

UCLA

**Computer
Science**



Recent Advances in Discrete Probabilistic Program Inference

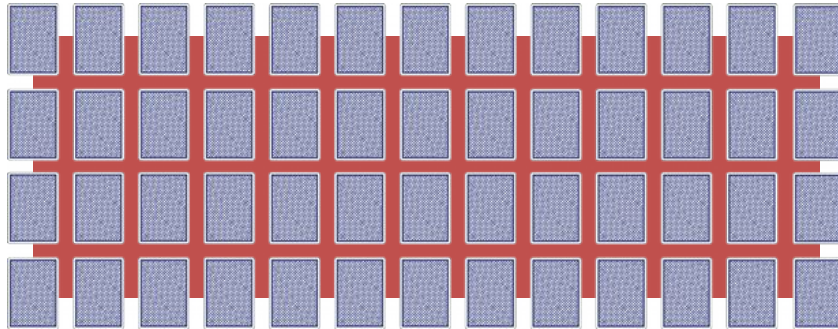
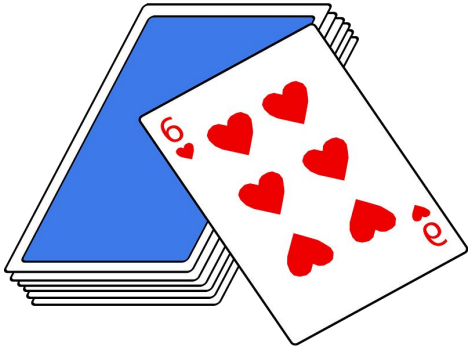
Guy Van den Broeck

VeriProP 2021 - Jul 19, 2021

What is the right abstraction for distributions?

Probabilistic graphical models is how we do probabilistic AI!

Graphical models of variable-level (in)dependence are a broken abstraction.

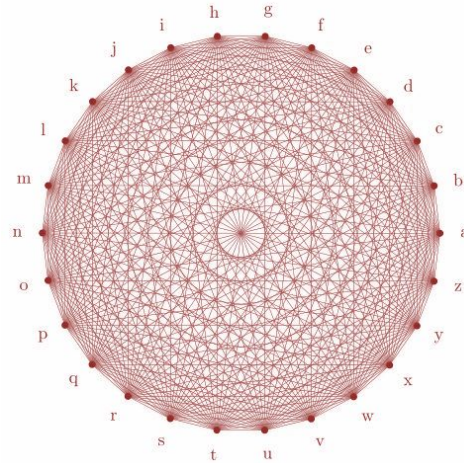


What is the right abstraction for distributions?

Probabilistic graphical models is how we do probabilistic AI!

Graphical models of variable-level (in)dependence are a broken abstraction.

3.14 $\text{Smokes}(x) \wedge \text{Friends}(x,y)$
 $\Rightarrow \text{Smokes}(y)$



What is the right abstraction for distributions?

Probabilistic graphical models is how we do probabilistic AI!

Graphical models of variable-level (in)dependence are a broken abstraction.

Bean Machine

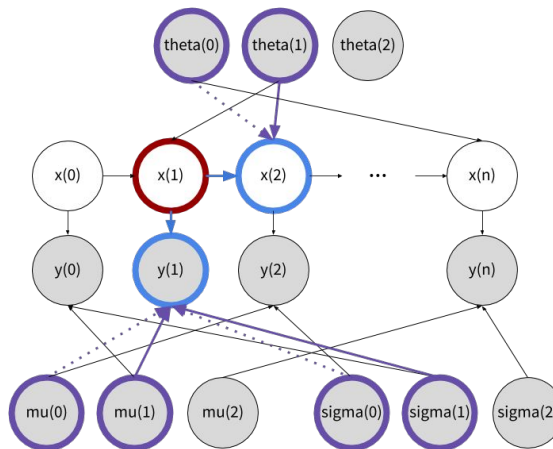
$$\mu_k \sim \text{Normal}(\alpha, \beta)$$

$$\sigma_k \sim \text{Gamma}(\nu, \rho)$$

$$\theta_k \sim \text{Dirichlet}(\kappa)$$

$$x_i \sim \begin{cases} \text{Categorical}(init) & \text{if } i = 0 \\ \text{Categorical}(\theta_{x_{i-1}}) & \text{if } i > 0 \end{cases}$$

$$y_i \sim \text{Normal}(\mu_{x_i}, \sigma_{x_i})$$



Computational Abstractions

Let us think of probability as something that is computed.

Abstraction = Structure of Computation

Two levels of abstraction:

Probabilistic Programs

“High-level code”

Probabilistic Circuits

“Machine code”

language design

compilation

program abstraction

**source-to-source
compilation**

compiler optimization

learning/
synthesis

hardware mapping

...

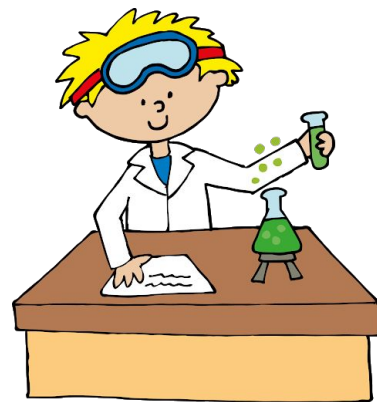
Probabilistic Programs



Motivation from the AI side: Making modern AI systems is **too hard**



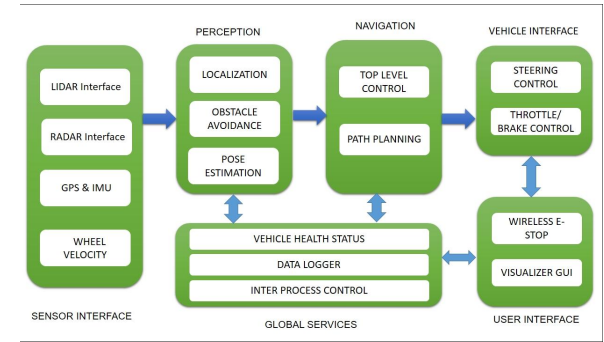
System Builders



Model Builders

AI System Builder

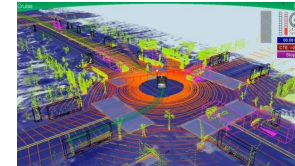
Need to integrate uncertainty over the whole system



20% chance of obstacle!



