CS7480: Topics in Programming Languages: Probabilistic Programming

Lecture 5: Exact Inference

Instructor: Steven Holtzen

Place: Northeastern University

Term: Fall 2021

Course webpage:

https://www.khoury.northeastern.edu/home/sholtzen/CS7480Fall21/



Course Update

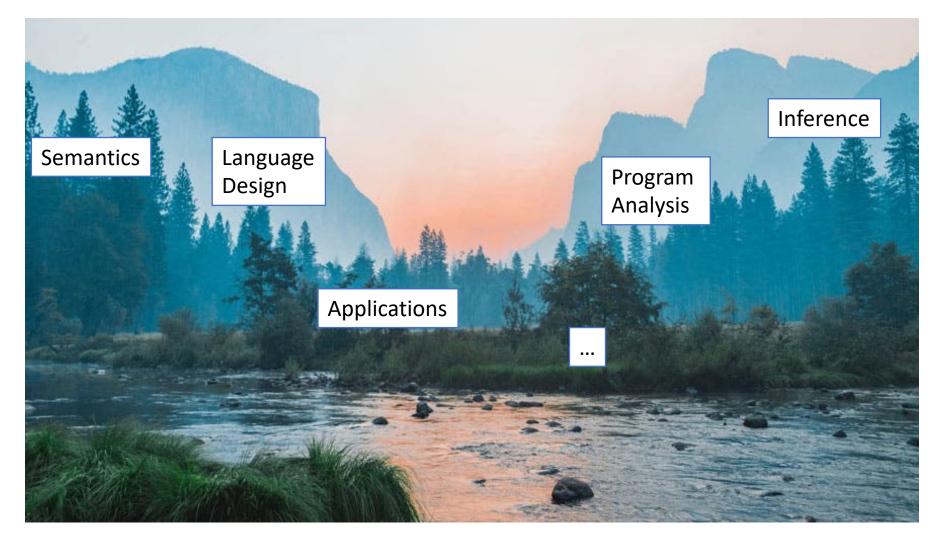
- Soon we will be switching to a paper-reading style course
- Check course webpage for updated calendar
- I will be picking the papers initially and we will likely spend a week or so on them to continue ramping up

Project Update

 A couple of minor bugs with the spec already found! Thanks John and Luke

- 1. Draw 5000 *total* samples for the sampling problems; spec was ambiguous
- 2. A problem with latex formatting for the parser
- I'll upload a fixed spec tomorrow, let you know on teams

The PPL Research Landscape



Inference Overview

 Automated probabilistic inference was one of the very first applications of computers

THE JOURNAL OF CHEMICAL PHYSICS

VOLUME 21, NUMBER 6

JUNE, 1953

Equation of State Calculations by Fast Computing Machines

NICHOLAS METROPOLIS, ARIANNA W. ROSENBLUTH, MARSHALL N. ROSENBLUTH, AND AUGUSTA H. TELLER,

Los Alamos Scientific Laboratory, Los Alamos, New Mexico

AND

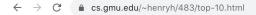
EDWARD Teller,* Department of Physics, University of Chicago, Chicago, Illinois (Received March 6, 1953)

A general method, suitable for fast computing machines, for investigating such properties as equations of state for substances consisting of interacting individual molecules is described. The method consists of a modified Monte Carlo integration over configuration space. Results for the two-dimensional rigid-sphere system have been obtained on the Los Alamos MANIAC and are presented here. These results are compared to the free volume equation of state and to a four-term virial coefficient expansion.



MANIAC I Los Alamos, 1953 © Corbis Images

Inference Overview

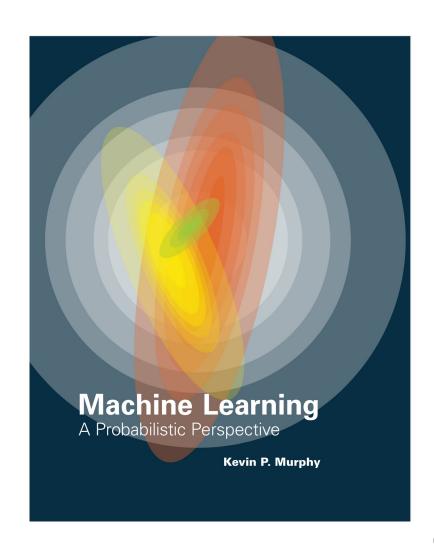


Top 10 Algorithms

The 10 Algorithms with the Greatest Influence on the Development and Practice of Science and Engineering in the 20th Century

