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

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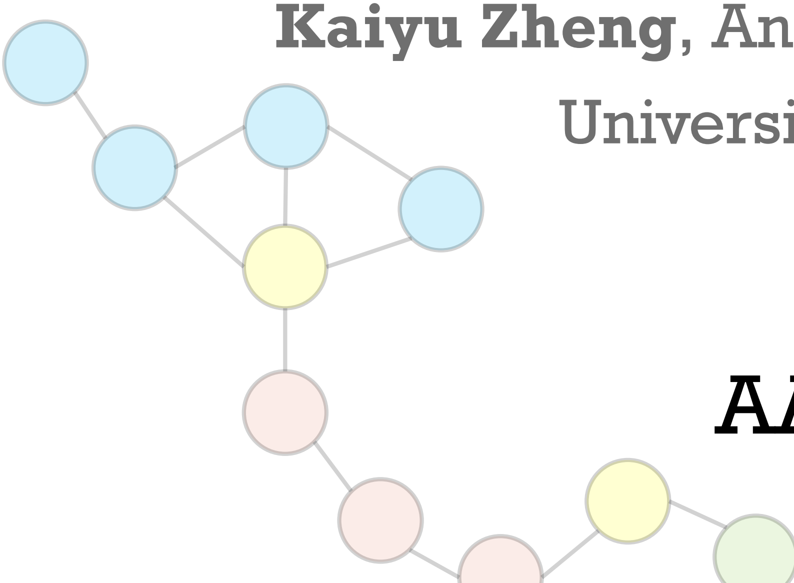
AAAI 2018

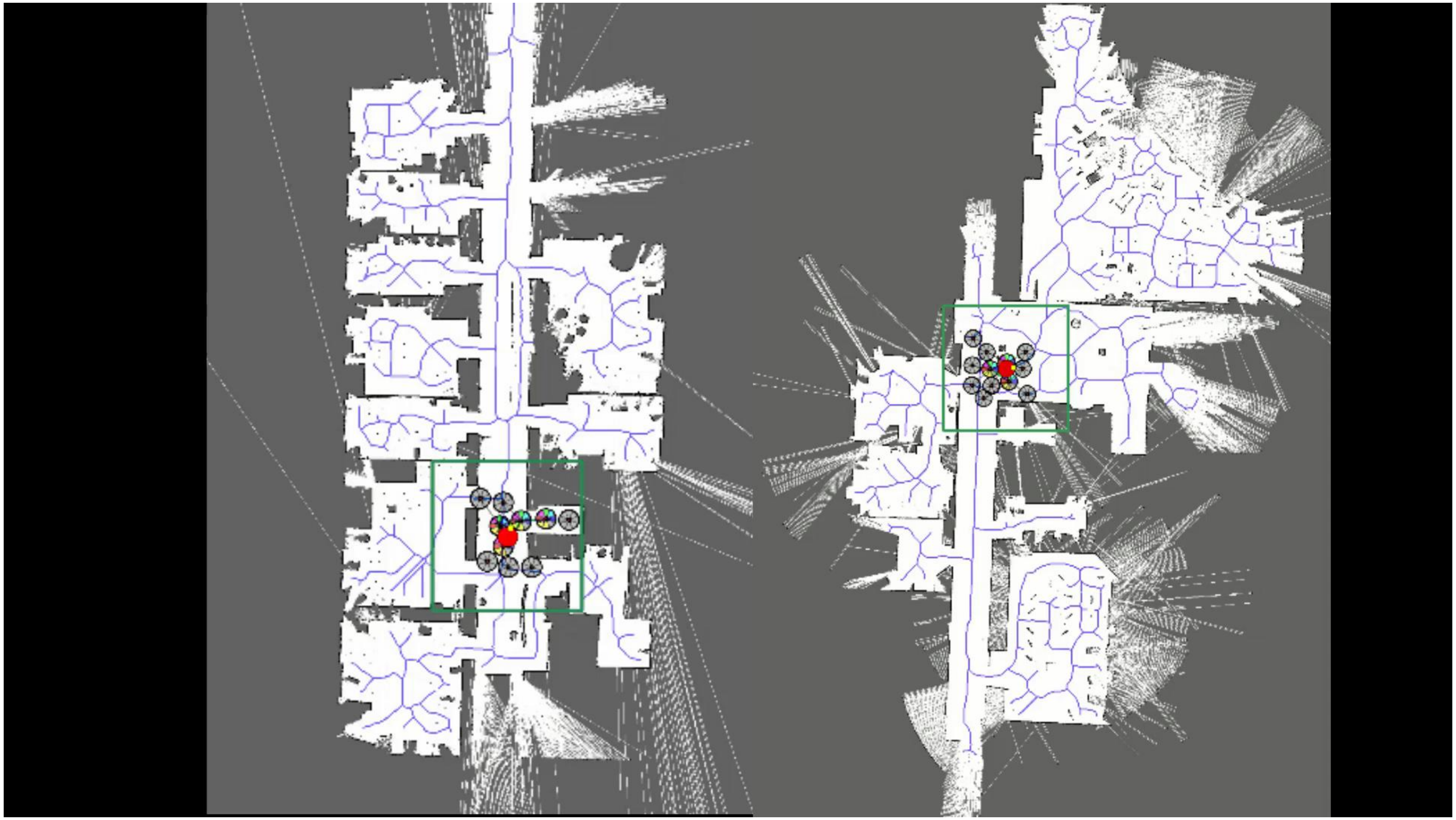


Motivation (Robotics)

Mobile Robots in Indoor Spaces

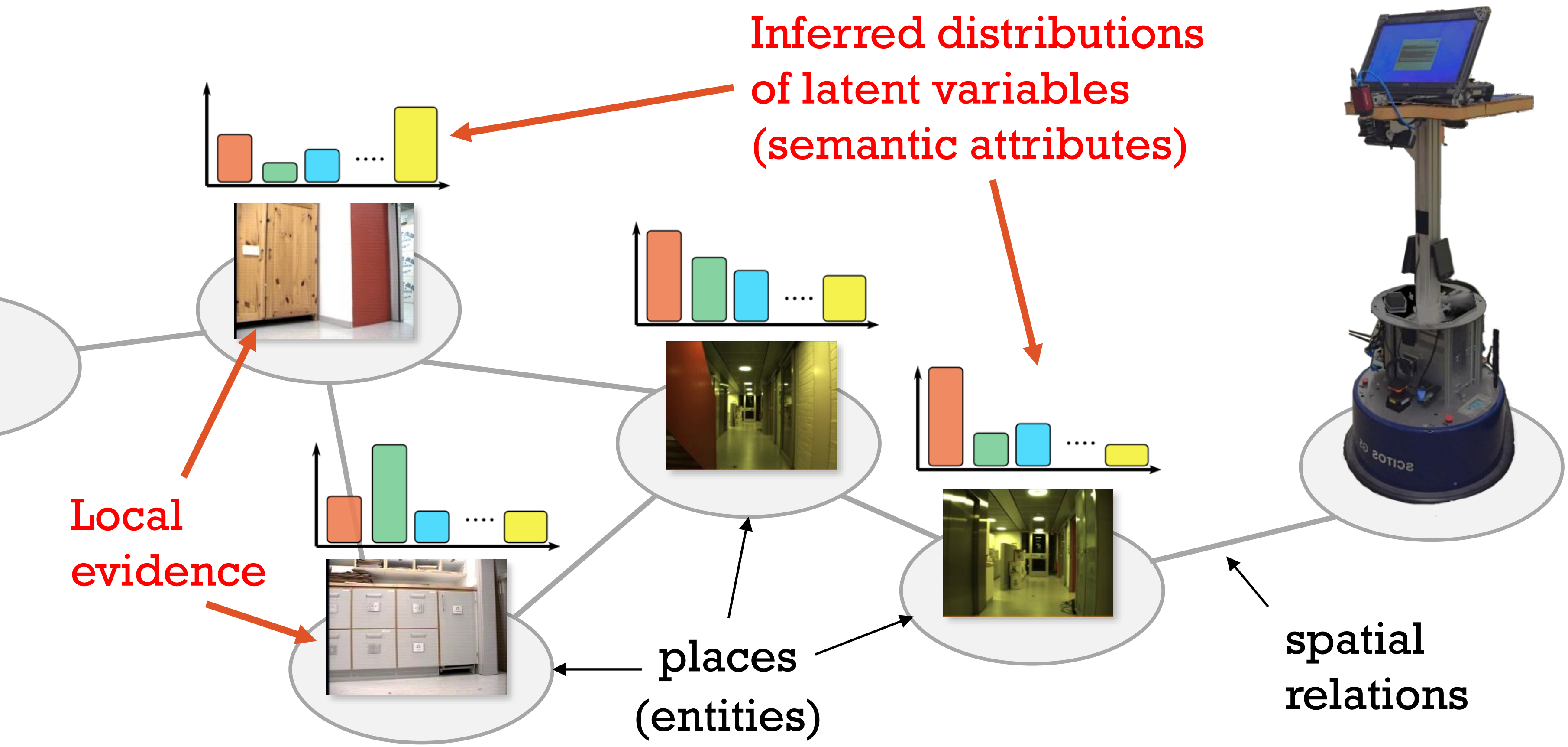
Motivation (Robotics)