94% chance of obstacle!



99% certain about current location

Inside the Self-Driving Tesla Fatal Accident

By ANJALI SINGHVI and KARL RUSSELL UPDATED July 12, 2016

The accident may have happened in part because the crash-avoidance system is designed to engage only when radar and computer vision systems agree that there is an obstacle, according to an industry executive with direct

AI Model Builder



“When you have the flu you have a cough 70% of the time”

“What is the probability that a patient with a fever has the flu?”



“Routers fail on average every 5 years”

“What is the probability that my packet will reach the target server?”
[SGTVV SIGCOMM'20]

Probabilistic Programs

```
let x = flip 0.5 in
let y = flip 0.7 in
let z = x || y in
let w = if z then
  my_func(x,y)
else
  ...
in
observe(z)
```

means “flip a coin, and
output true with probability $\frac{1}{2}$ ”

Standard (functional) programming
constructs: let, if, ...

means
“reject this execution if z is not true”

Why Probabilistic Programming?

- PPLs are proliferating



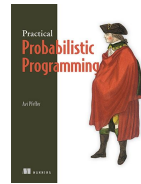
Edward



HackPPL



Stan



Figaro

Venture, Church, IBAL, WebPPL, Infer.NET, Tensorflow Probability, ProbLog, PRISM, LPADs, CLogic, CLP(BN), ICL, PHA, Primula, Storm, Gen, PRISM, PSI, Bean Machine, etc. ... *and many many more*

- Programming languages are humanity's biggest knowledge representation achievement!
- Programs should be AI models

Focus on Discrete Models

1. Real programs have inherently discrete structure (e.g. if-statements)
2. Discrete structure is inherent in many domains (graphs, text, ranking, etc.)
3. Many existing PPLs assume smooth and differentiable densities and do not handle discreteness well.



Does not support if-statements!

WebPPL

coroutines. Whenever a discrete variable is encountered in a program's execution, the program is suspended and resumed multiple times with all possible values in the support of that distribution. Listing 10, which implements a simple finite



[AADB+'19]

Discrete probabilistic programming is the important unsolved open problem!

Dice language for discrete probabilistic programs

<http://dicelang.cs.ucla.edu/>

[Holtzen et al. OOPSLA20]



Dice

The dice probabilistic programming language

[About](#) [GitHub](#)

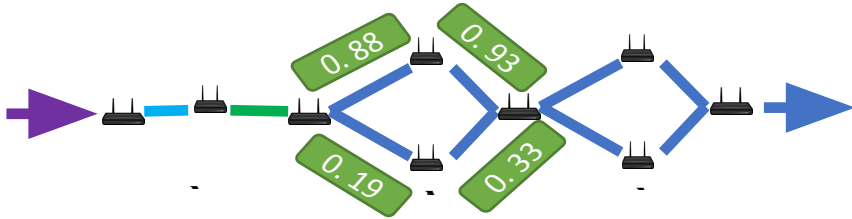
`dice` is a probabilistic programming language focused on fast exact inference for discrete probabilistic programs. For more information on `dice`, see the [about page](#).

Below is an online `dice` code demo. To run the example code, press the "Run" button.

```
1 fun sendChar(key: int(2), observation: int(2)) {
2   let gen = discrete(0.5, 0.25, 0.125, 0.125) in // sample a FooLang character
3   let enc = key + gen in // encrypt the character
4   observe observation == enc
5 }
6
7 // sample a uniform random key: A=0, B=1, C=2, D=3
8
9 let key = discrete(0.25, 0.25, 0.25, 0.25) in
10
11 // observe the ciphertext CCCC
12 let tnp = sendChar(key, int(2, 2)) in
13 let tnp = sendChar(key, int(2, 2)) in
14 let tnp = sendChar(key, int(2, 2)) in
15 let tnp = sendChar(key, int(2, 2)) in
16
17 key
```

Run

Network Verification in Dice



```
fun n1(init: bool) {  
  let l1succeed = flip 0.99 in  
  let l2succeed = flip 0.91 in  
  init && l1succeed && l2succeed  
}
```

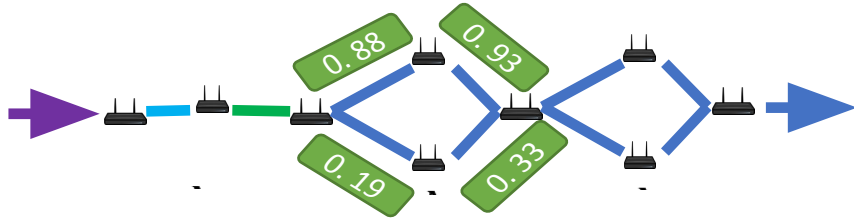
```
fun n2(init: bool) {  
  let routeChoice = flip 0.5 in  
  if routeChoice then  
    init && flip 0.88 && flip 0.93  
  else  
    init && flip 0.19 && flip 0.33  
}
```

ECMP equal-cost path
protocol: choose
randomly which router
to forward to

Main routine,
combines the
networks

`n2(n2(n1(true)))`

Network Verification i



This doesn't show all the language features of dice:

- Integers
- Tuples
- Bounded recursion
- Bayesian conditioning
- ...

```
fun n1(  
  let I1  
  let I2  
  init &  
}
```

