Probabilistic Machine Learning

Tom Schierenbeck, 15.02.2024

Universität Bremen

Artificial Intelligence

About Me

Name: Tom Schierenbeck

E-Mail: tom_sch@uni-bremen.de

GitHub: tomsch420

Position: PhD Student at the Institute for Artificial Intelligence

Involved in the Projects:

- PyCRAM, Cognitive Architecture for Robots in Python
- Probabilistic Modelling
- Lecturer for Knowledge Acquisition and Knowledge Representation
- Project Leader of FAME, Learning plans from Videos

About the Institute for Artificial Intelligence

- AI-Powered & Cognition-enabled Robotics
- Perception, reasoning, learning, knowledge, decision-making, prospection, planning, action
- Cognitive robot architecture
- Robot agents
- Open education, research and innovation
- Successful robot applications

Goals for Today

After this presentation you will know...

- What is probabilistic Machine Learning
- Which classes exist inside Probabilistic Machine Learning
- How models have to be designed to match certain requirements
- What are Nyga Distributions
- What are Joint Probability Trees

Probabilistic Machine Learning

What is it?

- Subfield of Machine Learning and Artificial Intelligence
- Expresses explicit uncertainty over predictions instead of single point estimates
- Answers are typically entire distributions about all possible answers instead of single predictions

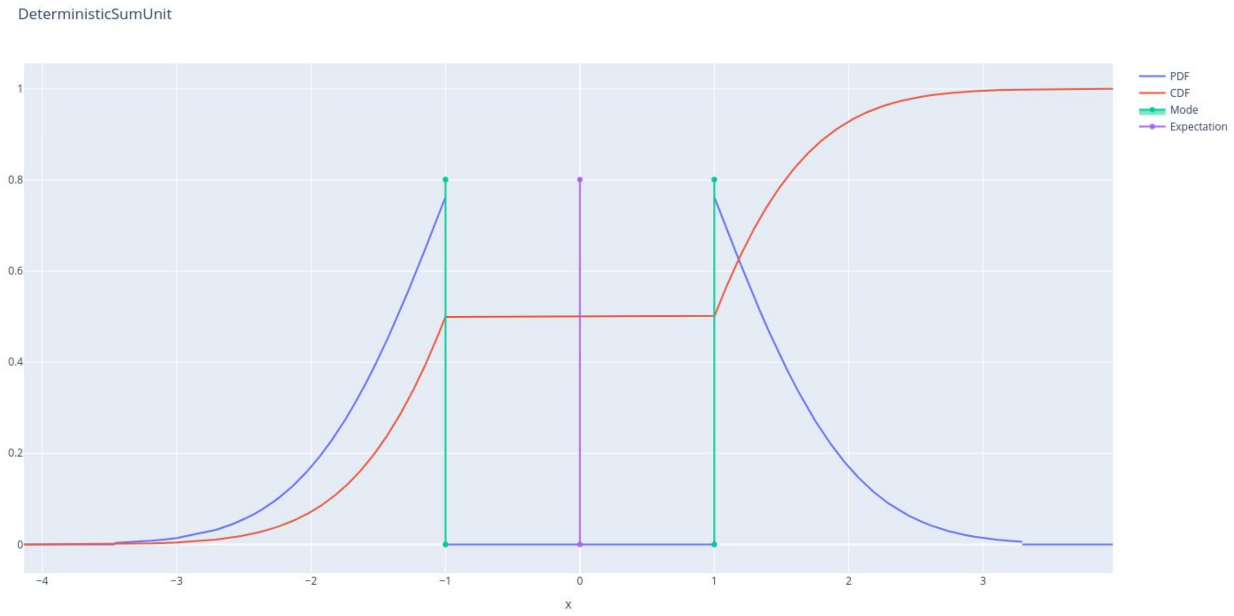
Why is it cool?

