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 Sum-Product Networks (GraphSPNs)

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

Leverages **Sum-Product Networks**
Graph-Structured Sum-Product Networks (GraphSPNs)

- Deep probabilistic model for SP
- Complex, noisy variable dependencies
- Template models dynamic graphs of varying size
Semantic Mapping Using GraphSPNs
Problem:

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

![Diagram of semantic mapping with labels: corridor, office, doorway, and other nodes connected with arrows and bar graphs for probability distribution](image)
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 each latent variable, there is a corresponding latent value.
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

Node associated with **incorrect** evidence

Node associated with **correct** evidence

20%

[Diagram showing nodes and evidence categories]
Results

![Noisified GraphSPN](image1)

![GraphSPN](image2)

![Groundtruth](image3)

**Noise Level →**

**Accuracy (%) →**

**Freiburg**

GraphSPN

MRFs

**Saarbrücken**

GraphSPN

MRFs

**Stockholm**

GraphSPN

MRFs
Experiment 2

Infer Placeholder Semantics

**Placeholder**
(Unexplored, no evidence)

Node associated with **incorrect** evidence

Node associated with **correct** evidence

Correct class

Incorrect class

Local evidence distribution $D(X)$
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.