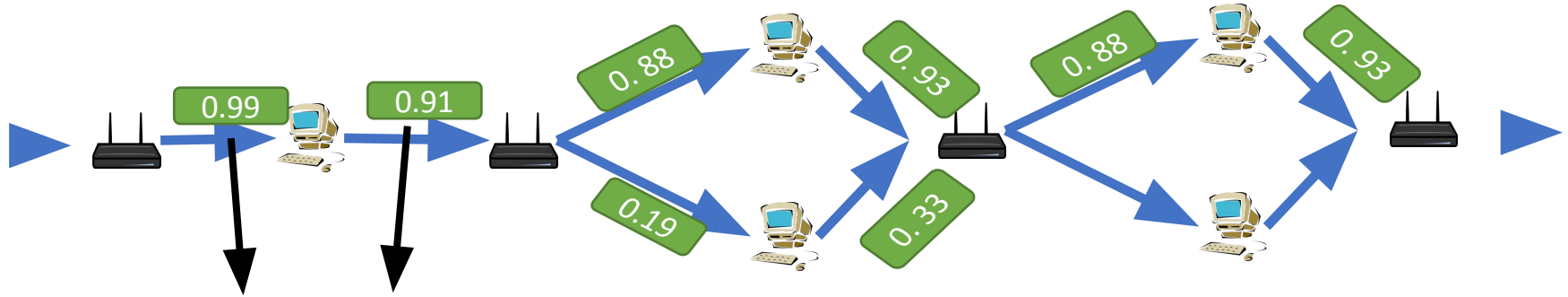
```
fun n2(init: bool) {  
  let routeChoice = flip 0.5 in  
  if routeChoice then  
    init && flip 0.88 && flip 0.93  
  else  
    init && flip 0.19 && flip 0.33  
}
```

ECMP equal-cost path protocol: choose randomly which router to forward to

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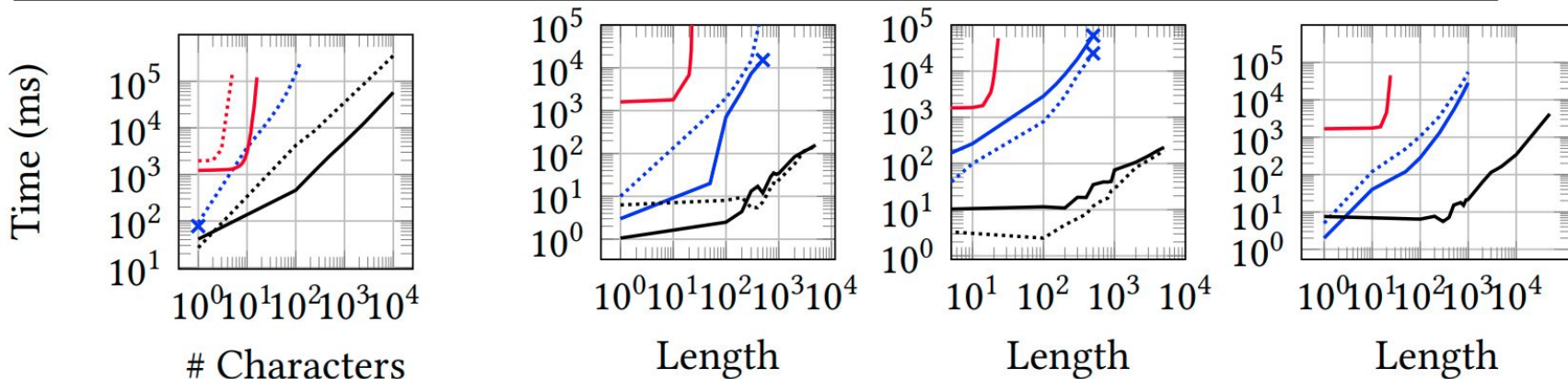
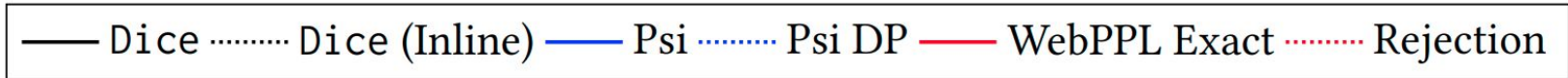
Probabilistic Program Inference



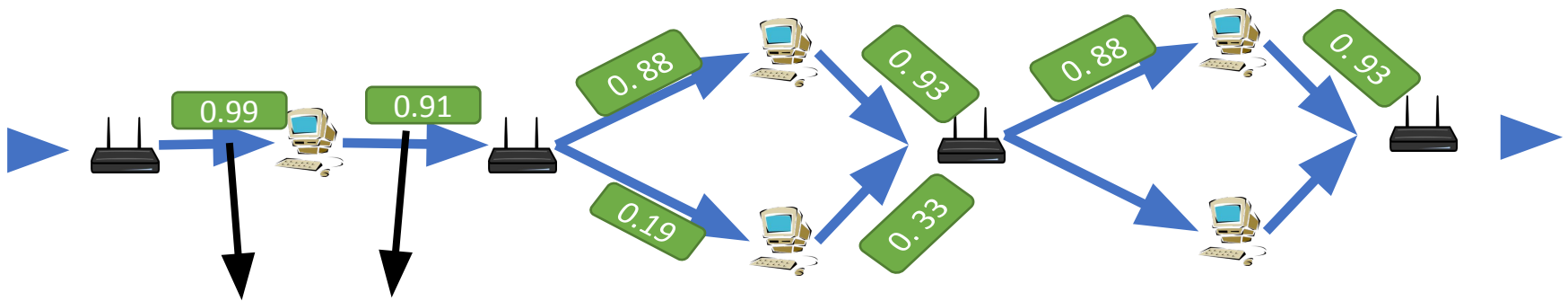
$$\begin{aligned} & 0.99 \times 0.91 \times 0.5 \times 0.88 \times 0.93 \times 0.5 \times 0.88 \times 0.93 \\ + & 0.99 \times 0.91 \times 0.5 \times 0.19 \times 0.33 \times 0.5 \times 0.88 \times 0.93 \\ + & \dots \end{aligned}$$

Probabilistic Program Inference

Path enumeration: find all of them!