- Key tool to automate tasks without specifying every detail
- Answers from machine learning systems are not taken for granted and come with attached probabilities
- Allows reasoning over every possible scenario

Conditional Expectation is not Enough

Most modern Machine Learning Algorithms calculate

$$\mathbb{E}(y \mid x)$$



Quantities of Interest

The most common queries to probability distributions are...

- Evaluation of the Likelihood $p(x)$
- Computing Integrals over Hyper Rectangles

$$p(E = e, Z \in \mathcal{I}) = \int_{\mathcal{I}} p(z, e) dZ$$

- Moments

$$\mathbb{M}_n(x) = \int (x - \mu)^n p(x) dx$$

- Finding the mode of the distribution

$$\hat{x} = \underset{x \in \mathcal{X}}{arg\,max}\; p(x)$$

The price to pay...

- The key operation in ordinary machine learning is optimization
- Integrals are the key operation to probabilistic machine learning
- Integration is computational very heavy and only doable under strict constraints
- We are interested in creating models that compute every interesting quantity in polynomial time
- Such constraints have been formalized in [1]

Probabilistic Circuits

Probabilistic Circuits are...

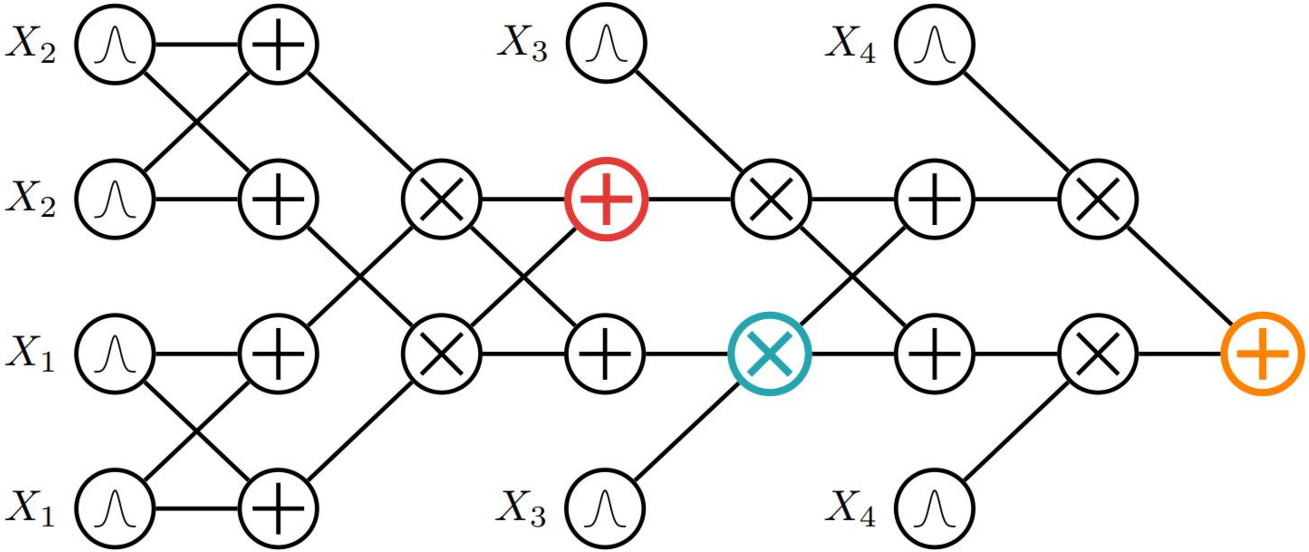
- The formalism that explains tractable inference
- Directed Acyclic Graphs that where the nodes are either…
  - a tractable distribution over encoded as a distribution unit $p(x)$
  - a product of PCs over subsets of

