

# Probabilistic Programming for Scientific Discovery

Lecture 1

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**Underlying Theoretical Ideas** 



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**Program Learning** 

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- 4 Lectures
  - 1. Foundational Knowledge
  - 2. Inference Engines & Introduction to Turing.jl
  - 3. Hierarchical Bayesian Approaches & Bayesian Deep Learning
  - 4. The Connection to Scientific Problems
- 3 Tutorials for Self-Paced Consumption
  - 1. In-Depth Introduction to Probabilistic Programming Systems with Turing.jl
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  - 3. Machine-Learning Based Design with Probabilistic Programming



- Example Applications of Probabilistic Programming
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  - 2. DreamCoder: Growing Generalizable, Interpretable Knowledge with Wake-Sleep Bayesian Program Learning
- Why do we even need Probabilistic Programming?
- Underlying Theoretical Ideas
- Different Types of Probabilistic Programming Systems



- Approaches to Inference the Inference Engine
- Practical Introduction to a Probabilistic Programming Framework
- Extending our learned ideas to a more complex example



- Bayesian Hierarchical Approaches
- Bayesian Deep Learning, including but not limited to
  - Inference Networks
  - Uncertainty Quantification
- Marrying Deep Learning Frameworks with Probabilistic Programming for Type 2 Machine Learning



- Interaction with Scientific Simulators
  - What types of simulators would I want to link to?
  - What are the hidden pitfalls?
- Areas of application
  - Robotics
  - Physics
  - Engineering
  - Machine-Learning Based Design
- Extensive Machine-Learning Based Design Example



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## **ETALUMIS**

Bringing Probabilistic Programming to Scientific Simulators at Scale

• Blub



## Growing Generalizable, Interpretable Knowledge with Wake-Sleep Bayesian Program Learning

- Constructs domain-specific languages (DSLs) for scientific problems combined with a neural network, which embodies a learned domain-specific search strategy
  - Learns both the system prior and the needed inference algorithm
- Practically constructs a library of symbolic abstractions in a wake-sleep manner and applies said library to the solving of the chosen problem at hand
- Utilizes wake-sleep learning
  - During sleep the system consolidates its abstractions from the programs found during wake and improves upon the neural network recognition model by imagining new samples
  - During wake the generative model is exploited on the problem domain to find the programs with the highest posterior probability



- Knowledge is accumulated in a multilayered hierarchy with knowledge and skills being successively learned over time, i.e. the knowledge is bootstrapped from very simple examples to ever more complex cases
- Can be broken down to a probabilistic inference procedure, i.e. observing task X and inferring program  $\rho_x$  to solve task  $x \in X$  combined with a prior distribution over program, which migh solve tasks in the domain

$$\begin{split} \rho_{x} &= \underset{\rho:}{\arg\max} \ P[\rho|x,L] \propto P[x|\rho] P[\rho|L], \text{ for each task } x \in X \\ &\qquad \qquad Wake \\ L &= \underset{L}{\arg\max} P[L] \prod_{x \in X} \underset{\rho \text{ a refactoring of } \rho_{x}}{\max} P[x|\rho] P[\rho|L] \\ \end{split} \qquad Sleep: Abstraction \end{split}$$

Train  $Q(\rho|x) \approx P[\rho|x,L]$ , where  $x \sim X$  ('replay') or  $x \sim L$  ('fantasy') Sleep: Dreaming



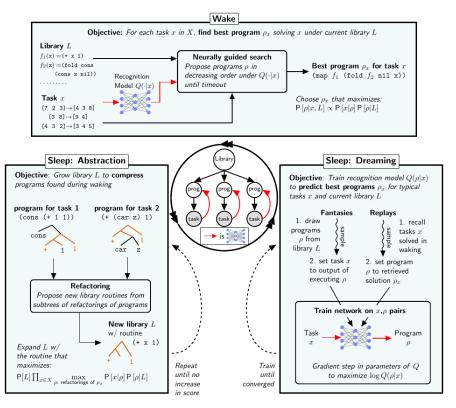
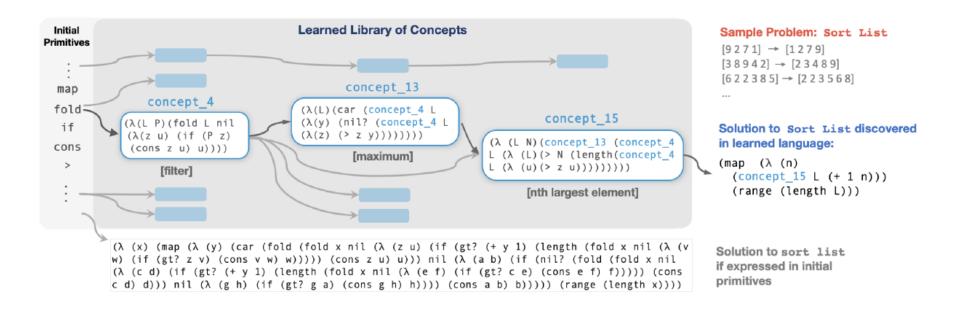


Figure: Algorithm Cycle of DreamCoder



• Due to its compositional nature, representations of problems can be bootstrapped from earlier, simpler version of the scientific task to more and more complex settings





• Applications from page 2



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