AI Programming

Kick Off

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Research Unit of Software Engineering

194.193 AI Programming: Organisation

All information on TISS/TUWEL and website:
`https://probprog-ai-tuwien.github.io/2025/`

Registration:

Deadline October 9th

Drop-date: October 20th

You have to complete A1 to officially register

Modality / Grading:

6-7 Lectures, 4 **individual** assignments (copying -> 0 marks)

2 assignment discussions (mandatory, Zoom), 1 project in groups of two, oral exam

Grading: 40% assignments, 60% project and oral exam

Elective:

066 645 Data Science

066 926 Business Informatics

066 937 Software Engineering & Internet Computing

Individual Assignments:

Jupyterlab (mostly Python, link in TUWEL)

A1 deadline 20.10.
A2 deadline 13.11.
Discussion A1 & A2 20.11. (Zoom, link in TUWEL)

A3 deadline 27.11.
A4 deadline 11.12.
Discussion A3 & A4 11.12. (Zoom, link in TUWEL)

194.193 AI Programming: Organisation

Group Project:

Work in pairs
Written report 09.01.
1) Apply probabilistic programming on real world data
2) Implement and evaluate inference algorithm

Oral exam:

26.01 - 30.01
in pairs
question catalog
questions on project

Outlook

- What is probabilistic programming?
- Probability Theory
- Probabilistic Modelling
- Bayesian Inference
- Probabilistic Programming Languages
- Applications

What is Probabilistic Programming?

What is Probabilistic Programming?

Textbook definition:

> *Probabilistic programming is a* ***programming paradigm*** *in which* ***probabilistic models*** *are specified and* ***inference*** *for these models is performed automatically.*

▷ Probabilistic models as programs

▷ Automatic posterior inference

(Explained later)

Where is the AI?

Probabilistic Programming is AI!

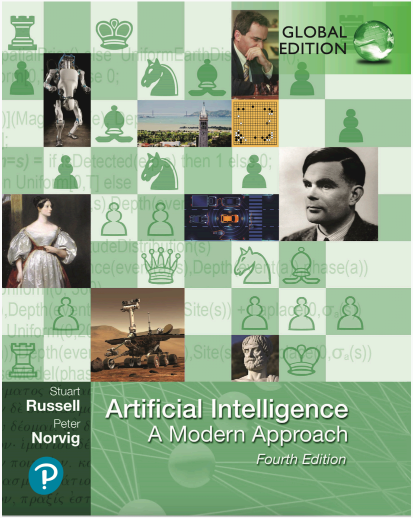
Machine Learning

- Programs define neural networks
- Data: input-output pairs
- Encodes how input maps to output
- Optimise parameters with automatic differentiation to minimise error in mapping
- Black-box approach

Probabilistic Programming

- Programs define probabilistic models
- Data: some observed data
- Encodes how unknown variables generated data
- Find distribution over unknown variables with automatic inference that ”fits” the data
- Explicit modelling + uncertainty quantification

Probabilistic Programming is AI!



IV Uncertain knowledge and reasoning

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Probabilistic Programming is AI!

What is thinking?

How can we describe the intelligent inferences made in everyday human reasoning?

How can we engineer intelligent machines?

Computational theory of mind

mind = computer

mental representations = computer programs

run(program)

thinking = running a program

Probabilistic Programming is AI!

What kind of programs can represent thinking?

Structure

Knowledge

Probability

Uncertainty

Why Probabilistic Programming?

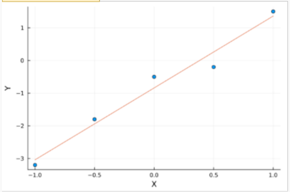
- Probabilistic models allow us to
  - incorporate prior knowledge
  - describe dependencies between variables
  - handle uncertainty
- Probabilistic programs specify probabilistic models
- Inference is concerned about updating our knowledge / belief about unknown or uncertain quantities in the program
- This is achieved by conditioning / constraining the model with observed data

Why Probabilistic Programming?

- Traditionally statisticians developed probabilistic models on paper and implemented inference algorithms
- **Probabilistic programming separates modelling from inference**
- **Expressivity:** Any probabilistic model can be implemented as a probabilistic program
- **General-purpose inference algorithms** + inference engineering
- **Enable incorporation of programming language and software engineering advances** (program analysis, debugging, visualisations,...)