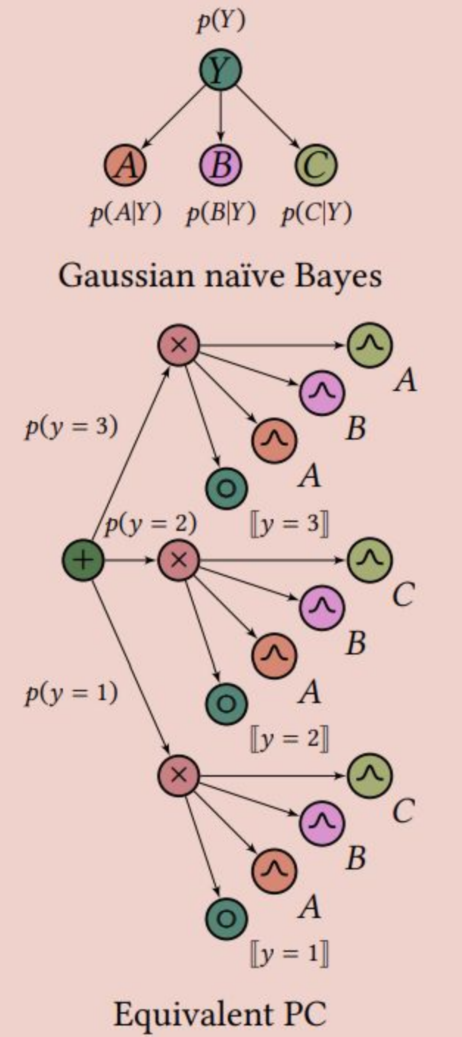
$$X : C(x) = \prod_i C_i(x)$$

  - a convex weighted sum of PCs over subsets of

$$X : C(x) = \sum_i w_i C_i(x)$$

Circuit Examples





Tractable Inference

A product node is decomposable if the scopes of its input units do not share variables.

A PC is decomposable if all of its product units are decomposable.

$$\phi(c_i) \cap \phi(c_j) = \emptyset, \forall c_i, c_j \in in(n), i \neq j$$

A sum node is deterministic if, for any fully-instantiated input, the output of at most one of its children is nonzero. Their input units do not share support.

A circuit is deterministic if all of its sum nodes are deterministic.