Semantic Maps



Motivation (Robotics)

Semantic Mapping

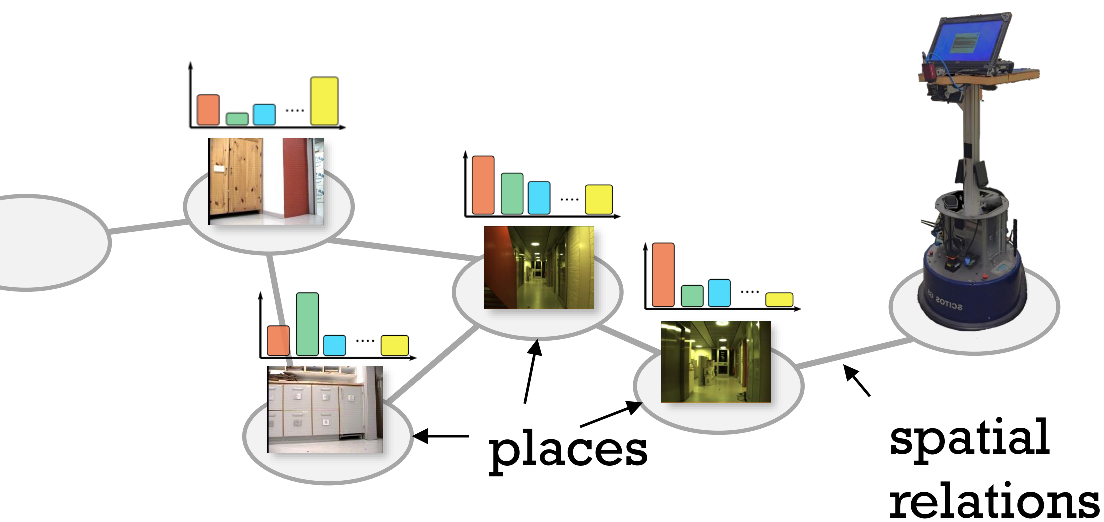


Motivation (Robotics)

Problelm:

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

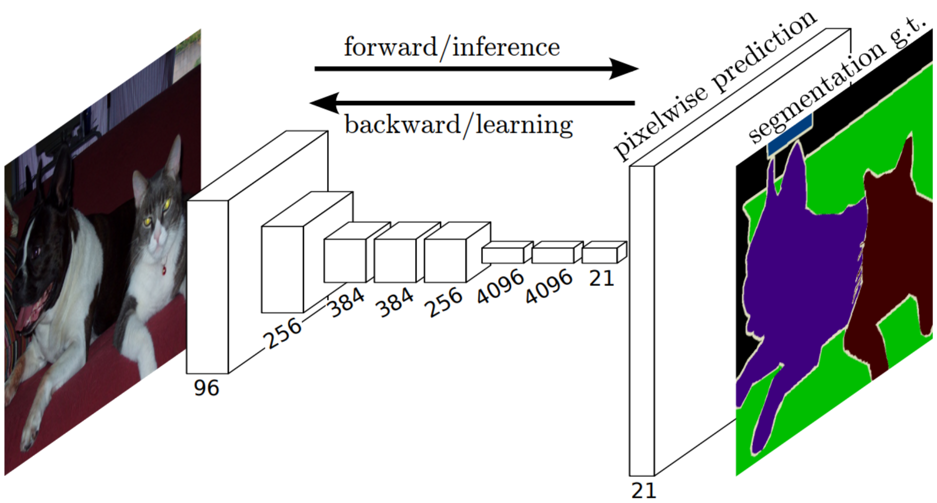


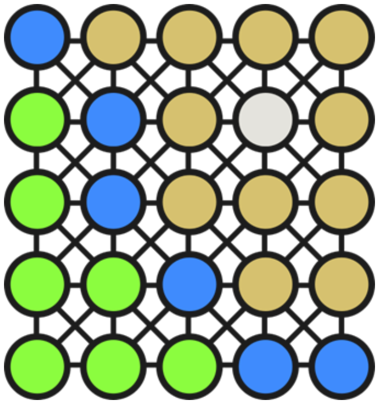
Figure from [Shelhamer et. al. PAMI'16]

[Schwing & Urtasun, ICML'15, Belanger & McCallum, ICML'16, Shelhamer et. al. PAMI'16]

Motivation (Machine Learning)

Recent Deep Structured Prediction Approaches

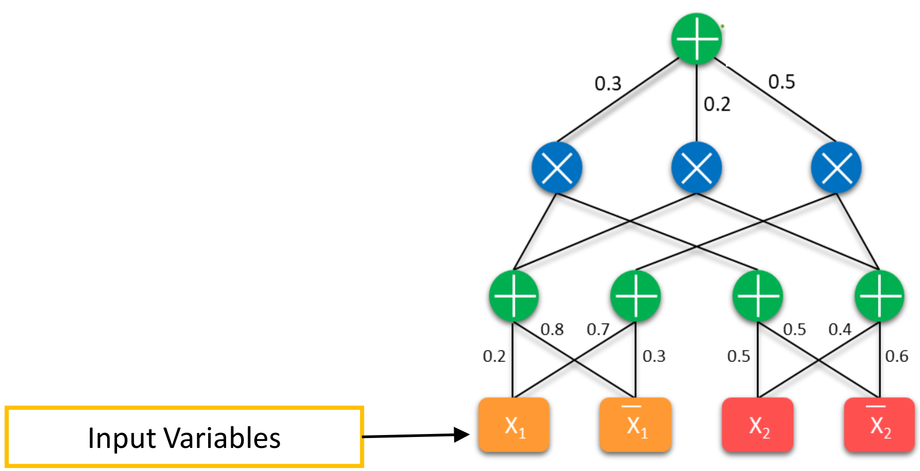
- **But…**
  - Strict constraints on variable interactions
  - Fixed number of variables
  - Static global structure
  - Often not probabilistic



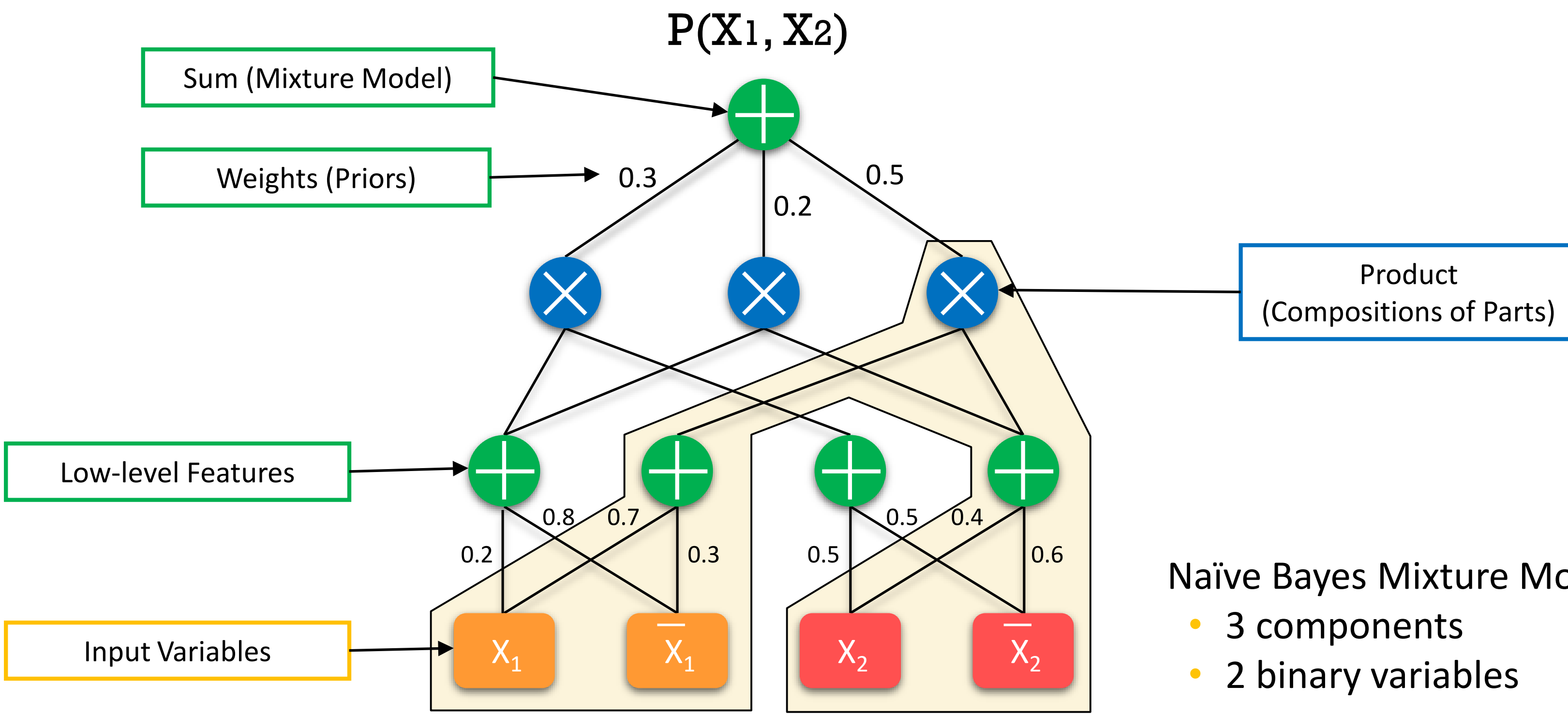
[Schwing & Urtasun, ICML'15, Belanger & McCallum, ICML'16, Shelhamer et. al. PAMI'16]