Key to Fast Inference: **Factorization** (product nodes)



$$\begin{aligned} & 0.99 \times 0.91 \times 0.5 \times 0.88 \times 0.93 \times 0.5 \times 0.88 \times 0.93 \\ + & 0.99 \times 0.91 \times 0.5 \times 0.19 \times 0.33 \times 0.5 \times 0.88 \times 0.93 \\ + & \dots \end{aligned}$$

Easy to see on the graph structure ...
how about on the program?

Symbolic Compilation in Dice

- Construct Boolean formula
- Satisfying assignments \approx paths
- Variables are flips
- Associate weights with flips
- Compile factorized circuit

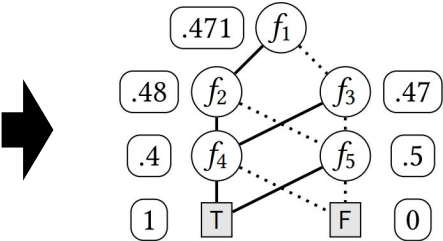
```

1  let x = flip1 0.1 in
2  let y = if x then flip2 0.2 else
3      flip3 0.3 in
4  let z = if y then flip4 0.4 else
5      flip5 0.5 in z

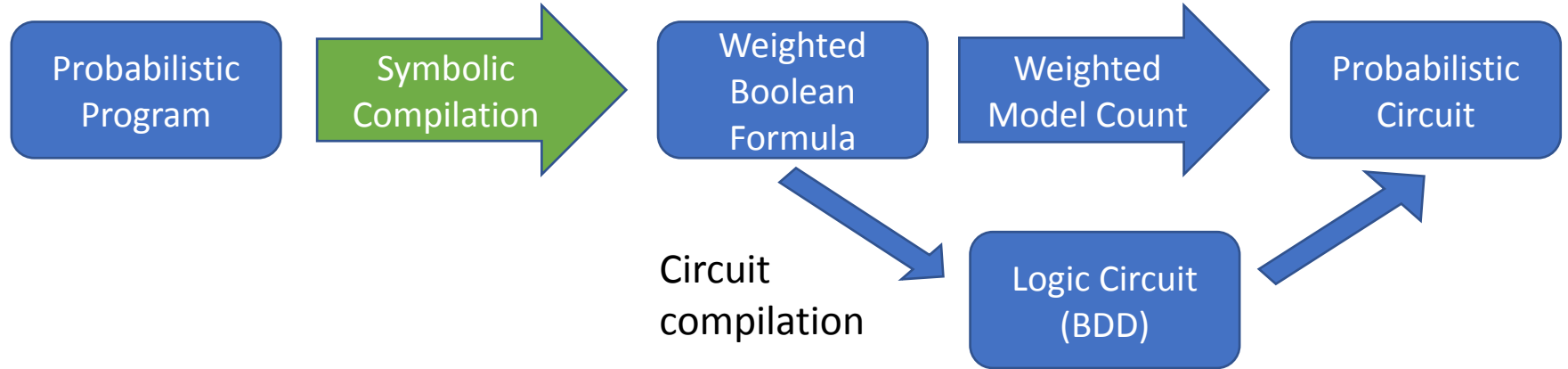
```

$$\underbrace{0.1}_{x=T} \cdot \underbrace{0.2}_{y=T} \cdot \underbrace{0.4}_{z=T} + \underbrace{0.1}_{x=T} \cdot \underbrace{0.8}_{y=F} \cdot \underbrace{0.5}_{z=T} + \underbrace{0.9}_{x=F} \cdot \underbrace{0.3}_{y=T} \cdot \underbrace{0.4}_{z=T} + \underbrace{0.9}_{x=F} \cdot \underbrace{0.7}_{y=F} \cdot \underbrace{0.5}_{z=T}$$

$$\blacktriangleright f_1 f_2 f_4 \vee f_1 \bar{f}_2 f_5 \vee \bar{f}_1 f_3 f_4 \vee \bar{f}_1 \bar{f}_3 f_5$$



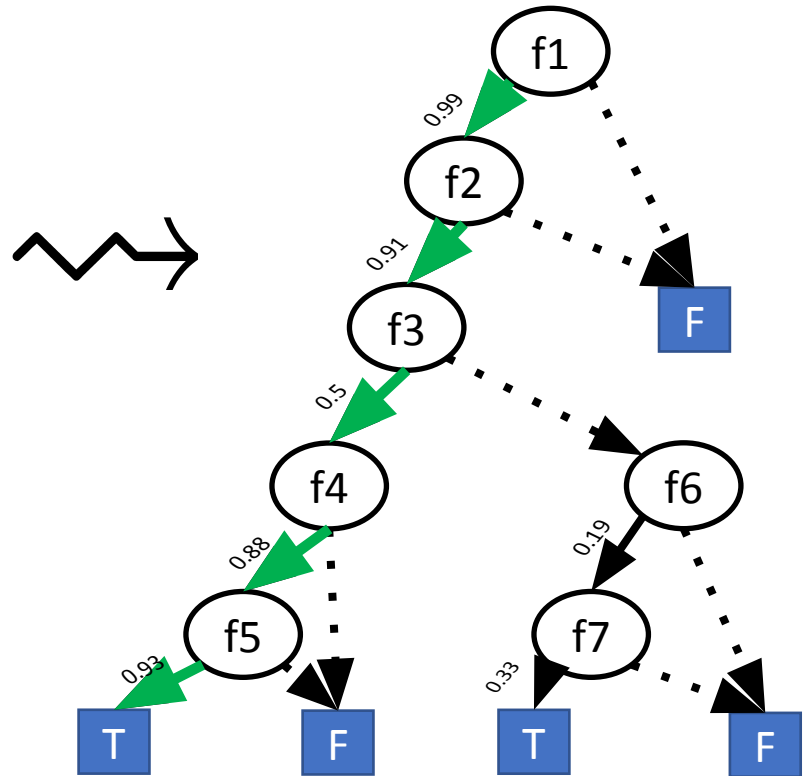
Symbolic Compilation in Dice



An *Equivalent* BDD to this Program

```
fun n1(init: bool) {  
  let l1succeed = True  
  let l2succeed = True  
  init && l1succeed && l2succeed  
}  
  
fun n2(init: bool) {  
  let rC = True  
  if rC then  
    init && True True  
  else  
    init && flip6 0.19 && flip7 0.33  
}
```