$$supp(c_i) \cap supp(c_j) = \emptyset, \forall c_i, c_j \in in(n), i \neq j$$

Nyga Distribution Tutorial

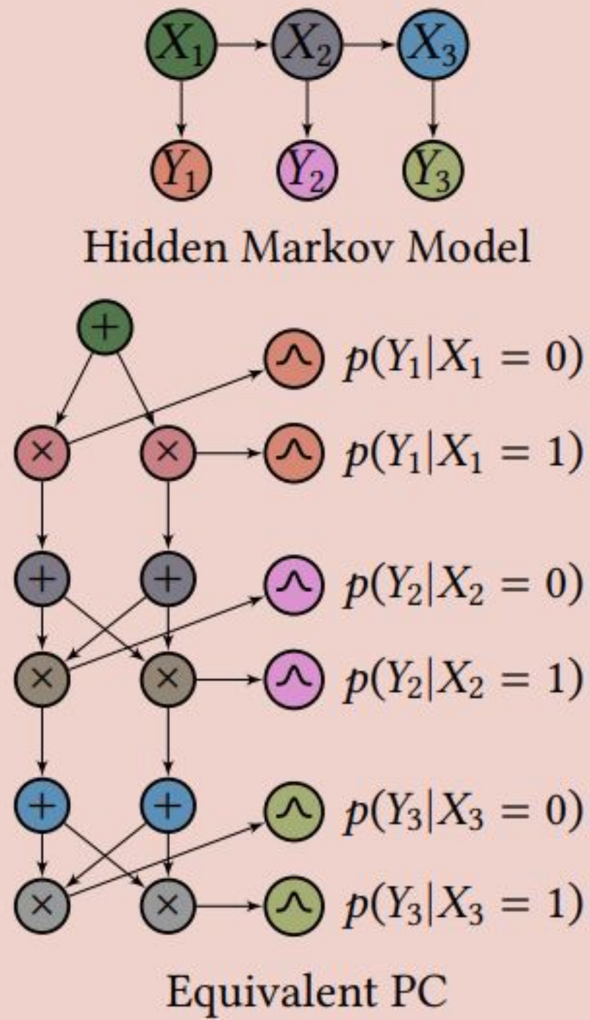
Joint Probability Trees Tutorial

Dynamic Circuits

- Consider that we now want to reason about dynamic worlds, such as time or relations
- Hidden Markov Models are a prominent example of doing so
- Since complexity of inference in PGMs is exponential heavy in their bounded treewidth, they also expand to relations pretty well
- Due to their shallow form JPTs offer a perfect interface for template modelling
- JPTs can be force to be marginal deterministic and hence provide the necessary amount of parameters to interact well with other (dynamic) concepts

Dynamic Models as Circuit

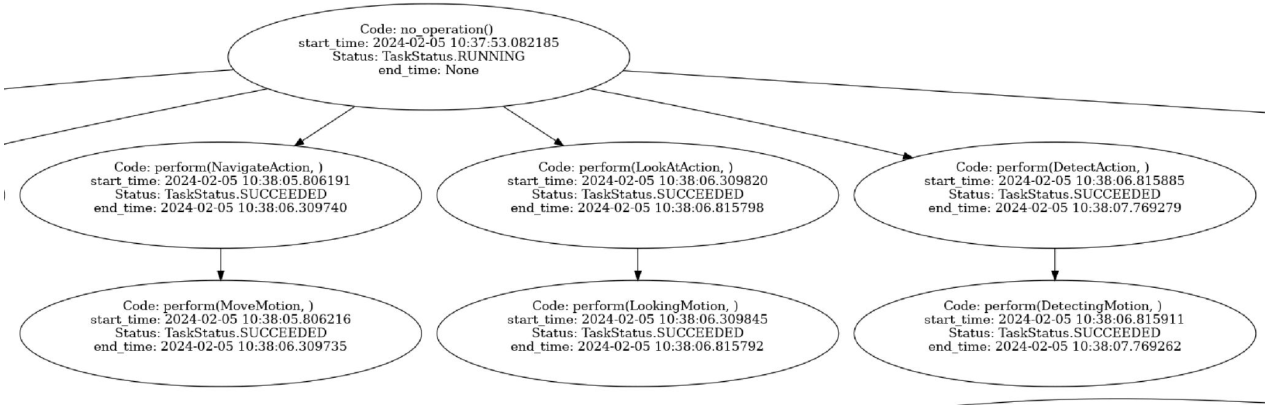
$$\sum_i \theta_i p_i(x) = P(i)P(x|i)$$



What is coming next?

- [Probabilistic Circuits in template models]
- SQL as query language for probabilistic circuits
- Large scale evaluation on template JPTs with PyCRAM
- Transformations in Circuits
- Convolutions of Circuits
- Metrics for Circuits

...



Research Implementation

- Flexible
- More general circuits
- Unified interface
- Higher Usability
- GitHub

Production Implementation

- Cython Backend
- JPTs only
- Basic Interface
- super fast
- GitHub

References

1. Choi, Y., Vergari, A., & Van den Broeck, G. (2020). Probabilistic circuits: A unifying framework for tractable probabilistic models. UCLA. URL: http://starai. cs. ucla. edu/papers/ProbCirc20. pdf.
2. Geh, Renato Lui Scalable Learning of Probabilistic Circuits / Renato Lui Geh; orientador, Denis Deratani Mauá. - São Paulo, 2022. 144 p.: il. Dissertação (Mestrado) - Programa de Pós-Graduação em Ciência da Computação / Instituto de Matemática e Estatística / Universidade de São Paulo. Bibliografia Versão corrigida 1. Circuitos probabilísticos. 2. Aprendizado de máquina. 3. Modelos probabilísticos. 4. Inteligência Artificial. I. Mauá, Denis Deratani. II. Título.
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Thanks for your attention!

JOINT PROBABILITY
TREES

Questions?

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