Sum-Product Networks

- Viewed in 2 ways:
  - Deep architecture
  - Graphical model
- Structure semantics:
  - Hierarchical mixture of parts



Sum-Product Networks



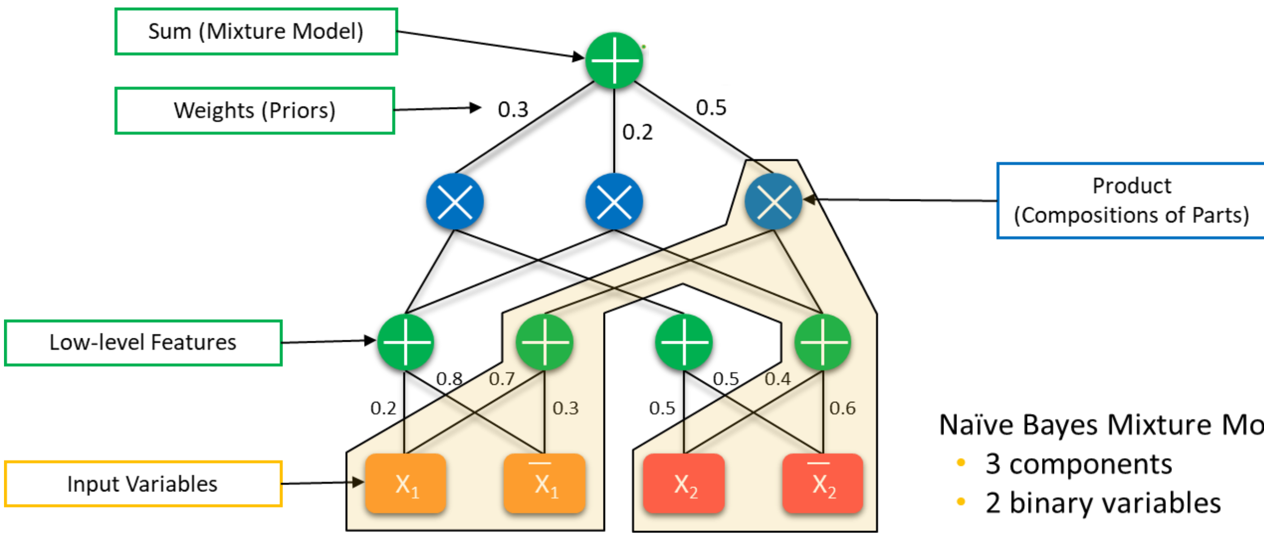
Naïve Bayes Mixture Model

- 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

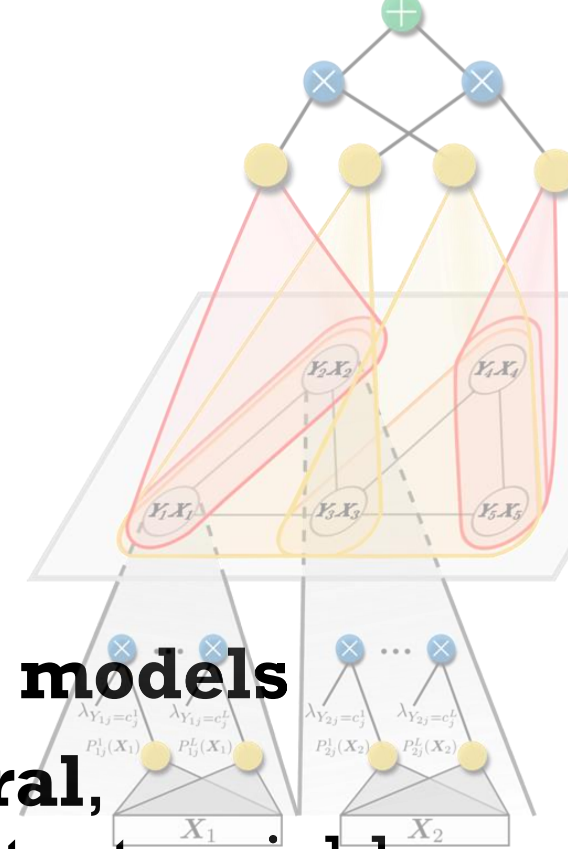


Naïve Bayes Mixture Model
- 3 components
- 2 binary variables

[Poon & Domingos, UAI'11,
Friesen & Domingos, ICML'16]