First Look at Probabilistic Programming

Data



$$y = \underbrace{k}_{\text{slope}} \cdot x + \underbrace{d}_{\text{intercept}}$$

Probabilistic Model

```julia
using Turing
@model function linear_regression(x, y)
    # prior over latents
    slope ~ Normal(0, 3)
    intercept ~ Normal(0, 3)

    # likelihood
    for i in 1:length(x)
        # y ≈ slope * x + intercept
        y[i] ~ Normal(slope * x[i] + intercept, 1.)
    end
end
```

Posterior Inference

```julia
using AdvancedMH
function do_inference()
    x = [-1., -0.5, 0.0, 0.5, 1.0]
    y = [-3.2, -1.8, -0.5, -0.2, 1.5]
    model = linear_regression(x, y)
    res = sample(model,
        MH(
            :slope => RandomWalkProposal(Normal(0,0.1)),
            :intercept => RandomWalkProposal(Normal(0,0.2))
        ),
        1000
    )
    maximum_a_posteriori_ix = argmax(res[:lp])
    return (
        res[:slope][maximum_a_posteriori_ix],
        res[:intercept][maximum_a_posteriori_ix]
    )
end
```

First Look at Probabilistic Programming

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end
```

Choice of Priors

Choice of Likelihood

Choice of Inference

Choice of Visualistation

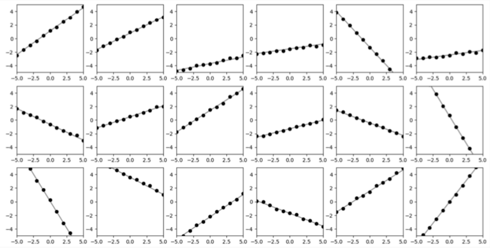
Feedback Cycle

SE for PPL Research in our research group

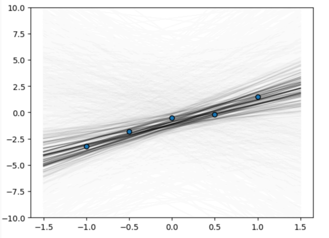
- Program Comprehension (Reasoning about Programs)
- Software Evolution (Reasoning about Change)
- Software Visualization (Reasoning about Large-scale Traces)
- Software Testing (Reasoning about Correctness)

First Look at Probabilistic Programming: Visualisation

Possible worlds according to model



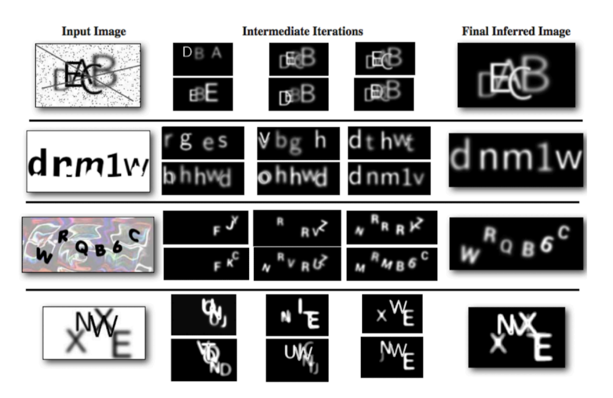
Posterior distribution



Applications

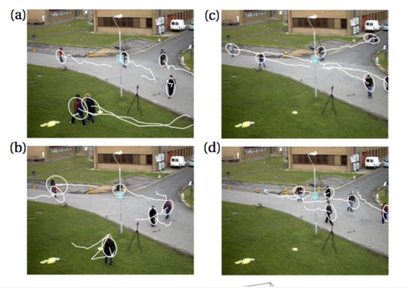
Captcha breaking

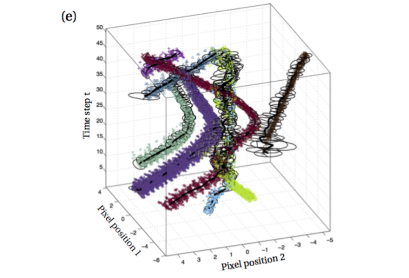
Mansinghka, V. K., Kulkarni, T. D., Perov, Y. N., & Tenenbaum, J. (2013). Approximate bayesian image interpretation using generative probabilistic graphics programs. Advances in Neural Information Processing Systems, 26.