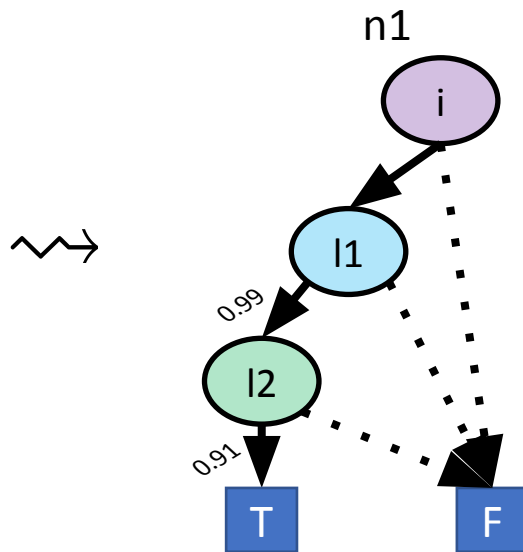
Now, how do we compile this?



Compiling the BDD Modularly

```
fun n1(init: bool) {  
  let l1succeed = flip 0.99 in  
  let l2succeed = flip 0.91 in  
  init && l1succeed && l2succeed  
}
```

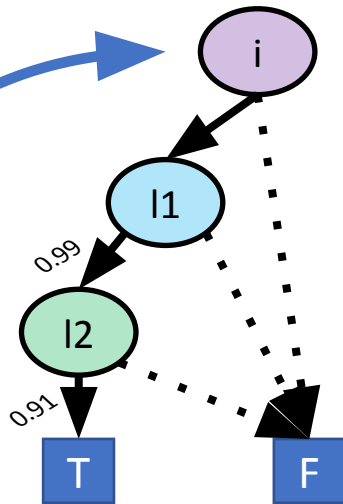
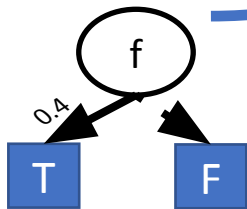
First, compile the function n1



Compiling the BDD Modularly

```
fun n1(init: bool) {  
  let l1succeed = flip 0.99 in  
  let l2succeed = flip 0.91 in  
  init && l1succeed && l2succeed  
}  
n1(flip 0.4)
```

flip 0.4

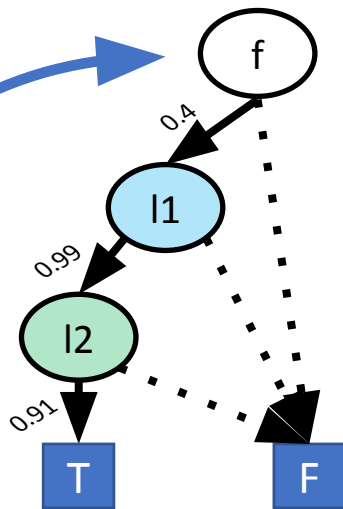
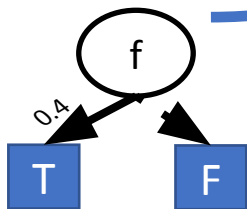


Then, to *call* n1, substitute for *i*

Compiling the BDD Modularly

```
fun n1(init: bool) {  
  let l1succeed = flip 0.99 in  
  let l2succeed = flip 0.91 in  
  init && l1succeed && l2succeed  
}  
n1(flip 0.4)
```

flip 0.4

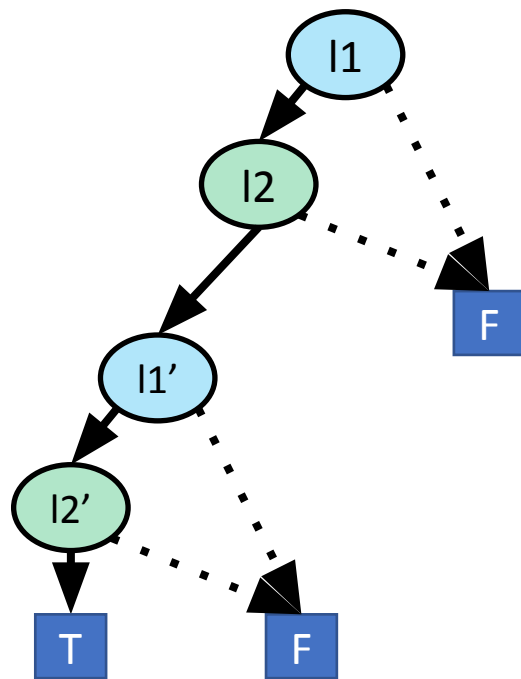


Then, to *call* n1, substitute for *i*

Compiling the BDD Modularly

```
fun n1(init: bool) {  
  let l1succeed = flip 0.99 in  
  let l2succeed = flip 0.91 in  
  init && l1succeed && l2succeed  
}  
n1(n1(true))
```

- Calling itself? Size (and therefore inference cost) grows *linearly*
- Build BDD for whole program by combining sub-programs **modularly**