Proposed Method

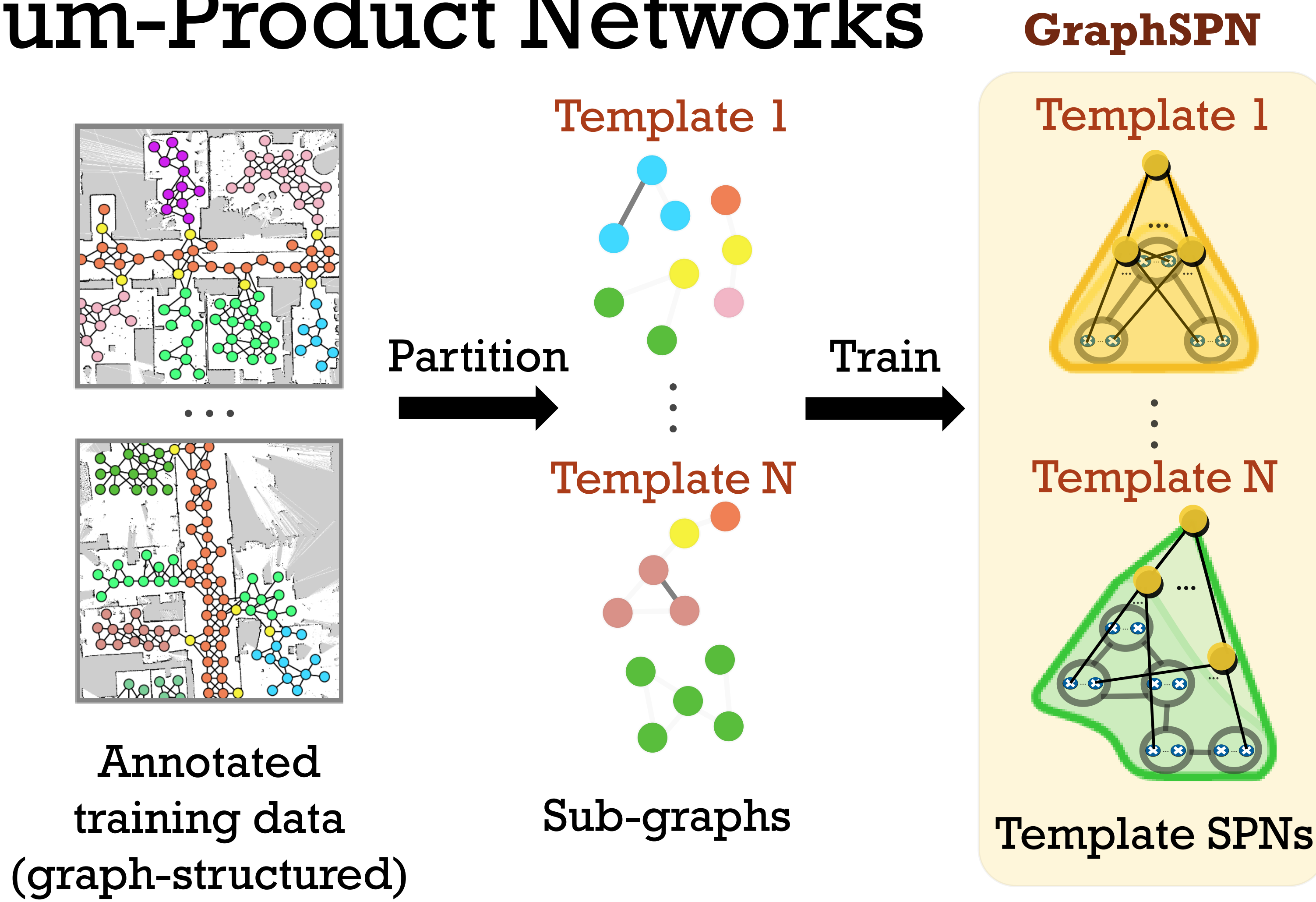
Graph-Structured Sum-Product Networks



- 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

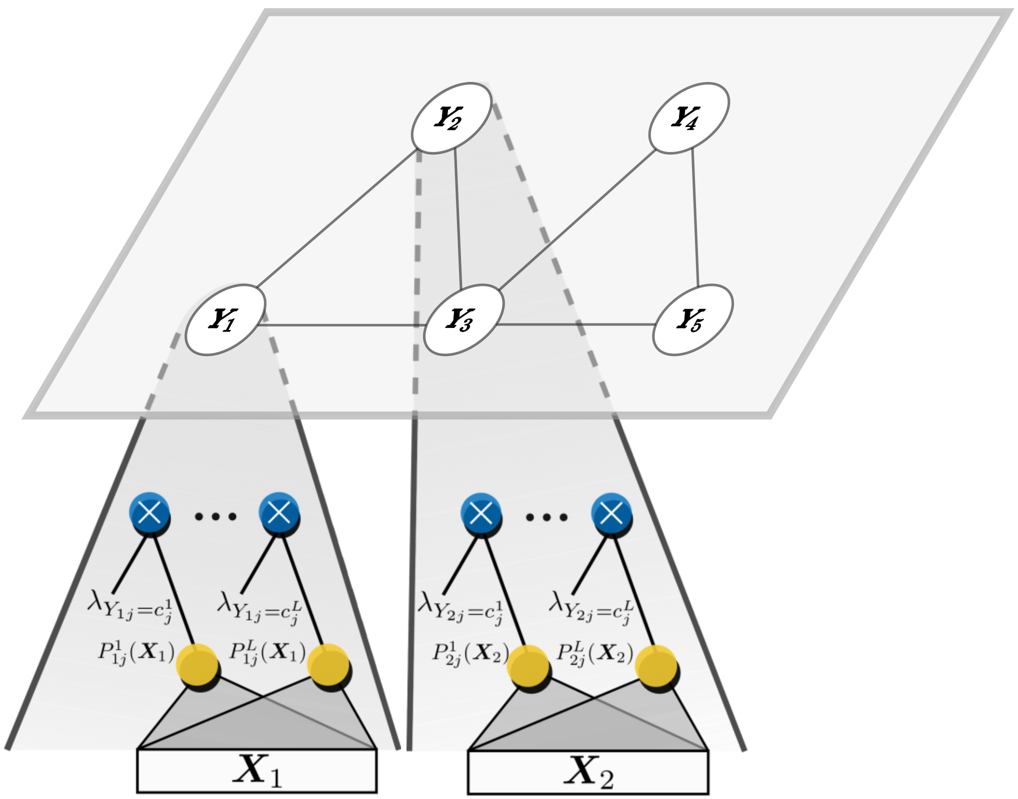
Learning General Knowledge

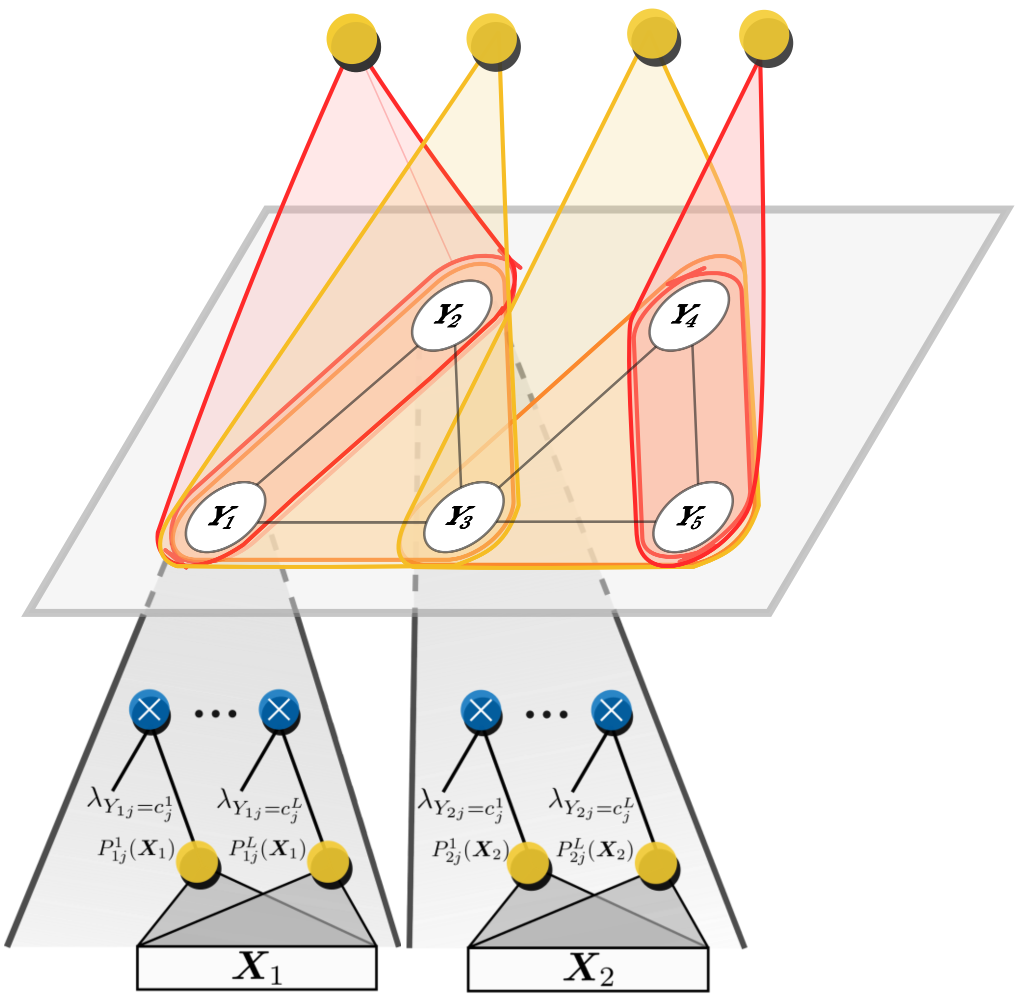
Graph-Structured Sum-Product Networks

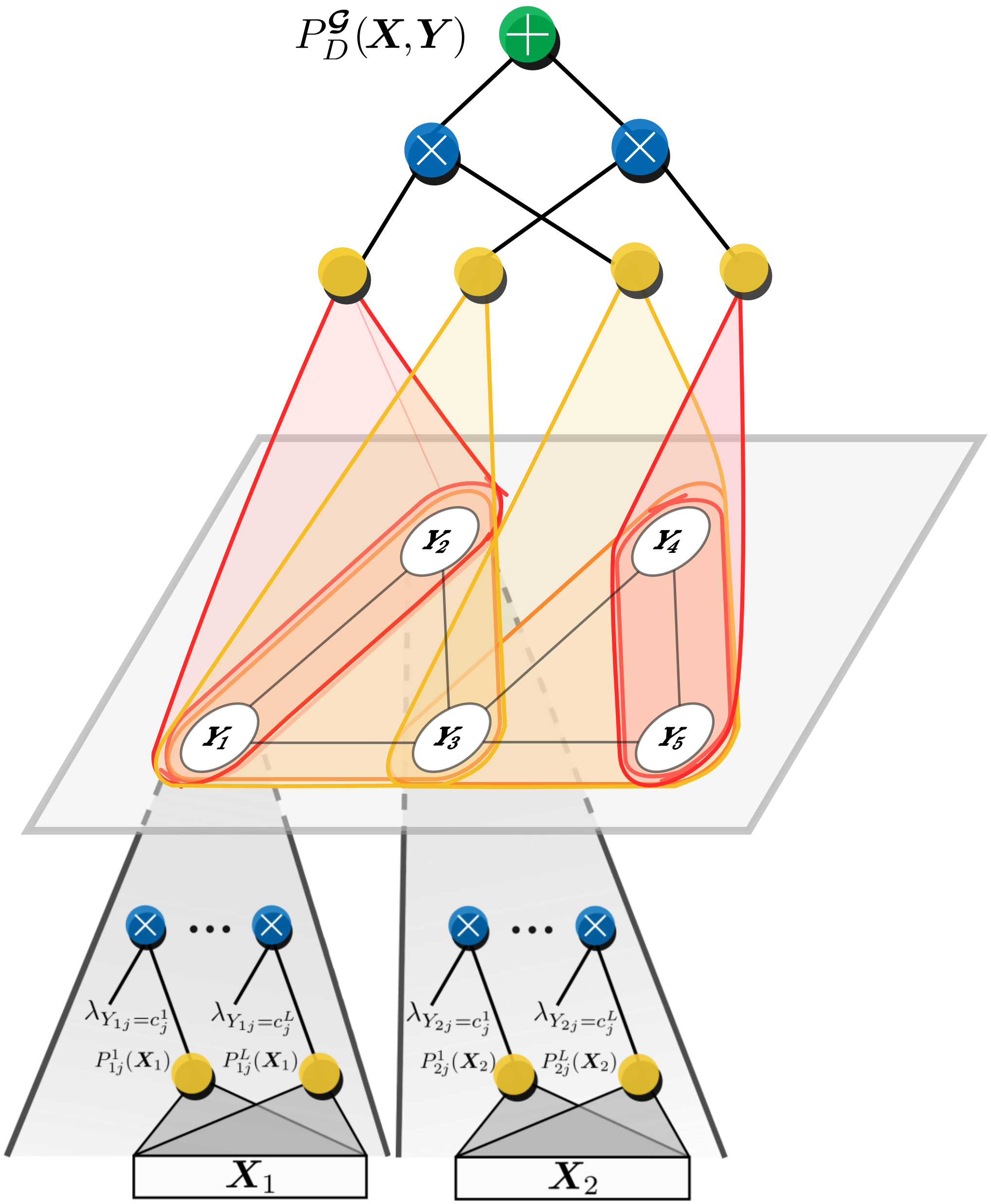


Instantiation for Specific Problem

Graph-Structured Sum-Product Networks

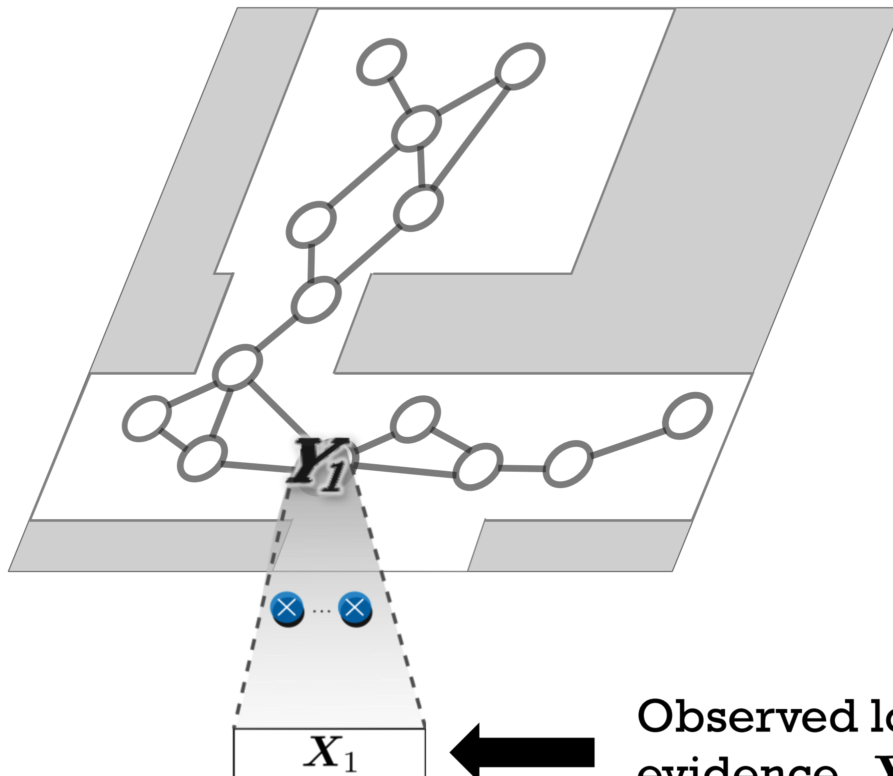



Y_2
Y_4
Y_1
Y_3
Y_5
$\lambda_{Y_{1j}=c_j^1}$
$\lambda_{Y_{1j}=c_j^L}$
$P_{1j}^1(\boldsymbol{X}_1)$