Object Tracking

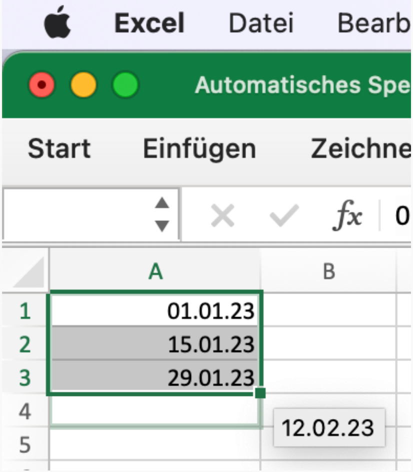
Neiswanger, W., Wood, F., & Xing, E. (2014, April). The dependent Dirichlet process mixture of objects for detection-free tracking and object modeling. In Artificial Intelligence and Statistics (pp. 660-668). PMLR.





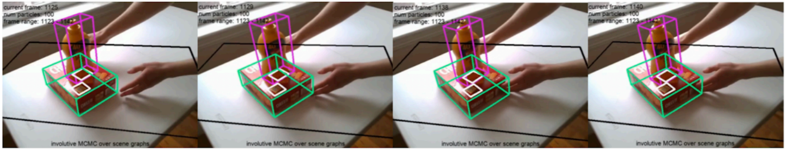
Excel Auto-Fill

Gulwani, S. (2011). Automating string processing in spreadsheets using input-output examples. ACM Sigplan Notices, 46(1), 317-330.



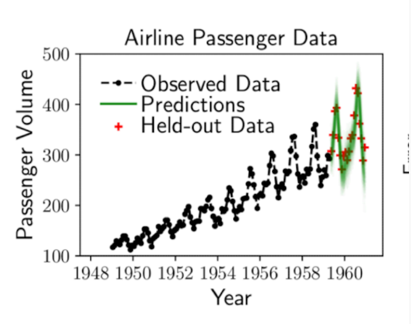
Pose Estimation

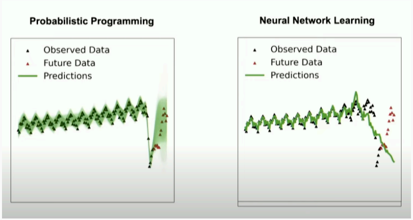
Cusumano-Towner, M. F. (2020). Gen: a high-level programming platform for probabilistic inference (Doctoral dissertation, Massachusetts Institute of Technology). Kulkarni, T. D., Kohli, P., Tenenbaum, J. B., & Mansinghka, V. (2015). Picture: A probabilistic programming language for scene perception. In Proceedings of the ieee conference on computer vision and pattern recognition (pp. 4390-4399).



(b) For each frame in (a), the inferred 6DoF object poses and object-object contact planes

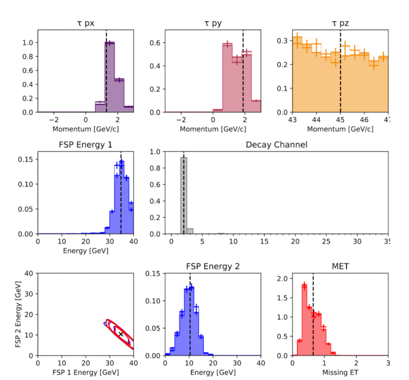
Cusumano-Towner, M. F. (2020). Gen: a high-level programming platform for probabilistic inference (Doctoral dissertation, Massachusetts Institute of Technology).





Hadron Collider

Baydin, A. G., Shao, L., Bhimji, W., Heinrich, L., Meadows, L., Liu, J., … & Wood, F. (2019, November). Etalumis: Bringing probabilistic programming to scientific simulators at scale. In Proceedings of the international conference for high performance computing, networking, storage and analysis (pp. 1-24).



Nuclear Test Detection

Arora, N. S., Russell, S., & Sudderth, E. (2013). NET-VISA: Network processing vertically integrated seismic analysis. Bulletin of the Seismological Society of America, 103(2A), 709-729.