Denotational Semantics + Formal Inference Rules

$$\llbracket v_1 \rrbracket (v) \triangleq (\delta(v_1))(v) \quad \llbracket \text{fst } (v_1, v_2) \rrbracket (v) \triangleq (\delta(v_1))(v) \quad \llbracket \text{snd } (v_1, v_2) \rrbracket (v) \triangleq (\delta(v_2))(v)$$

$$\llbracket \text{if } v_g \text{ then } e_1 \text{ else } e_2 \rrbracket (v) \triangleq \begin{cases} \llbracket e_1 \rrbracket (v) & \text{if } v_g = \top \\ \llbracket e_2 \rrbracket (v) & \text{if } v_g = \text{F} \\ 0 & \text{otherwise} \end{cases} \quad \llbracket \text{flip } \theta \rrbracket (v) \triangleq \begin{cases} \theta & \text{if } v = \top \\ 1 - \theta & \text{if } v = \text{F} \\ 0 & \text{otherwise} \end{cases}$$

$$\llbracket \text{observe } v_1 \rrbracket (v) \triangleq \begin{cases} 1 & \text{if } v_1 = \top \text{ and } v = \top, \\ 0 & \text{otherwise} \end{cases} \quad \llbracket f(v_1) \rrbracket (v) \triangleq ((T(f))(v_1))(v)$$

$$\llbracket \text{let } x = e_1 \text{ in } e_2 \rrbracket (v) \triangleq \sum_{v'} \llbracket e_1 \rrbracket (v') \times \llbracket e_2[x \mapsto v'] \rrbracket (v)$$

$$\frac{}{\top \rightsquigarrow (\top, \top, \emptyset)} \text{ (C-TRUE)} \quad \frac{}{\text{F} \rightsquigarrow (\text{F}, \top, \emptyset)} \text{ (C-FALSE)} \quad \frac{}{x \rightsquigarrow (\mathbf{x}, \top, \emptyset)} \text{ (C-IDENT)}$$

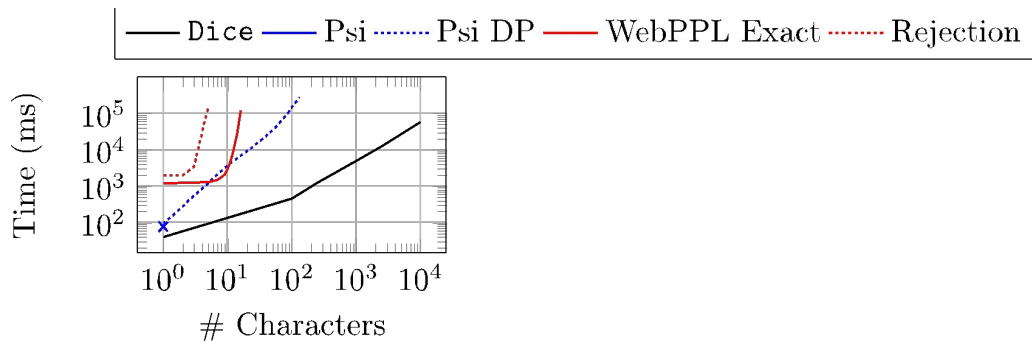
$$\frac{\text{fresh } \mathbf{f}}{\text{flip } \theta \rightsquigarrow (\mathbf{f}, \top, (\mathbf{f} \mapsto \theta, \top, \bar{\mathbf{f}} \mapsto 1 - \theta))} \text{ (C-FLIP)} \quad \frac{\text{aexp } \rightsquigarrow (\varphi, \top, \emptyset)}{\text{observe aexp } \rightsquigarrow (\top, \varphi, \emptyset)} \text{ (C-OBS)}$$

$$\frac{\text{aexp } \rightsquigarrow (\varphi_g, \top, \emptyset) \quad e_T \rightsquigarrow (\varphi_T, \gamma_T, w_T) \quad e_E \rightsquigarrow (\varphi_E, \gamma_E, w_E)}{\text{if aexp then } e_T \text{ else } e_E \rightsquigarrow \left(((\varphi_g \wedge \varphi_T) \vee ((\bar{\varphi}_g \wedge \varphi_E), ((\varphi_g \wedge \gamma_T) \vee ((\bar{\varphi}_g \wedge \gamma_E), w_T \cup w_E)) \right)} \text{ (C-ITE)}$$

$$\frac{e_1 \rightsquigarrow (\varphi_1, \gamma_1, w_1) \quad e_2 \rightsquigarrow (\varphi_2, \gamma_2, w_2)}{\text{let } x = e_1 \text{ in } e_2 \rightsquigarrow (\varphi_2[\mathbf{x} \mapsto \varphi_1], \gamma_1 \wedge \gamma_2[\mathbf{x} \mapsto \varphi_1], w_1 \cup w_2)} \text{ (C-LET)}$$