$P_{1j}^L(\boldsymbol{X}_1)$
$\lambda_{Y_{2j}=c_j^1}$
$\lambda_{Y_{2j}=c_j^L}$
$P_{2j}^1(\boldsymbol{X}_2)$
$P_{2j}^L(\boldsymbol{X}_2)$
$\boldsymbol{X}_1$
$\boldsymbol{X}_2$

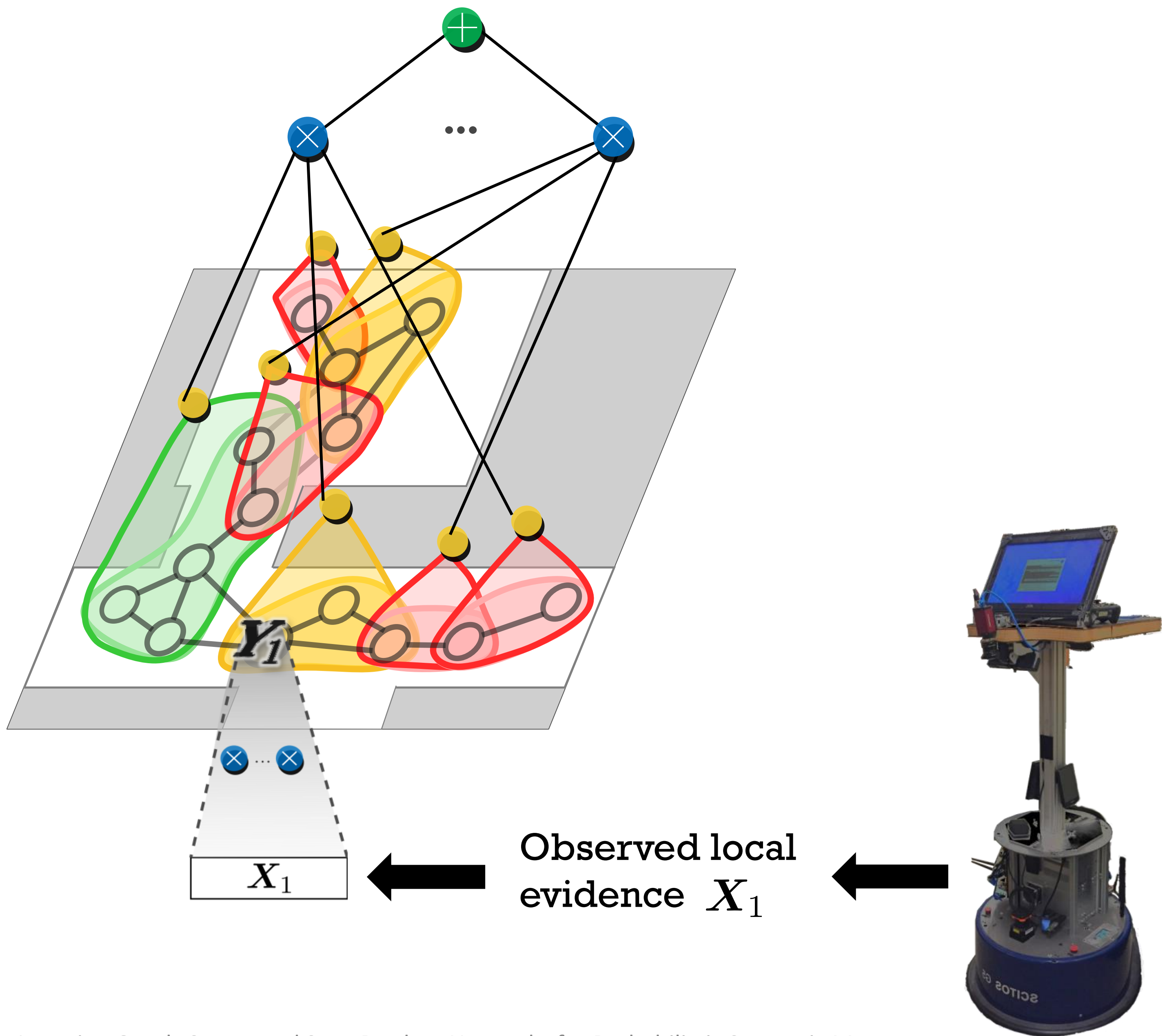

$P_D^{\mathcal{G}}(\boldsymbol{X},\boldsymbol{Y})$
Y_2
Y_4
Y_1
Y_3
Y_5
$\lambda_{Y_{1j}=c_j^1}$
$\lambda_{Y_{1j}=c_j^L}$
$P_{1j}^1(\boldsymbol{X}_1)$
$P_{1j}^L(\boldsymbol{X}_1)$
$\lambda_{Y_{2j}=c_j^1}$
$\lambda_{Y_{2j}=c_j^L}$
$P_{2j}^1(\boldsymbol{X}_2)$
$P_{2j}^L(\boldsymbol{X}_2)$
$\boldsymbol{X}_1$
$\boldsymbol{X}_2$