- Computing in Science & Engineering
 - Metropolis Algorithm for Monte Carlo
 - Simplex Method for Linear Programming
 - · Krylov Subspace Iteration Methods
 - The Decompositional Approach to Matrix Computations
 - The Fortran Optimizing Compiler
 - QR Algorithm for Computing Eigenvalues
 - Quicksort Algorithm for Sorting
 - Fast Fourier Transform
 - · Integer Relation Detection
 - · Fast Multipole Method

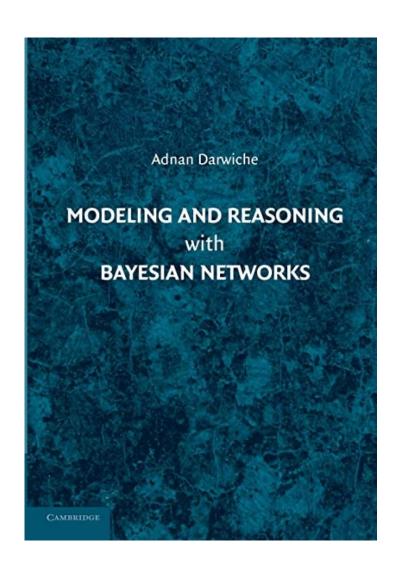
Resources on Inference



 Murphy, Kevin P. Machine learning: a probabilistic perspective. MIT press, 2012.

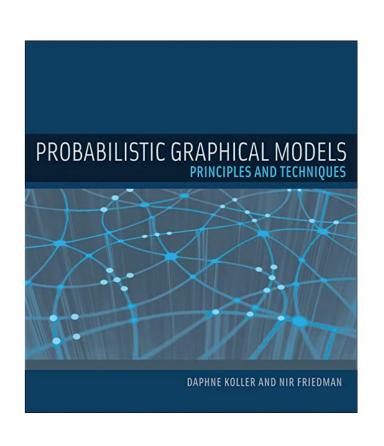
Chapters 20, 21, 22, 23,
24

Resources on Inference



- Darwiche, Adnan. Modeling and reasoning with Bayesian networks. Cambridge university press, 2009.
- Majority of the book is on inference
- Especially good reference for discrete inference

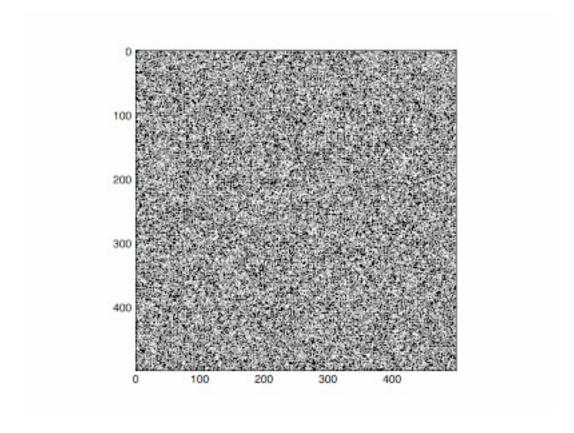
Resources on Inference



 Koller, Daphne, and Nir Friedman. Probabilistic graphical models: principles and techniques. MIT press, 2009.

Basically the whole book

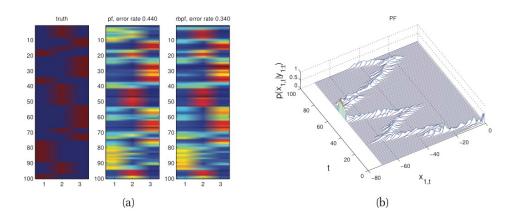
Application: Physics



Ising model

Source: https://upload.wikimedia.org/wikipedia/commons/e/e6/Ising_quench_b10.gif

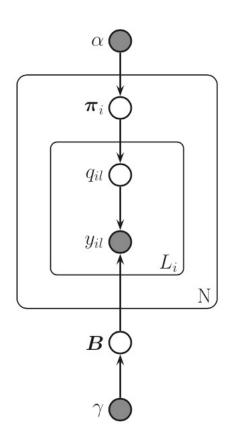
Application: State Localization



[Murphy 2021, pg. 835]

Figure 23.8 Belief states corresponding to Figure 23.7. (a) Discrete state. The system starts in state 2 (red x in Figure 23.7), then moves to state 3 (black * in Figure 23.7), returns briefly to state 2, then switches to state 1 (blue circle in Figure 23.7), etc. (b) Horizontal location (PF estimate). Figure generated by rbpfManeuverDemo, based on code by Nando de Freitas.

