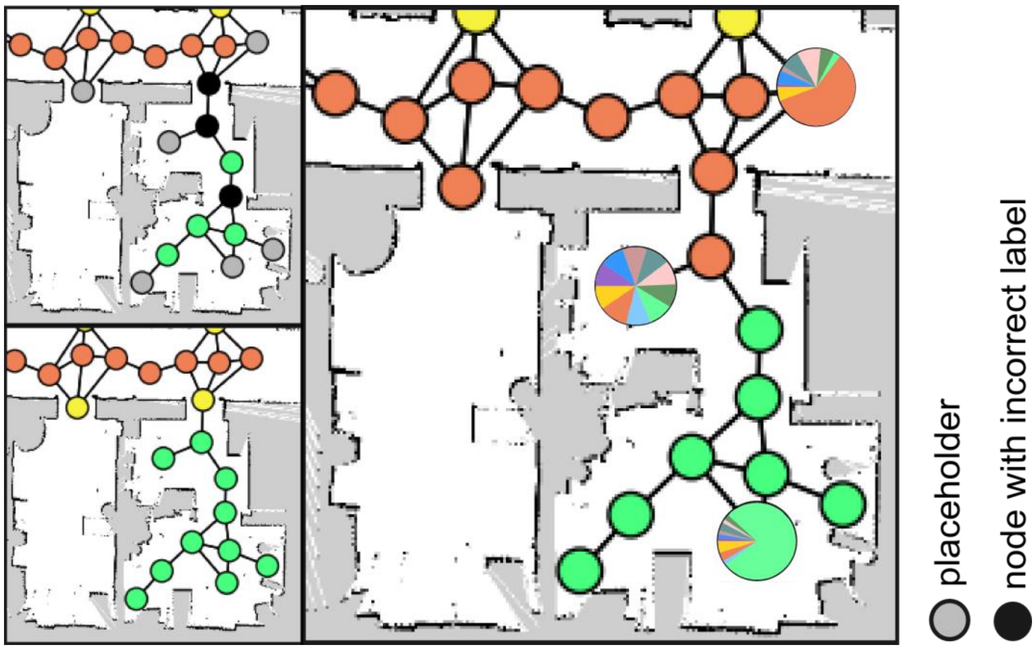

Freiburg
Saarbrücken
Stockholm
Accuracy (%) →
GraphSPN
MRFs
100
90
80
70
60
50
40
30
20
10
1
2
3
4
5
6
Noise Level →

Experiment 2

Infer Placeholder Semantics



Results: Marginal Inference over Placeholders



Accuracy over No. placeholders:

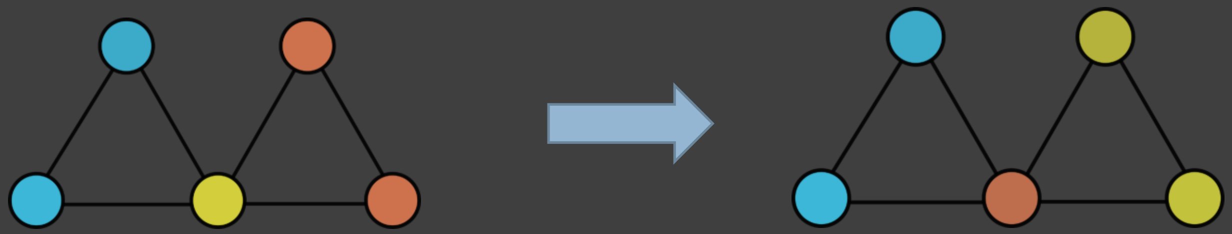
55% for GraphSPN

30% for MRFs

Experiment 3

Detect Novel Structure

- Investigate quality of likelihood produced by GraphSPNs
- Create **graphs** unseen during training by swapping categories (e.g. corridor with doorway):



- GraphSPNs were successful in this task, able to identify 90% novel structures, while having 10% false positive rate.

Conclusion & Future Work

- **Introduced** GraphSPNs
- Applied GraphSPNs to **model semantic maps**

- In the *future*, we look to:
  - Build a **unified SPN model** for hierarchical spatial knowledge representation.
  - **Extend** the use of GraphSPNs on other problems, such as semantic segmentation.