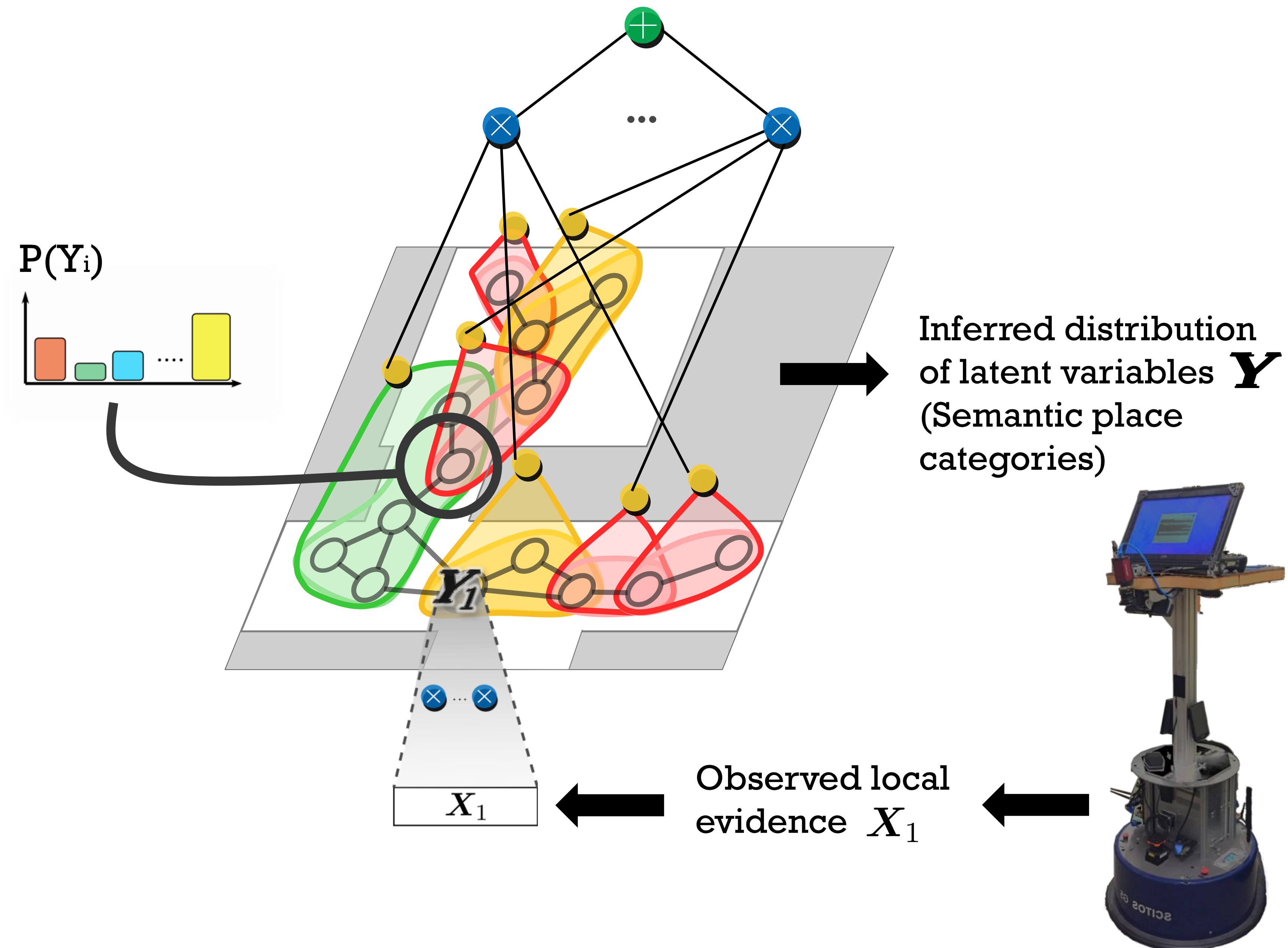
Experiments

GraphSPN for Semantic Mapping



Observed local evidence X_1

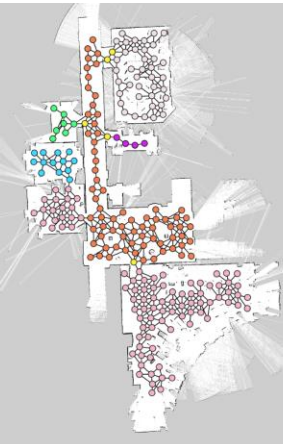
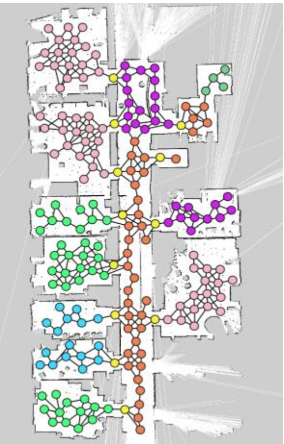

Y_1
X_1
Observed local evidence X_1


P(Yi)
....
Y1
X1
Inferred distribution of latent variables Y (Semantic place categories)
Observed local evidence X1
SCITOS G5