Application: Linguistics



Latent Dirichlet Allocation [Murphy 2012, pg. 981]

Application: Biology

communications biology

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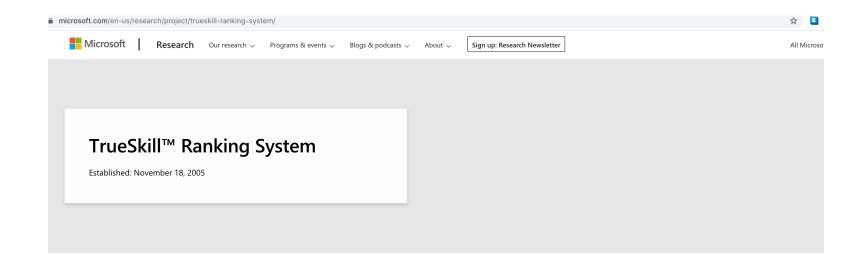
Article | Open Access | Published: 24 February 2021

Universal probabilistic programming offers a powerful approach to statistical phylogenetics

Fredrik Ronquist ⊡, Jan Kudlicka, Viktor Senderov, Johannes Borgström, Nicolas Lartillot, Daniel Lundén, Lawrence Murray, Thomas B. Schön & David Broman

Communications Biology 4, Article number: 244 (2021) | Cite this article

Application: Player Matchmaking





Publications

Overview

The TrueSkill ranking system is a skill based ranking system for Xbox Live developed at Microsoft Research. The purpose of a ranking system is to both identify and track the skills of gamers in a game (mode) in order to be able to match them into competitive matches. TrueSkill has been used to rank and match players in many different games, from Halo 3 to Forza Motorsport 7.

An improved version of the TrueSkill ranking system, named <u>TrueSkill 2</u>, launched with <u>Gears of War 4</u> and was later incorporated into <u>Halo</u> 5.

The classic TrueSkill ranking system only uses the final standings of all teams in a match in order to update the skill estimates (ranks) of all players in the match. The TrueSkill 2 ranking system also uses the individual scores of players in order to weight the contribution of each player to each team. As a result, TrueSkill 2 is much faster at figuring out the skill of a new player.

Inference and PPLs

• In many (successful!) cases, inference came before the associated probabilistic programming language



Bayesian Parameter Estimation

```
isBiasedCoin ~ flip 0.1;
if isBiasedCoin {
   flip1 ~ flip 0.01;
   flip2 ~ flip 0.01;
   flip3 ~ flip 0.01;
} else {
   flip1 ~ flip 0.5;
   flip2 \sim flip 0.5;
   flip3 \sim flip 0.5;
observe (&& flip1 (&& flip2
flip3));
return isBiasedCoin
```

- Have a *prior* probability that the coin is biased
- Given three observations, compute the *posterior* probability that the coin is biased
- Called Bayesian learning (or parameter estimation)

Inference and PPLs

- We saw how the PL community discovered PPLs
 - Semantics, verifying randomized algorithms

- The AI community discovered PPLs from the perspective of making inference accessible and general
 - "Separate modeling from reasoning"
 - Same motivation as graphical models

Inference Landscape

Exact inference

- Poly-tree algorithm
- Variable elimination
- Join-tree algorithm
- Inference via compilation
- Approximate Inference (next time)
 - Direct sampling
 - Importance sampling
 - Markov-Chain Monte Carlo (MCMC)
 - Inference via Optimization

Exact Inference

Conciseness & Tractability

The cost of inference is often in tension with the conciseness of the language

• We say a PPL A is more concise than PPL B if there is a polynomial space reduction from any program written in B to a program written in A

 Pretty informal definition, relies on a notion of equality between probabilistic programs in different languages that we yet to define

Conciseness Reduction

Reduction from Tabular to SimPLL statements

Α	В	Pr		B ~ flip 0.6;
1	1	0.2		if B {
1	0	0.3	$s_{=}$	A ~ flip $\frac{1}{3}$
0	1	0.4		} else {
0	0	0.1		A ~ flip 0.7!