Experimental Evaluation

- Example from text analysis: breaking a Caesar cipher

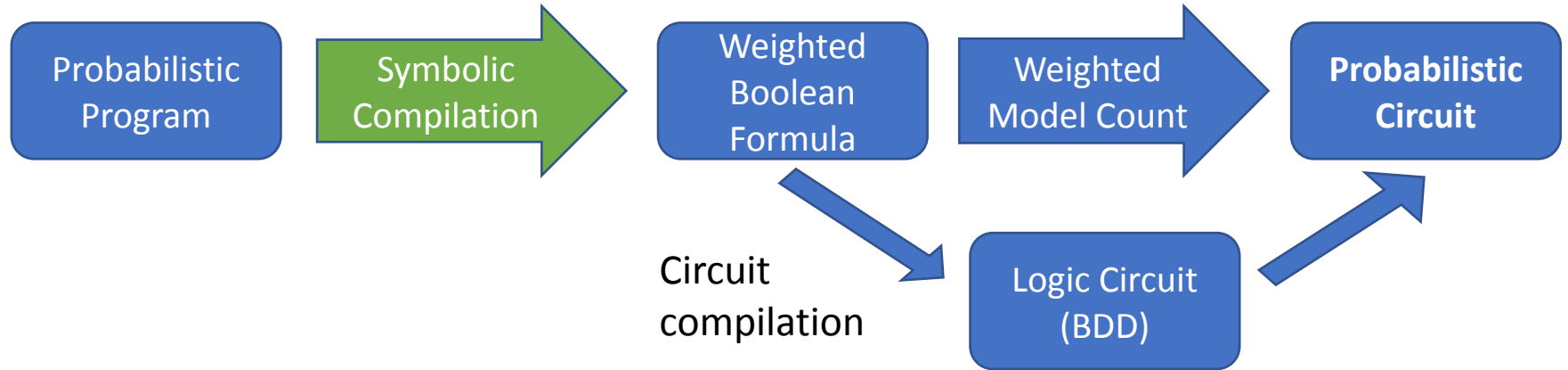


- Competitive with specialized Bayesian network solvers

More program paths than atoms in the universe

| Benchmark | Psi (ms) | DP (ms) | Dice (ms) | # Parameters | # Paths | BDD Size |
|------------|----------|----------|-------------|-------------------|------------------------|-------------------|
| Cancer | 772 | 46 | 13 | 10 | 1.1×10^3 | 28 |
| Survey | 2477 | 152 | 13 | 21 | 1.3×10^4 | 73 |
| Alarm | X | X | 25 | 509 | 1.0×10^{36} | 1.3×10^3 |
| Insurance | X | X | 212 | 984 | 1.2×10^{40} | 1.0×10^5 |
| Hepar2 | X | X | 54 | 48 | 2.9×10^{69} | 1.3×10^3 |
| Hailfinder | X | X | 618 | 2656 | 2.0×10^{76} | 6.5×10^4 |
| Pigs | X | X | 72 | 5618 | 7.3×10^{492} | 35 |
| Water | X | X | 2590 | 1.0×10^4 | 3.2×10^{54} | 5.1×10^4 |
| Munin | X | X | 1866 | 8.1×10^5 | 2.1×10^{1622} | 1.1×10^4 |

Symbolic Compilation in Dice to Probabilistic Circuits



Tractable representations of probability distributions, learnable from data, mapped to GPU/hardware, with many interesting properties!

Learn more about probabilistic circuits?



Tutorial (3h)

Probabilistic Circuits

*Inference
Representations
Learning
Theory*

Antonio Vergari
University of California, Los Angeles

Robert Peharz
TU Eindhoven

YooJung Choi
University of California, Los Angeles

Guy Van den Broeck
University of California, Los Angeles

September 14th, 2020 - Ghent, Belgium - ECML-PKDD 2020

<https://youtu.be/2RAG5-L9R70>

Overview Paper (80p)

Probabilistic Circuits: A Unifying Framework for Tractable Probabilistic Models*

YooJung Choi

Antonio Vergari

Guy Van den Broeck

Computer Science Department

University of California

Los Angeles, CA, USA

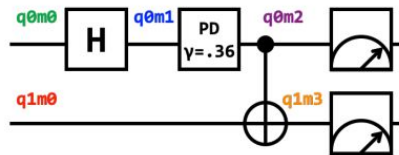
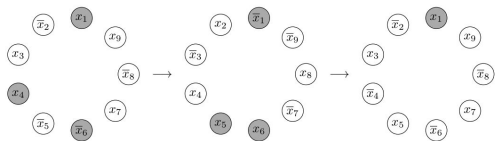
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| 2.2 | Probabilistic Queries | 6 |
| 2.3 | Tractable Probabilistic Inference | 8 |
| 2.4 | Properties of Tractable Probabilistic Models | 9 |

<http://starai.cs.ucla.edu/papers/ProbCirc20.pdf>

If you build it they will come

As soon as ***dice*** was put online people started using it in surprising ways we had not foreseen



Probabilistic Model Checking

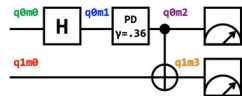


Prism



dice

Quantum Simulation



quantum circuit



probabilistic circuit

If you build it they will come

In both cases, ***dice*** outperforms existing specialized methods on important examples!

Probabilistic Model Checking

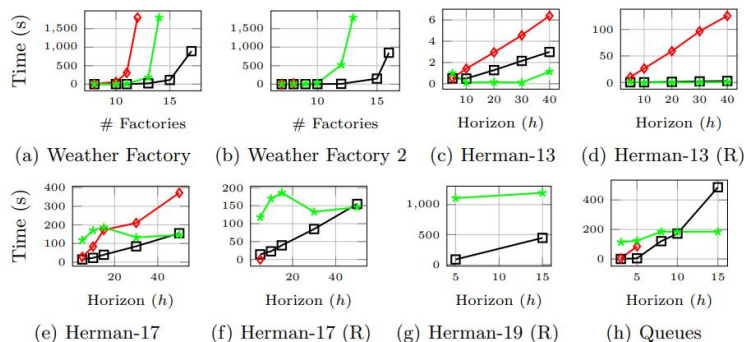
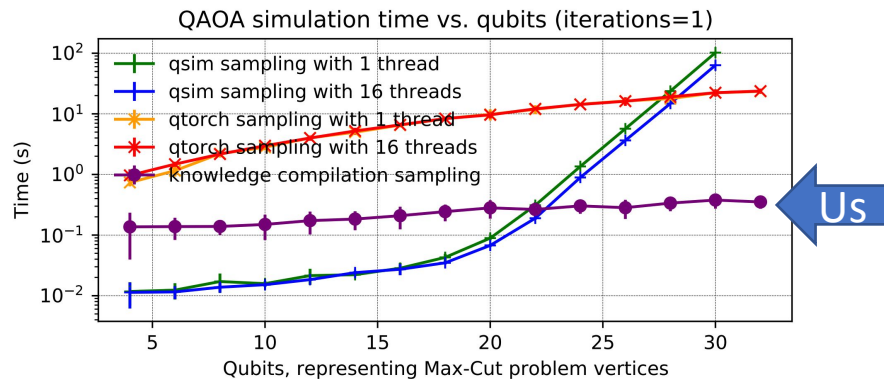


Fig. 9. Scaling plots comparing RUBICON (\square), STORM's symbolic engine (\diamond), and STORM's explicit engine (\triangle). An "(R)" in the caption denotes random parameters.