Experiments

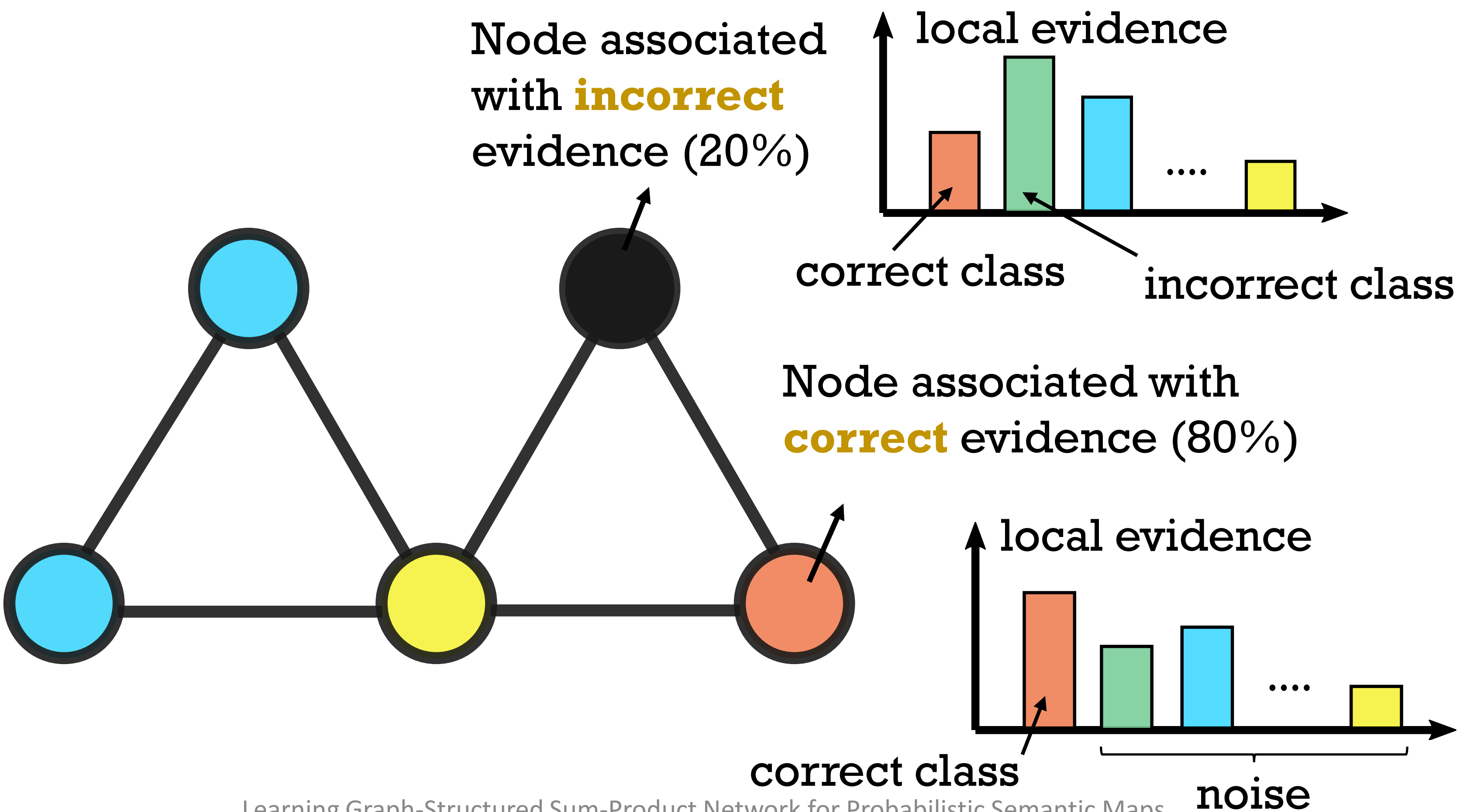
Dataset

- **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**

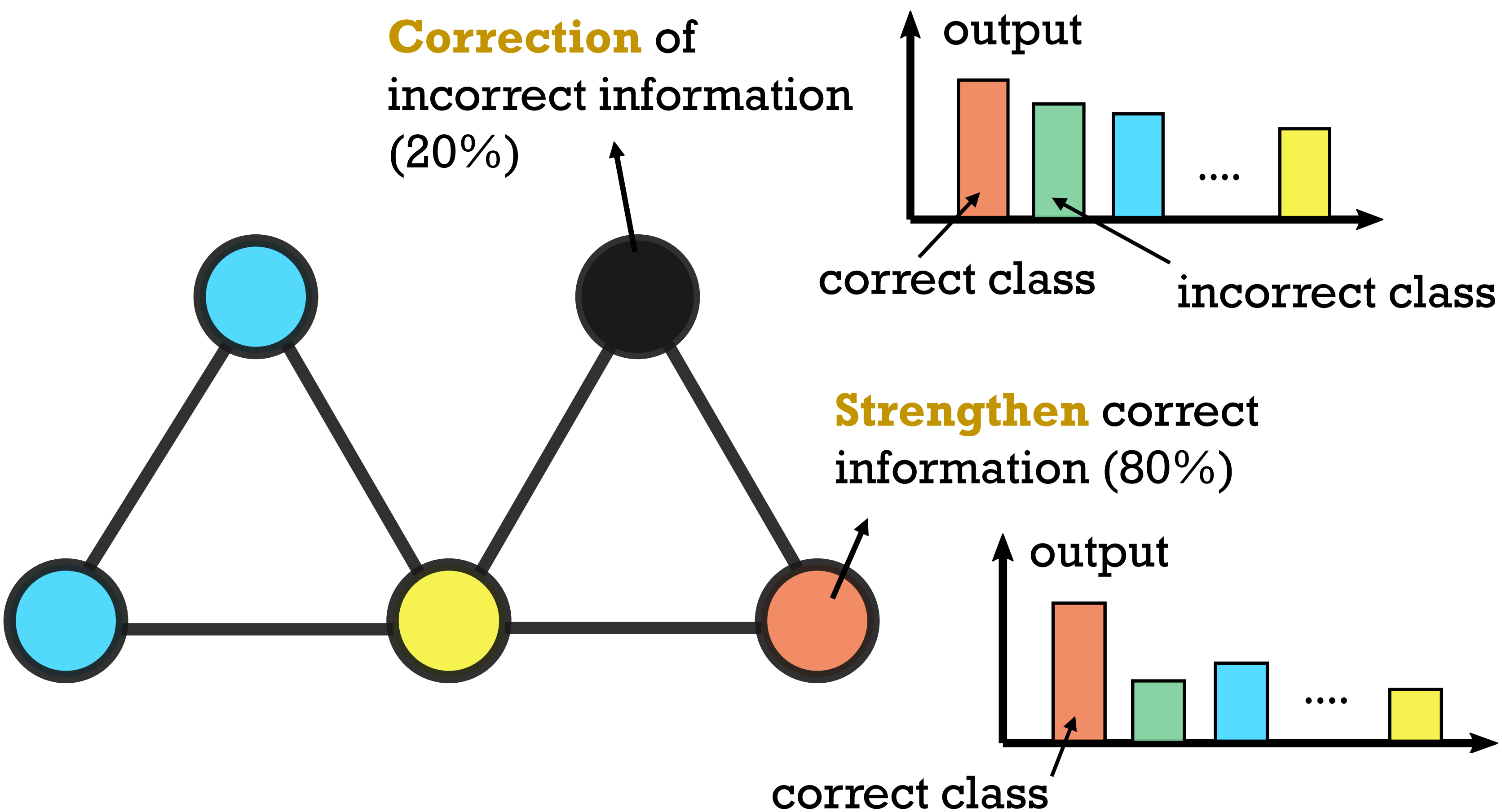

Experiment 1

Infer Latent Semantics based on Noisy Evidence



Experiment 1

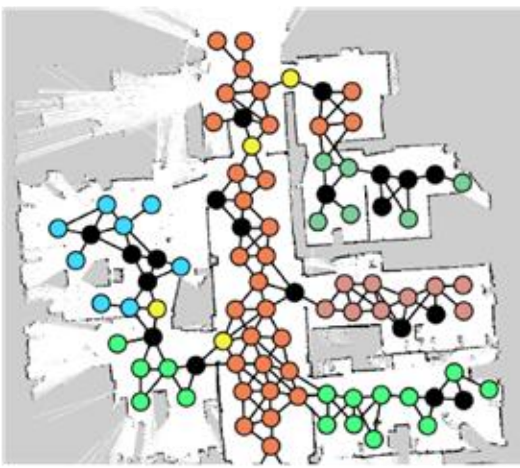
Infer Latent Semantics based on Noisy Evidence