 These programs are equal if they have the same semantics

$$[s](\{A \mapsto T, B \mapsto F\}) = 0.4 \times 0.75 = 0.3$$

Tables are Less Concise than SimPPL Programs

Consider the follow family of SimPPL programs

```
A ~ flip 0.1;
B ~ flip 0.2;
C ~ flip 0.3;
...
```

- Call this a family of programs Indep_n
- Claim: the size of a tabular representation of Indep_n grows exponentially in n
- ⇒ SimPPL is *more concise* than tables

Tractability—Conciseness Tradeoff

Simppl

- NP-hard inference test
- Programs can be linear in # variables

Conciseness

???????

Tabular

- Linear time inference
- Size of 2^n for n variables

Inference Tractability (In the size of the model)

Inference via Compilation

• Can we find an interesting probabilistic model somewhere in between SimPPL and Tabular that strikes a different tradeoff?

• Why is this useful? We can potentially compile SimPPL into this representation for inference

SimPPL
Slow inference :(
Very concise ©

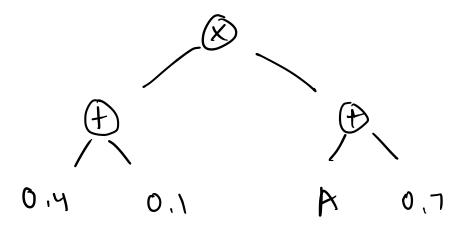
Compiler
(this step *might* be expensive because the target language will be less concise)

Magic Language

- Fast inference ©
- More concise than tables

Circuits

- An expression tree that describes a sequence of arithmetic computations
 - A well-known primitive in complexity theory

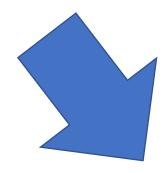


- Syntax:
 - Internal nodes: Add (+) and multiply (x)
 - Leaf nodes: Real values or variables
- Semantics:
 - Compute bottom-up, substituting variables for values

Encoding Tables to Polynomials

We can write a probability distribution as a multi-linear polynomial

A	В	Pr
1	1	0.2
1	0	0.3
0	1	0.4
0	0	0.1

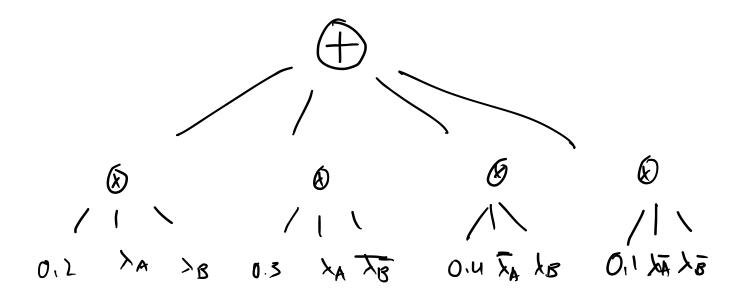


$$f(\lambda_A, \lambda_B, \bar{\lambda}_A, \bar{\lambda}_B) = 0.2\lambda_A\lambda_B + 0.3\lambda_A\bar{\lambda}_B + 0.4\bar{\lambda}_A\lambda_B + 0.1\bar{\lambda}_A\bar{\lambda}_B$$

• Semantically equivalent: to look up a row A=1, B=0, set $\lambda_A=1, \bar{\lambda}_A=0, \lambda_B=0, \bar{\lambda}_B=1$

Representing Polynomials as Circuits

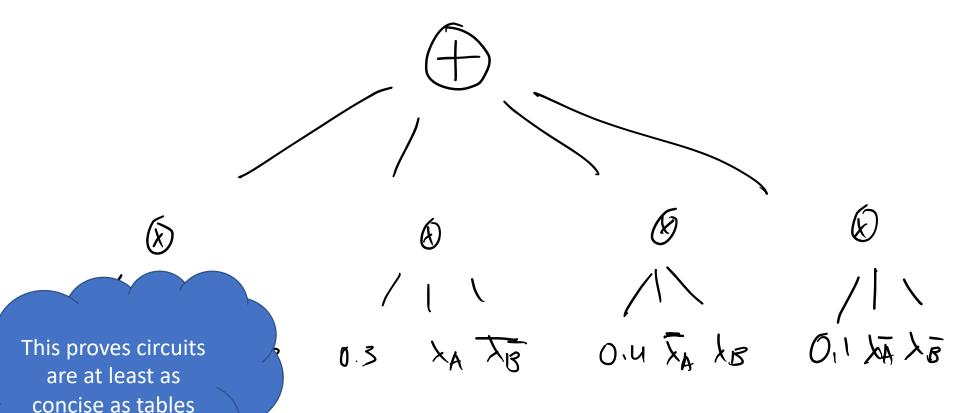
$$f(\lambda_A, \lambda_B, \bar{\lambda}_A, \bar{\lambda}_B) = 0.2\lambda_A\lambda_B + 0.3\lambda_A\bar{\lambda}_B + 0.4\bar{\lambda}_A\lambda_B + 0.1\bar{\lambda}_A\bar{\lambda}_B$$