Check out CAV talk video or ask Steven Holtzen, Sebastian Junges, or Marcell Vazquez-Chanlatte

Quantum Simulation



Competitive with well-known simulators like Google qsim and qtorch [FSC+ PloS one '18] !

Better Inference. How?

Exploit modularity - program structure

1. AI modularity:

Discover contextual independencies and **factorize**

2. PL modularity:

Compile procedure summaries and reuse at each call site

Reason about programs!

Compiler optimizations:

3. Flip hoisting optimization

4. Determinism, optimize integer representation, etc.

Flip Hoisting

```
1 let x = flip 0.1 in
2 let z = flip 0.2 in
3 let y = if x && z then flip 0.3
4     else if x && !z then flip 0.4
5     else flip 0.3
6 in y
```

≡

```
1 let x = flip 0.1 in let z = flip 0.2 in
2 let tmp = flip 0.3 in
3 let y = if x && z then tmp
4     else if x && !z then flip 0.4
5     else tmp
6 in y
```

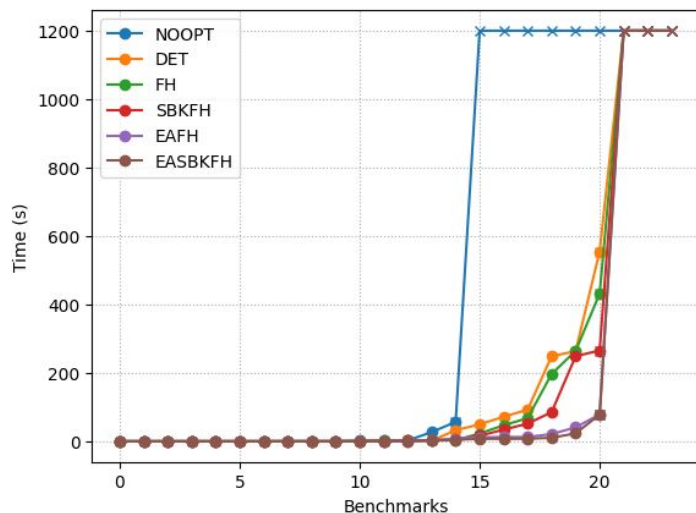
- Fewer flips = smaller compiled circuits = faster
- But, be careful with soundness:

```
flip 0.3 && flip 0.3
```

≠

```
let tmp = flip 0.3 in tmp && tmp;
```

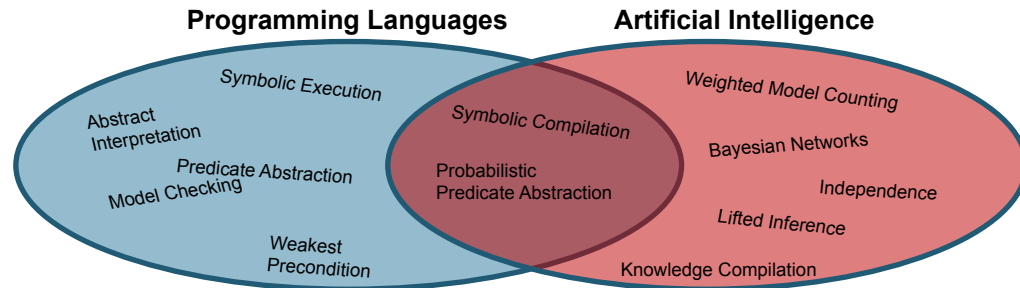
Compiler Optimization Experiments



| Benchmarks | No Opt | Det | FH | SBK+FH | Ea+FH | Ea+SBK+FH |
|------------|-------------|-------------|-------------|-------------|-------------|--------------|
| ALARM | 0.15 | 0.12 | 0.07 | 0.10 | 0.06 | 0.12 |
| ANDES | 56.73 | 32.48 | 3.44 | 3.42 | 12.57 | 7.47 |
| ASIA | 0.06 | 0.03 | 0.03 | 0.03 | 0.02 | 0.02 |
| BARLEY | - | - | - | - | - | - |
| CANCER | 0.04 | 0.03 | 0.03 | 0.03 | 0.02 | 0.02 |
| CHILD | 0.05 | 0.04 | 0.04 | 0.03 | 0.03 | 0.03 |
| DIABETES | - | - | - | - | - | - |
| EARTHQUAKE | 0.03 | 0.03 | 0.03 | 0.03 | 0.02 | 0.02 |
| HAILFINDER | 1.67 | 0.45 | 0.53 | 0.49 | 0.49 | 0.41 |
| HEPAR2 | 0.13 | 0.07 | 0.07 | 0.12 | 0.08 | 0.10 |
| INSURANCE | 0.17 | 0.08 | 0.07 | 0.14 | 0.16 | 0.13 |
| LINK | - | 263.38 | 264.32 | 265.53 | 78.75 | 78.10 |
| MILDEW | - | - | - | - | - | - |
| MUNIN | - | 71.80 | 47.01 | 34.19 | 11.86 | 7.52 |
| MUNIN1 | - | 49.73 | 22.95 | 16.34 | 8.23 | 3.67 |
| MUNIN2 | - | 248.78 | 196.96 | 85.39 | 21.26 | 10.45 |
| MUNIN3 | - | 554.62 | 431.62 | 248.68 | 40.87 | 23.37 |
| MUNIN4 | - | 92.44 | 67.73 | 51.72 | 12.70 | 7.66 |
| PATHFINDER | 2.28 | 1.73 | 2.51 | 5.20 | 1.96 | 4.64 |
| PIGS | 2.33 | 1.87 | 1.58 | 1.54 | 0.20 | 0.14 |
| SACHS | 0.04 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| SURVEY | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| WATER | 27.04 | 1.46 | 1.90 | 0.87 | 1.49 | 0.61 |
| WIN95PTS | 0.09 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |

Conclusions

- Are we already in the age of computational abstractions?
- Probabilistic programs as the new probabilistic knowledge representation language
- Fruitful synthesis of AI and PL/FM



Thanks

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References: <http://starai.cs.ucla.edu/publications/>