Learning Graph-Structured Sum-Product Networks for Probabilistic Semantic Maps

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AAAI 2018
Motivation (Robotics)

Mobile Robots in Indoor Spaces
Motivation (Robotics)
Semantic Maps
Motivation (Robotics)

Semantic Mapping

Inferred distributions of latent variables (semantic attributes)

Local evidence

places (entities)

spatial relations

Learning Graph-Structured Sum-Product Networks for Probabilistic Semantic Maps
Motivation (Robotics)

Problem:
Learn **general spatial relations** between things in the world
Estimate semantic attributes in **specific** environment?

- Model semantic map as a whole
- This is **Structured Prediction (SP)**
Motivation (Machine Learning)

Probabilistic Graphical Models

Pros:
- Probabilistic
- Generative
- Interpretable

Cons:
- Intractable exact inference

Examples:
Bayesian Network, Markov Random Field, Chain Graph  [Pronobis&Jensfelt ICRA’12]
Motivation (Machine Learning)

Recent Deep Structured Prediction Approaches

- End-to-end
- Remarkable results for visual data

Figure from [Shelhamer et al. PAMI’16]

Learning Graph-Structured Sum-Product Networks for Probabilistic Semantic Maps

[Schwing & Urtasun, ICML’15, Belanger & McCallum, ICML’16, Shelhamer et al. PAMI’16]
Motivation (Machine Learning)

Recent Deep Structured Prediction Approaches

• But…
  • **Strict constraints** on variable interactions
  • **Fixed** number of variables
  • **Static** global structure
  • Often **not probabilistic**

[Schwing & Urtasun, ICML’15, Belanger & McCallum, ICML’16, Shelhamer et. al. PAMI’16]
Sum-Product Networks

- Viewed in 2 ways:
  - Deep architecture
  - Graphical model

- Structure semantics:
  - Hierarchical mixture of parts
Sum-Product Networks

Naïve Bayes Mixture Model
- 3 components
- 2 binary variables

Poon & Domingos, UAI’11, Friesen & Domingos, ICML’16
Sum-Product Networks

• Learn conditional or joint distributions
• **Tractable** partition function, exact inference

Naïve Bayes Mixture Model
- 3 components
- 2 binary variables

[Poon & Domingos, UAI’11, Friesen & Domingos, ICML’16]
Proposed Method

Graph-Structured Sum-Product Networks

• Template-based approach
• Defined as a set of template SPN models
• Template models represent general, higher-order relations between latent variables
  • Applied to form a single distribution for a specific structured problem for inference
Learning General Knowledge

Graph-Structured Sum-Product Networks

Annotated training data (graph-structured)

Partition

Train

Template SPNs

Template 1

Template N

Sub-graphs

GraphSPN
Instantiation for Specific Problem

Graph-Structured Sum-Product Networks
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Experiments

GraphSPN for Semantic Mapping

Observed local evidence $X_1$
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Observed local evidence $X_1$
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Observed local evidence $X_1$

Inferred distribution of latent variables $Y$
(Semantic place categories)

$P(Y_i)$
Experiments

Dataset

- **99** semantic maps of 11 floors in **3 buildings** in different cities

- Cross-validation:
  - **Trained** on graphs from **2 buildings**
  - **Tested** on graphs from **remaining building**
Experiment 1

Infer Latent Semantics based on Noisy Evidence

Node associated with **incorrect** evidence (20%)

Node associated with **correct** evidence (80%)

local evidence

correct class

incorrect class

local evidence

noise
Experiment 1

Infer Latent Semantics based on Noisy Evidence

Correction of incorrect information (20%)

Strengthen correct information (80%)

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Experiment 1

Results: Inference Behavior

Similar results even **without local evidence** for some places
Experiment 1

Results: Increasing Noise

- Freiburg
  - GraphSPN
  - MRF (order 2)
  - MRF (order 3)

- Saarbrücken

- Stockholm
Experiment 2

Novelty Detection

See paper for more details
Conclusions

• Introduced **GraphSPNs**
  • Leverages **Sum-Product Networks**

- General approach to model arbitrary dynamic graphs
- Complex, noisy variable dependencies
- Inference based on instantiation of template models

• Applied GraphSPNs to **model semantic maps**
Ongoing Work

Unified Model for Spatial Knowledge

Semantics in global context

Global topology

Local place semantics

Sensory information

Unified Model

GraphSPN
This work!

DGSM
(Pronobis and Rao, IROS 2017)
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Thank you