• This circuit is called the *enumeration circuit*

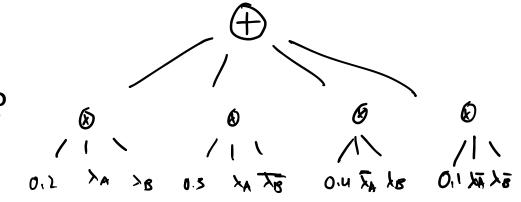
Representing Polynomials as Circuits

$$f(\lambda_A, \lambda_B, \bar{\lambda}_A, \bar{\lambda}_B) = 0.2\lambda_A\lambda_B + 0.3\lambda_A\bar{\lambda}_B + 0.4\bar{\lambda}_A\lambda_B + 0.1\bar{\lambda}_A\bar{\lambda}_B$$



Circuits

How hard is inference?

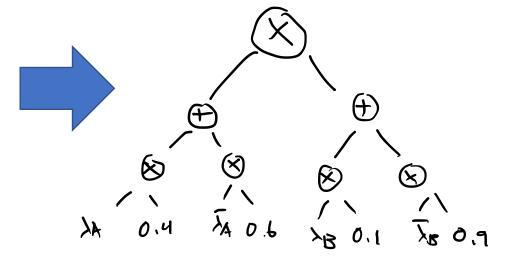


- For the above circuit, it's linear time in the size! Do a single pass bottom-up to compute any probability
 - Fast inference ©
- However... this enumeration circuit is large! It's exponential in #variables, just like tables
 - Not concise ☺

Circuits: Conciseness

- Can circuits be smaller than tables? Yes!
 - But they have to be different kinds of circuits than enumeration circuits
- Suppose A and B are independent
 - Then, we know $Pr(A, B) = Pr(A) \times Pr(B)$

	A	В	Pr				
	1	1	0.04				
			0.06				
Looks bigger, but							
sca	54						
number of variables \							
grows							



Tractability—Conciseness Tradeoff

NP-hard inference test Programs can be linear in # variables Conciseness **Tabular** Linear time inference Size of 2^n for n variables Inference Tractability

(In the size of the model)

Inference via Compilation

SimPPL Slow inference :(Very concise © Compiler
(this step *might* be expensive because the target language will be less concise)

Circuit Language

- Fast inference ©
- More concise than tables

- Next time:
 - More circuit languages
 - How to compile

Inference via Compilation

Been applied to do fast inference in a variety of domains

- Discrete Bayesian networks
 - Chavira, Mark, and Adnan Darwiche. "Compiling Bayesian networks with local structure." *IJCAI*. Vol. 5. 2005.
 - Chavira, Mark, Adnan Darwiche, and Manfred Jaeger. "Compiling relational Bayesian networks for exact inference." *International Journal of Approximate Reasoning* 42.1-2 (2006): 4-20.
- Probabilistic logic programs
 - Fierens, Daan, et al. "Inference in probabilistic logic programs using weighted CNF's." arXiv preprint arXiv:1202.3719 (2012).
- Discrete probabilistic programs
 - Holtzen, Steven, Guy Van den Broeck, and Todd Millstein. "Scaling exact inference for discrete probabilistic programs." *Proceedings of the ACM on Programming Languages* 4.00PSLA (2020): 1-31.

Conclusion

 One of the main jobs of a probabilistic programming language designer is to strike a useful balance between tractability and expressivity

 Research direction: exploring the space of languages with different tractability/conciseness tradeoffs

More About TPMs

- A growing field
 - Not just for discrete models [

Inference via Compilation

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