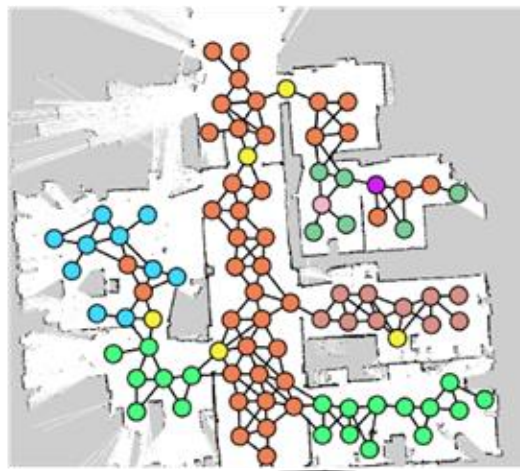
Experiment 1

Results: Inference Behavior

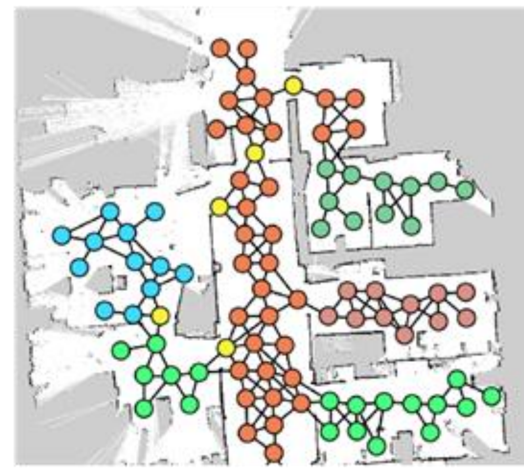
Noisified



GraphSPN



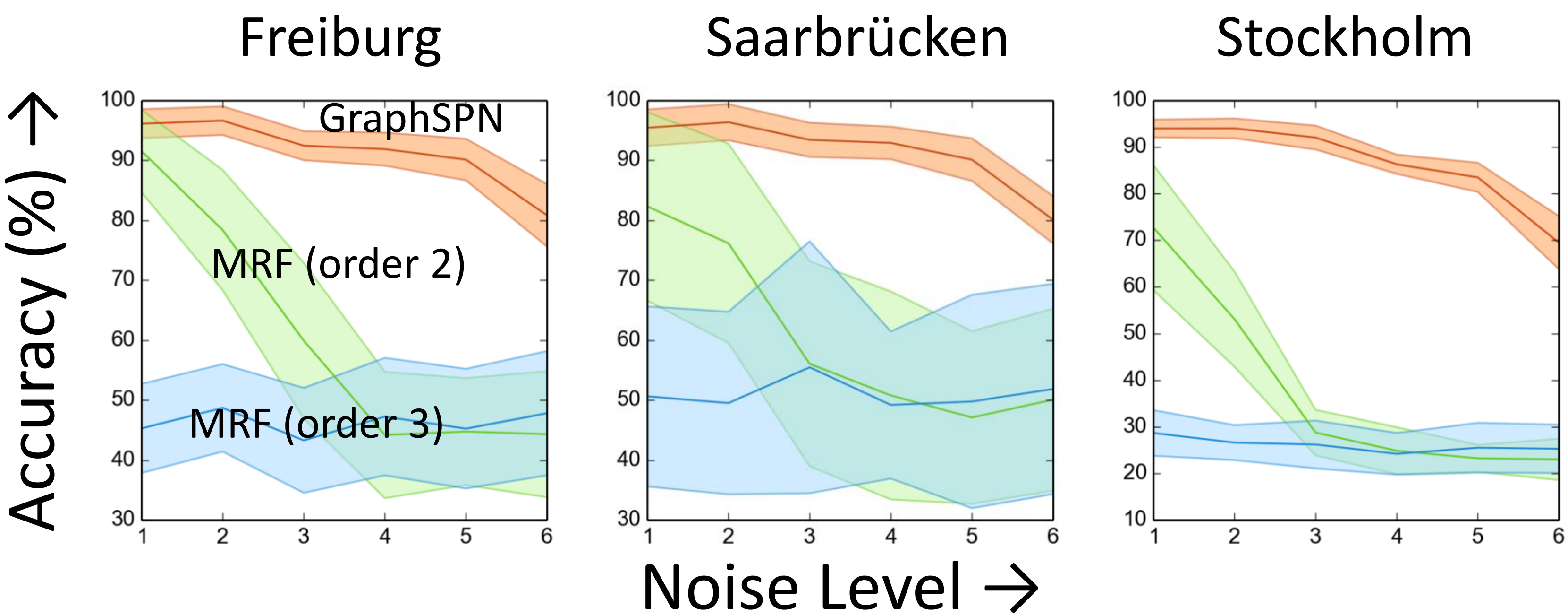
Groundtruth



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

Experiment 1

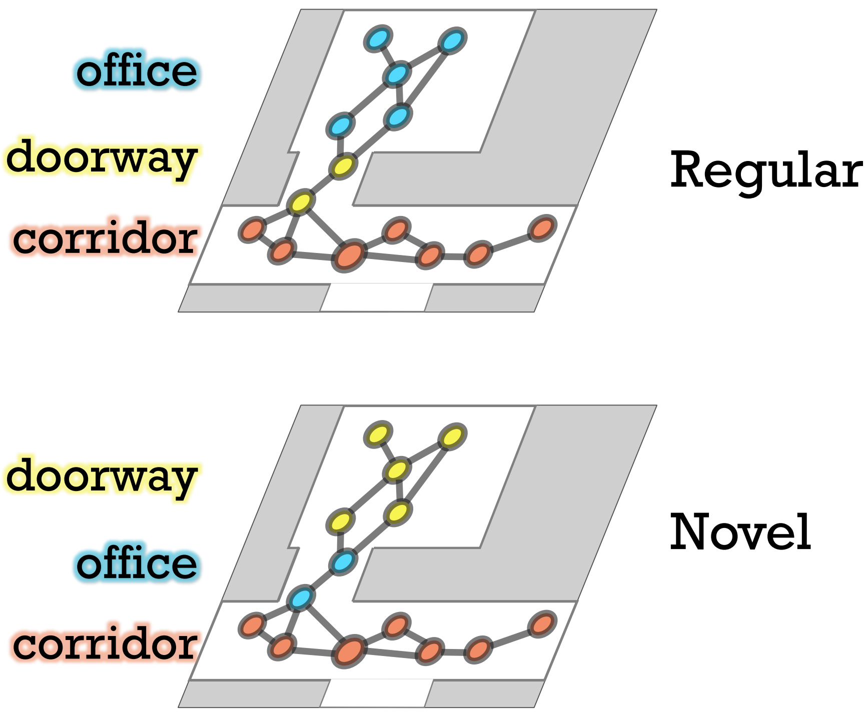
Results: Increasing Noise

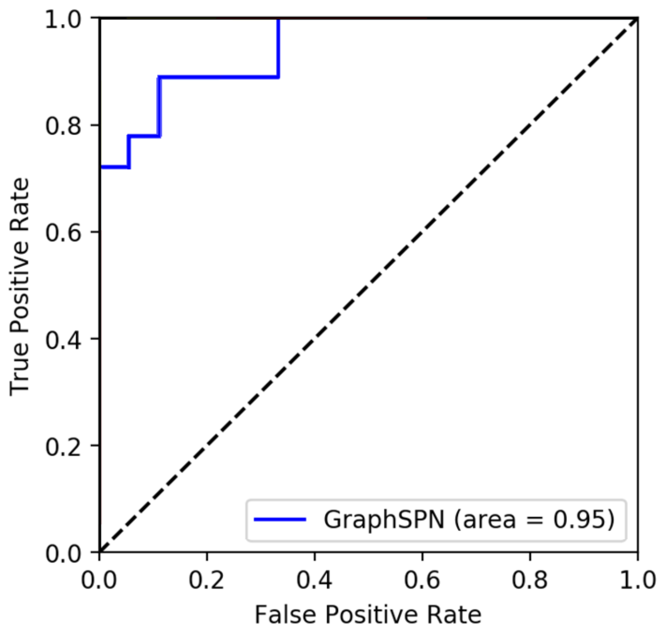


Experiment 2

Novelty Detection

See paper for more details





Conclusions

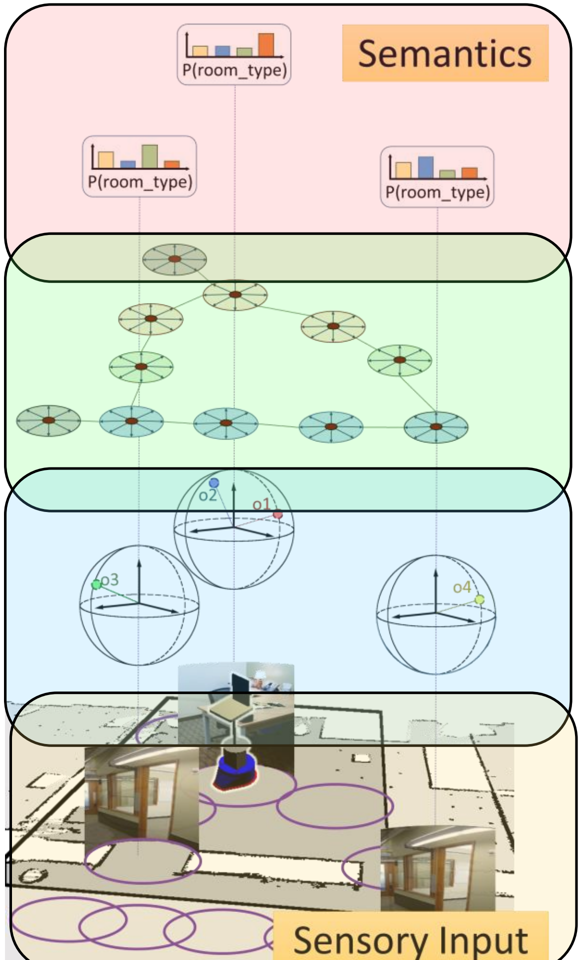
- Introduced **GraphSPNs**
    - Leverages **Sum-Product Networks**

General approach to model arbitrary dynamic graphs	Complex, noisy variable dependencies	Inference based on instantiaion 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

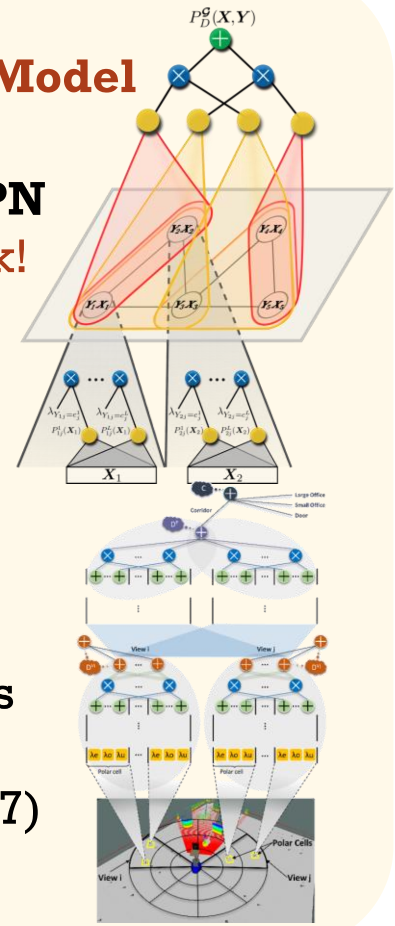
Unified Model

GraphSPN

This work!

DGSM

(Pronobis and Rao, IROS 2017)



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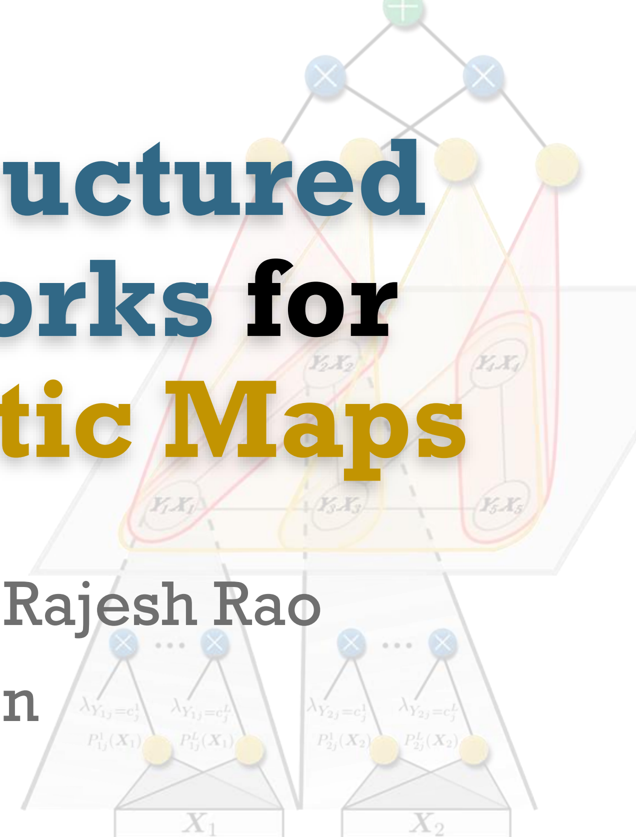
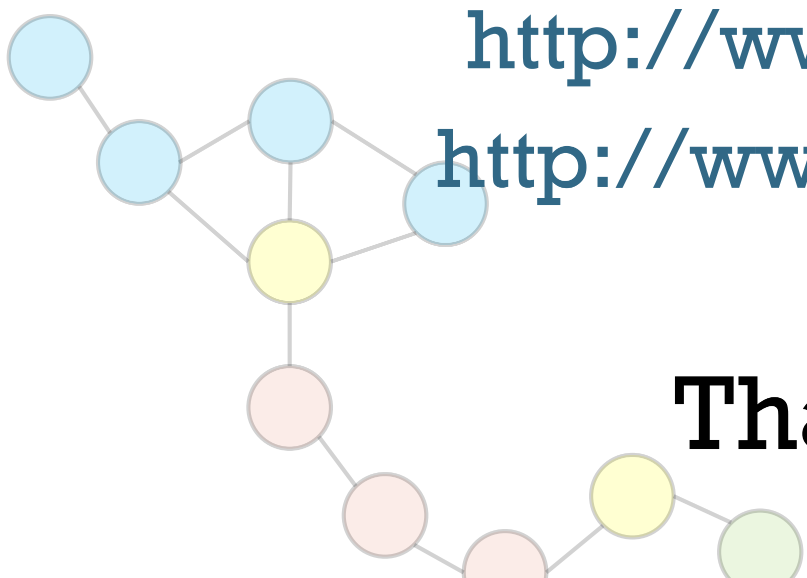


http://www.kaiyuzh.me
http://www.pronobis.pro



Thank you

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